SCIKITLEARN USER GUIDE
RELEASE 0213
SCIKITLEARN DEVELOPERS
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- NUMPY 1110
- SCIPY 0170
- JOBLIB 011

SCIKITLEARN PLOTTING CAPABILITIES IE FUNCTIONS START WITH “ PLOT ” REQUIRE MATPLOTLIB 151 SOME OF THE SCIKIT LEARN EXAMPLES MIGHT REQUIRE ONE OR MORE EXTRA DEPENDENCIES SCIKITIMAGE 0123 PANDAS 0180

WARNING SCIKITLEARN 020 WAS THE LAST VERSION TO SUPPORT PYTHON 27 AND PYTHON 34 SCIKITLEARN NOW REQUIRES PYTHON 35 OR NEWER

IF YOU ALREADY HAVE A WORKING INSTALLATION OF NUMPY AND SCIPY THE EASIEST WAY TO INSTALL SCIKITLEARN IS USING PIP

PIP INSTALL U SCIKITLEARN

ORCONDA

CONDA INSTALL SCIKITLEARN

IF YOU HAVE NOT INSTALLED NUMPY OR SCIPY YET YOU CAN ALSO INSTALL THESE USING CONDA OR PIP WHEN USING PIP PLEASE ENSURE THAT BINARY WHEELS ARE USED AND NUMPY AND SCIPY ARE NOT RECOMPILED FROM SOURCE WHICH CAN HAPPEN WHEN USING PARTICULAR CONFIGURATIONS OF OPERATING SYSTEM AND HARDWARE SUCH AS LINUX ON A RASPBERRY PI BUILDING NUMPY AND SCIPY FROM SOURCE CAN BE COMPLEX ESPECIALLY ON WINDOWS AND REQUIRES CAREFUL CONFIGURATION TO ENSURE THAT THEY LINK AGAINST AN OPTIMIZED IMPLEMENTATION OF LINEAR ALGEBRA ROUTINES INSTEAD USE A THIRDPARTY DISTRIBUTION AS DESCRIBED BELOW

IF YOU MUST INSTALL SCIKITLEARN AND ITS DEPENDENCIES WITH PIP YOU CAN INSTALL IT AS SCIKITLEARNALLDEPS THE MOST COMMON USE CASE FOR THIS IS IN A REQUIREMENTSTXT FILE USED AS PART OF AN AUTOMATED BUILD PROCESS FOR A PAAS APPLICATION OR A DOCKER IMAGE THIS OPTION IS NOT INTENDED FOR MANUAL INSTALLATION FROM THE COMMAND LINE
NOTE FOR INSTALLING ON PYPY PYPY3V510 NUMPY 1140 AND SCIPY 110 ARE REQUIRED
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CONDA UPDATE SCIKITLEARN
TO UNINSTALL SCIKITLEARN
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PLEASE MAKE SURE TO INCLUDE A MINIMAL REPRODUCTION CODE SNIPPET IDEALLY SHORTER THAN 10 LINES THAT HIGHLIGHTS YOUR PROBLEM ON A TOY DATASET FOR INSTANCE FROM SKLEARNDATASETS OR RANDOMLY GENERATED WITH FUNCTIONS OF NUMPY RANDOM WITH A FIXED RANDOM SEED PLEASE REMOVE ANY LINE OF CODE THAT IS NOT NECESSARY TO REPRODUCE YOUR PROBLEM THE PROBLEM SHOULD BE REPRODUCIBLE BY SIMPLY COPYPASTING YOUR CODE SNIPPET IN A PYTHON SHELL WITH SCIKITLEARN INSTALLED DO NOT FORGET TO INCLUDE THE IMPORT STATEMENTS
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FOR INSTANCE TO TRAIN A CLASSIFIER ALL YOU NEED IS A 2D ARRAY XFOR THE INPUT VARIABLES AND A 1D ARRAY YFOR THE TARGET VARIABLES THE ARRAY XHOLDS THE FEATURES AS COLUMNS AND SAMPLES AS ROWS THE ARRAY YCONTAINS INTEGER VALUES TO ENCODE THE CLASS MEMBERSHIP OF EACH SAMPLE IN X

128 HOW CAN I LOAD MY OWN DATASETS INTO A FORMAT USABLE BY SCIKITLEARN

GENERALLY SCIKITLEARN WORKS ON ANY NUMERIC DATA STORED AS NUMPY ARRAYS OR SCIPY SPARSE MATRICES OTHER TYPES THAT ARE CONVERTIBLE TO NUMERIC ARRAYS SUCH AS PANDAS DATAFRAME ARE ALSO ACCEPTABLE

FOR MORE INFORMATION ON LOADING YOUR DATA FILES INTO THESE USABLE DATA STRUCTURES PLEASE REFER TO LOADING EXTERNAL DATASETS

129 WHAT ARE THE INCLUSION CRITERIA FOR NEW ALGORITHMS

WE ONLY CONSIDER WELLESTABLISHED ALGORITHMS FOR INCLUSION A RULE OF THUMB IS AT LEAST 3 YEARS SINCE PUBLICATION 200 CITATIONS AND WIDE USE AND USEFULNESS A TECHNIQUE THAT PROVIDES A CLEARCUT IMPROVEMENT EG AN ENHANCED DATA STRUCTURE OR A MORE EFFICIENT APPROXIMATION TECHNIQUE ON A WIDELYUSED METHOD WILL ALSO BE CONSIDERED FOR INCLUSION FROM THE ALGORITHMS OR TECHNIQUES THAT MEET THE ABOVE CRITERIA ONLY THOSE WHICH FIT WELL WITHIN THE CURRENT API OF SCIKITLEARN THAT IS A FITPREDICTTRANSFORM INTERFACE AND ORDINARILY HAVING INPUTOUTPUT THAT IS A NUMPY ARRAY OR SPARSE MATRIX ARE ACCEPTED

THE CONTRIBUTOR SHOULD SUPPORT THE IMPORTANCE OF THE PROPOSED ADDITION WITH RESEARCH PAPERS ANDOR IMPLEMENTATIONS IN OTHER SIMILAR PACKAGES DEMONSTRATE ITS USEFULNESS VIA COMMON USECASESAPPLICATIONS AND CORROBORATE PERFORMANCE IMPROVEMENTS IF ANY WITH BENCHMARKS ANDOR PLOTS IT IS EXPECTED THAT THE PROPOSED ALGORITHM SHOULD OUTPERFORM THE METHODS THAT ARE ALREADY IMPLEMENTED IN SCIKITLEARN AT LEAST IN SOME AREAS

INCLUSION OF A NEW ALGORITHM SPEEDING UP AN EXISTING MODEL IS EASIER IF

• IT DOES NOT INTRODUCE NEW HYPERPARAMETERS AS IT MAKES THE LIBRARY MORE FUTUREPROOF
• IT IS EASY TO DOCUMENT CLEARLY WHEN THE CONTRIBUTION IMPROVES THE SPEED AND WHEN IT DOES NOT FOR INSTANCE “WHEN NFEATURES NSAMPLES”
• BENCHMARKS CLEARLY SHOW A SPEED UP

ALSO NOTE THAT YOUR IMPLEMENTATION NEED NOT BE IN SCIKITLEARN TO BE USED TOGETHER WITH SCIKITLEARN TOOLS YOU CAN IMPLEMENT YOUR FAVORITE ALGORITHM IN A SCIKITLEARN COMPATIBLE WAY UPLOAD IT TO GITHUB AND LET US KNOW WE WILL BE HAPPY TO LIST IT UNDER RELATED PROJECTS IF YOU ALREADY HAVE A PACKAGE ON GITHUB FOLLOWING THE SCIKITLEARN API YOU MAY ALSO BE INTERESTED TO LOOK AT SCIKITLEARNCONTRIB

1210 WHY ARE YOU SO SELECTIVE ON WHAT ALGORITHMS YOU INCLUDE IN SCIKITLEARN

CODE IS MAINTENANCE COST AND WE NEED TO BALANCE THE AMOUNT OF CODE WE HAVE WITH THE SIZE OF THE TEAM AND ADD TO THIS THE FACT THAT COMPLEXITY SCALES NON LINEARLY WITH THE NUMBER OF FEATURES THE PACKAGE RELIES ON CORE DEVELOPERS USING THEIR FREE TIME TO FIX BUGS MAINTAIN CODE AND REVIEW CONTRIBUTIONS ANY ALGORITHM THAT IS ADDED NEEDS FUTURE ATTENTION BY THE DEVELOPERS AT WHICH POINT THE ORIGINAL AUTHOR MIGHT LONG HAVE LOST INTEREST SEE ALSO WHAT ARE THE INCLUSION CRITERIA FOR NEW ALGORITHMS FOR A GREAT READ ABOUT LONGTERM MAINTENANCE ISSUES IN OPENSOURCE SOFTWARE LOOK AT THE EXECUTIVE SUMMARY OF ROADS AND BRIDGES

1211 WHY DID YOU REMOVE HMMS FROM SCIKITLEARN
SEEWILL YOU ADD GRAPHICAL MODELS OR SEQUENCE PREDICTION TO SCIKITLEARN
1212 WILL YOU ADD GRAPHICAL MODELS OR SEQUENCE PREDICTION TO SCIKITLEARN
NOT IN THE FORESEEABLE FUTURE SCIKITLEARN TRIES TO PROVIDE A UNIFIED API FOR THE BASIC TASKS IN MACHINE LEARNING WITH PIPELINES AND METAALGORITHMS LIKE GRID SEARCH TO TIE EVERYTHING TOGETHER THE REQUIRED CONCEPTS APIS ALGORITHMS AND EXPERTISE REQUIRED FOR STRUCTURED LEARNING ARE DIFFERENT FROM WHAT SCIKITLEARN HAS TO OFFER IF WE STARTED DOING ARBITRARY STRUCTURED LEARNING WE'D NEED TO REDESIGN THE WHOLE PACKAGE AND THE PROJECT WOULD LIKELY COLLAPSE UNDER ITS OWN WEIGHT
THERE ARE TWO PROJECT WITH API SIMILAR TO SCIKITLEARN THAT DO STRUCTURED PREDICTION
• PYSTRUCT HANDLES GENERAL STRUCTURED LEARNING FOCUSES ON SSVMS ON ARBITRARY GRAPH STRUCTURES WITH APPROXIMATE INFERENCE DEFINES THE NOTION OF SAMPLE AS AN INSTANCE OF THE GRAPH STRUCTURE
• SEQLEARN HANDLES SEQUENCES ONLY FOCUSES ON EXACT INFERENCE HAS HMMS BUT MOSTLY FOR THE SAKE OF COMPLETE NESS TREATS A FEATURE VECTOR AS A SAMPLE AND USES AN OFFSET ENCODING FOR THE DEPENDENCIES BETWEEN FEATURE VECTORS
1213 WILL YOU ADD GPU SUPPORT
NO OR AT LEAST NOT IN THE NEAR FUTURE THE MAIN REASON IS THAT GPU SUPPORT WILL INTRODUCE MANY SOFTWARE DEPENDENCIES AND INTRODUCE PLATFORM SPECIFIC ISSUES SCIKITLEARN IS DESIGNED TO BE EASY TO INSTALL ON A WIDE VARIETY OF PLATFORMS OUTSIDE OF NEURAL NETWORKS GPUS DON'T PLAY A LARGE ROLE IN MACHINE LEARNING TODAY AND MUCH LARGER GAINS IN SPEED CAN OFTEN BE ACHIEVED BY A CAREFUL CHOICE OF ALGORITHMS
1214 DO YOU SUPPORT PYPY
IN CASE YOU DIDN'T KNOW PYPY IS AN ALTERNATIVE PYTHON IMPLEMENTATION WITH A BUILTIN JUSTINTIME COMPILER EXPERI MENTAL SUPPORT FOR PYPY3V510 HAS BEEN ADDED WHICH REQUIRES NUMPY 1140 AND SCIPY 110
1215 HOW DO I DEAL WITH STRING DATA OR TREES GRAPHS
SCIKITLEARN ESTIMATORS ASSUME YOU'LL FEED THEM REALVALUED FEATURE VECTORS THIS ASSUMPTION IS HARDCODED IN PRETTY MUCH ALL OF THE LIBRARY HOWEVER YOU CAN FEED NONNUMERICAL INPUTS TO ESTIMATORS IN SEVERAL WAYS
IF YOU HAVE TEXT DOCUMENTS YOU CAN USE A TERM FREQUENCY FEATURES SEE TEXT FEATURE EXTRACTION FOR THE BUILTIN TEXT VECTORIZERS FOR MORE GENERAL FEATURE EXTRACTION FROM ANY KIND OF DATA SEE LOADING FEATURES FROM DICTS ANDFEATURE HASHING
ANOTHER COMMON CASE IS WHEN YOU HAVE NONNUMERICAL DATA AND A CUSTOM DISTANCE OR SIMILARITY METRIC ON THESE DATA EXAMPLES INCLUDE STRINGS WITH EDIT DISTANCE AKA LEVENSHTEIN DISTANCE EG DNA OR RNA SEQUENCES THESE CAN BE ENCODED AS NUMBERS BUT DOING SO IS PAINFUL AND ERRORPRONE WORKING WITH DISTANCE METRICS ON ARBITRARY DATA CAN BE DONE IN TWO WAYS
FIRSTLY MANY ESTIMATORS TAKE PRECOMPUTED DISTANCESIMILARITY MATRICES SO IF THE DATASET IS NOT TOO LARGE YOU CAN COMPUTE DISTANCES FOR ALL PAIRS OF INPUTS IF THE DATASET IS LARGE YOU CAN USE FEATURE VECTORS WITH ONLY ONE "FEATURE" WHICH IS AN INDEX INTO A SEPARATE DATA STRUCTURE AND SUPPLY A CUSTOM METRIC FUNCTION THAT LOOKS UP THE ACTUAL DATA IN THIS DATA STRUCTURE EG TO USE DBSCAN WITH LEVENSHTEIN DISTANCES

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 FROM LEVEN IMPORT LEVENSHTEIN
 IMPORT NUMPY AS NP
 FROM SKLEARNCLUSTER IMPORT DBSCAN
DATA ACCTCCTAGAAG ACCTACTAGAAGTT GAATATTAGGCCGA
 DEF LEVMETRICX Y
 I J INTX0 INTY0 EXTRACT INDICES
 RETURN LEVENSHTEINDATAI DATAJ

X NPARANGELENDATARESHAPE1 1
X
ARRAY0
1
2
 WE NEED TO SPECIFY ALGORITUMBRUTE AS THE DEFAULT ASSUMES
 A CONTINUOUS FEATURE SPACE
DBSCANX METRICLEVMETRIC EPS5 MINSAMPLES2 ALGORITHMBRUTE

0 1 ARRAY 0 0 1
THIS USES THE THIRDPARTY EDIT DISTANCE PACKAGE LEVEN
SIMILAR TRICKS CAN BE USED WITH SOME CARE FOR TREE KERNELS GRAPH KERNELS ETC
1216 WHY DO I SOMETIME GET A CRASHFREEZE WITH NJOBS 1 UNDER OSX OR LINUX
SEVERAL SCIKITLEARN TOOLS SUCH AS GRIDSEARCHCV ANDCROSSVALSCORE RELY INTERNALLY ON PYTHON'S
MULTIPROCESSING MODULE TO PARALLELIZE EXECUTION ONTO SEVERAL PYTHON PROCESSES BY PASSING NJOBS 1 AS
ARGUMENT
THE PROBLEM IS THAT PYTHON MULTIPROCESSING DOES AFORK SYSTEM CALL WITHOUT FOLLOWING IT WITH AN EXEC SYSTEM
CALL FOR PERFORMANCE REASONS MANY LIBRARIES LIKE SOME VERSIONS OF ACCELERATE VECLIB UNDER OSX SOME VERSIONS
OF MKL THE OPENMP RUNTIME OF GCC NVIDIA'S CUDA AND PROBABLY MANY OTHERS MANAGE THEIR OWN INTERNAL THREAD
POOL UPON A CALL TO FORK THE THREAD POOL STATE IN THE CHILD PROCESS IS CORRUPTED THE THREAD POOL BELIEVES IT HAS MANY
THREADS WHILE ONLY THE MAIN THREAD STATE HAS BEEN FORKED IT IS POSSIBLE TO CHANGE THE LIBRARIES TO MAKE THEM DETECT
WHEN A FORK HAPPENS AND REINITIALIZE THE THREAD POOL IN THAT CASE WE DID THAT FOR OPENBLAS MERGED UPSTREAM IN
MASTER SINCE 0210 AND WE CONTRIBUTED A PATCH TO GCC'S OPENMP RUNTIME NOT YET REVIEWED
BUT IN THE END THE REAL CULPRIT IS PYTHON'S MULTIPROCESSING THAT DOESFORK WITHOUTEXEC TO REDUCE THE OVERHEAD
OF STARTING AND USING NEW PYTHON PROCESSES FOR PARALLEL COMPUTING UNFORTUNATELY THIS IS A VIOLATION OF THE POSIX
STANDARD AND THEREFORE SOME SOFTWARE EDITORS LIKE APPLE REFUSE TO CONSIDER THE LACK OF FORKSAFETY IN ACCELERATE
VECLIB AS A BUG
IN PYTHON 34 IT IS NOW POSSIBLE TO CONFIGURE MULTIPROCESSING TO USE THE 'FORKSERVER' OR 'SPAWN' START METHODS
INSTEAD OF THE DEFAULT 'FORK' TO MANAGE THE PROCESS POOLS TO WORK AROUND THIS ISSUE WHEN USING SCIKITLEARN YOU
CAN SET THE JOBLIBSTARTMETHOD ENVIRONMENT VARIABLE TO 'FORKSERVER' HOWEVER THE USER SHOULD BE AWARE THAT
USING THE 'FORKSERVER' METHOD PREVENTS JOBLIBPARALLEL TO CALL FUNCTION INTERACTIVELY DEFINED IN A SHELL SESSION
IF YOU HAVE CUSTOM CODE THAT USES MULTIPROCESSING DIRECTLY INSTEAD OF USING IT VIA JOBLIB YOU CAN ENABLE THE
'FORKSERVER' MODE GLOBALLY FOR YOUR PROGRAM INSERT THE FOLLOWING INSTRUCTIONS IN YOUR MAIN SCRIPT
IMPORT MULTIPROCESSING
 OTHER IMPORTS CUSTOM CODE LOAD DATA DEFINE MODEL
IFNAME MAIN
MULTIPROCESSINGSETSTARTMETHODFORKSERVER

CALL SCIKITLEARN UTILS WITH NJOBS 1 HERE
YOU CAN FIND MORE DEFAULT ON THE NEW START METHODS IN THE MULTIPROCESSING DOCUMENTATION
1217 WHY DOES MY JOB USE MORE CORES THAN SPECIFIED WITH NJOBS UNDER OSX OR LINUX
THIS HAPPENS WHEN VECTORIZED NUMPY OPERATIONS ARE HANDLED BY LIBRARIES SUCH AS MKL OR OPENBLAS WHILE SCIKITLEARN ADHERES TO THE LIMIT SET BY NJOBS NUMPY OPERATIONS VECTORIZED USING MKL OR OPENBLAS WILL MAKE USE OF MULTIPLE THREADS WITHIN EACH SCIKITLEARN JOB THREAD OR PROCESS
THE NUMBER OF THREADS USED BY THE BLAS LIBRARY CAN BE SET VIA AN ENVIRONMENT VARIABLE FOR EXAMPLE TO SET THE MAXIMUM NUMBER OF THREADS TO SOME INTEGER VALUE N THE FOLLOWING ENVIRONMENT VARIABLES SHOULD BE SET
• FOR MKL EXPORT MKLNUMTHREADSN
• FOR OPENBLAS EXPORT OPENBLASNUMTHREADSN
1218 WHY IS THERE NO SUPPORT FOR DEEP OR REINFORCEMENT LEARNING WILL THERE BE SUPPORT FOR DEEP OR REINFORCEMENT LEARNING IN SCIKITLEARN
DEEP LEARNING AND REINFORCEMENT LEARNING BOTH REQUIRE A RICH VOCABULARY TO DEFINE AN ARCHITECTURE WITH DEEP LEARNING ADDITIONALLY REQUIRING GPUS FOR EFFICIENT COMPUTING HOWEVER NEITHER OF THESE FIT WITHIN THE DESIGN CONSTRAINTS OF SCIKITLEARN AS A RESULT DEEP LEARNING AND REINFORCEMENT LEARNING ARE CURRENTLY OUT OF SCOPE FOR WHAT SCIKITLEARN SEEKS TO ACHIEVE
YOU CAN FIND MORE INFORMATION ABOUT ADDITION OF GPU SUPPORT AT WILL YOU ADD GPU SUPPORT
1219 WHY IS MY PULL REQUEST NOT GETTING ANY ATTENTION
THE SCIKITLEARN REVIEW PROCESS TAKES A SIGNIFICANT AMOUNT OF TIME AND CONTRIBUTORS SHOULD NOT BE DISCOURAGED BY A LACK OF ACTIVITY OR REVIEW ON THEIR PULL REQUEST WE CARE A LOT ABOUT GETTING THINGS RIGHT THE FIRST TIME AS MAINTENANCE AND LATER CHANGE COMES AT A HIGH COST WE RARELY RELEASE ANY “EXPERIMENTAL” CODE SO ALL OF OUR CONTRIBUTIONS WILL BE SUBJECT TO HIGH USE IMMEDIATELY AND SHOULD BE OF THE HIGHEST QUALITY POSSIBLE INITIALLY
BEYOND THAT SCIKITLEARN IS LIMITED IN ITS REVIEWING BANDWIDTH MANY OF THE REVIEWERS AND CORE DEVELOPERS ARE WORKING ON SCIKITLEARN ON THEIR OWN TIME IF A REVIEW OF YOUR PULL REQUEST COMES SLOWLY IT IS LIKELY BECAUSE THE REVIEWERS ARE BUSY WE ASK FOR YOUR UNDERSTANDING AND REQUEST THAT YOU NOT CLOSE YOUR PULL REQUEST OR DISCONTINUE YOUR WORK SOLELY BECAUSE OF THIS REASON
1220 HOW DO I SET A RANDOMSTATE FOR AN ENTIRE EXECUTION
FOR TESTING AND REPLICABILITY IT IS OFTEN IMPORTANT TO HAVE THE ENTIRE EXECUTION CONTROLLED BY A SINGLE SEED FOR THE PSEUDO RANDOM NUMBER GENERATOR USED IN ALGORITHMS THAT HAVE A RANDOMIZED COMPONENT SCIKITLEARN DOES NOT USE ITS OWN GLOBAL RANDOM STATE WHENEVER A RANDOMSTATE INSTANCE OR AN INTEGER RANDOM SEED IS NOT PROVIDED AS AN ARGUMENT IT RELIES ON THE NUMPY GLOBAL RANDOM STATE WHICH CAN BE SET USING NUMPYRANDOMSEED FOR EXAMPLE TO SET AN EXECUTION’S NUMPY GLOBAL RANDOM STATE TO 42 ONE COULD EXECUTE THE FOLLOWING IN HIS OR HER SCRIPT
IMPORT NUMPY AS NP
NPRANDOMSEED42

HOWEVER A GLOBAL RANDOM STATE IS PRONE TO MODIFICATION BY OTHER CODE DURING EXECUTION THUS THE ONLY WAY TO ENSURE REPLICABILITY IS TO PASS RANDOMSTATE INSTANCES EVERYWHERE AND ENSURE THAT BOTH ESTIMATORS AND CROSSVALIDATION SPLITTERS HAVE THEIR RANDOMSTATE PARAMETER SET

1221 WHY DO CATEGORICAL VARIABLES NEED PREPROCESSING IN SCIKITLEARN COMPARED TO OTHER TOOLS

MOST OF SCIKITLEARN ASSUMES DATA IS IN NUMPY ARRAYS OR SCIPY SPARSE MATRICES OF A SINGLE NUMERIC DTYPE THESE DO NOT EXPLICITLY REPRESENT CATEGORICAL VARIABLES AT PRESENT THUS UNLIKE R'S DATAFRAMES OR PANDASDATAFRAME WE REQUIRE EXPLICIT CONVERSION OF CATEGORICAL FEATURES TO NUMERIC VALUES AS DISCUSSED IN ENCODING CATEGORICAL FEATURES SEE ALSO COLUMN TRANSFORMER WITH MIXED TYPES FOR AN EXAMPLE OF WORKING WITH HETEROGENEOUS EG CATEGORICAL AND NUMERIC DATA

1222 WHY DOES SCIKITLEARN NOT DIRECTLY WORK WITH FOR EXAMPLE PANDASDATAFRAME

THE HOMOGENEOUS NUMPY AND SCIPY DATA OBJECTS CURRENTLY EXPECTED ARE MOST EFFICIENT TO PROCESS FOR MOST OPERATIONS EXTENSIVE WORK WOULD ALSO BE NEEDED TO SUPPORT PANDAS CATEGORICAL TYPES RESTRICTING INPUT TO HOMOGENEOUS TYPES THEREFORE REDUCES MAINTENANCE COST AND ENCOURAGES USAGE OF EFFICIENT DATA STRUCTURES

13 SUPPORT

THERE ARE SEVERAL WAYS TO GET IN TOUCH WITH THE DEVELOPERS

131 MAILING LIST

- THE MAIN MAILING LIST IS SCIKITLEARN
- THERE IS ALSO A COMMIT LIST SCIKITLEARNCOMMITS WHERE UPDATES TO THE MAIN REPOSITORY AND TEST FAILURES GET NOTIFIED

132 USER QUESTIONS

- SOME SCIKITLEARN DEVELOPERS SUPPORT USERS ON STACKOVERFLOW USING THE SCIKITLEARN TAG
- FOR GENERAL THEORETICAL OR METHODOLOGICAL MACHINE LEARNING QUESTIONS STACK EXCHANGE IS PROBABLY A MORE SUITABLE VENUE

IN BOTH CASES PLEASE USE A DESCRIPTIVE QUESTION IN THE TITLE FIELD EG NO "PLEASE HELP WITH SCIKITLEARN" AS THIS IS NOT A QUESTION AND PUT DETAILS ON WHAT YOU TRIED TO ACHIEVE WHAT WERE THE EXPECTED RESULTS AND WHAT YOU OBSERVED INSTEAD IN THE DETAILS FIELD

CODE AND DATA SNIPPETS ARE WELCOME MINIMALISTIC UP TO 20 LINES LONG REPRODUCTION SCRIPT VERY HELPFUL

PLEASE DESCRIBE THE NATURE OF YOUR DATA AND THE HOW YOU PREPROCESSED IT WHAT IS THE NUMBER OF SAMPLES WHAT IS THE NUMBER AND TYPE OF FEATURES ID CATEGORICAL OR NUMERICAL AND FOR SUPERVISED LEARNING TASKS WHAT TARGET ARE YOUR TRYING TO PREDICT BINARY MULTICLASS 1 OUT OF NCLASSES OR MULTILABEL KOUT OFNCLASSES CLASSIFICATION OR CONTINUOUS VARIABLE REGRESSION

133 BUG TRACKER
IF YOU THINK YOU’VE ENCOUNTERED A BUG PLEASE REPORT IT TO THE ISSUE TRACKER
HTTPSGITHUBCOMSCIKITLEARNSCIKITLEARNISSUES
DON’T FORGET TO INCLUDE
• STEPS OR BETTER SCRIPT TO REPRODUCE
• EXPECTED OUTCOME
• OBSERVED OUTCOME OR PYTHON OR GDB TRACEBACKS
TO HELP DEVELOPERS FIX YOUR BUG FASTER PLEASE LINK TO A HTTPSGISTGITHUBCOM HOLDING A STANDALONE MINIMALISTIC PYTHON SCRIPT THAT REPRODUCES YOUR BUG AND OPTIONALLY A MINIMALISTIC SUBSAMPLE OF YOUR DATASET FOR INSTANCE EXPORTED AS CSV FILES USINGNUMPYSAVETXT
NOTE GISTS ARE GIT CLONEABLE REPOSITORIES AND THUS YOU CAN USE GIT TO PUSH DATAFILES TO THEM
134 IRC
SOME DEVELOPERS LIKE TO HANG OUT ON CHANNEL SCIKITLEARN ONIRCFREENODENET
IF YOU DO NOT HAVE AN IRC CLIENT OR ARE BEHIND A FIREWALL THIS WEB CLIENT WORKS FINE HTTPSWEBCHATFREENODENET
135 DOCUMENTATION RESOURCES
THIS DOCUMENTATION IS RELATIVE TO 0213 DOCUMENTATION FOR OTHER VERSIONS CAN BE FOUND HERE
PRINTABLE PDF DOCUMENTATION FOR OLD VERSIONS CAN BE FOUND HERE
14 RELATED PROJECTS
PROJECTS IMPLEMENTING THE SCIKITLEARN ESTIMATOR API ARE ENCOURAGED TO USE THE SCIKITLEARNCONTRIB TEMPLATE WHICH FACILITATES BEST PRACTICES FOR TESTING AND DOCUMENTING ESTIMATORS THE SCIKITLEARNCONTRIB GITHUB ORGANISATION ALSO ACCEPTS HIGHQUALITY CONTRIBUTIONS OF REPOSITORIES CONFORMING TO THIS TEMPLATE
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• SKLEARNXARRAY PROVIDES COMPATIBILITY OF SCIKITLEARN ESTIMATORS WITH XARRAY DATA STRUCTURES
AUTOML
• AUTOML AUTOMATED MACHINE LEARNING FOR PRODUCTION AND ANALYTICS BUILT ON SCIKITLEARN AND RELATED PROJECTS TRAINS A PIPELINE WTH ALL THE STANDARD MACHINE LEARNING STEPS TUNED FOR PREDICTION SPEED AND EASE OF TRANSFER TO PRODUCTION ENVIRONMENTS
• AUTOSKLEARN AN AUTOMATED MACHINE LEARNING TOOLKIT AND A DROPIN REPLACEMENT FOR A SCIKITLEARN ESTIMATOR

• TPOT AN AUTOMATED MACHINE LEARNING TOOLKIT THAT OPTIMIZES A SERIES OF SCIKITLEARN OPERATORS TO DESIGN A MACHINE LEARNING PIPELINE INCLUDING DATA AND FEATURE PREPROCESSORS AS WELL AS THE ESTIMATORS WORKS AS A DROPIN REPLACEMENT FOR A SCIKITLEARN ESTIMATOR
• SCIKITOPTIMIZE A LIBRARY TO MINIMIZE VERY EXPENSIVE AND NOISY BLACKBOX FUNCTIONS IT IMPLEMENTS SEVERAL METHODS FOR SEQUENTIAL MODELBASED OPTIMIZATION AND INCLUDES A REPLACEMENT FOR GRIDSEARCHCV OR RANDOMIZEDSEARCHCV TO DO CROSSVALIDATED PARAMETER SEARCH USING ANY OF THESE STRATEGIES

EXPERIMENTATION FRAMEWORKS

• REP ENVIRONMENT FOR CONDUCTING DATADRIVEN RESEARCH IN A CONSISTENT AND REPRODUCIBLE WAY
• ML FRONTEND PROVIDES DATASET MANAGEMENT AND SVM FITTINGPREDICTION THROUGH WEBBASED AND PROGRAMMATIC INTERFACES
• SCIKITLEARN LABORATORY A COMMANDLINE WRAPPER AROUND SCIKITLEARN THAT MAKES IT EASY TO RUN MACHINE LEARNING EXPERIMENTS WITH MULTIPLE LEARNERS AND LARGE FEATURE SETS
• XCESSIV IS A NOTEBOOKLIKE APPLICATION FOR QUICK SCALABLE AND AUTOMATED HYPERPARAMETER TUNING AND STACKED ENSEMBLING PROVIDES A FRAMEWORK FOR KEEPING TRACK OF MODELHYPERPARAMETER COMBINATIONS

MODEL INSPECTION AND VISUALISATION

• ELI5 A LIBRARY FOR DEBUGGINGINSPECTING MACHINE LEARNING MODELS AND EXPLAINING THEIR PREDICTIONS
• MLXTEND INCLUDES MODEL VISUALIZATION UTILITIES
• SCIKITPLOT A VISUALIZATION LIBRARY FOR QUICK AND EASY GENERATION OF COMMON PLOTS IN DATA ANALYSIS AND MACHINE LEARNING
• YELLOWBRICK A SUITE OF CUSTOM MATPLOTLIB VISUALIZERS FOR SCIKITLEARN ESTIMATORS TO SUPPORT VISUAL FEATURE ANALYSIS

MODEL SELECTION EVALUATION AND DIAGNOSTICS

MODEL EXPORT FOR PRODUCTION

• ONNXMLTOOLS SERIALIZES MANY SCIKITLEARN PIPELINES TO ONNX FOR INTERCHANGE AND PREDICTION
• SKLEARN2PMML SERIALIZATION OF A WIDE VARIETY OF SCIKITLEARN ESTIMATORS AND TRANSFORMERS INTO PMML WITH THE HELP OF JPMMLSKLEARN LIBRARY
• SKLEARNPORTER TRANSPILE TRAINED SCIKITLEARN MODELS TO C JAVA JAVASCRIPT AND OTHERS
• SKLEARNCOMPILEDTREES GENERATE A C IMPLEMENTATION OF THE PREDICT FUNCTION FOR DECISION TREES AND ENSEMBLES TRAINED BY SKLEARN USEFUL FOR LATENCYSENSITIVE PRODUCTION ENVIRONMENTS

142 OTHER ESTIMATORS AND TASKS

NOT EVERYTHING BELONGS OR IS MATURE ENOUGH FOR THE CENTRAL SCIKITLEARN PROJECT THE FOLLOWING ARE PROJECTS PROVIDING INTERFACES SIMILAR TO SCIKITLEARN FOR ADDITIONAL LEARNING ALGORITHMS INFRASTRUCTURES AND TASKS

STRUCTURED LEARNING

• SEQLEARN SEQUENCE CLASSIFICATION USING HMMS OR STRUCTURED PERCEPTRON
• HMMLEARN IMPLEMENTATION OF HIDDEN MARKOV MODELS THAT WAS PREVIOUSLY PART OF SCIKITLEARN
• PYSTRUCT GENERAL CONDITIONAL RANDOM FIELDS AND STRUCTURED PREDICTION
• POMEGRANATE PROBABILISTIC MODELLING FOR PYTHON WITH AN EMPHASIS ON HIDDEN MARKOV MODELS
• SKLEARNCRFSUITE LINEARCHAIN CONDITIONAL RANDOM FIELDS CRFSUITE WRAPPER WITH SKLEARNLIKE API

DEEP NEURAL NETWORKS ETC

• PYLEARN2 A DEEP LEARNING AND NEURAL NETWORK LIBRARY BUILD ON THEANO WITH SCIKITLEARN LIKE INTERFACE

• SKLEARNTHEANO SCIKITLEARN COMPATIBLE ESTIMATORS TRANSFORMERS AND DATASETS WHICH USE THEANO INTERNALLY
• NOLEARN A NUMBER OF WRAPPERS AND ABSTRACTIONS AROUND EXISTING NEURAL NETWORK LIBRARIES
• KERAS DEEP LEARNING LIBRARY CAPABLE OF RUNNING ON TOP OF EITHER TENSORFLOW OR THEANO
• LASAGNE A LIGHTWEIGHT LIBRARY TO BUILD AND TRAIN NEURAL NETWORKS IN THEANO
• SKORCH A SCIKITLEARN COMPATIBLE NEURAL NETWORK LIBRARY THAT WRAPS PYTORCH

BROAD SCOPE

• MLXTEND INCLUDES A NUMBER OF ADDITIONAL ESTIMATORS AS WELL AS MODEL VISUALIZATION UTILITIES
• SPARKITLEARN SCIKITLEARN API AND FUNCTIONALITY FOR PYSPARK'S DISTRIBUTED MODELLING

OTHER REGRESSION AND CLASSIFICATION

• XGBOOST OPTIMISED GRADIENT BOOSTED DECISION TREE LIBRARY
• MLENSEMBLE GENERALIZED ENSEMBLE LEARNING STACKING BLENDING SUBSEMBLE DEEP ENSEMBLES ETC
• LIGHTNING FAST STATEOFTHEART LINEAR MODEL SOLVERS SDCA ADAGRAD SVRG SAG ETC
• PYEARTH MULTIVARIATE ADAPTIVE REGRESSION SPLINES
• KERNEL REGRESSION IMPLEMENTATION OF NADARAYAWATSON KERNEL REGRESSION WITH AUTOMATIC BANDWIDTH SELECTION
• GPLEARN GENETIC PROGRAMMING FOR SYMBOLIC REGRESSION TASKS
• MULTIISOTONIC ISOTONIC REGRESSION ON MULTIDIMENSIONAL FEATURES
• SCIKITMULTILEARN MULTILABEL CLASSIFICATION WITH FOCUS ON LABEL SPACE MANIPULATION
• SEGLEARN TIME SERIES AND SEQUENCE LEARNING USING SLIDING WINDOW SEGMENTATION

DECOMPOSITION AND CLUSTERING

• LDA FAST IMPLEMENTATION OF LATENT DIRICHLET ALLOCATION IN CYTHON WHICH USES GIBBS SAMPLING
TO SAMPLE FROM THE TRUE POSTERIOR DISTRIBUTION SCIKITLEARN'S SKLEARNDECOMPOSITION
LATENTDIRICHLETALLOCATION IMPLEMENTATION USES VARIATIONAL INFERENCE TO SAMPLE FROM A TRACTABLE
APPROXIMATION OF A TOPIC MODEL'S POSTERIOR DISTRIBUTION
• SPARSE FILTERING UNSUPERVISED FEATURE LEARNING BASED ON SPARSEFILTERING
• KMODES KMODES CLUSTERING ALGORITHM FOR CATEGORICAL DATA AND SEVERAL OF ITS VARIATIONS
• HDBSCAN HDBSCAN AND ROBUST SINGLE LINKAGE CLUSTERING ALGORITHMS FOR ROBUST VARIABLE DENSITY CLUSTERING
• SPHERECLUSTER SPHERICAL KMEANS AND MIXTURE OF VON MISES FISHER CLUSTERING ROUTINES FOR DATA ON THE UNIT HYPER
SPHERE

PREPROCESSING

• CATEGORICALENCODING A LIBRARY OF SKLEARN COMPATIBLE CATEGORICAL VARIABLE ENCODERS
• IMBALANCEDLEARN VARIOUS METHODS TO UNDER AND OVERSAMPLE DATASETS

OTHER PACKAGES USEFUL FOR DATA ANALYSIS AND MACHINE LEARNING

• PANDAS TOOLS FOR WORKING WITH HETEROGENEOUS AND COLUMNAR DATA RELATIONAL QUERIES TIME SERIES AND BASIC STATIS
TICS
• THEANO A CPUGPU ARRAY PROCESSING FRAMEWORK GEARED TOWARDS DEEP LEARNING RESEARCH

• STATSMODELS ESTIMATING AND ANALYSING STATISTICAL MODELS MORE FOCUSED ON STATISTICAL TESTS AND LESS ON PREDICTION THAN SCIKITLEARN
• PYMC BAYESIAN STATISTICAL MODELS AND FITTING ALGORITHMS
• SACRED TOOL TO HELP YOU CONFIGURE ORGANIZE LOG AND REPRODUCE EXPERIMENTS
• SEABORN VISUALIZATION LIBRARY BASED ON MATPLOTLIB IT PROVIDES A HIGHLEVEL INTERFACE FOR DRAWING ATTRACTIVE STATISTICAL GRAPHICS
• DEEP LEARNING A CURATED LIST OF DEEP LEARNING SOFTWARE LIBRARIES

DOMAIN SPECIFIC PACKAGES

• SCIKITIMAGE IMAGE PROCESSING AND COMPUTER VISION IN PYTHON
• NATURAL LANGUAGE TOOLKIT NLTK NATURAL LANGUAGE PROCESSING AND SOME MACHINE LEARNING
• GENSIM A LIBRARY FOR TOPIC MODELLING DOCUMENT INDEXING AND SIMILARITY RETRIEVAL
• NILEARN MACHINE LEARNING FOR NEUROIMAGING
• ASTROML MACHINE LEARNING FOR ASTRONOMY
• MSMBUILDER MACHINE LEARNING FOR PROTEIN CONFORMATIONAL DYNAMICS TIME SERIES
• SCIKITSURPRISE A SCIKIT FOR BUILDING AND EVALUATING RECOMMENDER SYSTEMS

144 SNIPPETS AND TIDBITS

THE WIKI HAS MORE

15 ABOUT US

151 HISTORY

THIS PROJECT WAS STARTED IN 2007 AS A GOOGLE SUMMER OF CODE PROJECT BY DAVID COURNAPEAU LATER THAT YEAR MATTHIEU BRUCHER STARTED WORK ON THIS PROJECT AS PART OF HIS THESIS

IN 2010 FABIAN PEDREGOSA GAEL VAROQUAUX ALEXANDRE GRAMFORT AND VINCENT MICHEL OF INRIA TOOK LEADERSHIP OF THE PROJECT AND MADE THE FIRST PUBLIC RELEASE FEBRUARY THE 1ST 2010 SINCE THEN SEVERAL RELEASES HAVE APPEARED FOLLOWING A 3 MONTH CYCLE AND A THRIVING INTERNATIONAL COMMUNITY HAS BEEN LEADING THE DEVELOPMENT

152 GOVERNANCE

THE DECISION MAKING PROCESS AND GOVERNANCE STRUCTURE OF SCIKITLEARN IS LAID OUT IN THE GOVERNANCE DOCUMENT

153 AUTHORS

THE FOLLOWING PEOPLE ARE CURRENTLY CORE CONTRIBUTORS TO SCIKITLEARN’S DEVELOPMENT AND MAINTENANCE

PLEASE DO NOT EMAIL THE AUTHORS DIRECTLY TO ASK FOR ASSISTANCE OR REPORT ISSUES INSTEAD PLEASE SEE WHAT’S THE BEST WAY TO ASK QUESTIONS ABOUT SCIKITLEARN IN THE FAQ

SEE ALSO

154 EMERITUS CORE DEVELOPERS
THE FOLLOWING PEOPLE HAVE BEEN ACTIVE CONTRIBUTORS IN THE PAST BUT ARE NO LONGER ACTIVE IN THE PROJECT
• ALEXANDER FABISCH
• ALEXANDRE PASSOS
• ANGEL SOLER GOLLONET
• ARNAUD JOLY
• CHRIS GORGOLEWSKI
• DAVID COURNAPEAU
• DAVID WARDEFARLEY
• EDUARD DUCHESNAY
• FABIAN PEDRAGOSA
• GILLES LOUPPE
• JACOB SCHREIBER
• JAKE VANDERPLAS
• JAQUES GROBLER
• JARROD MILLMAN
• KYLE KASTNER
• LARS BUITINCK
• MANOJ KUMAR
• MATHIEU BLONDEL
• MATTHIEU BRUCHER
• NOEL DAWE
• PAOLO LOSI
• PETER PRETTENHOFER
• RAGHAV RAJAGOPALAN
• ROBERT LAYTON
• RON WEISS
• SATRAJIT GHOSH
• SHIQIAO DU
• THOUIS RAY JONES
• VINCENT DUBOURG
• VINCENT MICHEL
• VIRGILE FRITSCH
• WEI LI
15 ABOUT US 13

155 CITING SCIKITLEARN

IF YOU USE SCIKITLEARN IN A SCIENTIFIC PUBLICATION WE WOULD APPRECIATE CITATIONS TO THE FOLLOWING PAPER

SCIKITLEARN MACHINE LEARNING IN PYTHON PEDREGOSA ET AL JMLR 12 PP 28252830 2011

BIBTEX ENTRY

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ARTICLE SCIKITLEARN
TITLESCIKITLEARN MACHINE LEARNING INPYTHON
AUTHORPEDREGOSA F ANDVAROQUAUX G ANDGRAMFORT A ANDMICHEL V
ANDTHIRION B ANDGRISEL O ANDBLONDEL M ANDPRETTENHOFER P
ANDWEISS R ANDDUBOURG V ANDVANDERPLAS J ANDPASSOS A AND
COURNAPEAU D ANDBRUCHER M ANDPERROT M ANDDUCHESNAY E
JOURNALJOURNAL OF MACHINE LEARNING RESEARCH
VOLUME12
PAGES28252830
YEAR2011
```

IF YOU WANT TO CITE SCIKITLEARN FOR ITS API OR DESIGN YOU MAY ALSO WANT TO CONSIDER THE FOLLOWING PAPER

API DESIGN FOR MACHINE LEARNING SOFTWARE EXPERIENCES FROM THE SCIKITLEARN PROJECT BUITINCK ET AL 2013

BIBTEX ENTRY

```
INPROCEEDINGS SKLEARNAPI
AUTHOR LARS BUITINCK ANDGILLES LOUPPE ANDMATHIEU BLONDEL AND
FABIAN PEDREGOSA ANDANDREAS MUELLER ANDOLIVIER GRISEL AND
VLAD NICULAE ANDPETER PRETTENHOFER ANDALEXANDRE GRAMFORT
ANDJAQUES GROBLER ANDROBERT LAYTON ANDJAKE VANDERPLAS AND
ARNAUD JOLY ANDBRIAN HOLT ANDGAEL VAROQUAUX
TITLE API DESIGN FORMACHINE LEARNING SOFTWARE EXPERIENCES FROM
‹→THESCIKITLEARN
PROJECT
BOOKTITLE ECML PKDD WORKSHOP LANGUAGES FORDATA MINING ANDMACHINE
‹→LEARNING
YEAR 2013
PAGES 108122
```

156 ARTWORK

HIGH QUALITY PNG AND SVG LOGOS ARE AVAILABLE IN THE DOCLOGOS SOURCE DIRECTORY

157 FUNDING

INRIA ACTIVELY SUPPORTS THIS PROJECT IT HAS PROVIDED FUNDING FOR FABIAN PEDREGOSA 20102012 JAQUES GROB
LER 20122013 AND OLIVIER GRISEL 20132017 TO WORK ON THIS PROJECT FULLTIME IT ALSO HOSTS CODING SPRINTS AND
OTHER EVENTS
PARISSACLAY CENTER FOR DATA SCIENCE FUNDED ONE YEAR
FOR A DEVELOPER TO WORK ON THE PROJECT FULLTIME 20142015 AND 50 OF THE TIME OF GUILLAUME LEMAITRE 2016
2017
NYU MOORESLOAN DATA SCIENCE ENVIRONMENT FUNDED AN
DREAS MUELLER 20142016 TO WORK ON THIS PROJECT THE MOORESLOAN DATA SCIENCE ENVIRONMENT ALSO FUNDS SEV
ERAL STUDENTS TO WORK ON THE PROJECT PARTTIME
TÉLÉCOM PARIS
TECH FUNDED MANOJ KUMAR 2014 TOM DUPRÉ LA TOUR 2015 RAGHAV RV 20152017 THIERRY GUILLEMOT 2016
2017 AND ALBERT THOMAS 2017 TO WORK ON SCIKITLEARN
COLUMBIA UNIVERSITY FUNDS AN
DREAS MÜLLER SINCE 2016
ANDREAS MÜLLER ALSO RECEIVED A GRANT TO IMPROVE SCIKITLEARN
FROM THE ALFRED P SLOAN FOUNDATION IN 2017
THE UNIVERSITY OF

SCIKITLEARN USER GUIDE RELEASE 0213
SYDNEY FUNDS JOEL NOTHMAN SINCE JULY 2017
THE LABEX DIGI
COSME FUNDED NICOLAS GOIX 20152016 TOM DUPRÉ LA TOUR 20152016 AND 20172018 MATHURIN MASSIAS 2018
2019 TO WORK PART TIME ON SCIKITLEARN DURING THEIR PHDS IT ALSO FUNDED A SCIKITLEARN CODING SPRINT IN 2015
THE FOLLOWING STUDENTS WERE SPONSORED BY GOOGLE TO WORK ON
SCIKITLEARN THROUGH THE GOOGLE SUMMER OF CODE PROGRAM
• 2007 DAVID COURNAPEAU
• 2011 VLAD NICULAE
• 2012 VLAD NICULAE IMMANUEL BAYER
• 2013 KEMAL EREN NICOLAS TRÉSEGNIE
• 2014 HAMZEH ALSALHI ISSAM LARADJI MAHESHAKYA WIJEWARDENA MANOJ KUMAR
• 2015 RAGHAV RV WEI XUE
• 2016 NELSON LIU YENCHEN LIN
IT ALSO PROVIDED FUNDING FOR SPRINTS AND EVENTS AROUND SCIKITLEARN IF YOU WOULD LIKE TO PARTICIPATE IN THE NEXT GOOGLE SUMMER OF CODE PROGRAM PLEASE SEE THIS PAGE
THE NEURODEBIAN PROJECT PROVIDING DEBIAN PACKAGING AND CONTRIBUTIONS IS SUPPORTED BY DR JAMES V HAXBY DART MOUTH COLLEGE
THE PSF HELPED FIND AND MANAGE FUNDING FOR OUR 2011 GRANADA SPRINT MORE INFORMATION CAN BE FOUND HERE
TINYCLUES FUNDED THE 2011 INTERNATIONAL GRANADA SPRINT
DONATING TO THE PROJECT
IF YOU ARE INTERESTED IN DONATING TO THE PROJECT OR TO ONE OF OUR CODESPRINTS YOU CAN USE THE PAYPAL BUTTON BELOW OR THE NUMFOCUS DONATIONS PAGE IF YOU USE THE LATTER PLEASE INDICATE THAT YOU ARE DONATING FOR THE SCIKITLEARN PROJECT
ALL DONATIONS WILL BE HANDLED BY NUMFOCUS A NONPROFITORGANIZATION WHICH IS MANAGED BY A BOARD OF SCIPY COMMUNITY MEMBERS NUMFOCUS'S MISSION IS TO FOSTER SCIENTIFIC COMPUTING SOFTWARE IN PARTICULAR IN PYTHON AS A FISCAL HOME OF SCIKITLEARN IT ENSURES THAT MONEY IS AVAILABLE WHEN NEEDED TO KEEP THE PROJECT FUNDED AND AVAILABLE WHILE IN COMPLIANCE WITH TAX REGULATIONS
THE RECEIVED DONATIONS FOR THE SCIKITLEARN PROJECT MOSTLY WILL GO TOWARDS COVERING TRAVELEXPENSES FOR CODE SPRINTS AS WELL AS TOWARDS THE ORGANIZATION BUDGET OF THE PROJECT1
1REGARDING THE ORGANIZATION BUDGET IN PARTICULAR WE MIGHT USE SOME OF THE DONATED FUNDS TO PAY FOR OTHER PROJECT EXPENSES HOSTING OR CONTINUOUS INTEGRATION SERVICES

SCIKITLEARN USER GUIDE RELEASE 0213
NOTES
THE 2013 PARIS INTERNATIONAL SPRINT
FIG 11 IAP VII19 DYSCO
FOR MORE INFORMATION ON THIS SPRINT SEE HERE
158 INFRASTRUCTURE SUPPORT
• WE WOULD LIKE TO THANK RACKSPACE FOR PROVIDING US WITH A FREE RACKSPACE CLOUD ACCOUNT TO AUTOMATICALLY BUILD THE DOCUMENTATION AND THE EXAMPLE GALLERY FROM FOR THE DEVELOPMENT VERSION OF SCIKITLEARN USING THIS TOOL
• WE WOULD ALSO LIKE TO THANK SHINING PANDA FOR FREE CPU TIME ON THEIR CONTINUOUS INTEGRATION SERVER
16 WHO IS USING SCIKITLEARN
161 JPMORGAN
SCIKITLEARN IS AN INDISPENSABLE PART OF THE PYTHON MACHINE LEARNING TOOLKIT AT JPMORGAN IT IS VERY WIDELY USED ACROSS ALL PARTS OF THE BANK FOR CLASSIFICATION PREDICTIVE ANALYTICS AND VERY MANY OTHER MACHINE LEARNING TASKS ITS STRAIGHTFORWARD API ITS BREADTH OF ALGORITHMS AND THE QUALITY OF ITS DOCUMENTATION COMBINE TO MAKE SCIKITLEARN SIMULTANEOUSLY VERY APPROACHABLE AND VERY POWERFUL
STEPHEN SIMMONS VP ATHENA RESEARCH JPMORGAN
16 WHO IS USING SCIKITLEARN 17

162 SPOTIFY

SCIKITLEARN PROVIDES A TOOLBOX WITH SOLID IMPLEMENTATIONS OF A BUNCH OF STATEOFTHEART MODELS AND MAKES IT EASY TO PLUG THEM INTO EXISTING APPLICATIONS WE'VE BEEN USING IT QUITE A LOT FOR MUSIC RECOMMENDATIONS AT SPOTIFY AND I THINK IT'S THE MOST WELLDESIGNED ML PACKAGE I'VE SEEN SO FAR

ERIK BERNHARDSSON ENGINEERING MANAGER MUSIC DISCOVERY MACHINE LEARNING SPOTIFY

163 INRIA

AT INRIA WE USE SCIKITLEARN TO SUPPORT LEADINGEDGE BASIC RESEARCH IN MANY TEAMS PARIETAL FOR NEUROIMAGING LEAR FOR COMPUTER VISION VISAGES FOR MEDICAL IMAGE ANALYSIS PRIVATICS FOR SECURITY THE PROJECT IS A FANTASTIC TOOL TO ADDRESS DIFFICULT APPLICATIONS OF MACHINE LEARNING IN AN ACADEMIC ENVIRONMENT AS IT IS PERFORMANT AND VERSATILE BUT ALL EASYTOUSE AND WELL DOCUMENTED WHICH MAKES IT WELL SUITED TO GRAD STUDENTS

GAËL VAROQUAUX RESEARCH AT PARIETAL

164 BETAWORKS

BETAWORKS IS A NYCBASED STARTUP STUDIO THAT BUILDS NEW PRODUCTS GROWS COMPANIES AND INVESTS IN OTHERS OVER THE PAST 8 YEARS WE'VE LAUNCHED A HANDFUL OF SOCIAL DATA ANALYTICSDRIVEN SERVICES SUCH AS BITLY CHARTBEAT DIGG AND SCALE MODEL CONSISTENTLY THE BETAWORKS DATA SCIENCE TEAM USES SCIKITLEARN FOR A VARIETY OF TASKS FROM EXPLORATORY ANALYSIS TO PRODUCT DEVELOPMENT IT IS AN ESSENTIAL PART OF OUR TOOLKIT RECENT USES ARE INCLUDED IN DIGG'S NEW VIDEO RECOMMENDER SYSTEM AND PONCHO'S DYNAMIC HEURISTIC SUBSPACE CLUSTERING

GILAD LOTAN CHIEF DATA SCIENTIST

165 HUGGING FACE

AT HUGGING FACE WE’RE USING NLP AND PROBABILISTIC MODELS TO GENERATE CONVERSATIONAL ARTIFICIAL INTELLIGENCES THAT ARE FUN TO CHAT WITH DESPITE USING DEEP NEURAL NETS FOR A FEW OF OUR NLP TASKS SCIKITLEARN IS STILL THE BREADANDBUTTER OF OUR DAILY MACHINE LEARNING ROUTINE THE EASE OF USE AND PREDICTABILITY OF THE INTERFACE AS WELL AS THE STRAIGHTFORWARD MATHEMATICAL EXPLANATIONS THAT ARE HERE WHEN YOU NEED THEM IS THE KILLER FEATURE WE USE A VARIETY OF SCIKITLEARN MODELS IN PRODUCTION AND THEY ARE ALSO OPERATIONALLY VERY PLEASANT TO WORK WITH

JULIEN CHAUMOND CHIEF TECHNOLOGY OFFICER

166 EVERNOTE

BUILDING A CLASSIFIER IS TYPICALLY AN ITERATIVE PROCESS OF EXPLORING THE DATA SELECTING THE FEATURES THE ATTRIBUTES OF THE DATA BELIEVED TO BE PREDICTIVE IN SOME WAY TRAINING THE MODELS AND FINALLY EVALUATING THEM FOR MANY OF THESE TASKS WE RELIED ON THE EXCELLENT SCIKITLEARN PACKAGE FOR PYTHON

READ MORE

MARK AYZENSHTAT VP AUGMENTED INTELLIGENCE

167 TÉLÉCOM PARISTECH

AT TELECOM PARISTECH SCIKITLEARN IS USED FOR HANDSON SESSIONS AND HOME ASSIGNMENTS IN INTRODUCTORY AND ADVANCED MACHINE LEARNING COURSES THE CLASSES ARE FOR UNDERGRADS AND MASTERS STUDENTS THE GREAT BENEFIT OF SCIKITLEARN IS ITS FAST LEARNING CURVE THAT ALLOWS STUDENTS TO QUICKLY START WORKING ON INTERESTING AND MOTIVATING PROBLEMS

SCIKITLEARN USER GUIDE RELEASE 0213
ALEXANDRE GRAMFORT ASSISTANT PROFESSOR
168 BOOKINGCOM
AT BOOKINGCOM WE USE MACHINE LEARNING ALGORITHMS FOR MANY DIFFERENT APPLICATIONS SUCH AS RECOMMENDING HO TELS AND DESTINATIONS TO OUR CUSTOMERS DETECTING FRAUDULENT RESERVATIONS OR SCHEDULING OUR CUSTOMER SERVICE AGENTS SCIKITLEARN IS ONE OF THE TOOLS WE USE WHEN IMPLEMENTING STANDARD ALGORITHMS FOR PREDICTION TASKS ITS API AND DOC UMENTATIONS ARE EXCELLENT AND MAKE IT EASY TO USE THE SCIKITLEARN DEVELOPERS DO A GREAT JOB OF INCORPORATING STATE OF THE ART IMPLEMENTATIONS AND NEW ALGORITHMS INTO THE PACKAGE THUS SCIKITLEARN PROVIDES CONVENIENT ACCESS TO A WIDE SPECTRUM OF ALGORITHMS AND ALLOWS US TO READILY FIND THE RIGHT TOOL FOR THE RIGHT JOB
MELANIE MUELLER DATA SCIENTIST
169 AWEBER
THE SCIKITLEARN TOOLKIT IS INDISPENSABLE FOR THE DATA ANALYSIS AND MANAGEMENT TEAM AT AWEBER IT ALLOWS US TO DO AWESOME STUFF WE WOULD NOT OTHERWISE HAVE THE TIME OR RESOURCES TO ACCOMPLISH THE DOCUMENTATION IS EXCELLENT ALLOWING NEW ENGINEERS TO QUICKLY EVALUATE AND APPLY MANY DIFFERENT ALGORITHMS TO OUR DATA THE TEXT FEATURE EXTRACTION UTILITIES ARE USEFUL WHEN WORKING WITH THE LARGE VOLUME OF EMAIL CONTENT WE HAVE AT AWEBER THE RANDOMIZEDPCA IMPLEMENTATION ALONG WITH PIPELINING AND FEATUREUNIONS ALLOWS US TO DEVELOP COMPLEX MACHINE LEARNING ALGORITHMS EFFICIENTLY AND RELIABLY
ANYONE INTERESTED IN LEARNING MORE ABOUT HOW AWEBER DEPLOYS SCIKITLEARN IN A PRODUCTION ENVIRONMENT SHOULD CHECK OUT TALKS FROM PYDATA BOSTON BY AWEBER’S MICHAEL BECKER AVAILABLE AT HTTPSGITHUBCOMMDBECKERPYDATA2013
MICHAEL BECKER SOFTWARE ENGINEER DATA ANALYSIS AND MANAGEMENT NINJAS
1610 YHAT
THE COMBINATION OF CONSISTENT APIS THOROUGH DOCUMENTATION AND TOP NOTCH IMPLEMENTATION MAKE SCIKITLEARN OUR FAVORITE MACHINE LEARNING PACKAGE IN PYTHON SCIKITLEARN MAKES DOING ADVANCED ANALYSIS IN PYTHON ACCESSIBLE TO ANYONE AT YHAT WE MAKE IT EASY TO INTEGRATE THESE MODELS INTO YOUR PRODUCTION APPLICATIONS THUS ELIMINATING THE UNNECESSARY DEV TIME ENCOUNTERED PRODUCTIONIZING ANALYTICAL WORK
GREG LAMP COFOUNDER YHAT

1611 RANGESPAN

THE PYTHON SCIKITLEARN TOOLKIT IS A CORE TOOL IN THE DATA SCIENCE GROUP AT RANGESPAN ITS LARGE COLLECTION OF WELL DOCUMENTED MODELS AND ALGORITHMS ALLOW OUR TEAM OF DATA SCIENTISTS TO PROTOTYPE FAST AND QUICKLY ITERATE TO FIND THE RIGHT SOLUTION TO OUR LEARNING PROBLEMS WE FIND THAT SCIKITLEARN IS NOT ONLY THE RIGHT TOOL FOR PROTOTYPING BUT ITS CAREFUL AND WELL TESTED IMPLEMENTATION GIVE US THE CONFIDENCE TO RUN SCIKITLEARN MODELS IN PRODUCTION

JURGEN VAN GAEL DATA SCIENCE DIRECTOR AT RANGESPAN LTD

1612 BIRCHBOX

AT BIRCHBOX WE FACE A RANGE OF MACHINE LEARNING PROBLEMS TYPICAL TO ECOMMERCE PRODUCT RECOMMENDATION USER CLUSTERING INVENTORY PREDICTION TRENDS DETECTION ETC SCIKITLEARN LETS US EXPERIMENT WITH MANY MODELS ESPECIALLY IN THE EXPLORATION PHASE OF A NEW PROJECT THE DATA CAN BE PASSED AROUND IN A CONSISTENT WAY MODELS ARE EASY TO SAVE AND REUSE UPDATES KEEP US INFORMED OF NEW DEVELOPMENTS FROM THE PATTERN DISCOVERY RESEARCH COMMUNITY SCIKITLEARN IS AN IMPORTANT TOOL FOR OUR TEAM BUILT THE RIGHT WAY IN THE RIGHT LANGUAGE

THIERRY BERTINMAHIEUX BIRCHBOX DATA SCIENTIST

1613 BESTOFMEDIA GROUP

SCIKITLEARN IS OUR 1 TOOLKIT FOR ALL THINGS MACHINE LEARNING AT BESTOFMEDIA WE USE IT FOR A VARIETY OF TASKS EG SPAM FIGHTING AD CLICK PREDICTION VARIOUS RANKING MODELS THANKS TO THE VARIED STATEOFTHEART ALGORITHM IMPLEMENTATIONS PACKAGED INTO IT IN THE LAB IT ACCELERATES PROTOTYPING OF COMPLEX PIPELINES IN PRODUCTION I CAN SAY IT HAS PROVEN TO BE ROBUST AND EFFICIENT ENOUGH TO BE DEPLOYED FOR BUSINESS CRITICAL COMPONENTS

EUSTACHE DIEMERT LEAD SCIENTIST BESTOFMEDIA GROUP

1614 CHANGEORG
AT CHANGEORG WE AUTOMATE THE USE OF SCIKITLEARN'S RANDOMFORESTCLASSIFIER IN OUR PRODUCTION SYSTEMS TO DRIVE EMAIL TARGETING THAT REACHES MILLIONS OF USERS ACROSS THE WORLD EACH WEEK IN THE LAB SCIKITLEARN'S EASEOFUSE PERFORMANCE AND OVERALL VARIETY OF ALGORITHMS IMPLEMENTED HAS PROVED INVALUABLE IN GIVING US A SINGLE RELIABLE SOURCE TO TURN TO FOR OUR MACHINELEARNING NEEDS
VIJAY RAMESH SOFTWARE ENGINEER IN DATASCIENCE AT CHANGEORG
1615 PHIMECA ENGINEERING
AT PHIMECA ENGINEERING WE USE SCIKITLEARN ESTIMATORS AS SURROGATES FOR EXPENSIVETOEVALUATE NUMERICAL MODELS MOSTLY BUT NOT EXCLUSIVELY FINITEELEMENT MECHANICAL MODELS FOR SPEEDING UP THE INTENSIVE POSTPROCESSING OPERATIONS INVOLVED IN OUR SIMULATIONBASED DECISION MAKING FRAMEWORK SCIKITLEARN'S FITPREDICT API TOGETHER WITH ITS EFFICIENT CROSSVALIDATION TOOLS CONSIDERABLY EASES THE TASK OF SELECTING THE BESTFIT ESTIMATOR WE ARE ALSO USING SCIKITLEARN FOR ILLUSTRATING CONCEPTS IN OUR TRAINING SESSIONS TRAINEES ARE ALWAYS IMPRESSED BY THE EASEOFUSE OF SCIKITLEARN DESPITE THE APPARENT THEORETICAL COMPLEXITY OF MACHINE LEARNING
VINCENT DUBOURG PHIMECA ENGINEERING PHD ENGINEER
1616 HOWABOUTWE
AT HOWABOUTWE SCIKITLEARN LETS US IMPLEMENT A WIDE ARRAY OF MACHINE LEARNING TECHNIQUES IN ANALYSIS AND IN PRO DUCTION DESPITE HAVING A SMALL TEAM WE USE SCIKITLEARN'S CLASSIFICATION ALGORITHMS TO PREDICT USER BEHAVIOR ENABLING US TO FOR EXAMPLE ESTIMATE THE VALUE OF LEADS FROM A GIVEN TRAFFIC SOURCE EARLY IN THE LEAD'S TENURE ON OUR SITE ALSO OUR

USERS’ PROFILES CONSIST OF PRIMARILY UNSTRUCTURED DATA ANSWERS TO OPENENDED QUESTIONS SO WE USE SCIKITLEARN’S FEATURE EXTRACTION AND DIMENSIONALITY REDUCTION TOOLS TO TRANSLATE THESE UNSTRUCTURED DATA INTO INPUTS FOR OUR MATCHMAKING SYSTEM

DANIEL WEITZENFELD SENIOR DATA SCIENTIST AT HOWABOUTWE

1617 PEERINDEX

AT PEERINDEX WE USE SCIENTIFIC METHODOLOGY TO BUILD THE INFLUENCE GRAPH A UNIQUE DATASET THAT ALLOWS US TO IDENTIFY WHO’S REALLY INFLUENTIAL AND IN WHICH CONTEXT TO DO THIS WE HAVE TO TACKLE A RANGE OF MACHINE LEARNING AND PREDICTIVE MODELING PROBLEMS SCIKITLEARN HAS EMERGED AS OUR PRIMARY TOOL FOR DEVELOPING PROTOTYPES AND MAKING QUICK PROGRESS FROM PREDICTING MISSING DATA AND CLASSIFYING TWEETS TO CLUSTERING COMMUNITIES OF SOCIAL MEDIA USERS SCIKITLEARN PROVED USEFUL IN A VARIETY OF APPLICATIONS ITS VERY INTUITIVE INTERFACE AND EXCELLENT COMPATIBILITY WITH OTHER PYTHON TOOLS MAKES IT AND INDISPENSABLE TOOL IN OUR DAILY RESEARCH EFFORTS

FERENC HUSZAR SENIOR DATA SCIENTIST AT PEERINDEX

1618 DATAROBOT

DATAROBOT IS BUILDING NEXT GENERATION PREDICTIVE ANALYTICS SOFTWARE TO MAKE DATA SCIENTISTS MORE PRODUCTIVE AND SCIKITLEARN IS AN INTEGRAL PART OF OUR SYSTEM THE VARIETY OF MACHINE LEARNING TECHNIQUES IN COMBINATION WITH THE SOLID IMPLEMENTATIONS THAT SCIKITLEARN OFFERS MAKES IT A ONESTOPSHOPPING LIBRARY FOR MACHINE LEARNING IN PYTHON MOREOVER ITS CONSISTENT API WELLTESTED CODE AND PERMISSIVE LICENSING ALLOW US TO USE IT IN A PRODUCTION ENVIRONMENT SCIKITLEARN HAS LITERALLY SAVED US YEARS OF WORK WE WOULD HAVE HAD TO DO OURSELVES TO BRING OUR PRODUCT TO MARKET

JEREMY ACHIN CEO COFOUNDER DATAROBOT INC

1619 OKCUPID

WE’RE USING SCIKITLEARN AT OKCUPID TO EVALUATE AND IMPROVE OUR MATCHMAKING SYSTEM THE RANGE OF FEATURES IT HAS ESPECIALLY PREPROCESSING UTILITIES MEANS WE CAN USE IT FOR A WIDE VARIETY OF PROJECTS AND IT’S PERFORMANT ENOUGH TO HANDLE THE VOLUME OF DATA THAT WE NEED TO SORT THROUGH THE DOCUMENTATION IS REALLY THOROUGH AS WELL WHICH MAKES THE LIBRARY QUITE EASY TO USE

DAVID KOH SENIOR DATA SCIENTIST AT OKCUPID

1620 LOVELY

AT LOVELY WE STRIVE TO DELIVER THE BEST APARTMENT MARKETPLACE WITH RESPECT TO OUR USERS AND OUR LISTINGS FROM UNDERSTANDING USER BEHAVIOR IMPROVING DATA QUALITY AND DETECTING FRAUD SCIKITLEARN IS A REGULAR TOOL FOR GATHERING INSIGHTS PREDICTIVE MODELING AND IMPROVING OUR PRODUCT THE EASYTOREAD DOCUMENTATION AND INTUITIVE ARCHITECTURE OF THE API MAKES MACHINE LEARNING BOTH EXPLORABLE AND ACCESSIBLE TO A WIDE RANGE OF PYTHON DEVELOPERS I'M CONSTANTLY RECOMMENDING THAT MORE DEVELOPERS AND SCIENTISTS TRY SCIKITLEARN

SIMON FRID DATA SCIENTIST LEAD AT LOVELY

1621 DATA PUBLICA

DATA PUBLICA BUILDS A NEW PREDICTIVE SALES TOOL FOR COMMERCIAL AND MARKETING TEAMS CALLED CRADAR WE EXTENSIVELY USE SCIKITLEARN TO BUILD SEGMENTATIONS OF CUSTOMERS THROUGH CLUSTERING AND TO PREDICT FUTURE CUSTOMERS BASED ON PAST PARTNERSHIPS SUCCESS OR FAILURE WE ALSO CATEGORIZE COMPANIES USING THEIR WEBSITE COMMUNICATION THANKS TO SCIKITLEARN AND ITS MACHINE LEARNING ALGORITHM IMPLEMENTATIONS EVENTUALLY MACHINE LEARNING MAKES IT POSSIBLE TO DETECT WEAK SIGNALS THAT TRADITIONAL TOOLS CANNOT SEE ALL THESE COMPLEX TASKS ARE PERFORMED IN AN EASY AND STRAIGHTFORWARD WAY THANKS TO THE GREAT QUALITY OF THE SCIKITLEARN FRAMEWORK

GUILLAUME LEBOURGEOIS SAMUEL CHARRON DATA SCIENTISTS AT DATA PUBLICA

1622 MACHINALIS

SCIKITLEARN IS THE CORNERSTONE OF ALL THE MACHINE LEARNING PROJECTS CARRIED AT MACHINALIS IT HAS A CONSISTENT API A WIDE SELECTION OF ALGORITHMS AND LOTS OF AUXILIARY TOOLS TO DEAL WITH THE BOILERPLATE WE HAVE USED IT IN PRODUCTION EN VIRONMENTS ON A VARIETY OF PROJECTS INCLUDING CLICKTHROUGH RATE PREDICTION INFORMATION EXTRACTION AND EVEN COUNTING SHEEP

IN FACT WE USE IT SO MUCH THAT WE'VE STARTED TO FREEZE OUR COMMON USE CASES INTO PYTHON PACKAGES SOME OF THEM OPENSOURCED LIKE FEATUREFORGE SCIKITLEARN IN ONE WORD AWESOME

RAFAEL CARRASCOSA LEAD DEVELOPER

1623 SOLIDO
SCIKITLEARN IS HELPING TO DRIVE MOORE'S LAW VIA SOLIDO SOLIDO CREATES COMPUTERAIDED DESIGN TOOLS USED BY THE MAJORITY OF TOP20 SEMICONDUCTOR COMPANIES AND FABS TO DESIGN THE BLEEDINGEDGE CHIPS INSIDE SMARTPHONES AUTO MOBILES AND MORE SCIKITLEARN HELPS TO POWER SOLIDO'S ALGORITHMS FOR RAREEVENT ESTIMATION WORSTCASE VERIFICATION OPTIMIZATION AND MORE AT SOLIDO WE ARE PARTICULARLY FOND OF SCIKITLEARN'S LIBRARIES FOR GAUSSIAN PROCESS MODELS LARGESCALE REGULARIZED LINEAR REGRESSION AND CLASSIFICATION SCIKITLEARN HAS INCREASED OUR PRODUCTIVITY BECAUSE FOR MANY ML PROBLEMS WE NO LONGER NEED TO "ROLL OUR OWN" CODE THIS PYDATA 2014 TALK HAS DETAILS
TRENT MCCONAGHY FOUNDER SOLIDO DESIGN AUTOMATION INC
1624 INFONEA
WE EMPLOY SCIKITLEARN FOR RAPID PROTOTYPING AND CUSTOMMADE DATA SCIENCE SOLUTIONS WITHIN OUR INMEMORY BASED BUSINESS INTELLIGENCE SOFTWARE INFONEA® AS A WELLDOCUMENTED AND COMPREHENSIVE COLLECTION OF STATEOFTHEART ALGORITHMS AND PIPELINING METHODS SCIKITLEARN ENABLES US TO PROVIDE FLEXIBLE AND SCALABLE SCIENTIFIC ANALYSIS SOLUTIONS THUS SCIKITLEARN IS IMMENSELY VALUABLE IN REALIZING A POWERFUL INTEGRATION OF DATA SCIENCE TECHNOLOGY WITHIN SELF SERVICE BUSINESS ANALYTICS
THORSTEN KRANZ DATA SCIENTIST COMA SOFT AG
1625 DATAIKU
OUR SOFTWARE DATA SCIENCE STUDIO DSS ENABLES USERS TO CREATE DATA SERVICES THAT COMBINE ETL WITH MACHINE LEARNING OUR MACHINE LEARNING MODULE INTEGRATES MANY SCIKITLEARN ALGORITHMS THE SCIKITLEARN LIBRARY IS A PERFECT INTEGRATION WITH DSS BECAUSE IT OFFERS ALGORITHMS FOR VIRTUALLY ALL BUSINESS CASES OUR GOAL IS TO OFFER A TRANSPARENT AND FLEXIBLE TOOL THAT MAKES IT EASIER TO OPTIMIZE TIME CONSUMING ASPECTS OF BUILDING A DATA SERVICE PREPARING DATA AND TRAINING MACHINE LEARNING ALGORITHMS ON ALL TYPES OF DATA
FLORIAN DOUETTEAU CEO DATAIKU
1626 OTTO GROUP
HERE AT OTTO GROUP ONE OF GLOBAL BIG FIVE B2C ONLINE RETAILERS WE ARE USING SCIKITLEARN IN ALL ASPECTS OF OUR DAILY WORK FROM DATA EXPLORATION TO DEVELOPMENT OF MACHINE LEARNING APPLICATION TO THE PRODUCTIVE DEPLOYMENT OF THOSE SERVICES IT HELPS US TO TACKLE MACHINE LEARNING PROBLEMS RANGING FROM ECOMMERCE TO LOGISTICS IT CONSISTENT APIS ENABLED US TO BUILD THE PALLADIUM RESTAPI FRAMEWORK AROUND IT AND CONTINUOUSLY DELIVER SCIKITLEARN BASED SERVICES

SCIKITLEARN USER GUIDE RELEASE 0213
CHRISTIAN RAMMIG HEAD OF DATA SCIENCE OTTO GROUP
1627 ZOPA
AT ZOPA THE FIRST EVER PEERTOPEER LENDING PLATFORM WE EXTENSIVELY USE SCIKITLEARN TO RUN THE BUSINESS AND OPTIMIZE OUR USERS' EXPERIENCE IT POWERS OUR MACHINE LEARNING MODELS INVOLVED IN CREDIT RISK FRAUD RISK MARKETING AND PRICING AND HAS BEEN USED FOR ORIGINATING AT LEAST 1 BILLION GBP WORTH OF ZOPA LOANS IT IS VERY WELL DOCUMENTED POWERFUL AND SIMPLE TO USE WE ARE GRATEFUL FOR THE CAPABILITIES IT HAS PROVIDED AND FOR ALLOWING US TO DELIVER ON OUR MISSION OF MAKING MONEY SIMPLE AND FAIR
VLASIOS VASILEIOU HEAD OF DATA SCIENCE ZOPA
1628 MARS
SCIKITLEARN IS INTEGRAL TO THE MACHINE LEARNING ECOSYSTEM AT MARS WHETHER WE'RE DESIGNING BETTER RECIPES FOR PETFOOD OR CLOSELY ANALYSING OUR COCOA SUPPLY CHAIN SCIKITLEARN IS USED AS A TOOL FOR RAPIDLY PROTOTYPING IDEAS AND TAKING THEM TO PRODUCTION THIS ALLOWS US TO BETTER UNDERSTAND AND MEET THE NEEDS OF OUR CONSUMERS WORLDWIDE SCIKITLEARN'S FEATURERICH TOOLSET IS EASY TO USE AND EQUIPS OUR ASSOCIATES WITH THE CAPABILITIES THEY NEED TO SOLVE THE BUSINESS CHALLENGES THEY FACE EVERY DAY
MICHAEL FITZKE NEXT GENERATION TECHNOLOGIES SR LEADER MARS INC
17 RELEASE HISTORY
RELEASE NOTES FOR CURRENT AND RECENT RELEASES ARE DETAILED ON THIS PAGE WITH PREVIOUS RELEASES LINKED BELOW
TIP SUBSCRIBE TO SCIKITLEARN RELEASES ON LIBRARIESIO TO BE NOTIFIED WHEN NEW VERSIONS ARE RELEASED
171 LEGEND FOR CHANGELOGS
•MAJOR FEATURE SOMETHING BIG THAT YOU COULDN'T DO BEFORE
•FEATURE SOMETHING THAT YOU COULDN'T DO BEFORE
•EFFICIENCY AN EXISTING FEATURE NOW MAY NOT REQUIRE AS MUCH COMPUTATION OR MEMORY
•ENHANCEMENT A MISCELLANEOUS MINOR IMPROVEMENT
•FIX SOMETHING THAT PREVIOUSLY DIDN'T WORK AS DOCUMENTATED – OR ACCORDING TO REASONABLE EXPECTATIONS – SHOULD NOW WORK
•API C HANGE YOU WILL NEED TO CHANGE YOUR CODE TO HAVE THE SAME EFFECT IN THE FUTURE OR A FEATURE WILL BE REMOVED IN THE FUTURE

18 VERSION 0213

JULY 30 2019

181 CHANGED MODELS

THE FOLLOWING ESTIMATORS AND FUNCTIONS WHEN FIT WITH THE SAME DATA AND PARAMETERS MAY PRODUCE DIFFERENT MODELS FROM THE PREVIOUS VERSION THIS OFTEN OCCURS DUE TO CHANGES IN THE MODELLING LOGIC BUG FIXES OR ENHANCEMENTS OR IN RANDOM SAMPLING PROCEDURES

• THE V0200 RELEASE NOTES FAILED TO MENTION A BACKWARDS INCOMPATIBILITY IN METRICSMAKESCORER WHENNEEDSPROBATRUE ANDYTRUE IS BINARY NOW THE SCORER FUNCTION IS SUPPOSED TO ACCEPT A 1D YPRED IE PROBABILITY OF THE POSITIVE CLASS SHAPE NSAMPLES INSTEAD OF A 2D YPRED IE SHAPE NSAMPLES 2

182 CHANGELOG

SKLEARNCLUSTER

•FIXFIXED A BUG IN CLUSTERKMEANS WHERE COMPUTATION WITH INITRANDOM WAS SINGLE THREADED FOR NJOBS 1 ORNJOBS 1 12955 BY PRABAKARAN KUMARESSHAN

•FIXFIXED A BUG IN CLUSTEROPTICS WHERE USERS WERE UNABLE TO PASS FLOAT MINSAMPLES AND MINCLUSTERSIZE 14496 BY FABIAN KLOPFER AND HANMIN QIN

SKLEARNCOMPOSE

•FIXFIXED AN ISSUE IN COMPOSECOLUMNTRANSFORMER WHERE USING DATAFRAMES WHOSE COLUMN ORDER DIFFERS BETWEEN FUNC FIT AND FUNCTRANSFORM COULD LEAD TO SILENTLY PASSING INCORRECT COLUMNS TO THE REMAINDER TRANSFORMER 14237 BY ANDREAS SCHUDERER

SKLEARNDATASETS

•FIXDATASETSFETCHCALIFORNIAHOUSING DATASETSFETCHCOVTYPE DATASETS FETCHKDDCUP99 DATASETSFETCHOLIVETTIFACES DATASETSFETCHRCV1 AND DATASETSFETCHSPECIESDISTRIBUTIONS TRY TO PERSIST THE PREVIOUSLY CACHE USING THE NEW JOBLIB IF THE CACHED DATA WAS PERSISTED USING THE DEPRECATED SKLEARNEXTERNALSJOBLIB THIS BEHAVIOR IS SET TO BE DEPRECATED AND REMOVED IN V023 14197 BY ADRIN JALALI

SKLEARNENSEMBLE

•FIX FIX ZERO DIVISION ERROR IN HISTGRADIENTBOOSTINGCLASSIFIER AND HISTGRADIENTBOOSTINGREGRESSOR 14024 BY NICOLAS HUG

SKLEARNIMPUTE

•FIXFIXED A BUG IN IMPUTESIMPLEIMPUTER ANDIMPUTEITERATIVEIMPUTER SO THAT NO ERRORS ARE THROWN WHEN THERE ARE MISSING VALUES IN TRAINING DATA 13974 BY FRANK HOANG

SCIKITLEARN USER GUIDE RELEASE 0213
SKLEARNINSPECTION
•FIXFIXED A BUG IN INSPECTIONPLOTPARTIALDEPENDENCE WHERETARGET PARAMETER WAS NOT BE
ING TAKEN INTO ACCOUNT FOR MULTICLASS PROBLEMS 14393 BY GUILLEM G SUBIES
SKLEARNLINEARMODEL
•FIXFIXED A BUG IN LINEARMODELLOGISTICREGRESSIONCV WHEREREFITFALSE WOULD FAIL DE
PENDING ON THE MULTICLASS ANDPENALTY PARAMETERS REGRESSION INTRODUCED IN 021 14087 BY
NICOLAS HUG
•FIXCOMPATIBILITY FIX FOR LINEARMODELARDREGRESSION AND SCIPY130 ADAPTS TO UPSTREAM
CHANGES TO THE DEFAULT PINVH CUTOFF THRESHOLD WHICH OTHERWISE RESULTS IN POOR ACCURACY IN SOME CASES 14067
BY TIM STALEY
SKLEARNNEIGHBORS
•FIXFIXED A BUG IN NEIGHBORSNEIGHBORHOODCOMPONENTSANALYSIS WHERE THE VALIDATION OF INITIAL
PARAMETERS NCOMPONENTS MAXITER ANDTOL REQUIRED TOO STRICT TYPES 14092 BY JÉRÉMIE DU BOISBER
RANGER
SKLEARNTREE
•FIXFIXED BUG IN TREEEXPORTTEXT WHEN THE TREE HAS ONE FEATURE AND A SINGLE FEATURE NAME IS PASSED IN
14053 BY THOMAS FAN
•FIXFIXED AN ISSUE WITH PLOTTREE WHERE IT DISPLAYED ENTROPY CALCULATIONS EVEN FOR GINI CRITERION IN
DECISIONTREECLASSIFIERS 13947 BY FRANK HOANG
19 VERSION 0212
24 MAY 2019
191 CHANGELOG
SKLEARNDECOMPOSITION
•FIXFIXED A BUG IN CROSSDECOMPOSITIONCCA IMPROVING NUMERICAL STABILITY WHEN YIS CLOSE TO ZERO
13903 BY THOMAS FAN
SKLEARNMETRICS
•FIXFIXED A BUG IN METRICSPAIRWISEEUCLIDEANDISTANCES WHERE A PART OF THE DISTANCE MATRIX
WAS LEFT UNINSTANCIATED FOR SUFFIENTLY LARGE FLOAT32 DATASETS REGRESSION INTRODUCED IN 021 13910 BY JÉRÉMIE
DU BOISBERRANGER

SKLEARNPREPROCESSING
•FIXFIXED A BUG IN PREPROCESSINGONEHOTENCODER WHERE THE NEW DROP PARAMETER WAS NOT REFLECTED INGETFEATURENAMES 13894 BY JAMES MYATT
SKLEARNUTILSSPARSEFUNCS
•FIXFIXED A BUG WHERE MINMAXAXIS WOULD FAIL ON 32BIT SYSTEMS FOR CERTAIN LARGE INPUTS THIS AFFECTSPREPROCESSINGMAXABSSCALER PREPROCESSINGNORMALIZE ANDPREPROCESSING LABELBINARIZER 13741 BY RODDY MACSWEEN
110 VERSION 0211
17 MAY 2019
THIS IS A BUGFIX RELEASE TO PRIMARILY RESOLVE SOME PACKAGING ISSUES IN VERSION 0210 IT ALSO INCLUDES MINOR DOCU MENTATION IMPROVEMENTS AND SOME BUG FIXES
1101 CHANGELOG
SKLEARNINSPECTION
•FIXFIXED A BUG IN INSPECTIONPARTIALDEPENDENCE TO ONLY CHECK CLASSIFIER AND NOT REGRESSOR FOR THE MULTICLASSMULTIOUTPUT CASE 14309 BY GUILLAUME LEMAITRE
SKLEARNMETRICS
•FIXFIXED A BUG IN METRICSPAIRWISEDISTANCES WHERE IT WOULD RAISE ATTRIBUTEERROR FOR BOOLEAN METRICS WHEN XHAD A BOOLEAN DTYPE AND Y NONE 13864 BY PARESH MATHUR
•FIXFIXED TWO BUGS IN METRICSPAIRWISEDISTANCES WHENNJOBS 1 FIRST IT USED TO RETURN A DISTANCE MATRIX WITH SAME DTYPE AS INPUT EVEN FOR INTEGER DTYPE THEN THE DIAGONAL WAS NOT ZEROS FOR EUCLIDEAN METRIC WHEN YISX 13877 BY JÉRÉMIE DU BOISBERRANGER
SKLEARNNEIGHBORS
•FIXFIXED A BUG IN NEIGHBORSKERNELDENSITY WHICH COULD NOT BE RESTORED FROM A PICKLE IF SAMPLEWEIGHT HAD BEEN USED 13772 BY ADITYA VYAS
111 VERSION 0210
MAY 2019

1111 CHANGED MODELS

THE FOLLOWING ESTIMATORS AND FUNCTIONS WHEN FIT WITH THE SAME DATA AND PARAMETERS MAY PRODUCE DIFFERENT MODELS FROM THE PREVIOUS VERSION THIS OFTEN OCCURS DUE TO CHANGES IN THE MODELLING LOGIC BUG FIXES OR ENHANCEMENTS OR IN RANDOM SAMPLING PROCEDURES

•DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS FOR MULTICLASS CLASSIFICATION FIX

•DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS WITH 'EIGEN' SOLVER FIX

•LINEARMODELBAYESIANRIDGE FIX

• DECISION TREES AND DERIVED ENSEMBLES WHEN BOTH MAXDEPTH ANDMAXLEAFNODES ARE SET FIX

•LINEARMODELLOGISTICREGRESSION ANDLINEARMODELLOGISTICREGRESSIONCV WITH 'SAGA' SOLVER FIX

•ENSEMBLEGRADIENTBOOSTINGCLASSIFIER FIX

•SKLEARNFEATUREEXTRACTIONTEXTHASHINGVECTORIZER SKLEARN FEATUREEXTRACTIONTEXTTFIDFVECTORIZER AND SKLEARNFEATUREEXTRACTION TEXTCOUNTVECTORIZER FIX

•NEURALNETWORKMLPCLASSIFIER FIX

•SVMSVCDECISIONFUNCTION AND MULTICLASSONEVSONECLASSIFIER DECISIONFUNCTION FIX

•LINEARMODELSGDCLASSIFIER AND ANY DERIVED CLASSIFIERS FIX

• ANY MODEL USING THE LINEARMODELSAGSAGSOLVER FUNCTION WITH A 0SEED INCLUD INGLINEARMODELLOGISTICREGRESSION LINEARMODELLOGISTICREGRESSIONCV LINEARMODELRIDGE ANDLINEARMODELRIDGECV WITH 'SAG' SOLVER FIX

•LINEARMODELRIDGECV WHEN USING GENERALIZED CROSSVALIDATION WITH SPARSE INPUTS FIX

DETAILS ARE LISTED IN THE CHANGELOG BELOW

WHILE WE ARE TRYING TO BETTER INFORM USERS BY PROVIDING THIS INFORMATION WE CANNOT ASSURE THAT THIS LIST IS COMPLETE

1112 KNOWN MAJOR BUGS

• THE DEFAULT MAXITER FORLINEARMODELLOGISTICREGRESSION IS TOO SMALL FOR MANY SOLVERS GIVEN THE DEFAULTTOL IN PARTICULAR WE ACCIDENTALLY CHANGED THE DEFAULT MAXITER FOR THE LIBLINEAR SOLVER FROM 1000 TO 100 ITERATIONS IN 3591 RELEASED IN VERSION 016 IN A FUTURE RELEASE WE HOPE TO CHOOSE BETTER DEFAULT MAXITER ANDTOL HEURISTICALLY DEPENDING ON THE SOLVER SEE 13317

1113 CHANGELOG

SUPPORT FOR PYTHON 34 AND BELOW HAS BEEN OFFICIALLY DROPPED

SKLEARNBASE

•API C HANGE THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUT MULTIOUTPUTREGRESSOR 13157 BY HANMIN QIN

SCIKITLEARN USER GUIDE RELEASE 0213
SKLEARNCALIBRATION
•ENHANCEMENT ADDED SUPPORT TO BIN THE DATA PASSED INTO CALIBRATIONCALIBRATIONCURVE BY QUAN
TILES INSTEAD OF UNIFORMLY BETWEEN 0 AND 1 13086 BY SCOTT COLE
•ENHANCEMENT ALLOW NDIMENSIONAL ARRAYS AS INPUT FOR CALIBRATIONCALIBRATEDCLASSIFIERCV
13485 BY WILLIAM DE VAZELHES
SKLEARNCLUSTER
•MAJOR FEATURE A NEW CLUSTERING ALGORITHM CLUSTEROPTICS AN ALGORITM RELATED TO CLUSTER
DBSCAN THAT HAS HYPERPARAMETERS EASIER TO SET AND THAT SCALES BETTER BY SHANE ADRIN JALALI ERICH SCHUBERT
HANMIN QIN AND ASSIA BENBIHI
•FIXFIXED A BUG WHERE CLUSTERBIRCH COULD OCCASIONALLY RAISE AN ATTRIBUTEERROR 13651 BY JOEL NOTH
MAN
•FIXFIXED A BUG IN CLUSTERKMEANS WHERE EMPTY CLUSTERS WEREN'T CORRECTLY RELOCATED WHEN USING SAMPLE
WEIGHTS 13486 BY JÉRÉMIE DU BOISBERRANGER
•API C HANGE THENCOMPONENTS ATTRIBUTE IN CLUSTERAGGLOMERATIVECLUSTERING AND
CLUSTERFEATUREAGGLOMERATION HAS BEEN RENAMED TO NCONNECTEDCOMPONENTS 13427 BY
STEPHANE COUVREUR
•ENHANCEMENT CLUSTERAGGLOMERATIVECLUSTERING ANDCLUSTERFEATUREAGGLOMERATION
NOW ACCEPT A DISTANCETHRESHOLD PARAMETER WHICH CAN BE USED TO FIND THE CLUSTERS INSTEAD OF
NCLUSTERS 9069 BY VATHSALA ACHAR AND ADRIN JALALI
SKLEARNCOMPOSE
•API C HANGE COMPOSECOLUMNTRANSFORMER IS NO LONGER AN EXPERIMENTAL FEATURE 13835 BY HANMIN
QIN
SKLEARNDATASETS
•FIXADDED SUPPORT FOR 64BIT GROUP IDS AND POINTERS IN SVMLIGHT FILES 10727 BY BRYAN K WOODS
•FIXDATASETSLOADSAMPLEIMAGES RETURNS IMAGES WITH A DETERMINISTIC ORDER 13250 BY THOMAS
FAN
SKLEARNDECOMPOSITION
•ENHANCEMENT DECOMPOSITIONKERNELPCA NOW HAS DETERMINISTIC OUTPUT RESOLVED SIGN AMBIGUITY IN
EIGENVALUE DECOMPOSITION OF THE KERNEL MATRIX 13241 BY AURÉLIEN BELLET
•FIXFIXED A BUG IN DECOMPOSITIONKERNELPCA FITTRANSFORM NOW PRODUCES
THE CORRECT OUTPUT THE SAME AS FITTRANSFORM IN CASE OF NONREMOVED ZERO EIGENVALUES
REMOVEZEROEIGFALSE FITINVERSETRANSFORM WAS ALSO ACCELERATED BY USING THE SAME TRICK
ASFITTRANSFORM TO COMPUTE THE TRANSFORM OF X 12143 BY SYLVAIN MARIÉ
•FIXFIXED A BUG IN DECOMPOSITIONNMF WHEREINIT NNDSVD INIT NNDSVDA AND
INIT NNDSVDAR ARE ALLOWED WHEN NCOMPONENTS NFEATURES INSTEAD OFNCOMPONENTS
MINNSAMPLES NFEATURES 11650 BY HOSSEIN POURBOZORG AND ZIJIE ZJ POH
111 VERSION 0210 31

SCIKITLEARN USER GUIDE RELEASE 0213
•API C HANGE THE DEFAULT VALUE OF THE INIT ARGUMENT IN DECOMPOSITION
NONNEGATIVEFACTORIZATION WILL CHANGE FROM RANDOM TONONE IN VERSION 023 TO MAKE IT
CONSISTENT WITH DECOMPOSITIONNMF A FUTUREWARNING IS RAISED WHEN THE DEFAULT VALUE IS USED 12988
BY ZIJIE ZJ POH
SKLEARNDISCRIMINANTANALYSIS
•ENHANCEMENT DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS NOW PRESERVES
FLOAT32 ANDFLOAT64 DTYPES 8769 AND 11000 BY THIBAULT SEJOURNE
•FIXACHANGEDBEHAVIOURWARNING IS NOW RAISED WHEN DISCRIMINANTANALYSIS
LINEARDISCRIMINANTANALYSIS IS GIVEN AS PARAMETER NCOMPONENTS MINNFEATURES
NCLASSES 1 ANDNCOMPONENTS IS CHANGED TO MINNFEATURES NCLASSES 1 IF SO
PREVIOUSLY THE CHANGE WAS MADE BUT SILENTLY 11526 BY WILLIAM DE VAZELHES
•FIXFIXED A BUG IN DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS WHERE THE PRE
DICTED PROBABILITIES WOULD BE INCORRECTLY COMPUTED IN THE MULTICLASS CASE 6848 BY AGAMEMNON KRASOULIS
ANDGUILLAUME LEMAITRE
•FIXFIXED A BUG IN DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS WHERE THE PRE
DICTED PROBABILITIES WOULD BE INCORRECTLY COMPUTED WITH EIGEN SOLVER 11727 BY AGAMEMNON KRASOULIS
SKLEARNDUMMY
•FIXFIXED A BUG IN DUMMYDUMMYCLASSIFIER WHERE THEPREDICTPROBA METHOD WAS RETURNING INT32
ARRAY INSTEAD OF FLOAT64 FOR THE STRATIFIED STRATEGY 13266 BY CHRISTOS ARIDAS
•FIXFIXED A BUG IN DUMMYDUMMYCLASSIFIER WHERE IT WAS THROWING A DIMENSION MISMATCH ERROR IN
PREDICTION TIME IF A COLUMN VECTOR YWITHSHAPEN 1 WAS GIVEN AT FIT TIME 13545 BY NICK SORROS AND
ADRIN JALALI
SKLEARNENSEMBLE
•MAJOR FEATURE ADD TWO NEW IMPLEMENTATIONS OF GRADIENT BOOSTING TREES ENSEMBLE
HISTGRADIENTBOOSTINGCLASSIFIER ANDENSEMBLEHISTGRADIENTBOOSTINGREGRESSOR
THE IMPLEMENTATION OF THESE ESTIMATORS IS INSPIRED BY LIGHTGBM AND CAN BE ORDERS OF MAGNITUDE FASTER THAN
ENSEMBLEGRADIENTBOOSTINGREGRESSOR ANDENSEMBLEGRADIENTBOOSTINGCLASSIFIER
WHEN THE NUMBER OF SAMPLES IS LARGER THAN TENS OF THOUSANDS OF SAMPLES THE API OF THESE NEW ESTIMATORS
IS SLIGHTLY DIFFERENT AND SOME OF THE FEATURES FROM ENSEMBLEGRADIENTBOOSTINGCLASSIFIER AND
ENSEMBLEGRADIENTBOOSTINGREGRESSOR ARE NOT YET SUPPORTED
THESE NEW ESTIMATORS ARE EXPERIMENTAL WHICH MEANS THAT THEIR RESULTS OR THEIR API MIGHT CHANGE WITHOUT ANY
DEPRECATION CYCLE TO USE THEM YOU NEED TO EXPLICITLY IMPORT ENABLEHISTGRADIENTBOOSTING
 EXPLICITLY REQUIRE THIS EXPERIMENTAL FEATURE
 FROM SKLEARNEXPERIMENTAL IMPORT ENABLEHISTGRADIENTBOOSTING NOQA
 NOW YOU CAN IMPORT NORMALLY FROM SKLEARNENSEMBLE
 FROM SKLEARNENSEMBLE IMPORT HISTGRADIENTBOOSTINGCLASSIFIER
12807 BY NICOLAS HUG
•FEATURE ADDENSEMBLEVOTINGREGRESSOR WHICH PROVIDES AN EQUIVALENT OF ENSEMBLE
VOTINGCLASSIFIER FOR REGRESSION PROBLEMS 12513 BY RAMIL NUGMANOV AND MOHAMED ALI JAMAOUI

•EFFICIENCY MAKEENSEMBLEISOLATIONFOREST PREFER THREADS OVER PROCESSES WHEN RUNNING WITH NJOBS 1 AS THE UNDERLYING DECISION TREE FIT CALLS DO RELEASE THE GIL THIS CHANGES REDUCES MEMORY USAGE AND COMMUNICATION OVERHEAD 12543 BY ISAAC STORCH AND OLIVIER GRISEL
•EFFICIENCY MAKEENSEMBLEISOLATIONFOREST MORE MEMORY EFFICIENT BY AVOIDING KEEPING IN MEMORY EACH TREE PREDICTION 13260 BY NICOLAS GOIX
•EFFICIENCY ENSEMBLEISOLATIONFOREST NOW USES CHUNKS OF DATA AT PREDICTION STEP THUS CAPPING THE MEMORY USAGE 13283 BY NICOLAS GOIX
•EFFICIENCY SKLEARNENSEMBLEGRADIENTBOOSTINGCLASSIFIER ANDSKLEARNENSEMBLE GRADIENTBOOSTINGREGRESSOR NOW KEEP THE INPUT YASFLOAT64 TO AVOID IT BEING COPIED INTERNALLY BY TREES 13524 BY ADRIN JALALI
•ENHANCEMENT MINIMIZED THE VALIDATION OF X IN ENSEMBLEADABOOSTCLASSIFIER ANDENSEMBLE ADABOOSTREGRESSOR 13174 BY CHRISTOS ARIDAS
•ENHANCEMENT ENSEMBLEISOLATIONFOREST NOW EXPOSES WARMSTART PARAMETER ALLOWING ITERATIVE ADDITION OF TREES TO AN ISOLATION FOREST 13496 BY PETER MARKO
•FIXTHE VALUES OF FEATUREIMPORTANCES IN ALL RANDOM FOREST BASED MODELS IE ENSEMBLERANDOMFORESTCLASSIFIER ENSEMBLERANDOMFORESTREGRESSOR ENSEMBLEEXTRATREESCLASSIFIER ENSEMBLEEXTRATREESREGRESSOR ENSEMBLE RANDOMTREESEMBEDDING ENSEMBLEGRADIENTBOOSTINGCLASSIFIER ANDENSEMBLE GRADIENTBOOSTINGREGRESSOR NOW
–SUM UP TO1
–ALL THE SINGLE NODE TREES IN FEATURE IMPORTANCE CALCULATION ARE IGNORED
–IN CASE ALL TREES HAVE ONLY ONE SINGLE NODE IE A ROOT NODE FEATURE IMPORTANCES WILL BE AN ARRAY OF ALL ZEROS
13636 AND 13620 BY ADRIN JALALI
•FIXFIXED A BUG IN ENSEMBLEGRADIENTBOOSTINGCLASSIFIER ANDENSEMBLE GRADIENTBOOSTINGREGRESSOR WHICH DIDN’T SUPPORT SCIKITLEARN ESTIMATORS AS THE INITIAL ESTIMATOR ALSO ADDED SUPPORT OF INITIAL ESTIMATOR WHICH DOES NOT SUPPORT SAMPLE WEIGHTS 12436 BY JÉRÉMIE DU BOISBERRANGER AND 12983 BY NICOLAS HUG
•FIXFIXED THE OUTPUT OF THE AVERAGE PATH LENGTH COMPUTED IN ENSEMBLEISOLATIONFOREST WHEN THE INPUT IS EITHER 0 1 OR 2 13251 BY ALBERT THOMAS AND JOSHUAKENNETHJONES
•FIXFIXED A BUG IN ENSEMBLEGRADIENTBOOSTINGCLASSIFIER WHERE THE GRADIENTS WOULD BE INCOR RECTLY COMPUTED IN MULTICLASS CLASSIFICATION PROBLEMS 12715 BY NICOLAS HUG
•FIXFIXED A BUG IN ENSEMBLEGRADIENTBOOSTINGCLASSIFIER WHERE VALIDATION SETS FOR EARLY STOP PING WERE NOT SAMPLED WITH STRATIFICATION 13164 BY NICOLAS HUG
•FIXFIXED A BUG IN ENSEMBLEGRADIENTBOOSTINGCLASSIFIER WHERE THE DEFAULT INITIAL PREDICTION OF A MULTICLASS CLASSIFIER WOULD PREDICT THE CLASSES PRIORS INSTEAD OF THE LOG OF THE PRIORS 12983 BY NICOLAS HUG
•FIXFIXED A BUG IN ENSEMBLERANDOMFORESTCLASSIFIER WHERE THEPREDICT METHOD WOULD ERROR FOR MULTICLASS MULTIOUTPUT FORESTS MODELS IF ANY TARGETS WERE STRINGS 12834 BY ELIZABETH SANDER
•FIXFIXED A BUG IN ENSEMBLEGRADIENTBOOSTINGLOSSFUNCTION ANDENSEMBLE GRADIENTBOOSTINGLEASTSQUARESERROR WHERE THE DEFAULT VALUE OF LEARNINGRATE IN UPDATETERMINALREGIONS IS NOT CONSISTENT WITH THE DOCUMENT AND THE CALLER FUNCTIONS NOTE HOWEVER THAT DIRECTLY USING THESE LOSS FUNCTIONS IS DEPRECATED 6463 BY MOVELIKERIVER
•FIXENSEMBLEPARTIALDEPENDENCE AND CONSEQUENTLY THE NEW VERSION SKLEARNINSPECTION PARTIALDEPENDENCE NOW TAKES SAMPLE WEIGHTS INTO ACCOUNT FOR THE PARTIAL DEPENDENCE COMPUTATION WHEN THE GRADIENT BOOSTING MODEL HAS BEEN TRAINED WITH SAMPLE WEIGHTS 13193 BY SAMUEL O RONSIN

•API C HANGE ENSEMBLEPARTIALDEPENDENCE ANDENSEMBLEPLOTPARTIALDEPENDENCE
ARE NOW DEPRECATED IN FAVOR OF INSPECTIONPARTIALDEPENDENCE ANDINSPECTION
PLOTPARTIALDEPENDENCE 12599 BY TREVOR STEPHENS AND NICOLAS HUG
•FIXENSEMBLEVOTINGCLASSIFIER ANDENSEMBLEVOTINGREGRESSOR WERE FAILING DURING FIT IN
ONE OF THE ESTIMATORS WAS SET TO NONE ANDSAMPLEWEIGHT WAS NOTNONE 13779 BY GUILLAUME LEMAITRE
•API C HANGE ENSEMBLEVOTINGCLASSIFIER ANDENSEMBLEVOTINGREGRESSOR ACCEPTDROP
TO DISABLE AN ESTIMATOR IN ADDITION TO NONE TO BE CONSISTENT WITH OTHER ESTIMATORS IE PIPELINE
FEATUREUNION ANDCOMPOSECOLUMNTRANSFORMER 13780 BY GUILLAUME LEMAITRE
SKLEARNEXTERNALS
•API C HANGE DEPRECATED EXTERNALSSIX SINCE WE HAVE DROPPED SUPPORT FOR PYTHON 27 12916 BY HAN
MIN QIN
SKLEARNFEATUREEXTRACTION
•FIXIFINPUTFILE ORINPUTFILENAME AND A CALLABLE IS GIVEN AS THE ANALYZER SKLEARN
FEATUREEXTRACTIONTEXTHASHINGVECTORIZER SKLEARNFEATUREEXTRACTIONTEXT
TFIDFVECTORIZER ANDSKLEARNFEATUREEXTRACTIONTEXTCOUNTVECTORIZER NOW READ
THE DATA FROM THE FILES AND THEN PASS IT TO THE GIVEN ANALYZER INSTEAD OF PASSING THE FILE NAMES OR THE
FILE OBJECTS TO THE ANALYZER 13641 BY ADRIN JALALI
SKLEARNIMPUTE
•MAJOR FEATURE ADDEDIMPUTEITERATIVEIMPUTER WHICH IS A STRATEGY FOR IMPUTING MISSING VALUES
BY MODELING EACH FEATURE WITH MISSING VALUES AS A FUNCTION OF OTHER FEATURES IN A ROUNDROBIN FASHION 8478
AND 12177 BY SERGEY FELDMAN AND BEN LAWSON
THE API OF ITERATIVEIMPUTER IS EXPERIMENTAL AND SUBJECT TO CHANGE WITHOUT ANY DEPRECATION CYCLE TO USE THEM
YOU NEED TO EXPLICITLY IMPORT ENABLEITERATIVEIMPUTER
FROM SKLEARNEXPERIMENTAL IMPORT ENABLEITERATIVEIMPUTER NOQA
NOW YOU CAN IMPORT NORMALLY FROM SKLEARNIMPUTE
FROM SKLEARNIMPUTE IMPORT ITERATIVEIMPUTER
•FEATURE THEIMPUTESIMPLEIMPUTER ANDIMPUTEITERATIVEIMPUTER HAVE A NEW PARAMETER
ADDINDICATOR WHICH SIMPLY STACKS A IMPUTEMISSINGINDICATOR TRANSFORM INTO THE OUTPUT OF
THE IMPUTER'S TRANSFORM THAT ALLOWS A PREDICTIVE ESTIMATOR TO ACCOUNT FOR MISSINGNESS 12583 13601 BY
DANYLO BAIBAK
•FIXINIMPUTEMISSINGINDICATOR AVOID IMPLICIT DENSIFICATION BY RAISING AN EXCEPTION IF INPUT IS SPARSE
ADDMISSINGVALUES PROPERTY IS SET TO 0 13240 BY BARTOSZ TELENCZUK
•FIXFIXED TWO BUGS IN IMPUTEMISSINGINDICATOR FIRST WHEN XIS SPARSE ALL THE NONZERO NON MISSING
VALUES USED TO BECOME EXPLICIT FALSE IN THE TRANSFORMED DATA THEN WHEN FEATURESMISSINGONLY
ALL FEATURES USED TO BE KEPT IF THERE WERE NO MISSING VALUES AT ALL 13562 BY JÉRÉMIE DU BOISBERRANGER
SKLEARNINSPECTION
NEW SUBPACKAGE

SCIKITLEARN USER GUIDE RELEASE 0213
•FEATURE PARTIAL DEPENDENCE PLOTS INSPECTIONPLOTPARTIALDEPENDENCE ARE NOW SUPPORTED FOR ANY REGRESSOR OR CLASSIFIER PROVIDED THAT THEY HAVE A PREDICTPROBA METHOD 12599 BY TREVOR STEPHENS AND NICOLAS HUG
SKLEARNISOTONIC
•FEATURE ALLOW DIFFERENT DTYPES SUCH AS FLOAT32 IN ISOTONICISOTONICREGRESSION 8769 BY VLAD NICULAE
SKLEARNLINEARMODEL
•ENHANCEMENT LINEARMODELRIDGE NOW PRESERVES FLOAT32 ANDFLOAT64 DTYPES 8769 AND 11000 BY GUILLAUME LEMAITRE AND JOAN MASSICH
•FEATURE LINEARMODELLOGISTICREGRESSION AND LINEARMODEL LOGISTICREGRESSIONCV NOW SUPPORT ELASTICNET PENALTY WITH THE 'SAGA' SOLVER 11646 BY NICOLAS HUG
•FEATURE ADDEDLINEARMODELLARSPATHGRAM WHICH IS LINEARMODELLARSPATH IN THE SUFFICIENT STATS MODE ALLOWING USERS TO COMPUTE LINEARMODELLARSPATH WITHOUT PROVIDING XANDY 11699 BY KUAI YU
•EFFICIENCY LINEARMODELMAKEDATASET NOW PRESERVES FLOAT32 ANDFLOAT64 DTYPES REDUCING MEMORY CONSUMPTION IN STOCHASTIC GRADIENT SAG AND SAGA SOLVERS 8769 AND 11000 BY NELLE VAROQUAUX ARTHUR IMBERT GUILLAUME LEMAITRE AND JOAN MASSICH
•ENHANCEMENT LINEARMODELLOGISTICREGRESSION NOW SUPPORTS AN UNREGULARIZED OBJECTIVE WHEN PENALTYNONE IS PASSED THIS IS EQUIVALENT TO SETTING CNPINF WITH L2 REGULARIZATION NOT SUPPORTED BY THE LIBLINEAR SOLVER 12860 BY NICOLAS HUG
•ENHANCEMENT SPARSECG SOLVER INLINEARMODELRIDGE NOW SUPPORTS FITTING THE INTERCEPT IE FITINTERCEPTTRUE WHEN INPUTS ARE SPARSE 13336 BY BARTOSZ TELENCZUK
•ENHANCEMENT THE COORDINATE DESCENT SOLVER USED IN LASSO ELASTICNET ETC NOW ISSUES A CONVERGENCEWARNING WHEN IT COMPLETES WITHOUT MEETING THE DESIRED TOLERANBCE 11754 AND 13397 BY BRENT FAGAN AND ADRIN JALALI
•FIXFIXED A BUG IN LINEARMODELLOGISTICREGRESSION ANDLINEARMODEL LOGISTICREGRESSIONCV WITH 'SAGA' SOLVER WHERE THE WEIGHTS WOULD NOT BE CORRECTLY UPDATED IN SOME CASES 11646 BY TOM DUPRE LA TOUR
•FIXFIXED THE POSTERIOR MEAN POSTERIOR COVARIANCE AND RETURNED REGULARIZATION PARAMETERS IN LINEARMODELBAYESIANRIDGE THE POSTERIOR MEAN AND THE POSTERIOR COVARIANCE WERE NOT THE ONES COMPUTED WITH THE LAST UPDATE OF THE REGULARIZATION PARAMETERS AND THE RETURNED REGULARIZATION PARAMETERS WERE NOT THE FINAL ONES ALSO FIXED THE FORMULA OF THE LOG MARGINAL LIKELIHOOD USED TO COMPUTE THE SCORE WHEN COMPUTESCORETRUE 12174 BY ALBERT THOMAS
•FIXFIXED A BUG IN LINEARMODELLASSOLARSIC WHERE USER INPUT COPYXFALSE AT INSTANCE CRE ATION WOULD BE OVERRIDDEN BY DEFAULT PARAMETER VALUE COPYXTRUE INFIT 12972 BY LUCIO FERNANDEZ ARJONA
•FIXFIXED A BUG IN LINEARMODELLINEARREGRESSION THAT WAS NOT RETURNING THE SAME COEFFECIENTS AND INTERCEPTS WITH FITINTERCEPTTRUE IN SPARSE AND DENSE CASE 13279 BY ALEXANDRE GRAMFORT
•FIXFIXED A BUG IN LINEARMODELHUBERREGRESSOR THAT WAS BROKEN WHEN XWAS OF DTYPE BOOL 13328 BY ALEXANDRE GRAMFORT

•FIXFIXED A PERFORMANCE ISSUE OF SAGA ANDSAG SOLVERS WHEN CALLED IN A JOBLIBPARALLEL SETTING WITH NJOBS 1 ANDBACKENDTHREADING CAUSING THEM TO PERFORM WORSE THAN IN THE SEQUENTIAL CASE 13389 BY PIERRE GLASER
•FIXFIXED A BUG IN LINEARMODELSTOCHASTICGRADIENTBASESGDCLASSIFIER THAT WAS NOT DETERMINISTIC WHEN TRAINED IN A MULTICLASS SETTING ON SEVERAL THREADS 13422 BY CLÉMENT DOUMOURO
•FIX FIXED BUG IN LINEARMODELRIDGEREGRESSION LINEARMODELRIDGE ANDLINEARMODELRIDGECLASSIFIER THAT CAUSED UNHANDLED EXCEPTION FOR ARGUMENTS RETURNINTERCEPTTRUE ANDSOLVERAUTO DEFAULT OR ANY OTHER SOLVER DIFFERENT FROM SAG 13363 BY BARTOSZ TELENCZUK
•FIXLINEARMODELRIDGEREGRESSION WILL NOW RAISE AN EXCEPTION IF RETURNINTERCEPTTRUE AND SOLVER IS DIFFERENT FROM SAG PREVIOUSLY ONLY WARNING WAS ISSUED 13363 BY BARTOSZ TELENCZUK
•FIXLINEARMODELRIDGEREGRESSION WILL CHOOSE SPARSECG SOLVER FOR SPARSE INPUTS WHEN SOLVERAUTO ANDSAMPLEWEIGHT IS PROVIDED PREVIOUSLY CHOLESKY SOLVER WAS SELECTED 13363 BY BARTOSZ TELENCZUK
•API C HANGE THE USE OFLINEARMODELLARSPATH WITHXNONE WHILE PASSING GRAM IS DEPRECATED IN VERSION 021 AND WILL BE REMOVED IN VERSION 023 USE LINEARMODELLARSPATHGRAM INSTEAD 11699 BY KUAI YU
•API C HANGE LINEARMODELLOGISTICREGRESSIONPATH IS DEPRECATED IN VERSION 021 AND WILL BE REMOVED IN VERSION 023 12821 BY NICOLAS HUG
•FIXLINEARMODELRIDGECV WITH GENERALIZED CROSSVALIDATION NOW CORRECTLY FITS AN INTERCEPT WHEN FITINTERCEPTTRUE AND THE DESIGN MATRIX IS SPARSE 13350 BY JÉRÔME DOCKÈS

SKLEARNMANIFOLD

•EFFICIENCY MAKEMANIFOLDTSNETRUSTWORTHINESS USE AN INVERTED INDEX INSTEAD OF AN NPWHERE LOOKUP TO FIND THE RANK OF NEIGHBORS IN THE INPUT SPACE THIS IMPROVES EFFICIENCY IN PARTICULAR WHEN COMPUTED WITH LOTS OF NEIGHBORS ANDOR SMALL DATASETS 9907 BY WILLIAM DE VAZELHES

SKLEARNMETRICS

•FEATURE ADDED THEMETRICSMAXERROR METRIC AND A CORRESPONDING MAXERROR SCORER FOR SINGLE OUTPUT REGRESSION 12232 BY KRISHNA SANGEETH
•FEATURE ADDMETRICSMULTILABELCONFUSIONMATRIX WHICH CALCULATES A CONFUSION MATRIX WITH TRUE POSITIVE FALSE POSITIVE FALSE NEGATIVE AND TRUE NEGATIVE COUNTS FOR EACH CLASS THIS FACILITATES THE CALCULATION OF SETWISE METRICS SUCH AS RECALL SPECIFICITY FALL OUT AND MISS RATE 11179 BY SHANGWU YAO AND JOEL NOTHMAN
•FEATURE METRICSJACCARDSCORE HAS BEEN ADDED TO CALCULATE THE JACCARD COEFFICIENT AS AN EVALUA TION METRIC FOR BINARY MULTILABEL AND MULTICLASS TASKS WITH AN INTERFACE ANALOGOUS TO METRICSF1SCORE 13151 BY GAURAV DHINGRA AND JOEL NOTHMAN
•FEATURE ADDEDMETRICSPAIRWISEHAVERSINEDISTANCES WHICH CAN BE ACCESSED WITH METRICPAIRWISE THROUGHMETRICSPAIRWISEDISTANCES AND ESTIMATORS HAVERSINE DISTANCE WAS PREVIOUSLY AVAILABLE FOR NEAREST NEIGHBORS CALCULATION 12568 BY WEI XUE EMMANUEL ARIAS AND JOEL NOTHMAN
•EFFICIENCY FASTERMETRICSPAIRWISEDISTANCES WITH NJOBS 1 BY USING A THREADBASED BACKEND INSTEAD OF PROCESSBASED BACKENDS 8216 BY PIERRE GLASER AND ROMUALD MENUET
•EFFICIENCY THE PAIRWISE MANHATTAN DISTANCES WITH SPARSE INPUT NOW USES THE BLAS SHIPPED WITH SCIPY INSTEAD OF THE BUNDLED BLAS 12732 BY JÉRÉMIE DU BOISBERRANGER

•ENHANCEMENT USE LABEL ACCURACY INSTEAD OF MICROAVERAGE ONMETRICS
CLASSIFICATIONREPORT TO AVOID CONFUSION MICROAVERAGE IS ONLY SHOWN FOR MULTILABEL OR
MULTICLASS WITH A SUBSET OF CLASSES BECAUSE IT IS OTHERWISE IDENTICAL TO ACCURACY 12334 BY EMMANUEL ARIAS
JOEL NOTHMAN AND ANDREAS MÜLLER
•ENHANCEMENT ADDEDBETA PARAMETER TO METRICSHOMOGENEITYCOMPLETENESSVMEASURE AND
METRICSVMEASURESCORE TO CONFIGURE THE TRADEOFF BETWEEN HOMOGENEITY AND COMPLETENESS 13607
BY STEPHANE COUVREUR AND AND IVAN SANCHEZ
•FIXTHE METRIC METRICSR2SCORE IS DEGENERATE WITH A SINGLE SAMPLE AND NOW IT RETURNS NAN AND RAISES
EXCEPTIONSUNDEFINEDMETRICWARNING 12855 BY PAWEL SENDYK
•FIXFIXED A BUG WHERE METRICSBRIERSCORELOSS WILL SOMETIMES RETURN INCORRECT RESULT WHEN THERE'S
ONLY ONE CLASS IN YTRUE 13628 BY HANMIN QIN
•FIXFIXED A BUG IN METRICSLABELRANKINGAVERAGEPRECISIONSCORE WHERE SAMPLEWEIGHT
WASN'T TAKEN INTO ACCOUNT FOR SAMPLES WITH DEGENERATE LABELS 13447 BY DAN ELLIS
•API C HANGE THE PARAMETER LABELS INMETRICSHAMMINGLOSS IS DEPRECATED IN VERSION 021 AND WILL
BE REMOVED IN VERSION 023 10580 BY RESHAMA SHAIKH AND SANDRA MITROVIC
•FIXTHE FUNCTION METRICSPAIRWISEEUCLIDEANDISTANCES AND THEREFORE SEVERAL ESTIMATORS WITH
METRICEUCLIDEAN SUFFERED FROM NUMERICAL PRECISION ISSUES WITH FLOAT32 FEATURES PRECISION HAS
BEEN INCREASED AT THE COST OF A SMALL DROP OF PERFORMANCE 13554 BY CELELIBI AND JÉRÉMIE DU BOISBERRANGER
•API C HANGE METRICSJACCARDSIMILARITYSCORE IS DEPRECATED IN FAVOUR OF THE MORE CONSISTENT
METRICSJACCARDSCORE THE FORMER BEHAVIOR FOR BINARY AND MULTICLASS TARGETS IS BROKEN 13151 BY
JOEL NOTHMAN
SKLEARNMIXTURE
•FIXFIXED A BUG IN MIXTUREBASEMIXTURE AND THEREFORE ON ESTIMATORS BASED ON IT IE MIXTURE
GAUSSIANMIXTURE ANDMIXTUREBAYESIANGAUSSIANMIXTURE WHEREFITPREDICT ANDFIT
PREDICT WERE NOT EQUIVALENT 13142 BY JÉRÉMIE DU BOISBERRANGER
SKLEARNMODELSELECTION
•FEATURE CLASSESGRIDSEARCHCV ANDRANDOMIZEDSEARCHCV NOW ALLOW FOR REFITCALLABLE TO ADD FLEX
IBILITY IN IDENTIFYING THE BEST ESTIMATOR SEE BALANCE MODEL COMPLEXITY AND CROSSVALIDATED SCORE 11354 BY
WENHAO ZHANG JOEL NOTHMAN AND ADRIN JALALI
•ENHANCEMENT CLASSESGRIDSEARCHCV RANDOMIZEDSEARCHCV AND METHODS CROSSVALSCORE
CROSSVALPREDICT CROSSVALIDATE NOW PRINT TRAIN SCORES WHEN RETURNTRAINSCORES IS
TRUE AND VERBOSE 2 FORLEARNINGCURVE ANDVALIDATIONCURVE ONLY THE LATTER IS REQUIRED 12613
AND 12669 BY MARC TORRELLAS
•ENHANCEMENT SOME CV SPLITTER CLASSES AND MODELSELECTIONTRAINTESTSPLIT NOW RAISE
VALUEERROR WHEN THE RESULTING TRAINING SET IS EMPTY 12861 BY NICOLAS HUG
•FIXFIXED A BUG WHERE MODELSELECTIONSTRATIFIEDKFOLD SHUFFLES EACH CLASS'S SAMPLES WITH THE
SAMERANDOMSTATE MAKINGSHUFFLETRUE INEFFECTIVE 13124 BY HANMIN QIN
•FIXADDED ABILITY FOR MODELSELECTIONCROSSVALPREDICT TO HANDLE MULTILABEL AND
MULTIOUTPUTMULTICLASS TARGETS WITH PREDICTPROBA TYPE METHODS 8773 BY STEPHEN HOOVER
•FIXFIXED AN ISSUE IN CROSSVALPREDICT WHEREMETHODPREDICTPROBA RETURNED ALWAYS 00
WHEN ONE OF THE CLASSES WAS EXCLUDED IN A CROSSVALIDATION FOLD 13366 BY GUILLAUME FOURNIER

SKLEARNMULTICLASS
•FIXFIXED AN ISSUE IN MULTICLASSONEVSONECLASSIFIERDECISIONFUNCTION WHERE THE DECI
SIONFUNCTION VALUE OF A GIVEN SAMPLE WAS DIFFERENT DEPENDING ON WHETHER THE DECISIONFUNCTION WAS EVALUATED
ON THE SAMPLE ALONE OR ON A BATCH CONTAINING THIS SAME SAMPLE DUE TO THE SCALING USED IN DECISIONFUNCTION
10440 BY JONATHAN OHAYON
SKLEARNMULTIOUTPUT
•FIXFIXED A BUG IN MULTIOUTPUTMULTIOUTPUTCLASSIFIER WHERE THE PREDICTPROBA METHOD INCOR
RECTLY CHECKED FOR PREDICTPROBA ATTRIBUTE IN THE ESTIMATOR OBJECT 12222 BY REBEKAH KIM
SKLEARNNEIGHBORS
•MAJOR FEATURE ADDEDNEIGHBORSNEIGHBORHOODCOMPONENTSANALYSIS FOR METRIC LEARNING
WHICH IMPLEMENTS THE NEIGHBORHOOD COMPONENTS ANALYSIS ALGORITHM 10058 BY WILLIAM DE VAZELHES AND
JOHN CHIOTELLIS
•API C HANGE METHODS IN NEIGHBORSNEARESTNEIGHBORS KNEIGHBORS RADIUSNEIGHBORS
KNEIGHBORSGRAPH RADIUSNEIGHBORSGRAPH NOW RAISE NOTFITTEDERROR RATHER THAN
ATTRIBUTEERROR WHEN CALLED BEFORE FIT 12279 BY KRISHNA SANGEETH
SKLEARNNEURALNETWORK
•FIXFIXED A BUG IN NEURALNETWORKMLPCLASSIFIER ANDNEURALNETWORKMLPREGRESSOR
WHERE THE OPTION SHUFFLEFALSE WAS BEING IGNORED 12582 BY SAM WATERBURY
•FIXFIXED A BUG IN NEURALNETWORKMLPCLASSIFIER WHERE VALIDATION SETS FOR EARLY STOPPING WERE NOT
SAMPLED WITH STRATIFICATION IN THE MULTILABEL CASE HOWEVER SPLITS ARE STILL NOT STRATIFIED 13164 BY NICOLAS HUG
SKLEARNPIPELINE
•FEATURE PIPELINEPIPELINE CAN NOW USE INDEXING NOTATION EG MYPIPELINE01 TO EXTRACT A
SUBSEQUENCE OF STEPS AS ANOTHER PIPELINE INSTANCE A PIPELINE CAN ALSO BE INDEXED DIRECTLY TO EXTRACT A PARTICULAR
STEP EGMYPIPELINESVC RATHER THAN ACCESSING NAMEDSTEPS 2568 BY JOEL NOTHMAN
•FEATURE ADDED OPTIONAL PARAMETER VERBOSE INPIPELINEPIPELINE COMPOSE
COLUMNTRANSFORMER ANDPIPELINEFEATUREUNION AND CORRESPONDING MAKE HELPERS FOR SHOWING
PROGRESS AND TIMING OF EACH STEP 11364 BY BAZE PETRUSHEV KARAN DESAI JOEL NOTHMAN AND THOMAS FAN
•ENHANCEMENT PIPELINEPIPELINE NOW SUPPORTS USING PASSTHROUGH AS A TRANSFORMER WITH THE
SAME EFFECT AS NONE 11144 BY THOMAS FAN
•ENHANCEMENT PIPELINEPIPELINE IMPLEMENTS LEN AND THEREFORE LENPIPELINE RETURNS THE
NUMBER OF STEPS IN THE PIPELINE 13439 BY LAKSHYA KD
SKLEARNPREPROCESSING
•FEATURE PREPROCESSINGONEHOTENCODER NOW SUPPORTS DROPPING ONE FEATURE PER CATEGORY WITH A NEW
DROP PARAMETER 12908 BY DREW JOHNSTON
•EFFICIENCY PREPROCESSINGONEHOTENCODER ANDPREPROCESSINGORDINALENCODER NOW HAN
DLE PANDAS DATAFRAMES MORE EFFICIENTLY 13253 BY MAIKIA

•EFFICIENCY MAKEPREPROCESSINGMULTILABELBINARIZER CACHE CLASS MAPPINGS INSTEAD OF CALCULAT
ING IT EVERY TIME ON THE FLY 12116 BY EKATERINA KRIVICH AND JOEL NOTHMAN
•EFFICIENCY PREPROCESSINGPOLYNOMIALFEATURES NOW SUPPORTS COMPRESSED SPARSE ROW CSR MA
TRICES AS INPUT FOR DEGREES 2 AND 3 THIS IS TYPICALLY MUCH FASTER THAN THE DENSE CASE AS IT SCALES WITH MATRIX
DENSITY AND EXPANSION DEGREE ON THE ORDER OF DENSITYDEGREE AND IS MUCH MUCH FASTER THAN THE COMPRESSED
SPARSE COLUMN CSC CASE 12197 BY ANDREW NYSTROM
•EFFICIENCY SPEED IMPROVEMENT IN PREPROCESSINGPOLYNOMIALFEATURES IN THE DENSE CASE ALSO
ADDED A NEW PARAMETER ORDER WHICH CONTROLS OUTPUT ORDER FOR FURTHER SPEED PERFORMANCES 12251 BY TOM
DUPRE LA TOUR
•FIXFIXED THE CALCULATION OVERFLOW WHEN USING A FLOAT16 DTYPE WITH PREPROCESSINGSTANDARDSCALER
13007 BY RAFFAELLO BALUYOT
•FIXFIXED A BUG IN PREPROCESSINGQUANTILETRANSFORMER ANDPREPROCESSING
QUANTILETRANSFORM TO FORCE NQUANTILES TO BE AT MOST EQUAL TO NSAMPLES VALUES OF NQUANTILES
LARGER THAN NSAMPLES WERE EITHER USELESS OR RESULTING IN A WRONG APPROXIMATION OF THE CUMULATIVE DISTRIBUTION
FUNCTION ESTIMATOR 13333 BY ALBERT THOMAS
•API C HANGE THE DEFAULT VALUE OF COPY INPREPROCESSINGQUANTILETRANSFORM WILL CHANGE FROM
FALSE TO TRUE IN 023 IN ORDER TO MAKE IT MORE CONSISTENT WITH THE DEFAULT COPY VALUES OF OTHER FUNCTIONS IN
PREPROCESSING AND PREVENT UNEXPECTED SIDE EFFECTS BY MODIFYING THE VALUE OF XINPLACE 13459 BY HUNTER
MCGUSHION
SKLEARNSVM
•FIXFIXED AN ISSUE IN SVMSVCDECISIONFUNCTION WHENDECISIONFUNCTIONSHAPEOVR
THE DECISIONFUNCTION VALUE OF A GIVEN SAMPLE WAS DIFFERENT DEPENDING ON WHETHER THE DECISIONFUNCTION WAS
EVALUATED ON THE SAMPLE ALONE OR ON A BATCH CONTAINING THIS SAME SAMPLE DUE TO THE SCALING USED IN DECI
SIONFUNCTION 10440 BY JONATHAN OHAYON
SKLEARNTREE
•FEATURE DECISION TREES CAN NOW BE PLOTTED WITH MATPLOTLIB USING TREEPLOTTREE WITHOUT RELYING ON THE
DOT LIBRARY REMOVING A HARDTOINSTALL DEPENDENCY 8508 BY ANDREAS MÜLLER
•FEATURE DECISION TREES CAN NOW BE EXPORTED IN A HUMAN READABLE TEXTUAL FORMAT USING TREE
EXPORTTEXT 6261 BY GIUSEPPE VETTIGLI
•FEATURE GETNLEAVES ANDGETDEPTH HAVE BEEN ADDED TO TREEBASEDECISIONTREE
AND CONSEQUENTLY ALL ESTIMATORS BASED ON IT INCLUDING TREEDECISIONTREECLASSIFIER TREE
DECISIONTREEREGRESSOR TREEEXTRATREECLASSIFIER ANDTREEEXTRATREEREGRESSOR
12300 BY ADRIN JALALI
•FIXTREES AND FORESTS DID NOT PREVIOUSLY PREDICT MULTIOUTPUT CLASSIFICATION TARGETS WITH STRING LABELS DESPITE
ACCEPTING THEM IN FIT 11458 BY MITAR MILUTINOVIC
•FIXFIXED AN ISSUE WITH TREEBASEDECISIONTREE AND CONSEQUENTLY ALL ESTIMATORS BASED
ON IT INCLUDING TREEDECISIONTREECLASSIFIER TREEDECISIONTREEREGRESSOR TREE
EXTRATREECLASSIFIER ANDTREEEXTRATREEREGRESSOR WHERE THEY USED TO EXCEED THE GIVEN
MAXDEPTH BY 1 WHILE EXPANDING THE TREE IF MAXLEAFNODES ANDMAXDEPTH WERE BOTH SPECIFIED BY
THE USER PLEASE NOTE THAT THIS ALSO AFFECTS ALL ENSEMBLE METHODS USING DECISION TREES 12344 BY ADRIN JALALI

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SKLEARNUTILS

•FEATURE UTILSRESAMPLE NOW ACCEPTS A STRATIFY PARAMETER FOR SAMPLING ACCORDING TO CLASS DISTRIBU TIONS 13549 BY NICOLAS HUG

•API C HANGE DEPRECATED WARNONDTYPE PARAMETER FROM UTILSCHECKARRAY ANDUTILS CHECKXY ADDED EXPLICIT WARNING FOR DTYPE CONVERSION IN CHECKPAIRWISEARRAYS IF THEMETRIC BEING PASSED IS A PAIRWISE BOOLEAN METRIC 13382 BY PRATHMESH SAVALE

MULTIPLE MODULES

•MAJOR FEATURE THEREPR METHOD OF ALL ESTIMATORS USED WHEN CALLING PRINTESTIMATOR HAS BEEN ENTIRELY REWRITTEN BUILDING ON PYTHON'S PRETTY PRINTING STANDARD LIBRARY ALL PARAMETERS ARE PRINTED BY DEFAULT BUT THIS CAN BE ALTERED WITH THE PRINTCHANGEDONLY OPTION INSKLEARNSETCONFIG 11705 BY NICOLAS HUG

•MAJOR FEATURE ADD ESTIMATORS TAGS THESE ARE ANNOTATIONS OF ESTIMATORS THAT ALLOW PROGRAMMATIC INSPECTION OF THEIR CAPABILITIES SUCH AS SPARSE MATRIX SUPPORT SUPPORTED OUTPUT TYPES AND SUPPORTED METHODS ESTIMATOR TAGS ALSO DETERMINE THE TESTS THAT ARE RUN ON AN ESTIMATOR WHEN CHECKESTIMATOR IS CALLED READ MORE IN THEUSER GUIDE 8022 BY ANDREAS MÜLLER

•EFFICIENCY MEMORY COPIES ARE AVOIDED WHEN CASTING ARRAYS TO A DIFFERENT DTYPE IN MULTIPLE ESTIMATORS 11973 BY ROMAN YURCHAK

•FIXFIXED A BUG IN THE IMPLEMENTATION OF THE OURRANDR HELPER FUNCTION THAT WAS NOT BEHAVING CONSISTENTLY ACROSS PLATFORMS 13422 BY MADHURA PARIKH AND CLÉMENT DOUMOURO

MISCELLANEOUS

•ENHANCEMENT JOBLIB IS NO LONGER VENDORED IN SCIKITLEARN AND BECOMES A DEPENDENCY MINIMAL SUPPORTED VERSION IS JOBLIB 011 HOWEVER USING VERSION 013 IS STRONGLY RECOMMENDED 13531 BY ROMAN YURCHAK

1114 CHANGES TO ESTIMATOR CHECKS

THESE CHANGES MOSTLY AFFECT LIBRARY DEVELOPERS

• ADDCHECKFITIDEMPOTENT TOCHECKESTIMATOR WHICH CHECKS THAT WHEN FITIS CALLED TWICE WITH THE SAME DATA THE OUPUT OF PREDICT PREDICTPROBA TRANSFORM AND DECISIONFUNCTION DOES NOT CHANGE 12328 BY NICOLAS HUG

• MANY CHECKS CAN NOW BE DISABLED OR CONFIGURED WITH ESTIMATOR TAGS 8022 BY ANDREAS MÜLLER

1115 CODE AND DOCUMENTATION CONTRIBUTORS

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FRANK HOANG FIBINSE XAVIER' FINN O'SHEA GABRIEL MARZINOTTO GABRIEL VACALIUC GABRIELE CALVO GAEL VAROQUAUX GAURAVAHLAWAT GIUSEPPE VETTIGLI GREG GANDENBERGER GUILLAUME FOURNIER GUILLAUME LEMAITRE GUSTAVO DE MARI PEREIRA HANMIN QIN HAROLDFOX HHULUQI HUNTER MCGUSHION IAN SANDERS JACKLANGERMAN JACOPO NOTARSTEFANO JAKIRKHAM JAMES BOURBEAU JAN KOCH JAN S JANVANRIJN JARROD MILLMAN JDETHURENS JEREMIEDBB JF JOAAK JOAN MASSICH JOEL NOTHMAN JONATHAN OHAYON JORIS VAN DEN BOSSCHE JOSEPHSALMON JÉRÉMIE MÉHAULT KATRIN LEINWE BER KEN KMS15 KOEN KOSSORI ARUKU KRISHNA SANGEETH KUAI YU KULBEAR KUSHAL CHAUHAN KYLE JACKSON LAKSHYA KD LEANDRO HERMIDA LEE YI JIE JOEL LILY XIONG LISA SARAH THOMAS LOIC ESTEVE LOUIB LUKFA MAIKIA MAILLIAM MANIMARAN MANUEL LÓPEZIBÁÑEZ MARC TORRELLAS MARCO GAIDO MARCO GORELLI MARCOGORELLI MARINELM MARK HANNEL MARTIN GUBRI MASSTRAN MATHURINM MATTHEW ROESCHKE MAX COPELAND MELSYT MFERRARI3 MICKAËL SCHOENT GEN MING LI MITAR MOHAMMAD AFTAB MOHAMMED ABDELAAL MOHAMMED IBRAHEEM MUHAMMAD HASSAAN RAFIQUE MWESTT NAOYA IIJIMA NICHOLAS SMITH NICOLAS GOIX NICOLAS HUG NIKOLAY SHEBANOV OLEKSANDR PAVLYK OLIVER RAUSCH OLIVIER GRISEL ORESTIS OSMAN OWEN FLANAGAN PAUL PACZUSKI PAVEL SORIANO PAVLOS KALLIS PAWEL SENDYK PEAY PETER PETER COCK PETER HAUSAMANN PETER MARKO PIERRE GLASER PIERRETALLOTTE PIM DE HAAN PIOTR SZYMA ´NSKI PRABAKARAN KUMARESSHAN PRADEEP REDDY RAAMANA PRATHMESH SAVALE PULKIT MALOO QUENTIN BATISTA RADOSTIN STOY ANOV RAF BALUYOT RAJDEEP DUA RAMIL NUGMANOV RAÚL GARCÍA CALVO REBEKAH KIM RESHAMA SHAIKH ROHAN LEKHWANI ROHAN SINGH ROHAN VARMA ROHIT KAPOOR ROMAN FELDBAUER ROMAN YURCHAK ROMUALD M ROOPAM SHARMA RYAN RÜDIGER BUSCHE SAM WATERBURY SAMUEL O RONSIN SANDROCASAGRANDE SCOTT COLE SCOTT LOWE SE BASTIAN RASCHKA SHANGWU YAO SHIVAM KOTWALIA SHIYU DUAN SMARIE SRIHARSHA HATWAR STEPHEN HOOVER STEPHEN TIERNEY STÉPHANE COUVREUR SURGAN12 SYLVAINLAN TAKINGITCASUAL TASHAY GREEN THIBSEJ THOMAS FAN THOMAS J FAN THOMAS MOREAU TOM DUPRÉ LA TOUR TOMMY TULIO CASAGRANDE UMAR FAROUK UMAR UTKARSH UPADHYAY VINAYAK MEHTA VISHAAL KAPOOR VIVEK KUMAR VLAD NICULAE VQEAN3 WENHAO ZHANG WILLIAM DE VAZELHES XHAN XING HAN LU XINYULIU12 YAROSLAV HALCHENKO ZACH GRIFFITH ZACH MILLER ZAYD HAMMOUDEH ZHUYI XUE ZIJIE ZJ POH

112 VERSION 0204

JULY 30 2019

THIS IS A BUGFIX RELEASE WITH SOME BUG FIXES APPLIED TO VERSION 0203

1121 CHANGELOG

THE BUNDLED VERSION OF JOBLIB WAS UPGRADED FROM 0130 TO 0132

SKLEARNCLUSTER

•FIXFIXED A BUG IN CLUSTERKMEANS WHERE KMEANS INITIALISATION COULD RARELY RESULT IN AN INDEXERROR 11756 BY JOEL NOTHMAN

SKLEARNCOMPOSE

•FIXFIXED AN ISSUE IN COMPOSECOLUMNTRANSFORMER WHERE USING DATAFRAMES WHOSE COLUMN ORDER DIFFERS BETWEEN FUNC FIT AND FUNCTRANSFORM COULD LEAD TO SILENTLY PASSING INCORRECT COLUMNS TO THE REMAINDER TRANSFORMER 14237 BY ANDREAS SCHUDERER

SKLEARNMODELSELECTION

•FIXFIXED A BUG WHERE MODELSELECTIONSTRATIFIEDKFOLD SHUFFLES EACH CLASS'S SAMPLES WITH THE SAMERANDOMSTATE MAKINGSHUFFLETRUE INEFFECTIVE 13124 BY HANMIN QIN

SKLEARNNEIGHBORS
•FIXFIXED A BUG IN NEIGHBORSKERNELDENSITY WHICH COULD NOT BE RESTORED FROM A PICKLE IF SAMPLEWEIGHT HAD BEEN USED 13772 BY ADITYA VYAS

113 VERSION 0203

MARCH 1 2019

THIS IS A BUGFIX RELEASE WITH SOME MINOR DOCUMENTATION IMPROVEMENTS AND ENHANCEMENTS TO FEATURES RELEASED IN 0200

1131 CHANGELOG

SKLEARNCLUSTER
•FIXFIXED A BUG IN CLUSTERKMEANS WHERE COMPUTATION WAS SINGLE THREADED WHEN NJOBS 1 OR NJOBS 1 12949 BY PRABAKARAN KUMARESSHAN
SKLEARNCOMPOSE
•FIXFIXED A BUG IN COMPOSECOLUMNTRANSFORMER TO HANDLE NEGATIVE INDEXES IN THE COLUMNS LIST OF THE TRANSFORMERS 12946 BY PIERRE TALLOTTE
SKLEARNCOVARIANCE
•FIXFIXED A REGRESSION IN COVARIANCEGRAPHICALLASSO SO THAT THE CASE NFEATURES2 IS HANDLED CORRECTLY 13276 BY AURÉLIEN BELLET
SKLEARNDECOMPOSITION
•FIXFIXED A BUG IN DECOMPOSITIONSPARSEENCODE WHERE COMPUTATION WAS SINGLE THREADED WHEN NJOBS 1 ORNJOBS 1 13005 BY PRABAKARAN KUMARESSHAN
SKLEARNDATASETS
•EFFICIENCY SKLEARNDATASETSFETCHOPENML NOW LOADS DATA BY STREAMING AVOIDING HIGH MEMORY USAGE 13312 BY JORIS VAN DEN BOSSCHE
SKLEARNFEATUREEXTRACTION
•FIXFIXED A BUG IN FEATUREEXTRACTIONTEXTCOUNTVECTORIZER WHICH WOULD RESULT IN THE SPARSE FEATURE MATRIX HAVING CONFLICTING INDPTR ANDINDICES PRECISIONS UNDER VERY LARGE VOCABULARIES 11295 BY GABRIEL VACALIUC

SKLEARNIMPUTE
•FIXADD SUPPORT FOR NONNUMERIC DATA IN SKLEARNIMPUTEMISSINGINDICATOR WHICH WAS NOT SUP
PORTED WHILE SKLEARNIMPUTESIMPLEIMPUTER WAS SUPPORTING THIS FOR SOME IMPUTATION STRATEGIES
13046 BY GUILLAUME LEMAITRE
SKLEARNLINEARMODEL
•FIXFIXED A BUG IN LINEARMODELMULTITASKELASTICNET ANDLINEARMODEL
MULTITASKLASSO WHICH WERE BREAKING WHEN WARMSTART TRUE 12360 BY AAKANKSHA JOSHI
SKLEARNPREPROCESSING
•FIXFIXED A BUG IN PREPROCESSINGKBINSDISCRETIZER WHERESTRATEGYKMEANS FAILS WITH AN
ERROR DURING TRANSFORMATION DUE TO UNSORTED BIN EDGES 13134 BY SANDRO CASAGRANDE
•FIXFIXED A BUG IN PREPROCESSINGONEHOTENCODER WHERE THE DEPRECATION OF
CATEGORICALFEATURES WAS HANDLED INCORRECTLY IN COMBINATION WITH HANDLEUNKNOWNIGNORE
12881 BY JORIS VAN DEN BOSSCHE
•FIXBINS WHOSE WIDTH ARE TOO SMALL IE 1E8 ARE REMOVED WITH A WARNING IN PREPROCESSING
KBINSDISCRETIZER 13165 BY HANMIN QIN
SKLEARNSVM
•FIXFIXED A BUG IN SVMSVC SVMNUSVC SVMSVR SVMNUSVR ANDSVMONECLASSSVM WHERE THE
SCALE OPTION OF PARAMETER GAMMA IS ERRONEOUSLY DEFINED AS 1 NFEATURES XSTD IT'S NOW
DEFINED AS1 NFEATURES XVAR 13221 BY HANMIN QIN
1132 CODE AND DOCUMENTATION CONTRIBUTORS
WITH THANKS TO
ADRIN JALALI AGAMEMNON KRASOULIS ALBERT THOMAS ANDREAS MUELLER AURÉLIEN BELLET BERTRANDHAUT BHARAT RAGHU
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LEMAITRE HANMIN QIN JOAAK JOEL NOTHMAN JORIS VAN DEN BOSSCHE JÉRÉMIE MÉHAULT KMS15 KOSSORI ARUKU LAK
SHYA KD MAIKIA MANUEL LÓPEZIBÁÑEZ MARCO GORELLI MARCOGORELLI MFERRARI3 MICKAËL SCHOENTGEN NICOLAS HUG
PAVLOS KALLIS PIERRE GLASER PIERRETALLOTTE PRABAKARAN KUMARESSHAN RESHAMA SHAIKH ROHIT KAPOOR ROMAN YURCHAK
SANDROCASAGRANDE TASHAY GREEN THOMAS FAN VISHAAL KAPOOR ZHUYI XUE ZIJIE ZJ POH
114 VERSION 0202
DECEMBER 20 2018
THIS IS A BUGFIX RELEASE WITH SOME MINOR DOCUMENTATION IMPROVEMENTS AND ENHANCEMENTS TO FEATURES RELEASED IN
0200

1141 CHANGED MODELS

THE FOLLOWING ESTIMATORS AND FUNCTIONS WHEN FIT WITH THE SAME DATA AND PARAMETERS MAY PRODUCE DIFFERENT MODELS FROM THE PREVIOUS VERSION THIS OFTEN OCCURS DUE TO CHANGES IN THE MODELLING LOGIC BUG FIXES OR ENHANCEMENTS OR IN RANDOM SAMPLING PROCEDURES

- SKLEARNNEIGHBORS WHENMETRICJACCARD BUG FIX
- USE OFSEUCLIDEAN ORMAHALANOBIS METRICS IN SOME CASES BUG FIX

1142 CHANGELOG

SKLEARNCOMPOSE

- FIXFIXED AN ISSUE IN COMPOSEMAKECOLUMNTRANSFORMER WHICH RAISES UNEXPECTED ERROR WHEN COLUMNS IS PANDAS INDEX OR PANDAS SERIES 12704 BY HANMIN QIN

SKLEARNMETRICS

- FIX FIXED A BUG IN METRICSPAIRWISEDISTANCES ANDMETRICS PAIRWISEDISTANCESCHUNKED WHERE PARAMETERS VOFSEUCLIDEAN ANDVIOFMAHALANOBIS METRICS WERE COMPUTED AFTER THE DATA WAS SPLIT INTO CHUNKS INSTEAD OF BEING PRECOMPUTED ON WHOLE DATA 12701 BY JEREMIE DU BOISBERRANGER

SKLEARNNEIGHBORS

- FIXFIXEDSKLEARNNEIGHBORSDISTANCEMETRIC JACCARD DISTANCE FUNCTION TO RETURN 0 WHEN TWO ALL ZERO VECTORS ARE COMPARED 12685 BY THOMAS FAN

SKLEARNUTILS

- FIXCALLINGUTILSCHECKARRAY ONPANDASSERIES WITH CATEGORICAL DATA WHICH RAISED AN ERROR IN 0200 NOW RETURNS THE EXPECTED OUTPUT AGAIN 12699 BY JORIS VAN DEN BOSSCHE

1143 CODE AND DOCUMENTATION CONTRIBUTORS

WITH THANKS TO

ADANHAWTH ADRIN JALALI ALBERT THOMAS ANDREAS MUELLER DAN STINE FEDA CURIC HANMIN QIN JAN S JEREMIEDBB JOEL NOTHMAN JORIS VAN DEN BOSSCHE JOSEPHSALMON KATRIN LEINWEBER LOIC ESTEVE MUHAMMAD HASSAAN RAFIQUE NICOLAS HUG OLIVIER GRISEL PAUL PACZUSKI RESHAMA SHAIKH SAM WATERBURY SHIVAM KOTWALIA THOMAS FAN

115 VERSION 0201

NOVEMBER 21 2018

THIS IS A BUGFIX RELEASE WITH SOME MINOR DOCUMENTATION IMPROVEMENTS AND ENHANCEMENTS TO FEATURES RELEASED IN 0200 NOTE THAT WE ALSO INCLUDE SOME API CHANGES IN THIS RELEASE SO YOU MIGHT GET SOME EXTRA WARNINGS AFTER UPDATING FROM 0200 TO 0201

1151 CHANGED MODELS

THE FOLLOWING ESTIMATORS AND FUNCTIONS WHEN FIT WITH THE SAME DATA AND PARAMETERS MAY PRODUCE DIFFERENT MODELS FROM THE PREVIOUS VERSION THIS OFTEN OCCURS DUE TO CHANGES IN THE MODELLING LOGIC BUG FIXES OR ENHANCEMENTS OR IN RANDOM SAMPLING PROCEDURES

•DECOMPOSITIONINCREMENTALPCA BUG FIX

1152 CHANGELOG

SKLEARNCLUSTER

•EFFICIENCY MAKECLUSTERMEANSHIFT NO LONGER TRY TO DO NESTED PARALLELISM AS THE OVERHEAD WOULD HURT PERFORMANCE SIGNIFICANTLY WHEN NJOBS 1 12159 BY OLIVIER GRISEL

•FIXFIXED A BUG IN CLUSTERDBSCAN WITH PRECOMPUTED SPARSE NEIGHBORS GRAPH WHICH WOULD ADD EXPLICITLY ZEROS ON THE DIAGONAL EVEN WHEN ALREADY PRESENT 12105 BY TOM DUPRE LA TOUR

SKLEARNCOMPOSE

•FIXFIXED AN ISSUE IN COMPOSECOLUMNTRANSFORMER WHEN STACKING COLUMNS WITH TYPES NOT CONVERTIBLE TO A NUMERIC 11912 BY ADRIN JALALI

•API C HANGE COMPOSECOLUMNTRANSFORMER NOW APPLIES THE SPARSETHRESHOLD EVEN IF ALL TRANS FORMATION RESULTS ARE SPARSE 12304 BY ANDREAS MÜLLER

•API C HANGE COMPOSEMAKECOLUMNTRANSFORMER NOW EXPECTS TRANSFORMER COLUMNS IN STEAD OFCOLUMNS TRANSFORMER TO KEEP CONSISTENT WITH COMPOSECOLUMNTRANSFORMER 12339 BY ADRIN JALALI

SKLEARNDATASETS

•FIXDATASETSFETCHOPENML TO CORRECTLY USE THE LOCAL CACHE 12246 BY JAN N VAN RIJN

•FIXDATASETSFETCHOPENML TO CORRECTLY HANDLE IGNORE ATTRIBUTES AND ROW ID ATTRIBUTES 12330 BY JAN N VAN RIJN

•FIXFIXED INTEGER OVERFLOW IN DATASETSMAKECLASSIFICATION FOR VALUES OF NINFORMATIVE PA RAMETER LARGER THAN 64 10811 BY ROMAN FELDBAUER

•FIXFIXED OLIVETTI FACES DATASET DESCR ATTRIBUTE TO POINT TO THE RIGHT LOCATION IN DATASETS FETCHOLIVETTIFACES 12441 BY JÉRÉMIE DU BOISBERRANGER

•FIXDATASETSFETCHOPENML TO RETRY DOWNLOADING WHEN READING FROM LOCAL CACHE FAILS 12517 BY THOMAS FAN

SKLEARNDECOMPOSITION

•FIXFIXED A REGRESSION IN DECOMPOSITIONINCREMENTALPCA WHERE 0200 RAISED AN ERROR IF THE NUMBER OF SAMPLES IN THE FINAL BATCH FOR FITTING INCREMENTALPCA WAS SMALLER THAN NCOMPONENTS 12234 BY MING LI

SKLEARNENSEMBLE

•FIX FIXED A BUG MOSTLY AFFECTING ENSEMBLERANDOMFORESTCLASSIFIER WHERE CLASSWEIGHTBALANCEDSUBSAMPLE FAILED WITH MORE THAN 32 CLASSES 12165 BY JOEL NOTHMAN

•FIXFIXED A BUG AFFECTING ENSEMBLEBAGGINGCLASSIFIER ENSEMBLEBAGGINGREGRESSOR AND ENSEMBLEISOLATIONFOREST WHEREMAXFEATURES WAS SOMETIMES ROUNDED DOWN TO ZERO 12388 BY CONNOR TANN

SKLEARNFEATUREEXTRACTION

•FIXFIXED A REGRESSION IN V0200 WHERE FEATUREEXTRACTIONTEXTCOUNTVECTORIZER AND OTHER TEXT VECTORIZERS COULD ERROR DURING STOP WORDS VALIDATION WITH CUSTOM PREPROCESSORS OR TOKENIZERS 12393 BY ROMAN YURCHAK

SKLEARNLINEARMODEL

•FIXLINEARMODELSGDCLASSIFIER AND VARIANTS WITH EARLYSTOPPINGTRUE WOULD NOT USE A CONSISTENT VALIDATION SPLIT IN THE MULTICLASS CASE AND THIS WOULD CAUSE A CRASH WHEN USING THOSE ESTIMATORS AS PART OF PARALLEL PARAMETER SEARCH OR CROSSVALIDATION 12122 BY OLIVIER GRISEL

•FIXFIXED A BUG AFFECTING SGDCLASSIFIER IN THE MULTICLASS CASE EACH ONEVERSUSALL STEP IS RUN IN A JOBLIBPARALLEL CALL AND MUTATING A COMMON PARAMETER CAUSING A SEGMENTATION FAULT IF CALLED WITHIN A BACKEND USING PROCESSES AND NOT THREADS WE NOW USE REQUIRESHAREDMEM AT THEJOBLIBPARALLEL INSTANCE CREATION 12518 BY PIERRE GLASER AND OLIVIER GRISEL

SKLEARNMETRICS

•FIXFIXED A BUG IN METRICSPAIRWISEPAIRWISEDISTANCESARGMINMIN WHICH RETURNED THE SQUARE ROOT OF THE DISTANCE WHEN THE METRIC PARAMETER WAS SET TO “EUCLIDEAN” 12481 BY JÉRÉMIE DU BOISBER RANGER

•FIXFIXED A BUG IN METRICSPAIRWISEPAIRWISEDISTANCESCHUNKED WHICH DIDN’T ENSURE THE DIAGONAL IS ZERO FOR EUCLIDEAN DISTANCES 12612 BY ANDREAS MÜLLER

•API C HANGE THEMETRICSCALINSKIHARABAZSCORE HAS BEEN RENAMED TO METRICS CALINSKIHARABASZSCORE AND WILL BE REMOVED IN VERSION 023 12211 BY LISA THOMAS MARK HANNEL AND MELISSA FERRARI

SKLEARNMIXTURE

•FIXENSURE THAT THE FITPREDICT METHOD OF MIXTUREGAUSSIANMIXTURE ANDMIXTURE BAYESIANGAUSSIANMIXTURE ALWAYS YIELD ASSIGNMENTS CONSISTENT WITH FIT FOLLOWED BY PREDICT EVEN IF THE CONVERGENCE CRITERION IS TOO LOOSE OR NOT MET 12451 BY OLIVIER GRISEL

SKLEARNNEIGHBORS

•FIXFORCE THE PARALLELISM BACKEND TO THREADING FORNEIGHBORSKDTREE ANDNEIGHBORSBALLTREE IN PYTHON 27 TO AVOID PICKLING ERRORS CAUSED BY THE SERIALIZATION OF THEIR METHODS 12171 BY THOMAS MOREAU

SCIKITLEARN USER GUIDE RELEASE 0213

SKLEARNPREPROCESSING

•FIXFIXED BUG IN PREPROCESSINGORDINALENCODER WHEN PASSING MANUALLY SPECIFIED CATEGORIES 12365 BY JORIS VAN DEN BOSSCHE

•FIXFIXED BUG IN PREPROCESSINGKBINSDISCRETIZER WHERE THETRANSFORM METHOD MUTATES THE ENCODER ATTRIBUTE THE TRANSFORM METHOD IS NOW THREAD SAFE 12514 BY HANMIN QIN

•FIXFIXED A BUG IN PREPROCESSINGPOWERTRANSFORMER WHERE THE YEOJOHNSON TRANSFORM WAS INCOR RECT FOR LAMBDA PARAMETERS OUTSIDE OF 0 2 12522 BY NICOLAS HUG

•FIXFIXED A BUG IN PREPROCESSINGONEHOTENCODER WHERE TRANSFORM FAILED WHEN SET TO IGNORE UN KNOWN NUMPY STRINGS OF DIFFERENT LENGTHS 12471 BY GABRIEL MARZINOTTO

•API C HANGE THE DEFAULT VALUE OF THE METHOD ARGUMENT IN PREPROCESSINGPOWERTRANSFORM WILL BE CHANGED FROM BOXCOX TOYEOJOHNSON TO MATCHPREPROCESSINGPOWERTRANSFORMER IN VER SION 023 A FUTUREWARNING IS RAISED WHEN THE DEFAULT VALUE IS USED 12317 BY ERIC CHANG

SKLEARNUTILS

•FIXUSE FLOAT64 FOR MEAN ACCUMULATOR TO AVOID FLOATING POINT PRECISION ISSUES IN PREPROCESSING STANDARDSCALER ANDDECOMPOSITIONINCREMENTALPCA WHEN USING FLOAT32 DATASETS 12338 BY BAUKS

•FIXCALLINGUTILSCHECKARRAY ONPANDASSERIES WHICH RAISED AN ERROR IN 0200 NOW RETURNS THE EXPECTED OUTPUT AGAIN 12625 BY ANDREAS MÜLLER

MISCELLANEOUS

•FIXWHEN USING SITE JOBLIB BY SETTING THE ENVIRONMENT VARIABLE SKLEARNSITEJOBLIB ADDED COMPATI BILITY WITH JOBLIB 011 IN ADDITION TO 012 12350 BY JOEL NOTHMAN AND ROMAN YURCHAK

•FIXMAKE SURE TO AVOID RAISING FUTUREWARNING WHEN CALLING NPVSTACK WITH NUMPY 116 AND LATER USE LIST COMPREHENSIONS INSTEAD OF GENERATOR EXPRESSIONS IN MANY LOCATIONS OF THE SCIKITLEARN CODE BASE 12467 BY OLIVIER GRISEL

•API C HANGE REMOVED ALL MENTIONS OF SKLEARNEXTERNALSJOBLIB AND DEPRECATED JOBLIB METHODS EXPOSED IN SKLEARNUTILS EXCEPT FOR UTILSPARALLELBACKEND ANDUTILS REGISTERPARALLELBACKEND WHICH ALLOW USERS TO CONFIGURE PARALLEL COMPUTATION IN SCIKITLEARN OTHER FUNCTIONALITIES ARE PART OF JOBLIB PACKAGE AND SHOULD BE USED DIRECTLY BY INSTALLING IT THE GOAL OF THIS CHANGE IS TO PREPARE FOR UNVENDORING JOBLIB IN FUTURE VERSION OF SCIKITLEARN 12345 BY THOMAS MOREAU

1153 CODE AND DOCUMENTATION CONTRIBUTORS

WITH THANKS TO

ADRIN JALALI ANDREA NAVARRETE ANDREAS MUELLER BAUKS BENJASTUDIO CHEUK TING HO CONNOSSOR COREY LEVIN SON DAN STINE DATENKIEKER DENIS KATAEV DILLON GARDNER DMITRY VUKOLOV DOUGAL J SUTHERLAND EDWARD J BROWN ERIC CHANG FEDERICO CASELLI GABRIEL MARZINOTTO GAEL VAROQUAUX GAURAVAHLAWAT GUSTAVO DE MARI PEREIRA HAN MIN QIN HAROLDFOX JACKLANGERMAN JACOPO NOTARSTEFANO JANVANRIJN JDETHURENS JEREMIEDBB JOEL NOTHMAN JORIS VAN DEN BOSSCHE KOEN KUSHAL CHAUHAN LEE YI JIE JOEL LILY XIONG MAILLIAM MARK HANNEL MELSYT MING LI NICHOLAS SMITH NICOLAS HUG NIKOLAY SHEBANOV OLEKSANDR PAVLYK OLIVIER GRISEL PETER HAUSAMANN PIERRE GLASER PULKIT MALOO QUENTIN BATISTA RADOSTIN STOYANOV RAMIL NUGMANOV REBEKAH KIM RESHAMA SHAIKH ROHAN SINGH ROMAN FELDBAUER ROMAN YURCHAK ROOPAM SHARMA SAM WATERBURY SCOTT LOWE SEBASTIAN RASCHKA STEPHEN TIER NEY SYLVAINLAN TAKINGITCASUAL THOMAS FAN THOMAS MOREAU TOM DUPRÉ LA TOUR TULIO CASAGRANDE UTKARSH UPADHYAY XING HAN LU YAROSLAV HALCHENKO ZACH MILLER

SCIKITLEARN USER GUIDE RELEASE 0213

116 VERSION 0200

SEPTEMBER 25 2018

THIS RELEASE PACKS IN A MOUNTAIN OF BUG FIXES FEATURES AND ENHANCEMENTS FOR THE SCIKITLEARN LIBRARY AND IMPROVEMENTS TO THE DOCUMENTATION AND EXAMPLES THANKS TO OUR CONTRIBUTORS

THIS RELEASE IS DEDICATED TO THE MEMORY OF RAGHAV RAJAGOPALAN

WARNING VERSION 020 IS THE LAST VERSION OF SCIKITLEARN TO SUPPORT PYTHON 27 AND PYTHON 34 SCIKITLEARN 021 WILL REQUIRE PYTHON 35 OR HIGHER

1161 HIGHLIGHTS

WE HAVE TRIED TO IMPROVE OUR SUPPORT FOR COMMON DATASCIENCE USECASES INCLUDING MISSING VALUES CATEGORICAL VARIABLES HETEROGENEOUS DATA AND FEATURESTARGETS WITH UNUSUAL DISTRIBUTIONS MISSING VALUES IN FEATURES REPRESENTED BY NANS ARE NOW ACCEPTED IN COLUMNWISE PREPROCESSING SUCH AS SCALERS EACH FEATURE IS FITTED DISREGARDING NANS AND DATA CONTAINING NANS CAN BE TRANSFORMED THE NEW IMPUTE MODULE PROVIDES ESTIMATORS FOR LEARNING DESPITE MISSING DATA

COLUMNTRANSFORMER HANDLES THE CASE WHERE DIFFERENT FEATURES OR COLUMNS OF A PANDASDATAFRAME NEED DIFFERENT PREPROCESSING STRING OR PANDAS CATEGORICAL COLUMNS CAN NOW BE ENCODED WITH ONEHOTENCODER OR ORDINALENCODER

TRANSFORMEDTARGETREGRESSOR HELPS WHEN THE REGRESSION TARGET NEEDS TO BE TRANSFORMED TO BE MODELED POWERTRANSFORMER ANDKBINSDISCRETIZER JOINQUANTILETRANSFORMER AS NONLINEAR TRANSFORMATIONS BEYOND THIS WE HAVE ADDED SAMPLEWEIGHT SUPPORT TO SEVERAL ESTIMATORS INCLUDING KMEANS BAYESIANRIDGE ANDKERNELDENSITY AND IMPROVED STOPPING CRITERIA IN OTHERS INCLUDING MLPREGRESSOR GRADIENTBOOSTINGREGRESSOR ANDSGDREGRESSOR

THIS RELEASE IS ALSO THE FIRST TO BE ACCOMPANIED BY A GLOSSARY OF COMMON TERMS AND API ELEMENTS DEVELOPED BY JOEL NOTHMAN THE GLOSSARY IS A REFERENCE RESOURCE TO HELP USERS AND CONTRIBUTORS BECOME FAMILIAR WITH THE TERMINOLOGY AND CONVENTIONS USED IN SCIKITLEARN

SORRY IF YOUR CONTRIBUTION DIDN’T MAKE IT INTO THE HIGHLIGHTS THERE’S A LOT HERE

1162 CHANGED MODELS

THE FOLLOWING ESTIMATORS AND FUNCTIONS WHEN FIT WITH THE SAME DATA AND PARAMETERS MAY PRODUCE DIFFERENT MODELS FROM THE PREVIOUS VERSION THIS OFTEN OCCURS DUE TO CHANGES IN THE MODELLING LOGIC BUG FIXES OR ENHANCEMENTS OR IN RANDOM SAMPLING PROCEDURES

- CLUSTERMEANSHIFT BUG FIX
- DECOMPOSITIONINCREMENTALPCA IN PYTHON 2 BUG FIX
- DECOMPOSITIONSPARSEPCA BUG FIX
- ENSEMBLEGRADIENTBOOSTINGCLASSIFIER BUG FIX AFFECTING FEATURE IMPORTANCES
- ISOTONICISOTONICREGRESSION BUG FIX
- LINEARMODELARDREGRESSION BUG FIX
- LINEARMODELLOGISTICREGRESSIONCV BUG FIX
- LINEARMODELORTHOGONALMATCHINGPURSUIT BUG FIX

•LINEARMODELPASSIVEAGGRESSIVECLASSIFIER BUG FIX
•LINEARMODELPASSIVEAGGRESSIVEREGRESSOR BUG FIX
•LINEARMODELPERCEPTRON BUG FIX
•LINEARMODELSGDCLASSIFIER BUG FIX
•LINEARMODELSGDREGRESSOR BUG FIX
•METRICSROCAUCSCORE BUG FIX
•METRICSROCCURVE BUG FIX
•NEURALNETWORKBASEMULTILAYERPERCEPTRON BUG FIX
•NEURALNETWORKMLPCLASSIFIER BUG FIX
•NEURALNETWORKMLPREGRESSOR BUG FIX
• THE V0190 RELEASE NOTES FAILED TO MENTION A BACKWARDS INCOMPATIBILITY WITH MODELSELECTION
STRATIFIEDKFOLD WHENSHUFFLETRUE DUE TO 7823
DETAILS ARE LISTED IN THE CHANGELOG BELOW
WHILE WE ARE TRYING TO BETTER INFORM USERS BY PROVIDING THIS INFORMATION WE CANNOT ASSURE THAT THIS LIST IS COMPLETE
1163 KNOWN MAJOR BUGS
• 11924 LINEARMODELLOGISTICREGRESSIONCV WITHSOLVERLBFGS AND
MULTICLASSMULTINOMIAL MAY BE NONDETERMINISTIC OR OTHERWISE BROKEN ON MACOS THIS AP
PEARS TO BE THE CASE ON TRAVIS CI SERVERS BUT HAS NOT BEEN CONFIRMED ON PERSONAL MACBOOKS THIS ISSUE HAS
BEEN PRESENT IN PREVIOUS RELEASES
• 9354METRICSPAIRWISEEUCLIDEANDISTANCES WHICH IS USED SEVERAL TIMES THROUGHOUT THE LI
BRARY GIVES RESULTS WITH POOR PRECISION WHICH PARTICULARLY AFFECTS ITS USE WITH 32BIT FLOAT INPUTS THIS BECAME
MORE PROBLEMATIC IN VERSIONS 018 AND 019 WHEN SOME ALGORITHMS WERE CHANGED TO AVOID CASTING 32BIT DATA
INTO 64BIT
1164 CHANGELOG
SUPPORT FOR PYTHON 33 HAS BEEN OFFICIALLY DROPPED
SKLEARNCLUSTER
•MAJOR FEATURE CLUSTERAGGLOMERATIVECLUSTERING NOW SUPPORTS SINGLE LINKAGE CLUSTERING VIA
LINKAGESINGLE 9372 BY LELAND MCINNES AND STEVE ASTELS
•FEATURE CLUSTERKMEANS ANDCLUSTERMINIBATCHKMEANS NOW SUPPORT SAMPLE WEIGHTS VIA NEW
PARAMETERSAMPLEWEIGHT INFIT FUNCTION 10933 BY JOHANNES HANSEN
•EFFICIENCY CLUSTERKMEANS CLUSTERMINIBATCHKMEANS ANDCLUSTERKMEANS PASSED WITH
ALGORITHMFULL NOW ENFORCES ROWMAJOR ORDERING IMPROVING RUNTIME 10471 BY GAURAV DHINGRA
•EFFICIENCY CLUSTERDBSCAN NOW IS PARALLELIZED ACCORDING TO NJOBS REGARDLESS OF ALGORITHM 8003
BY JOËL BILLAUD
•ENHANCEMENT CLUSTERKMEANS NOW GIVES A WARNING IF THE NUMBER OF DISTINCT CLUSTERS FOUND IS SMALLER
THANNCLUSTERS THIS MAY OCCUR WHEN THE NUMBER OF DISTINCT POINTS IN THE DATA SET IS ACTUALLY SMALLER THAN
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•FIXFIXED A BUG WHERE THE FIT METHOD OFCLUSTERAFFINITYPROPAGATION STORED CLUSTER CENTERS AS 3D ARRAY INSTEAD OF 2D ARRAY IN CASE OF NONCONVERGENCE FOR THE SAME CLASS FIXED UNDEFINED AND ARBITRARY BEHAVIOR IN CASE OF TRAINING DATA WHERE ALL SAMPLES HAD EQUAL SIMILARITY 9612 BY JONATAN SAMOOCHA
•FIXFIXED A BUG IN CLUSTERSPECTRALCLUSTERING WHERE THE NORMALIZATION OF THE SPECTRUM WAS USING A DIVISION INSTEAD OF A MULTIPLICATION 8129 BY JAN MARGETA GUILLAUME LEMAITRE AND DEVANSH D
•FIXFIXED A BUG IN CLUSTERKMEANSELKAN WHERE THE RETURNED ITERATION WAS 1 LESS THAN THE CORRECT VALUE ALSO ADDED THE MISSING NITER ATTRIBUTE IN THE DOCSTRING OF CLUSTERKMEANS 11353 BY JEREMIE DU BOISBERRANGER
•FIXFIXED A BUG IN CLUSTERMEANSHIFT WHERE THE ASSIGNED LABELS WERE NOT DETERMINISTIC IF THERE WERE MULTIPLE CLUSTERS WITH THE SAME INTENSITIES 11901 BY ADRIN JALALI
•API C HANGE DEPRECATE POOLINGFUNC UNUSED PARAMETER IN CLUSTER AGGLOMERATIVECLUSTERING 9875 BY KUMAR ASHUTOSH

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• NEW MODULE
•MAJOR FEATURE ADDEDCOMPOSECOLUMNTRANSFORMER WHICH ALLOWS TO APPLY DIFFERENT TRANSFORMERS TO DIFFERENT COLUMNS OF ARRAYS OR PANDAS DATAFRAMES 9012 BY ANDREAS MÜLLER AND JORIS VAN DEN BOSSCHE AND 11315 BY THOMAS FAN
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•EFFICIENCY RUNTIME IMPROVEMENTS TO COVARIANCEGRAPHICALLASSO 9858 BY STEVEN BROWN
•API C HANGE THECOVARIANCEGRAPHLASSO COVARIANCEGRAPHLASSO ANDCOVARIANCE GRAPHLASSOCV HAVE BEEN RENAMED TO COVARIANCEGRAPHICALLASSO COVARIANCE GRAPHICALLASSO ANDCOVARIANCEGRAPHICALLASSOCV RESPECTIVELY AND WILL BE REMOVED IN VERSION 022 9993 BY ARTIEM KRINITSYN

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•MAJOR FEATURE ADDEDDATASETSFETCHOPENML TO FETCH DATASETS FROM OPENML OPENML IS A FREE OPEN DATA SHARING PLATFORM AND WILL BE USED INSTEAD OF MLDATA AS IT PROVIDES BETTER SERVICE AVAILABILITY 9908 BY ANDREAS MÜLLER AND JAN N VAN RIJN
•FEATURE INDATASETSMAKEBLOBS ONE CAN NOW PASS A LIST TO THE NSAMPLES PARAMETER TO INDICATE THE NUMBER OF SAMPLES TO GENERATE PER CLUSTER 8617 BY MASKANI FILALI MOHAMED AND KONSTANTINOS KATRIOPLAS
•FEATURE ADDFILENAME ATTRIBUTE TO DATASETS THAT HAVE A CSV FILE 9101 BY ALEX33 AND MASKANI FILALI MOHAMED
•FEATURE RETURNXY PARAMETER HAS BEEN ADDED TO SEVERAL DATASET LOADERS 10774 BY CHRIS CATALFO
•FIXFIXED A BUG IN DATASETSLOADBOSTON WHICH HAD A WRONG DATA POINT 10795 BY TAKESHI YOSHIZAWA
•FIXFIXED A BUG IN DATASETSLOADIRIS WHICH HAD TWO WRONG DATA POINTS 11082 BY SADHANA SRINI VASAN AND HANMIN QIN

•FIXFIXED A BUG IN DATASETSFETCHKDDCUP99 WHERE DATA WERE NOT PROPERLY SHUFFLED 9731 BY NICO
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•FIXFIXED A BUG IN DATASETSMAKECIRCLES WHERE NO ODD NUMBER OF DATA POINTS COULD BE GENERATED
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•API C HANGE DEPRECATED SKLEARNDATASETSFETCHMLDATA TO BE REMOVED IN VERSION 022 ML
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•FEATURE F IXDECOMPOSITIONSPARSEPCA NOW EXPOSES NORMALIZECOMPONENTS WHEN SET TO
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•FIXFIX FOR UNINFORMATIVE ERROR IN DECOMPOSITIONINCREMENTALPCA NOW AN ERROR IS RAISED IF THE
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•FIXFIXED AN UNDERFLOW IN CALCULATING KLDIVERGENCE FOR DECOMPOSITIONNMF 10142 BY TOM DUPRE LA
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•FEATURE DUMMYDUMMYCLASSIFIER ANDDUMMYDUMMYREGRESSOR NOW ONLY REQUIRE X TO BE AN OB
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•FEATURE DUMMYDUMMYCLASSIFIER ANDDUMMYDUMMYREGRESSOR CAN NOW BE SCORED WITHOUT SUP
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•FEATURE ENSEMBLEBAGGINGREGRESSOR ANDENSEMBLEBAGGINGCLASSIFIER CAN NOW BE FIT
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•FEATURE ADDEDNAMEDESTIMATORS PARAMETER IN ENSEMBLEVOTINGCLASSIFIER TO ACCESS FITTED
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•FIXFIXED A BUG WHEN FITTING ENSEMBLEGRADIENTBOOSTINGCLASSIFIER ORENSEMBLE
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•FIXFIXED A BUG IN ENSEMBLEGRADIENTBOOSTINGREGRESSOR ANDENSEMBLE
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•API C HANGE CLASSES DERIVED FROM ENSEMBLEBASEBAGGING THE ATTRIBUTE ESTIMATORSSAMPLES
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THE MASK OF THE SAMPLES SELECTED FOR EACH BOOTSTRAP INDICES ALLOWS TO REPEAT SAMPLES WHILE MASK DOES NOT ALLOW
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•FEATURE ENABLE THE CALL TO GETFEATURENAMES IN UNFITTED FEATUREEXTRACTIONTEXT
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•FIXFIXED A BUG IN FEATUREEXTRACTIONIMAGEEXTRACTPATCHES2D WHICH WOULD THROW AN
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•FIXFIXED A BUG IN LOGISTICLOGISTICREGRESSIONPATH TO ENSURE THAT THE RETURNED COEFFICIENTS ARE CORRECT WHEN MULTICLASSMULTINOMIAL PREVIOUSLY SOME OF THE COEFFICIENTS WOULD OVERRIDE EACH OTHER LEADING TO INCORRECT RESULTS IN LINEARMODELLOGISTICREGRESSIONCV 11724 BY NICOLAS HUG
•FIXFIXED A BUG IN LINEARMODELLOGISTICREGRESSION WHERE WHEN USING THE PARAMETER MULTICLASSMULTINOMIAL THEPREDICTPROBA METHOD WAS RETURNING INCORRECT PROBABILITIES IN THE CASE OF BINARY OUTCOMES 9939 BY ROGER WESTOVER
•FIXFIXED A BUG IN LINEARMODELLOGISTICREGRESSIONCV WHERE THESCORE METHOD ALWAYS COM PUTES ACCURACY NOT THE METRIC GIVEN BY THE SCORING PARAMETER 10998 BY THOMAS FAN
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•FIXFIXED A BUG IN LINEARMODELORTHOGONALMATCHINGPURSUIT THAT WAS BROKEN WHEN SETTING NORMALIZEFALSE 10071 BY ALEXANDRE GRAMFORT
•FIXFIXED A BUG IN LINEARMODELARDREGRESSION WHICH CAUSED INCORRECTLY UPDATED ESTIMATES FOR THE STANDARD DEVIATION AND THE COEFFICIENTS 10153 BY JÖRG DÖPFERT
•FIXFIXED A BUG IN LINEARMODELARDREGRESSION ANDLINEARMODELBAYESIANRIDGE WHICH CAUSED NAN PREDICTIONS WHEN FITTED WITH A CONSTANT TARGET 10095 BY JÖRG DÖPFERT
•FIXFIXED A BUG IN LINEARMODELRIDGECLASSIFIERCV WHERE THE PARAMETER STORECVVALUES WAS NOT IMPLEMENTED THOUGH IT WAS DOCUMENTED IN CVVALUES AS A WAY TO SET UP THE STORAGE OF CROSS VALIDATION VALUES FOR DIFFERENT ALPHAS 10297 BY MABEL VILLALBAJIMÉNEZ
•FIXFIXED A BUG IN LINEARMODELELASTICNET WHICH CAUSED THE INPUT TO BE OVERRIDDEN WHEN USING PARAMETERCOPYXTRUE ANDCHECKINPUTFALSE 10581 BY YACINE MAZARI
•FIXFIXED A BUG IN SKLEARNLINEARMODELLASSO WHERE THE COEFFICIENT HAD WRONG SHAPE WHEN FITINTERCEPTFALSE 10687 BY MARTIN HAHN
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•FIX FIXED A BUG IN LINEARMODELSGDCLASSIFIER LINEARMODEL SGDREGRESSOR LINEARMODELPASSIVEAGGRESSIVECLASSIFIER LINEARMODEL PASSIVEAGGRESSIVEREGRESSOR ANDLINEARMODELPERCEPTRON WHERE THE STOPPING CRITERION WAS STOPPING THE ALGORITHM BEFORE CONVERGENCE A PARAMETER NITERNOCHANGE WAS ADDED AND SET BY DEFAULT TO 5 PREVIOUS BEHAVIOR IS EQUIVALENT TO SETTING THE PARAMETER TO 1 9043 BY TOM DUPRE LA TOUR
•FIXFIXED A BUG WHERE LIBLINEAR AND LIBSVMBASED ESTIMATORS WOULD SEGFAULT IF PASSED A SCIPYSPARSE MATRIX WITH 64BIT INDICES THEY NOW RAISE A VALUEERROR 11327 BY KARAN DHINGRA AND JOEL NOTHMAN
•API C HANGE THE DEFAULT VALUES OF THE SOLVER ANDMULTICLASS PARAMETERS OF LINEARMODEL LOGISTICREGRESSION WILL CHANGE RESPECTIVELY FROM LIBLINEAR ANDOVR IN VERSION 020 TO LBFGS ANDAUTO IN VERSION 022 A FUTUREWARNING IS RAISED WHEN THE DEFAULT VALUES ARE USED 11905 BY TOM DUPRE LA TOUR AND JOEL NOTHMAN
•API C HANGE DEPRECATEPOSITIVETRUE OPTION INLINEARMODELLARS AS THE UNDERLYING IMPLEMEN TATION IS BROKEN USE LINEARMODELLASSO INSTEAD 9837 BY ALEXANDRE GRAMFORT

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•API C HANGE NITER MAY VARY FROM PREVIOUS RELEASES IN LINEARMODELLOGISTICREGRESSION WITHSOLVERLBFGS ANDLINEARMODELHUBERREGRESSOR FOR SCIPY 100 THE OPTIMIZER COULD PERFORM MORE THAN THE REQUESTED MAXIMUM NUMBER OF ITERATIONS NOW BOTH ESTIMATORS WILL REPORT AT MOST MAXITER ITERATIONS EVEN IF MORE WERE PERFORMED 10723 BY JOEL NOTHMAN

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•FEATURE SUPPORT SPARSE INPUT IN MANIFOLDISOMAPFIT 8554 BY LELAND MCINNES
•FEATURE MANIFOLDTSNETRUSTWORTHINESS ACCEPTS METRICS OTHER THAN EUCLIDEAN 9775 BY WILLIAM DE VAZELHES
•FIXFIXED A BUG IN MANIFOLDSPECTRALEMBEDDING WHERE THE NORMALIZATION OF THE SPECTRUM WAS USING A DIVISION INSTEAD OF A MULTIPLICATION 8129 BY JAN MARGETA GUILLAUME LEMAITRE AND DEVANSH D
•API C HANGE F EATURE DEPRECATE PRECOMPUTED PARAMETER IN FUNCTION MANIFOLDTSNE TRUSTWORTHINESS INSTEAD THE NEW PARAMETER METRIC SHOULD BE USED WITH ANY COMPATIBLE METRIC IN CLUDING ‘PRECOMPUTED’ IN WHICH CASE THE INPUT MATRIX XSHOULD BE A MATRIX OF PAIRWISE DISTANCES OR SQUARED DISTANCES 9775 BY WILLIAM DE VAZELHES
•API C HANGE DEPRECATEPRECOMPUTED PARAMETER IN FUNCTION MANIFOLDTSNETRUSTWORTHINESS INSTEAD THE NEW PARAMETER METRIC SHOULD BE USED WITH ANY COMPATIBLE METRIC INCLUDING ‘PRECOMPUTED’ IN WHICH CASE THE INPUT MATRIX XSHOULD BE A MATRIX OF PAIRWISE DISTANCES OR SQUARED DISTANCES 9775 BY WILLIAM DE VAZELHES

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•MAJOR FEATURE ADDED THE METRICSBALANCEDACCURACYSCORE METRIC AND A CORRESPONDING BALANCEDACCURACY SCORER FOR BINARY AND MULTICLASS CLASSIFICATION 8066 BY XYGUO AND AMAN DALMIA AND 10587 BY JOEL NOTHMAN
•FEATURE PARTIAL AUC IS AVAILABLE VIA MAXFPR PARAMETER IN METRICSROCAUCSCORE 3840 BY ALEXANDER NIEDERBÜHL
•FEATURE A SCORER BASED ON METRICSBRIERSCORELOSS IS ALSO AVAILABLE 9521 BY HANMIN QIN
•FEATURE ADDED CONTROL OVER THE NORMALIZATION IN METRICSNORMALIZEDMUTUALINFOSCORE AND METRICSADJUSTEDMUTUALINFOSCORE VIA THEAVERAGEMETHOD PARAMETER IN VERSION 022 THE DEFAULT NORMALIZER FOR EACH WILL BECOME THE ARITHMETIC MEAN OF THE ENTROPIES OF EACH CLUSTERING 11124 BY ARYA MCCARTHY
•FEATURE ADDEDOUTPUTDICT PARAMETER IN METRICSCLASSIFICATIONREPORT TO RETURN CLASSIFI CATION STATISTICS AS DICTIONARY 11160 BY DAN BARKHORN
•FEATURE METRICSCLASSIFICATIONREPORT NOW REPORTS ALL APPLICABLE AVERAGES ON THE GIVEN DATA IN CLUDING MICRO MACRO AND WEIGHTED AVERAGE AS WELL AS SAMPLES AVERAGE FOR MULTILABEL DATA 11679 BY ALEXANDER PACHA
•FEATURE METRICSAVERAGEPRECISIONSCORE NOW SUPPORTS BINARY YTRUE OTHER THAN0 1 OR 1 1 THROUGHPOSLABEL PARAMETER 9980 BY HANMIN QIN
•FEATURE METRICSLABELRANKINGAVERAGEPRECISIONSCORE NOW SUPPORTS SAMPLEWEIGHT 10845 BY JOSE PEREZPARRAS TOLEDANO

•FEATURE ADDDENSEOUTPUT PARAMETER TO METRICSPAIRWISELINEARKERNEL WHEN FALSE AND
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•FIXFIXED A BUG IN METRICSPRECISIONRECALLFSCORESUPPORT WHEN TRUNCATED
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•FIXFIXED A BUG DUE TO FLOATING POINT ERROR IN METRICSROCAUCSCORE WITH NONINTEGER SAMPLE WEIGHTS
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•FIXFIXED A BUG WHERE METRICSROCCURVE SOMETIMES STARTS ON YAXIS INSTEAD OF 0 0 WHICH IS IN
CONSISTENT WITH THE DOCUMENT AND OTHER IMPLEMENTATIONS NOTE THAT THIS WILL NOT INFLUENCE THE RESULT FROM
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•FIXFIXED A BUG TO AVOID INTEGER OVERFLOW CASTED PRODUCT TO 64 BITS INTEGER IN METRICS
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•FIXFIXED A BUG WHERE METRICSAVERAGEPRECISIONSCORE WILL SOMETIMES RETURN NAN WHEN
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•FIXFIXED A BUG IN METRICSFOWLKESMALLOWSSCORE TO AVOID INTEGER OVERFLOW CASTED RETURN VALUE
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•API C HANGE DEPRECATEREORDER PARAMETER IN METRICSAUC AS IT'S NO LONGER REQUIRED FOR METRICS
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•API C HANGE THEBATCHSIZE PARAMETER TO METRICSPAIRWISEDISTANCESARGMINMIN AND
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•FEATURE ADDRETURNESTIMATOR PARAMETER IN MODELSELECTIONCROSSVALIDATE TO RETURN ES
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•FEATURE NEWREFITTIME ATTRIBUTE WILL BE STORED IN MODELSELECTIONGRIDSEARCHCV AND
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•FEATURE EXPOSEERRORSCORE PARAMETER IN MODELSELECTIONCROSSVALIDATE
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•API C HANGE THE DEFAULT NUMBER OF CROSSVALIDATION FOLDS CVAND THE DEFAULT NUMBER OF SPLITS NSPLITS IN
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•API C HANGE THE DEFAULT OF IID PARAMETER OF MODELSELECTIONGRIDSEARCHCV AND
MODELSELECTIONRANDOMIZEDSEARCHCV WILL CHANGE FROM TRUE TOFALSE IN VERSION 022 TO
CORRESPOND TO THE STANDARD DEFINITION OF CROSSVALIDATION AND THE PARAMETER WILL BE REMOVED IN VERSION
024 ALTOGETHER THIS PARAMETER IS OF GREATEST PRACTICAL SIGNIFICANCE WHERE THE SIZES OF DIFFERENT TEST SETS IN
CROSSVALIDATION WERE VERY UNEQUAL IE IN GROUPBASED CV STRATEGIES 9085 BY LAURENT DIRER AND ANDREAS
MÜLLER
•API C HANGE THE DEFAULT VALUE OF THE ERRORSCORE PARAMETER IN MODELSELECTIONGRIDSEARCHCV
ANDMODELSELECTIONRANDOMIZEDSEARCHCV WILL CHANGE TO NPNAN IN VERSION 022 10677 BY
KIRILL ZHDANOVICH
•API C HANGE CHANGED VALUEERROR EXCEPTION RAISED IN MODELSELECTIONPARAMETERSAMPLER TO A
USERWARNING FOR CASE WHERE THE CLASS IS INSTANTIATED WITH A GREATER VALUE OF NITER THAN THE TOTAL SPACE OF
PARAMETERS IN THE PARAMETER GRID NITER NOW ACTS AS AN UPPER BOUND ON ITERATIONS 10982 BY JULIET LAWTON
•API C HANGE INVALID INPUT FOR MODELSELECTIONPARAMETERGRID NOW RAISES TYPEERROR 10928 BY
SOLUTUS IMMENSUS
SKLEARNMULTIOUTPUT
•MAJOR FEATURE ADDEDMULTIOUTPUTREGRESSORCHAIN FOR MULTITARGET REGRESSION 9257 BY KUMAR
ASHUTOSH
SKLEARNNAIVEBAYES
•MAJOR FEATURE ADDEDNAIVEBAYESCOMPLEMENTNB WHICH IMPLEMENTS THE COMPLEMENT NAIVE BAYES
CLASSIFIER DESCRIBED IN RENNIE ET AL 2003 8190 BY MICHAEL A ALCORN
•FEATURE ADDVARSMOOTHING PARAMETER IN NAIVEBAYESGAUSSIANNB TO GIVE A PRECISE CONTROL OVER
VARIANCES CALCULATION 9681 BY DMITRY MOTTL

•FIXFIXED A BUG IN NAIVEBAYESGAUSSIANNB WHICH INCORRECTLY RAISED ERROR FOR PRIOR LIST WHICH SUMMED TO 1 10005 BY GAURAV DHINGRA
•FIXFIXED A BUG IN NAIVEBAYESMULTINOMIALNB WHICH DID NOT ACCEPT VECTOR VALUED PSEUDOCOUNTS ALPHA 10346 BY TOBIAS MADSEN

SKLEARNNEIGHBORS

•EFFICIENCY NEIGHBORSRADIUSNEIGHBORSREGRESSOR AND NEIGHBORS RADIUSNEIGHBORSCLASSIFIER ARE NOW PARALLELIZED ACCORDING TO NJOBS REGARDLESS OF ALGORITHM 10887 BY JOËL BILLAUD
•EFFICIENCY NEAREST NEIGHBORS QUERY METHODS ARE NOW MORE MEMORY EFFICIENT WHEN ALGORITHMBRUTE 11136 BY JOEL NOTHMAN AND AMAN DALMIA
•FEATURE ADDSAMPLEWEIGHT PARAMETER TO THE FIT METHOD OF NEIGHBORSKERNELDENSITY TO ENABLE WEIGHTING IN KERNEL DENSITY ESTIMATION 4394 BY SAMUEL O RONSIN
•FEATURE NOVELTY DETECTION WITH NEIGHBORSLOCALOUTLIERFACTOR ADD A NOVELTY PARAM ETER TONEIGHBORSLOCALOUTLIERFACTOR WHEN NOVELTY IS SET TO TRUE NEIGHBORS LOCALOUTLIERFACTOR CAN THEN BE USED FOR NOVELTY DETECTION IE PREDICT ON NEW UNSEEN DATA AVAILABLE PREDICTION METHODS ARE PREDICT DECISIONFUNCTION ANDSCORESAMPLES BY DEFAULT NOVELTY IS SET TOFALSE AND ONLY THE FITPREDICT METHOD IS AVAIABLE BY ALBERT THOMAS
•FIXFIXED A BUG IN NEIGHBORSNEARESTNEIGHBORS WHERE FITTING A NEARESTNEIGHBORS MODEL FAILS WHEN A THE DISTANCE METRIC USED IS A CALLABLE AND B THE INPUT TO THE NEARESTNEIGHBORS MODEL IS SPARSE 9579 BY THOMAS KOBER
•FIXFIXED A BUG SO PREDICT INNEIGHBORSRADIUSNEIGHBORSREGRESSOR CAN HANDLE EMPTY NEIGH BOR SET WHEN USING NON UNIFORM WEIGHTS ALSO RAISES A NEW WARNING WHEN NO NEIGHBORS ARE FOUND FOR SAMPLES 9655 BY ANDREAS BJERRENIELSEN
•FIX E FFICIENCY FIXED A BUG IN KDTREE CONSTRUCTION THAT RESULTS IN FASTER CONSTRUCTION AND QUERYING TIMES 11556 BY JAKE VANDERPLAS
•FIXFIXED A BUG IN NEIGHBORSKDTREE ANDNEIGHBORSBALLTREE WHERE PICKLED TREE OBJECTS WOULD CHANGE THEIR TYPE TO THE SUPER CLASS BINARYTREE 11774 BY NICOLAS HUG

SKLEARNNEURALNETWORK

•FEATURE ADD NITERNOCHANGE PARAMETER IN NEURALNETWORKBASEMULTILAYERPERCEPTRON NEURALNETWORKMLPREGRESSOR ANDNEURALNETWORKMLPCLASSIFIER TO GIVE CONTROL OVER MAXIMUM NUMBER OF EPOCHS TO NOT MEET TOL IMPROVEMENT 9456 BY NICHOLAS NADEAU
•FIXFIXED A BUG IN NEURALNETWORKBASEMULTILAYERPERCEPTRON NEURALNETWORK MLPREGRESSOR ANDNEURALNETWORKMLPCLASSIFIER WITH NEWNITERNOCHANGE PARAMETER NOW AT 10 FROM PREVIOUSLY HARDCODED 2 9456 BY NICHOLAS NADEAU
•FIXFIXED A BUG IN NEURALNETWORKMLPREGRESSOR WHERE FITTING QUIT UNEXPECTEDLY EARLY DUE TO LOCAL MINIMA OR FLUCTUATIONS 9456 BY NICHOLAS NADEAU

SKLEARNPIPELINE

•FEATURE THEPREDICT METHOD OF PIPELINEPIPELINE NOW PASSES KEYWORD ARGUMENTS ON TO THE PIPELINE'S LAST ESTIMATOR ENABLING THE USE OF PARAMETERS SUCH AS RETURNSTD IN A PIPELINE WITH CAUTION 9304 BY BRENO FREITAS

•API C HANGE PIPELINEFEATUREUNION NOW SUPPORTS DROP AS A TRANSFORMER TO DROP FEATURES 11144
BY THOMAS FAN
SKLEARNPREPROCESSING
•MAJOR FEATURE EXPANDEDPREPROCESSINGONEHOTENCODER TO ALLOW TO ENCODE CATEGORICAL STRING
FEATURES AS A NUMERIC ARRAY USING A ONEHOT OR DUMMY ENCODING SCHEME AND ADDED PREPROCESSING
ORDINALENCODER TO CONVERT TO ORDINAL INTEGERS THOSE TWO CLASSES NOW HANDLE ENCODING OF ALL FEATURE TYPES
ALSO HANDLES STRINGVALUED FEATURES AND DERIVES THE CATEGORIES BASED ON THE UNIQUE VALUES IN THE FEATURES INSTEAD
OF THE MAXIMUM VALUE IN THE FEATURES 9151 AND 10521 BY VIGHNESH BIRODKAR AND JORIS VAN DEN BOSSCHE
•MAJOR FEATURE ADDEDPREPROCESSINGKBINSDISCRETIZER FOR TURNING CONTINUOUS FEATURES INTO CAT
EGORICAL OR ONEHOT ENCODED FEATURES 7668 9647 10195 10192 11272 11467 AND 11505 BY HENRY
LIN HANMIN QIN TOM DUPRE LA TOUR AND GIOVANNI GIUSEPPE COSTA
•MAJOR FEATURE ADDEDPREPROCESSINGPOWERTRANSFORMER WHICH IMPLEMENTS THE YEOJOHNSON
AND BOXCOX POWER TRANSFORMATIONS POWER TRANSFORMATIONS TRY TO FIND A SET OF FEATUREWISE PARAMETRIC TRANS
FORMATIONS TO APPROXIMATELY MAP DATA TO A GAUSSIAN DISTRIBUTION CENTERED AT ZERO AND WITH UNIT VARIANCE THIS IS
USEFUL AS A VARIANCESTABILIZING TRANSFORMATION IN SITUATIONS WHERE NORMALITY AND HOMOSCEDASTICITY ARE DESIRABLE
10210 BY ERIC CHANG AND MANITEJA NANDANA AND 11520 BY NICOLAS HUG
•MAJOR FEATURE NAN VALUES ARE IGNORED AND HANDLED IN THE FOLLOWING PREPROCESSING METHODS
PREPROCESSINGMAXABSSCALER PREPROCESSINGMINMAXSCALER PREPROCESSING
ROBUSTSCALER PREPROCESSINGSTANDARDSCALER PREPROCESSINGPOWERTRANSFORMER
PREPROCESSINGQUANTILETRANSFORMER CLASSES AND PREPROCESSINGMAXABSSCALE
PREPROCESSINGMINMAXSCALE PREPROCESSINGROBUSTSCALE PREPROCESSINGSCALE
PREPROCESSINGPOWERTRANSFORM PREPROCESSINGQUANTILETRANSFORM FUNCTIONS RESPEC
TIVELY ADDRESSED IN ISSUES 11011 11005 11308 11206 11306 AND 10437 BY LUCIJA GREGOV AND
GUILLAUME LEMAITRE
•FEATURE PREPROCESSINGPOLYNOMIALFEATURES NOW SUPPORTS SPARSE INPUT 10452 BY AMAN
DALMIA AND JOEL NOTHMAN
•FEATURE PREPROCESSINGROBUSTSCALER ANDPREPROCESSINGROBUSTSCALE CAN BE FITTED US
ING SPARSE MATRICES 11308 BY GUILLAUME LEMAITRE
•FEATURE PREPROCESSINGONEHOTENCODER NOW SUPPORTS THE GETFEATURENAMES METHOD TO OBTAIN THE
TRANSFORMED FEATURE NAMES 10181 BY NIRVAN ANJIRBAG AND JORIS VAN DEN BOSSCHE
•FEATURE A PARAMETER CHECKINVERSE WAS ADDED TO PREPROCESSINGFUNCTIONTRANSFORMER TO
ENSURE THAT FUNC ANDINVERSEFUNC ARE THE INVERSE OF EACH OTHER 9399 BY GUILLAUME LEMAITRE
•FEATURE THETRANSFORM METHOD OFSKLEARNPREPROCESSINGMULTILABELBINARIZER NOW IG
NORES ANY UNKNOWN CLASSES A WARNING IS RAISED STATING THE UNKNOWN CLASSES CLASSES FOUND WHICH ARE IGNORED
10913 BY RODRIGO AGUNDEZ
•FIXFIXED BUGS IN PREPROCESSINGLABELENCODER WHICH WOULD SOMETIMES THROW ERRORS WHEN
TRANSFORM ORINVERSETRANSFORM WAS CALLED WITH EMPTY ARRAYS 10458 BY MAYUR KULKARNI
•FIXFIX VALUEERROR IN PREPROCESSINGLABELENCODER WHEN USING INVERSETRANSFORM ON UNSEEN
LABELS 9816 BY CHARLIE NEWEY
•FIXFIX BUG INPREPROCESSINGONEHOTENCODER WHICH DISCARDED THE DTYPE WHEN RETURNING A SPARSE
MATRIX OUTPUT 11042 BY DANIEL MORALES
•FIXFIXFIT ANDPARTIALFIT INPREPROCESSINGSTANDARDSCALER IN THE RARE CASE WHEN
WITHMEANFALSE ANDWITHSTDFALSE WHICH WAS CRASHING BY CALLING FIT MORE THAN ONCE AND GIVING
INCONSISTENT RESULTS FOR MEAN WHETHER THE INPUT WAS A SPARSE OR A DENSE MATRIX MEAN WILL BE SET TO NONE
116 VERSION 0200 59

WITH BOTH SPARSE AND DENSE INPUTS NSAMPLESSEEN WILL BE ALSO REPORTED FOR BOTH INPUT TYPES 11235 BY GUILLAUME LEMAITRE

•API C HANGE DEPRECATE NVALUES ANDCATEGORICALFEATURES PARAMETERS AND ACTIVEFEATURES FEATUREINDICES ANDNVALUES ATTRIBUTES OF PREPROCESSING ONEHOTENCODER THENVALUES PARAMETER CAN BE REPLACED WITH THE NEW CATEGORIES PA RAMETER AND THE ATTRIBUTES WITH THE NEW CATEGORIES ATTRIBUTE SELECTING THE CATEGORICAL FEA TURES WITH THE CATEGORICALFEATURES PARAMETER IS NOW BETTER SUPPORTED USING THE COMPOSE COLUMNTRANSFORMER 10521 BY JORIS VAN DEN BOSSCHE

•API C HANGE DEPRECATEPREPROCESSINGIMPUTER AND MOVE THE CORRESPONDING MODULE TO IMPUTE SIMPLEIMPUTER 9726 BY KUMAR ASHUTOSH

•API C HANGE THEAXIS PARAMETER THAT WAS IN PREPROCESSINGIMPUTER IS NO LONGER PRESENT IN IMPUTESIMPLEIMPUTER THE BEHAVIOR IS EQUIVALENT TO AXIS0 IMPUTE ALONG COLUMNS ROW WISE IMPUTATION CAN BE PERFORMED WITH FUNCTIONTRANSFORMER EG FUNCTIONTRANSFORMERLAMBDA X SIMPLEIMPUTERFITTRANSFORMXTT 10829 BY GUILLAUME LEMAITRE AND GILBERTO OLIMPIO

•API C HANGE THE NAN MARKER FOR THE MISSING VALUES HAS BEEN CHANGED BETWEEN THE PREPROCESSING IMPUTER AND THE IMPUTESIMPLEIMPUTER MISSINGVALUESNAN SHOULD NOW BE MISSINGVALUESNPNAN 11211 BY JEREMIE DU BOISBERRANGER

•API C HANGE INPREPROCESSINGFUNCTIONTRANSFORMER THE DEFAULT OF VALIDATE WILL BE FROM TRUE TOFALSE IN 022 10655 BY GUILLAUME LEMAITRE

SKLEARNSVM

•FIXFIXED A BUG IN SVMSVC WHERE WHEN THE ARGUMENT KERNEL IS UNICODE IN PYTHON2 THE PREDICTPROBA METHOD WAS RAISING AN UNEXPECTED TYPEERROR GIVEN DENSE INPUTS 10412 BY JIONGYAN ZHANG

•API C HANGE DEPRECATERANDOMSTATE PARAMETER IN SVMONECLASSSVM AS THE UNDERLYING IMPLEMEN TATION IS NOT RANDOM 9497 BY ALBERT THOMAS

•API C HANGE THE DEFAULT VALUE OF GAMMA PARAMETER OF SVMSVC NUSVC SVRNUSVR ONECLASSSVM WILL CHANGE FROM AUTO TOSCALE IN VERSION 022 TO ACCOUNT BETTER FOR UNSCALED FEATURES 8361 BY GAURAV DHINGRA AND TING NEO

SKLEARNTREE

•ENHANCEMENT ALTHOUGH PRIVATE AND HENCE NOT ASSURED API STABILITY TREECRITERION CLASSIFICATIONCRITERION ANDTREECRITERIONREGRESSIONCRITERION MAY NOW BE CIM PORTED AND EXTENDED 10325 BY CAMIL STAPS

•FIXFIXED A BUG IN TREEBASEDECISIONTREE WITHSPLITTERBEST WHERE SPLIT THRESHOLD COULD BECOME INFINITE WHEN VALUES IN X WERE NEAR INFINITE 10536 BY JONATHAN OHAYON

•FIXFIXED A BUG IN TREEMAE TO ENSURE SAMPLE WEIGHTS ARE BEING USED DURING THE CALCULATION OF TREE MAE IM PURITY PREVIOUS BEHAVIOUR COULD CAUSE SUBOPTIMAL SPLITS TO BE CHOSEN SINCE THE IMPURITY CALCULATION CONSIDERED ALL SAMPLES TO BE OF EQUAL WEIGHT IMPORTANCE 11464 BY JOHN STOTT

SKLEARNUTILS

•FEATURE UTILSCHECKARRAY ANDUTILSCHECKXY NOW HAVEACCEPTLARGESPARSE TO CON TROL WHETHER SCIPYSPARSE MATRICES WITH 64BIT INDICES SHOULD BE REJECTED 11327 BY KARAN DHINGRA AND JOEL NOTHMAN

•EFFICIENCY F IXAVOID COPYING THE DATA IN UTILSCHECKARRAY WHEN THE INPUT DATA IS A MEMMAP AND COPYFALSE 10663 BY ARTHUR MENSCH AND LOÏC ESTÈVE
•API C HANGE UTILSCHECKARRAY YIELD AFUTUREWARNING INDICATING THAT ARRAYS OF BYTESSTRINGS WILL BE INTERPRETED AS DECIMAL NUMBERS BEGINNING IN VERSION 022 10229 BY RYAN LEE

MULTIPLE MODULES

•FEATURE API C HANGE MORE CONSISTENT OUTLIER DETECTION API ADD A SCORESAMPLES METHOD INSVMONECLASSSVM ENSEMBLEISOLATIONFOREST NEIGHBORSLOCALOUTLIERFACTOR COVARIANCEELLIPTICENVELOPE IT ALLOWS TO ACCESS RAW SCORE FUNCTIONS FROM ORIGINAL PA PERS A NEW OFFSET PARAMETER ALLOWS TO LINK SCORESAMPLES ANDDECISIONFUNCTION METHODS THE CONTAMINATION PARAMETER OF ENSEMBLEISOLATIONFOREST ANDNEIGHBORS LOCALOUTLIERFACTOR DECISIONFUNCTION METHODS IS USED TO DEFINE THIS OFFSET SUCH THAT OUTLIERS RESP INLIERS HAVE NEGATIVE RESP POSITIVE DECISIONFUNCTION VALUES BY DEFAULT CONTAMINATION IS KEPT UNCHANGED TO 01 FOR A DEPRECATION PERIOD IN 022 IT WILL BE SET TO “AUTO” THUS USING METHODSPECIFIC SCORE OFFSETS IN COVARIANCEELLIPTICENVELOPE DECISIONFUNCTION METHOD THE RAWVALUES PARAMETER IS DEPRECATED AS THE SHIFTED MAHALANOBIS DISTANCE WILL BE ALWAYS RETURNED IN 022 9015 BY NICOLAS GOIX
•FEATURE API C HANGE ABEHAVIOUR PARAMETER HAS BEEN INTRODUCED IN ENSEMBLE ISOLATIONFOREST TO ENSURE BACKWARD COMPATIBILITY IN THE OLD BEHAVIOUR THE DECISIONFUNCTION IS INDEPENDENT OF THE CONTAMINATION PARAMETER A THRESHOLD ATTRIBUTE DEPENDING ON THE CONTAMINATION PARAMETER IS THUS USED IN THE NEW BEHAVIOUR THE DECISIONFUNCTION IS DEPENDENT ON THE CONTAMINATION PARAMETER IN SUCH A WAY THAT 0 BECOMES ITS NATURAL THRESHOLD TO DETECT OUTLIERS SET TING BEHAVIOUR TO “OLD” IS DEPRECATED AND WILL NOT BE POSSIBLE IN VERSION 022 BESIDE THE BEHAVIOUR PARAMETER WILL BE REMOVED IN 024 11553 BY NICOLAS GOIX
•API C HANGE ADDED CONVERGENCE WARNING TO SVMLINEARSVC ANDLINEARMODEL LOGISTICREGRESSION WHENVERBOSE IS SET TO 0 10881 BY ALEXANDRE SEVIN
•API C HANGE CHANGED WARNING TYPE FROM USERWARNING TOEXCEPTIONSCONVERGENCEWARNING FOR FAILING CONVERGENCE IN LINEARMODELLOGISTICREGRESSIONPATH LINEARMODEL RANSACREGRESSOR LINEARMODELRIDGEREGRESSION GAUSSIANPROCESS GAUSSIANPROCESSREGRESSOR GAUSSIANPROCESSGAUSSIANPROCESSCLASSIFIER DECOMPOSITIONFASTICA CROSSDECOMPOSITIONPLSCANONICAL CLUSTER AFFINITYPROPAGATION ANDCLUSTERBIRCH 10306 BY JONATHAN SIEBERT

MISCELLANEOUS

•MAJOR FEATURE A NEW CONFIGURATION PARAMETER WORKINGMEMORY WAS ADDED TO CONTROL MEMORY CON SUMPTION LIMITS IN CHUNKED OPERATIONS SUCH AS THE NEW METRICSPAIRWISEDISTANCESCHUNKED SEE LIMITING WORKING MEMORY 10280 BY JOEL NOTHMAN AND AMAN DALMIA
•FEATURE THE VERSION OF JOBLIB BUNDLED WITH SCIKITLEARN IS NOW 012 THIS USES A NEW DEFAULT MULTIPROCESS ING IMPLEMENTATION NAMED LOKY WHILE THIS MAY INCUR SOME MEMORY AND COMMUNICATION OVERHEAD IT SHOULD PROVIDE GREATER CROSSPLATFORM STABILITY THAN RELYING ON PYTHON STANDARD LIBRARY MULTIPROCESSING 11741 BY THE JOBLIB DEVELOPERS ESPECIALLY THOMAS MOREAU AND OLIVIER GRISEL
•FEATURE AN ENVIRONMENT VARIABLE TO USE THE SITE JOBLIB INSTEAD OF THE VENDORED ONE WAS ADDED ENVIRONMENT VARIABLES THE MAIN API OF JOBLIB IS NOW EXPOSED IN SKLEARNUTILS 11166 BY GAEL VAROQUAUX
•FEATURE ADD ALMOST COMPLETE PYPY 3 SUPPORT KNOWN UNSUPPORTED FUNCTIONALITIES ARE DATASETS LOADSVMLIGHTFILE FEATUREEXTRACTIONFEATUREHASHER ANDFEATUREEXTRACTION TEXTHASHINGVECTORIZER FOR RUNNING ON PYPY PYPY3V510 NUMPY 1140 AND SCIPY 110 ARE REQUIRED 11010 BY RONAN LAMY AND ROMAN YURCHAK

•FEATURE A UTILITY METHOD SKLEARNSHOWVERSIONS WAS ADDED TO PRINT OUT INFORMATION RELEVANT FOR DEBUGGING IT INCLUDES THE USER SYSTEM THE PYTHON EXECUTABLE THE VERSION OF THE MAIN LIBRARIES AND BLAS BINDING INFORMATION 11596 BY ALEXANDRE BOUCAUD
•FIXFIXED A BUG WHEN SETTING PARAMETERS ON METAESTIMATOR INVOLVING BOTH A WRAPPED ESTIMATOR AND ITS PA RAMETER 9999 BY MARCUS V OSS AND JOEL NOTHMAN
•FIXFIXED A BUG WHERE CALLING SKLEARNBASECLONE WAS NOT THREAD SAFE AND COULD RESULT IN A “POP FROM EMPTY LIST” ERROR 9569 BY ANDREAS MÜLLER
•API C HANGE THE DEFAULT VALUE OF NJOBS IS CHANGED FROM 1TONONE IN ALL RELATED FUNCTIONS AND CLASSES NJOBSNONE MEANSUNSET IT WILL GENERALLY BE INTERPRETED AS NJOBS1 UNLESS THE CURRENT JOBLIB PARALLEL BACKEND CONTEXT SPECIFIES OTHERWISE SEE GLOSSARY FOR ADDITIONAL INFORMATION NOTE THAT THIS CHANGE HAPPENS IMMEDIATELY IE WITHOUT A DEPRECATION CYCLE 11741 BY OLIVIER GRISEL
•FIXFIXED A BUG IN VALIDATION HELPERS WHERE PASSING A DASK DATAFRAME RESULTS IN AN ERROR 12462 BY ZACHARIAH MILLER

1165 CHANGES TO ESTIMATOR CHECKS

THESE CHANGES MOSTLY AFFECT LIBRARY DEVELOPERS
• CHECKS FOR TRANSFORMERS NOW APPLY IF THE ESTIMATOR IMPLEMENTS TRANSFORM REGARDLESS OF WHETHER IT INHERITS FROM SKLEARNBASETRANSFORMERMIXIN 10474 BY JOEL NOTHMAN
• CLASSIFIERS ARE NOW CHECKED FOR CONSISTENCY BETWEEN DECISIONFUNCTION AND CATEGORICAL PREDICTIONS 10500 BY NARINE KOKHLIKYAN
• ALLOW TESTS IN UTILSESTIMATORCHECKSCHECKESTIMATOR TO TEST FUNCTIONS THAT ACCEPT PAIRWISE DATA 9701 BY KYLE JOHNSON
• ALLOWUTILSESTIMATORCHECKSCHECKESTIMATOR TO CHECK THAT THERE IS NO PRIVATE SETTINGS APART FROM PARAMETERS DURING ESTIMATOR INITIALIZATION 9378 BY HERILALAINA RAKOTOARISON
• THE SET OF CHECKS IN UTILSESTIMATORCHECKSCHECKESTIMATOR NOW INCLUDES A CHECKSETPARAMS TEST WHICH CHECKS THAT SETPARAMS IS EQUIVALENT TO PASSING PARAMETERS IN INIT AND WARNS IF IT ENCOUNTERS PARAMETER VALIDATION 7738 BY ALVIN CHIANG
• ADD INVARIANCE TESTS FOR CLUSTERING METRICS 8102 BY ANKITA SINHA AND GUILLAUME LEMAITRE
• ADDCHECKMETHODSSUBSETINVARIANCE TOCHECKESTIMATOR WHICH CHECKS THAT ESTIMATOR METHODS ARE INVARIANT IF APPLIED TO A DATA SUBSET 10428 BY JONATHAN OHAYON
• ADD TESTS IN UTILSESTIMATORCHECKSCHECKESTIMATOR TO CHECK THAT AN ESTIMATOR CAN HANDLE READONLY MEMMAP INPUT DATA 10663 BY ARTHUR MENSCH AND LOÏC ESTÈVE
•CHECKSAMPLEWEIGHTSPANDASSERIES NOW USES 8 RATHER THAN 6 SAMPLES TO ACCOMMODATE FOR THE DEFAULT NUMBER OF CLUSTERS IN CLUSTERKMEANS 10933 BY JOHANNES HANSEN
• ESTIMATORS ARE NOW CHECKED FOR WHETHER SAMPLEWEIGHTNONE EQUATES TO SAMPLEWEIGHTNP ONES 11558 BY SERGUL AYDORE

1166 CODE AND DOCUMENTATION CONTRIBUTORS

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211217613 AARSHAY JAIN ABSOLUTELYNOWARRANTY ADAM GREENHALL ADAM KLECZEWSKI ADAM RICHIEHALFORD ADELR ADITYADAFLAPURKAR ADRIN JALALI AIDAN FITZGERALD AISHGRT1 AKASH SHIVRAM ALAN LIDDELL ALAN YEE ALBERT THOMAS

ALEXANDER LENAIL ALEXANDERN ALEXANDRE BOUCAUD ALEXANDRE GRAMFORT ALEXANDRE SEVIN ALEX EGG ALVARO PEREZ DIAZ AMANDA AMAN DALMIA ANDREAS BJERRENIELSEN ANDREAS MUELLER ANDREW PENG ANGUS WILLIAMS ANIRUDDHA DAVE ANNAAYZENSHTAT ANTHONY GITTER ANTONIO QUINONEZ ANUBHAV MARWAHA ARIK PAMNANI ARTHUR OZGA ARTIEM K ARUNAVA ARYA MCCARTHY ATTRACTADORE AURÉLIEN BELLET AURÉLIEN GERON AYUSH GUPTA BALAKUMARAN MANOHA RAN BANGDA SUN BARRY HART BASTIAN VENTHUR BEN LAWSON BENN ROTH BRENO FREITAS BRENT YI BRETT KOONCE CAIO OLIVEIRA CAMIL STAPS CCLAUSS CHADY KAMAR CHARLIE BRUMMITT CHARLIE NEWEY CHRIS CHRIS CHRIS CATALFO CHRIS FOSTER CHRIS HOLDGRAF CHRISTIAN BRAUNE CHRISTIAN HIRSCH CHRISTIAN HOGAN CHRISTOPHER JENNESS CLEMENT JOUDET CNX CWITTE DALLAS CARD DAN BARKHORN DANIEL DANIEL FERREIRA DANIEL GOMEZ DANIEL KLEVEBRING DANIELLE SHWED DANIEL MOHNS DANIL BAIBAK DARIUS MORAWIEC DAVID BEACH DAVID BURNS DAVID KIRKBY DAVID NICHOL SON DAVID PICKUP DEREK DIDI BARZEV DIEGODLH DILLON GARDNER DILLON NIEDERHUT DILUTEDSAUCE DLOVELL DMITRY MOTTL DMITRY PETROV DOR COHEN DOUGLAS DUHAIME EKATERINA TUZOVA ERIC CHANG ERIC DEAN SANCHEZ ERICH SCHU BERT EUNJI FANGCHIEH CHOU FARAHSAEED FELIX FÉLIX RAIMUNDO FENX FILIPJ8 FRANKHUI FRANZ WOMPNER FREIJA DESCAMPS FRSI GABRIELE CALVO GAEL VAROQUAUX GAURAV DHINGRA GEORGI PEEV GIL FORSYTH GIOVANNI GIUSEPPE COSTA GKEVINYEN5418 GONCALORODRIGUES GRYLLOS PROKOPIS GUILLAUME LEMAITRE GUILLAUME “VERMEILLE” SANCHEZ GUSTAVO DE MARI PEREIRA HAKAA1 HANMIN QIN HENRY LIN HONG HONGHE HOSSEIN POURBOZORG HRISTO HUNAN ROS TOMYAN IAMPAT IVAN PANICO JAEWON CHUNG JAKE VANDERPLAS JAKIRKHAM JAMES BOURBEAU JAMES MALCOLM JAMIE COX JAN KOCH JAN MARGETA JAN SCHLÜTER JANVANRIJN JASON WOLOSONOVICH JC LIU JEB BEARER JEREMIEDBB JIMMY WAN JINKUN WANG JIONGYAN ZHANG JJABL JKLEINT JOAN MASSICH JOËL BILLAUD JOEL NOTHMAN JOHANNES HANSEN JOHNSTOTT JONATAN SAMOOCHA JONATHAN OHAYON JÖRG DÖPFERT JORIS VAN DEN BOSSCHE JOSE PEREZPARRAS TOLEDANO JOSEPHSALMON JOTASI JSCHENDEL JULIAN KUHLMANN JULIEN CHAUMOND JULIETCL JUSTIN SHENK KARL F KASPER PRIMDAL LAURITZEN KATRIN LEINWEBER KIRILL KSEMB KUAI YU KUMAR ASHUTOSH KYEONGPIL KANG KYE TAYLOR KYLEDROGO LELAND MCINNES LÉO DS LIAM GERON LIUTONG ZHOU LIZAO LI LKJCALC LOIC ESTEVE LOUIB LUCIANO VIOLA LUCIJA GREGOV LUIS OSA LUIS PEDRO COELHO LUKE M CRAIG LUKE PERSOLA MABEL MABEL VILLALBA MANITEJA NANDANA MARKI WANCHYSHYN MARK ROTH MARKUS MÜLLER MARSGUY MARTIN GUBRI MARTINHAHN MARTINKOKOS MATHURINM MATTHIAS FEURER MAX COPELAND MAYUR KULKARNI MEGHANN AGARWAL MELANIE GOETZ MICHAEL A ALCORN MINGHUI LIU MING LI MINH LE MOHAMED ALI JAMAOUI MOHAMED MASKANI MOHAMMAD SHAHEBAZ MUAYYAD ALSADI NABARUN PAL NA GARJUNA KUMAR NAOYA KANAI NARENDRAN SANTHANAM NARINEK NATHANIEL SAUL NATHAN SUH NICHOLAS NADEAU PENG A VS NICK HOH NICOLAS GOIX NICOLAS HUG NICOLAU WERNECK NIELSENMARKUS11 NIHAR SHETH NIKITA TITOV NILESH KEVLANI NIRVAN ANJIRBAG NOTMATTHANCOCK NZW OLEKSANDR PAVLYK OLIBLUM90 OLIVER RAUSCH OLIVIER GRISEL OREN MILMAN OSAID REHMAN NASIR PASBI PATRICK FERNANDES PATRICK OLDEN PAUL PACZUSKI PEDRO MORALES PETER PETER ST JOHN PIERREABLIN PIETRUH PINAKI NATH CHOWDHURY PIOTR SZYMA ´NSKI PRADEEP REDDY RAAMANA PRAVAR D MAHAJAN PRAVARMAHAJAN QINGYING CHEN RAGHAV RV RAJENDRA ARORA RAKOTOARISON HERILALAINA RAMESHWAR BHASKARAN RANKYLAU RASUL KERIMOV REIICHIRO NAKANO ROB ROMAN KOSOBRODOV ROMAN YURCHAK RONAN LAMY RRAGUNDEZ RÜDIGER BUSCHE RYAN SACHIN KELKAR SAGNIK BHATTACHARYA SAILESH CHOYAL SAM RADHAKRISHNAN SAM STEINGOLD SAMUEL BELL SAMUEL O RONSIN SAQIB NIZAM SHAMSI SATISH J SAURABH GUPTA SCOTT GIGANTE SEBASTIAN FLEN NERHAG SEBASTIAN RASCHKA SEBASTIEN DUBOIS SÉBASTIEN LERIQUE SEBASTIN SANTY SERGEY FELDMAN SERGEY MELDERIS SERGUL AYDORE SHAHEBAZ SHALIL AWALEY SHANGWU YAO SHARAD VIJALAPURAM SHARAN YALBURGI SHENHANC78 SHIVAM RASTOGI SHU HAORAN SIFTIKHA SINCLERT PÉREZ SOLUTUSIMMENSUS SOMYA ANAND SRAJAN PALIWAL SRIHARSHA HATWAR SRI KRISHNA STEFAN VAN DER WALT STEPHEN MCDOWELL STEVEN BROWN SYONEKURA TAEHOON LEE TAKANORI HAYASHI TARCUSX TAYLOR G SMITH THERILEY106 THOMAS THOMAS FAN THOMAS HEAVEY TOBIAS MADSEN TOBYCHEESE TOM AUGSPURGER TOM DUPRÉ LA TOUR TOMMY TREVOR STEPHENS TRISHNENDU GHORAI TULIO CASAGRANDE TWOSIGMAJAB UMAR FAROUK UMAR URVANG PATEL UTKARSH UPADHYAY VADIM MARKOVTSEV VARUN AGRAWAL VATHSALA ACHAR VILHELM VON EHREN HEIM VINAYAK MEHTA VINIT VINOD KUMAR L VIRAJ MAVANI VIRAJ NAVKAL VIVEK KUMAR VLAD NICULAE VQEAN3 VRIS HANK BHARDWAJ VUFG WALLYGAUZE WARUT VIJITBENJARONK WDEVAZELHES WENHAO ZHANG WES BARNETT WILL WILLIAM DE VAZELHES WILL ROSENFELD XIN XIONG YIMING PAUL LI YMAZARI YUFENG ZACH GRIFFITH ZÉ VINÍCIUS ZHENQING HU ZHIQING XIAO ZIJIE ZJ POH

117 PREVIOUS RELEASES

1171 VERSION 0192

JULY 2018

SCIKITLEARN USER GUIDE RELEASE 0213
THIS RELEASE IS EXCLUSIVELY IN ORDER TO SUPPORT PYTHON 37
RELATED CHANGES
•NITER MAY VARY FROM PREVIOUS RELEASES IN LINEARMODELLOGISTICREGRESSION WITH
SOLVERLBFGS ANDLINEARMODELHUBERREGRESSOR FOR SCIPY 100 THE OPTIMIZER COULD
PERFORM MORE THAN THE REQUESTED MAXIMUM NUMBER OF ITERATIONS NOW BOTH ESTIMATORS WILL REPORT AT MOST
MAXITER ITERATIONS EVEN IF MORE WERE PERFORMED 10723 BY JOEL NOTHMAN
1172 VERSION 0191
OCTOBER 23 2017
THIS IS A BUGFIX RELEASE WITH SOME MINOR DOCUMENTATION IMPROVEMENTS AND ENHANCEMENTS TO FEATURES RELEASED IN
0190
NOTE THERE MAY BE MINOR DIFFERENCES IN TSNE OUTPUT IN THIS RELEASE DUE TO 9623 IN THE CASE WHERE MULTIPLE SAMPLES
HAVE EQUAL DISTANCE TO SOME SAMPLE
CHANGELOG
API CHANGES
• REVERTED THE ADDITION OF METRICSNDCGSCORE ANDMETRICSDCGSCORE WHICH HAD BEEN MERGED INTO
VERSION 0190 BY ERROR THE IMPLEMENTATIONS WERE BROKEN AND UNDOCUMENTED
•RETURNTRAINSCORE WHICH WAS ADDED TO MODELSELECTIONGRIDSEARCHCV
MODELSELECTIONRANDOMIZEDSEARCHCV ANDMODELSELECTIONCROSSVALIDATE IN
VERSION 0190 WILL BE CHANGING ITS DEFAULT VALUE FROM TRUE TO FALSE IN VERSION 021 WE FOUND THAT CALCULATING
TRAINING SCORE COULD HAVE A GREAT EFFECT ON CROSS VALIDATION RUNTIME IN SOME CASES USERS SHOULD EXPLICITLY
SETRETURNTRAINSCORE TO FALSE IF PREDICTION OR SCORING FUNCTIONS ARE SLOW RESULTING IN A DELETERIOUS
EFFECT ON CV RUNTIME OR TO TRUE IF THEY WISH TO USE THE CALCULATED SCORES 9677 BY KUMAR ASHUTOSH AND JOEL
NOTHMAN
•CORRELATIONMODELS ANDREGRESSIONMODELS FROM THE LEGACY GAUSSIAN PROCESSES IMPLEMENTATION
HAVE BEEN BELATEDLY DEPRECATED 9717 BY KUMAR ASHUTOSH
BUG FIXES
• AVOID INTEGER OVERFLOWS IN METRICSMATTHEWSCORRCOEF 9693 BY SAM STEINGOLD
• FIXED A BUG IN THE OBJECTIVE FUNCTION FOR MANIFOLDTSNE BOTH EXACT AND WITH THE BARNESHUT APPROXIMATION
WHENNCOMPONENTS 3 9711 BY GONCALORODRIGUES
• FIX REGRESSION IN MODELSELECTIONCROSSVALPREDICT WHERE IT RAISED AN ERROR WITH
METHODPREDICTPROBA FOR SOME PROBABILISTIC CLASSIFIERS 9641 BY JAMES BOURBEAU
• FIXED A BUG WHERE DATASETSMAKECLASSIFICATION MODIFIED ITS INPUT WEIGHTS 9865 BY SACHIN
KELKAR
•MODELSELECTIONSTRATIFIEDSHUFFLESPLIT NOW WORKS WITH MULTIOUTPUT MULTICLASS OR MULTILABEL
DATA WITH MORE THAN 1000 COLUMNS 9922 BY CHARLIE BRUMMITT
• FIXED A BUG WITH NESTED AND CONDITIONAL PARAMETER SETTING EG SETTING A PIPELINE STEP AND ITS PARAMETER AT THE
SAME TIME 9945 BY ANDREAS MÜLLER AND JOEL NOTHMAN

SCIKITLEARN USER GUIDE RELEASE 0213
REGRESSIONS IN 0190 FIXED IN 0191
• FIXED A BUG WHERE PARALLELISED PREDICTION IN RANDOM FORESTS WAS NOT THREADSAFE AND COULD RARELY RESULT IN ARBITRARY ERRORS 9830 BY JOEL NOTHMAN
• FIX REGRESSION IN MODELSELECTIONCROSSVALPREDICT WHERE IT NO LONGER ACCEPTED XAS A LIST 9600 BY RASUL KERIMOV
• FIXED HANDLING OF CROSSVALPREDICT FOR BINARY CLASSIFICATION WITH METHODDECISIONFUNCTION 9593 BY REIICHIRO NAKANO AND CORE DEVS
• FIX REGRESSION IN PIPELINEPIPELINE WHERE IT NO LONGER ACCEPTED STEPS AS A TUPLE 9604 BY JORIS VAN DEN BOSSCHE
• FIX BUG WHERE NITER WAS NOT PROPERLY DEPRECATED LEAVING NITER UNAVAILABLE FOR INTERIM USE INLINEARMODELSGDCLASSIFIER LINEARMODELSGDREGRESSOR LINEARMODEL PASSIVEAGGRESSIVECLASSIFIER LINEARMODELPASSIVEAGGRESSIVEREGRESSOR AND LINEARMODELPERCEPTRON 9558 BY ANDREAS MÜLLER
• DATASET FETCHERS MAKE SURE TEMPORARY FILES ARE CLOSED BEFORE REMOVING THEM WHICH CAUSED ERRORS ON WINDOWS 9847 BY JOAN MASSICH
• FIXED A REGRESSION IN MANIFOLDTSNE WHERE IT NO LONGER SUPPORTED METRICS OTHER THAN ‘EUCLIDEAN’ AND ‘PRE COMPUTED’ 9623 BY OLI BLUM
ENHANCEMENTS
• OUR TEST SUITE AND UTILSESTIMATORCHECKSCHECKESTIMATORS CAN NOW BE RUN WITHOUT NOSE IN STALLED 9697 BY JOAN MASSICH
• TO IMPROVE USABILITY OF VERSION 019’S PIPELINEPIPELINE CACHINGMEMORY NOW ALLOWS JOBLIB MEMORY INSTANCES THIS MAKE USE OF THE NEW UTILSVALIDATIONCHECKMEMORY HELPER ISSUE 9584 BY KUMAR ASHUTOSH
• SOME FIXES TO EXAMPLES 9750 9788 9815
• MADE A FUTUREWARNING IN SGDBASED ESTIMATORS LESS VERBOSE 9802 BY VRISHANK BHARDWAJ
CODE AND DOCUMENTATION CONTRIBUTORS
WITH THANKS TO
JOEL NOTHMAN LOIC ESTEVE ANDREAS MUELLER KUMAR ASHUTOSH VRISHANK BHARDWAJ HANMIN QIN RASUL KERIMOV JAMES BOURBEAU NAGARJUNA KUMAR NATHANIEL SAUL OLIVIER GRISEL ROMAN YURCHAK REIICHIRO NAKANO SACHIN KELKAR SAM STEINGOLD YAROSLAV HALCHENKO DIEGODLH FELIX GONCALORODRIGUES JKLEINT OLIBLUM90 PASBI ANTHONY GITTER BEN LAWSON CHARLIE BRUMMITT DIDI BARZEV GAEL VAROQUAUX JOAN MASSICH JORIS VAN DEN BOSSCHE NIELSENMARKUS11
1173 VERSION 019
AUGUST 12 2017
HIGHLIGHTS
WE ARE EXCITED TO RELEASE A NUMBER OF GREAT NEW FEATURES INCLUDING NEIGHBORSLOCALOUTLIERFACTOR FOR ANOMALY DETECTION PREPROCESSINGQUANTILETRANSFORMER FOR ROBUST FEATURE TRANSFORMATION AND THEMULTIOUTPUTCLASSIFIERCHAIN METAESTIMATOR TO SIMPLY ACCOUNT FOR DEPENDENCIES BETWEEN CLASSES
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IN MULTILABEL PROBLEMS WE HAVE SOME NEW ALGORITHMS IN EXISTING ESTIMATORS SUCH AS MULTIPLICATIVE UP
DATE INDECOMPOSITIONNMF AND MULTINOMIAL LINEARMODELLOGISTICREGRESSION WITH L1 LOSS USE
SOLVERSAGA
CROSS VALIDATION IS NOW ABLE TO RETURN THE RESULTS FROM MULTIPLE METRIC EVALUATIONS THE NEW MODELSELECTION
CROSSVALIDATE CAN RETURN MANY SCORES ON THE TEST DATA AS WELL AS TRAINING SET PERFORMANCE AND TIMINGS AND WE
HAVE EXTENDED THE SCORING ANDREFIT PARAMETERS FOR GRIDRANDOMIZED SEARCH TO HANDLE MULTIPLE METRICS
YOU CAN ALSO LEARN FASTER FOR INSTANCE THE NEW OPTION TO CACHE TRANSFORMATIONS INPIPELINEPIPELINE MAKES
GRID SEARCH OVER PIPELINES INCLUDING SLOW TRANSFORMATIONS MUCH MORE EFFICIENT AND YOU CAN PREDICT FASTER IF YOU'RE
SURE YOU KNOW WHAT YOU'RE DOING YOU CAN TURN OFF VALIDATING THAT THE INPUT IS FINITE USING CONFIGCONTEXT
WE'VE MADE SOME IMPORTANT FIXES TOO WE'VE FIXED A LONGSTANDING IMPLEMENTATION ERROR IN METRICS
AVERAGEPRECISIONSCORE SO PLEASE BE CAUTIOUS WITH PRIOR RESULTS REPORTED FROM THAT FUNCTION A NUMBER
OF ERRORS IN THE MANIFOLDTSNE IMPLEMENTATION HAVE BEEN FIXED PARTICULARLY IN THE DEFAULT BARNESHUT APPROX
IMATIONSEMISUPERVISEDLABELSPREADING ANDSEMISUPERVISEDLABELPROPAGATION HAVE HAD
SUBSTANTIAL FIXES LABELPROPAGATION WAS PREVIOUSLY BROKEN LABELSPREADING SHOULD NOW CORRECTLY RESPECT ITS ALPHA
PARAMETER
CHANGED MODELS
THE FOLLOWING ESTIMATORS AND FUNCTIONS WHEN FIT WITH THE SAME DATA AND PARAMETERS MAY PRODUCE DIFFERENT MODELS
FROM THE PREVIOUS VERSION THIS OFTEN OCCURS DUE TO CHANGES IN THE MODELLING LOGIC BUG FIXES OR ENHANCEMENTS OR IN
RANDOM SAMPLING PROCEDURES
•CLUSTERKMEANS WITH SPARSE X AND INITIAL CENTROIDS GIVEN BUG FIX
•CROSSDECOMPOSITIONPLSREGRESSION WITHSCALETRUE BUG FIX
•ENSEMBLEGRADIENTBOOSTINGCLASSIFIER ANDENSEMBLEGRADIENTBOOSTINGREGRESSOR
WHEREMINIMPURITYSPLIT IS USED BUG FIX
• GRADIENT BOOSTING LOSSQUANTILE BUG FIX
•ENSEMBLEISOLATIONFOREST BUG FIX
•FEATURESELECTIONSELECTFDR BUG FIX
•LINEARMODELRANSACREGRESSOR BUG FIX
•LINEARMODELLASSOLARS BUG FIX
•LINEARMODELLASSOLARSIC BUG FIX
•MANIFOLDTSNE BUG FIX
•NEIGHBORSNEARESTCENTROID BUG FIX
•SEMISUPERVISEDLABELSPREADING BUG FIX
•SEMISUPERVISEDLABELPROPAGATION BUG FIX
• TREE BASED MODELS WHERE MINWEIGHTFRACTIONLEAF IS USED ENHANCEMENT
•MODELSELECTIONSTRATIFIEDKFOLD WITHSHUFFLETRUE THIS CHANGE DUE TO 7823 WAS NOT MEN
TIONED IN THE RELEASE NOTES AT THE TIME
DETAILS ARE LISTED IN THE CHANGELOG BELOW
WHILE WE ARE TRYING TO BETTER INFORM USERS BY PROVIDING THIS INFORMATION WE CANNOT ASSURE THAT THIS LIST IS COMPLETE

SCIKITLEARN USER GUIDE RELEASE 0213
CHANGELOG
NEW FEATURES
CLASSIFIERS AND REGRESSORS
• ADDEDMULTIOUTPUTCLASSIFIERCHAIN FOR MULTILABEL CLASSIFICATION BY ADAM KLECZEWSKI
• ADDED SOLVER SAGA THAT IMPLEMENTS THE IMPROVED VERSION OF STOCHASTIC AVERAGE GRADIENT IN LINEARMODELLOGISTICREGRESSION ANDLINEARMODELRIDGE IT ALLOWS THE USE OF L1 PENALTY WITH MULTINOMIAL LOGISTIC LOSS AND BEHAVES MARGINALLY BETTER THAN 'SAG' DURING THE FIRST EPOCHS OF RIDGE AND LOGISTIC REGRESSION 8446 BY ARTHUR MENSCH
OTHER ESTIMATORS
• ADDED THE NEIGHBORSLOCALOUTLIERFACTOR CLASS FOR ANOMALY DETECTION BASED ON NEAREST NEIGHBORS 5279 BY NICOLAS GOIX AND ALEXANDRE GRAMFORT
• ADDED PREPROCESSINGQUANTILETRANSFORMER CLASS AND PREPROCESSING QUANTILETRANSFORM FUNCTION FOR FEATURES NORMALIZATION BASED ON QUANTILES 8363 BY DENIS ENGEMANN GUILLAUME LEMAITRE OLIVIER GRISEL RAGHAV RV THIERRY GUILLEMOT AND GAEL VAROQUAUX
• THE NEW SOLVER MU IMPLEMENTS A MULTIPLICATE UPDATE IN DECOMPOSITIONNMF ALLOWING THE OPTIMIZATION OF ALL BETADIVERGENCES INCLUDING THE FROBENIUS NORM THE GENERALIZED KULLBACKLEIBLER DIVERGENCE AND THE ITAKURASAITO DIVERGENCE 5295 BY TOM DUPRE LA TOUR
MODEL SELECTION AND EVALUATION
•MODELSELECTIONGRIDSEARCHCV ANDMODELSELECTIONRANDOMIZEDSEARCHCV NOW SUPPORT SIMULTANEOUS EVALUATION OF MULTIPLE METRICS REFER TO THE SPECIFYING MULTIPLE METRICS FOR EVALUATION SECTION OF THE USER GUIDE FOR MORE INFORMATION 7388 BY RAGHAV RV
• ADDED THE MODELSELECTIONCROSSVALIDATE WHICH ALLOWS EVALUATION OF MULTIPLE METRICS THIS FUNC TION RETURNS A DICT WITH MORE USEFUL INFORMATION FROM CROSSVALIDATION SUCH AS THE TRAIN SCORES FIT TIMES AND SCORE TIMES REFER TO THE CROSSVALIDATE FUNCTION AND MULTIPLE METRIC EVALUATION SECTION OF THE USERGUIDE FOR MORE INFORMATION 7388 BY RAGHAV RV
• ADDEDMETRICSMEANSQUAREDLOGERROR WHICH COMPUTES THE MEAN SQUARE ERROR OF THE LOGARITHMIC TRANSFORMATION OF TARGETS PARTICULARLY USEFUL FOR TARGETS WITH AN EXPONENTIAL TREND 7655 BY KARAN DESAI
• ADDEDMETRICSDCGSCORE ANDMETRICSNDCGSCORE WHICH COMPUTE DISCOUNTED CUMULATIVE GAIN DCG AND NORMALIZED DISCOUNTED CUMULATIVE GAIN NDCG 7739 BY DAVID GASQUEZ
• ADDED THE MODELSELECTIONREPEATEDKFOLD ANDMODELSELECTION REPEATEDSTRATIFIEDKFOLD 8120 BY NEERAJ GANGWAR
MISCELLANEOUS
• VALIDATION THAT INPUT DATA CONTAINS NO NAN OR INF CAN NOW BE SUPPRESSED USING CONFIGCONTEXT AT YOUR OWN RISK THIS WILL SAVE ON RUNTIME AND MAY BE PARTICULARLY USEFUL FOR PREDICTION TIME 7548 BY JOEL NOTHMAN
• ADDED A TEST TO ENSURE PARAMETER LISTING IN DOCSTRINGS MATCH THE FUNCTIONCLASS SIGNATURE 9206 BY ALEXANDRE GRAMFORT AND RAGHAV RV
ENHANCEMENTS
TREES AND ENSEMBLES
• THEMINWEIGHTFRACTIONLEAF CONSTRAINT IN TREE CONSTRUCTION IS NOW MORE EFFICIENT TAKING A FAST PATH TO DECLARE A NODE A LEAF IF ITS WEIGHT IS LESS THAN 2 THE MINIMUM NOTE THAT THE CONSTRUCTED TREE WILL BE DIFFERENT FROM PREVIOUS VERSIONS WHERE MINWEIGHTFRACTIONLEAF IS USED 7441 BY NELSON LIU

•ENSEMBLEGRADIENTBOOSTINGCLASSIFIER ANDENSEMBLEGRADIENTBOOSTINGREGRESSOR NOW SUPPORT SPARSE INPUT FOR PREDICTION 6101 BY IBRAIM GANIEV
•ENSEMBLEVOTINGCLASSIFIER NOW ALLOWS CHANGING ESTIMATORS BY USING ENSEMBLE VOTINGCLASSIFIERSETPARAMS AN ESTIMATOR CAN ALSO BE REMOVED BY SETTING IT TO NONE 7674 BY YICHUAN LIU
•TREEEXPORTGRAPHVIZ NOW SHOWS CONFIGURABLE NUMBER OF DECIMAL PLACES 8698 BY GUILLAUME LEMAITRE
• ADDEDFLATTENTRANSFORM PARAMETER TO ENSEMBLEVOTINGCLASSIFIER TO CHANGE OUTPUT SHAPE OF TRANSFORM METHOD TO 2 DIMENSIONAL 7794 BY IBRAIM GANIEV AND HERILALAINA RAKOTOARISON

LINEAR KERNELIZED AND RELATED MODELS

•LINEARMODELSGDCLASSIFIER LINEARMODELSGDREGRESSOR LINEARMODEL PASSIVEAGGRESSIVECLASSIFIER LINEARMODELPASSIVEAGGRESSIVEREGRESSOR AND LINEARMODELPERCEPTRON NOW EXPOSE MAXITER ANDTOL PARAMETERS TO HANDLE CONVERGENCE MORE PRECISELYNITER PARAMETER IS DEPRECATED AND THE FITTED ESTIMATOR EXPOSES A NITER ATTRIBUTE WITH ACTUAL NUMBER OF ITERATIONS BEFORE CONVERGENCE 5036 BY TOM DUPRE LA TOUR
• ADDED AVERAGE PARAMETER TO PERFORM WEIGHT AVERAGING IN LINEARMODEL PASSIVEAGGRESSIVECLASSIFIER 4939 BY ANDREA ESULI
•LINEARMODELRANSACREGRESSOR NO LONGER THROWS AN ERROR WHEN CALLING FIT IF NO INLIERS ARE FOUND IN ITS FIRST ITERATION FURTHERMORE CAUSES OF SKIPPED ITERATIONS ARE TRACKED IN NEWLY ADDED ATTRIBUTES NSKIPS 7914 BY MICHAEL HORRELL
• INGAUSSIANPROCESSGAUSSIANPROCESSREGRESSOR METHOD PREDICT IS A LOT FASTER WITH RETURNSTDTRUE 8591 BY HADRIEN BERTRAND
• ADDEDRETURNSTD TOPREDICT METHOD OFLINEARMODELARDREGRESSION ANDLINEARMODEL BAYESIANRIDGE 7838 BY SERGEY FELDMAN
• MEMORY USAGE ENHANCEMENTS PREVENT CAST FROM FLOAT32 TO FLOAT64 IN LINEARMODEL MULTITASKELASTICNET LINEARMODELLOGISTICREGRESSION WHEN USING NEWTONCG SOLVER AND LINEARMODELRIDGE WHEN USING SVD SPARSECG CHOLESKY OR LSQR SOLVERS 8835 8061 BY JOAN MASSICH AND NICOLAS CORDIER AND THIERRY GUILLEMOT

OTHER PREDICTORS

• CUSTOM METRICS FOR THE NEIGHBORS BINARY TREES NOW HAVE FEWER CONSTRAINTS THEY MUST TAKE TWO 1DARRAYS AND RETURN A FLOAT 6288 BY JAKE VANDERPLAS
•ALGORITHMAUTO INNEIGHBORS ESTIMATORS NOW CHOOSES THE MOST APPROPRIATE ALGORITHM FOR ALL INPUT TYPES AND METRICS 9145 BY HERILALAINA RAKOTOARISON AND REDDY CHINTHALA

DECOMPOSITION MANIFOLD LEARNING AND CLUSTERING

•CLUSTERMINIBATCHKMEANS ANDCLUSTERKMEANS NOW USE SIGNIFICANTLY LESS MEMORY WHEN ASSIGNING DATA POINTS TO THEIR NEAREST CLUSTER CENTER 7721 BY JON CRALL
•DECOMPOSITIONPCA DECOMPOSITIONINCREMENTALPCA ANDDECOMPOSITION TRUNCATEDSVD NOW EXPOSE THE SINGULAR VALUES FROM THE UNDERLYING SVD THEY ARE STORED IN THE ATTRIBUTESINGULARVALUES LIKE INDECOMPOSITIONINCREMENTALPCA 7685 BY TOMMY LÖFSTEDT
•DECOMPOSITIONNMF NOW FASTER WHEN BETALOSS0 9277 BY HONGKAHJUN
• MEMORY IMPROVEMENTS FOR METHOD BARNESHUT INMANIFOLDTSNE 7089 BY THOMAS MOREAU AND OLIVIER GRISEL
• OPTIMIZATION SCHEDULE IMPROVEMENTS FOR BARNESHUT MANIFOLDTSNE SO THE RESULTS ARE CLOSER TO THE ONE FROM THE REFERENCE IMPLEMENTATION LVDMAATENBHTSNE BY THOMAS MOREAU AND OLIVIER GRISEL

• MEMORY USAGE ENHANCEMENTS PREVENT CAST FROM FLOAT32 TO FLOAT64 IN DECOMPOSITIONPCA AND DECOMPOSITIONRANDOMIZEDSVDLOWRANK 9067 BY RAGHAV RV

PREPROCESSING AND FEATURE SELECTION

• ADDEDNORMORDER PARAMETER TO FEATURESELECTIONSELECTFROMMODEL TO ENABLE SELECTION OF THE NORM ORDER WHEN COEF IS MORE THAN 1D 6181 BY ANTOINE WENDLINGER
• ADDED ABILITY TO USE SPARSE MATRICES IN FEATURESELECTIONFREGRESSION WITHCENTERTRUE 8065 BY DANIEL LEJEUNE
• SMALL PERFORMANCE IMPROVEMENT TO NGRAM CREATION IN FEATUREEXTRACTIONTEXT BY BINDING METHODS FOR LOOPS AND SPECIALCASING UNIGRAMS 7567 BY JAYE DOEPKE
• RELAX ASSUMPTION ON THE DATA FOR THE KERNELAPPROXIMATIONSKEWEDCHI2SAMPLER SINCE THE SKEWEDCHI2 KERNEL IS DEFINED ON THE OPEN INTERVAL −□□□□□□□□□□ ∞□ THE TRANSFORM FUNCTION SHOULD NOT CHECK WHETHER X 0 BUT WHETHER X SELFSKEWEDNESS 7573 BY ROMAIN BRAULT
• MADE DEFAULT KERNEL PARAMETERS KERNELDEPENDENT IN KERNELAPPROXIMATIONNYSTROEM 5229 BY SAURABH BANSOD AND ANDREAS MÜLLER

MODEL EVALUATION AND METAESTIMATORS

•PIPELINEPIPELINE IS NOW ABLE TO CACHE TRANSFORMERS WITHIN A PIPELINE BY USING THE MEMORY CONSTRUCTOR PARAMETER 7990 BY GUILLAUME LEMAITRE
•PIPELINEPIPELINE STEPS CAN NOW BE ACCESSED AS ATTRIBUTES OF ITS NAMEDSTEPS ATTRIBUTE 8586 BY HERILALAINA RAKOTOARISON
• ADDEDSAMPLEWEIGHT PARAMETER TO PIPELINEPIPELINESCORE 7723 BY MIKHAIL KOROBOV
• ADDED ABILITY TO SET NJOBS PARAMETER TO PIPELINEMAKEUNION ATYPEERROR WILL BE RAISED FOR ANY OTHER KWARGS 8028 BY ALEXANDER BOOTH
•MODELSELECTIONGRIDSEARCHCV MODELSELECTIONRANDOMIZEDSEARCHCV AND MODELSELECTIONCROSSVALSCORE NOW ALLOW ESTIMATORS WITH CALLABLE KERNELS WHICH WERE PREVIOUSLY PROHIBITED 8005 BY ANDREAS MÜLLER
•MODELSELECTIONCROSSVALPREDICT NOW RETURNS OUTPUT OF THE CORRECT SHAPE FOR ALL VALUES OF THE ARGUMENTMETHOD 7863 BY AMAN DALMIA
• ADDEDSHUFFLE ANDRANDOMSTATE PARAMETERS TO SHUFFLE TRAINING DATA BEFORE TAKING PREFIXES OF IT BASED ON TRAINING SIZES IN MODELSELECTIONLEARNINGCURVE 7506 BY NARINE KOKHLIKYAN
•MODELSELECTIONSTRATIFIEDSHUFFLESPLIT NOW WORKS WITH MULTIOUTPUT MULTICLASS OR MULTILABEL DATA 9044 BY VLAD NICULAE
• SPEED IMPROVEMENTS TO MODELSELECTIONSTRATIFIEDSHUFFLESPLIT 5991 BY ARTHUR MENSCH AND JOEL NOTHMAN
• ADDSHUFFLE PARAMETER TO MODELSELECTIONTRAINTESTSPLIT 8845 BY THEMRMAX
•MULTIOUTPUTMULTIOUTPUTREGRESSOR ANDMULTIOUTPUTMULTIOUTPUTCLASSIFIER NOW SUPPORT ONLINE LEARNING USING PARTIALFIT ISSUE8053 BY PENG YU
• ADDMAXTRAINSIZE PARAMETER TO MODELSELECTIONTIMESERIESSPLIT 8282 BY AMAN DALMIA
• MORE CLUSTERING METRICS ARE NOW AVAILABLE THROUGH METRICSGETSCORER ANDSCORING PARAMETERS 8117 BY RAGHAV RV
• A SCORER BASED ON METRICSEXPLAINEDVARIANCESCORE IS ALSO AVAILABLE 9259 BY HANMIN QIN

METRICS

•METRICSMATTHEWSCORRCOEF NOW SUPPORT MULTICLASS CLASSIFICATION 8094 BY JON CRALL

• ADDSAMPLEWEIGHT PARAMETER TO METRICSCOHENKAPPASCORE 8335 BY VICTOR POUGHON
MISCELLANEOUS
•UTILSCHECKESTIMATOR NOW ATTEMPTS TO ENSURE THAT METHODS TRANSFORM PREDICT ETC DO NOT SET ATTRIBUTES ON THE ESTIMATOR 7533 BY EKATERINA KRIVICH
• ADDED TYPE CHECKING TO THE ACCEPTSPARSE PARAMETER IN UTILSVALIDATION METHODS THIS PARAMETER NOW ACCEPTS ONLY BOOLEAN STRING OR LISTTUPLE OF STRINGS ACCEPTSPARSENONE IS DEPRECATED AND SHOULD BE REPLACED BY ACCEPTSPARSEFALSE 7880 BY JOSH KARNOFSKY
• MAKE IT POSSIBLE TO LOAD A CHUNK OF AN SVMLIGHT FORMATTED FILE BY PASSING A RANGE OF BYTES TO DATASETS LOADSVMLIGHTFILE 935 BY OLIVIER GRISEL
•DUMMYDUMMYCLASSIFIER ANDDUMMYDUMMYREGRESSOR NOW ACCEPT NONFINITE FEATURES 8931 BY ATTRACTADORE
BUG FIXES
TREES AND ENSEMBLES
• FIXED A MEMORY LEAK IN TREES WHEN USING TREES WITH CRITERIONMAE 8002 BY RAGHAV RV
• FIXED A BUG WHERE ENSEMBLEISOLATIONFOREST USES AN AN INCORRECT FORMULA FOR THE AVERAGE PATH LENGTH 8549 BY PETER WANG
• FIXED A BUG WHERE ENSEMBLEADABOOSTCLASSIFIER THROWSZERODIVISIONERROR WHILE FITTING DATA WITH SINGLE CLASS LABELS 7501 BY DOMINIK KRZEMINSKI
• FIXED A BUG IN ENSEMBLEGRADIENTBOOSTINGCLASSIFIER ANDENSEMBLE GRADIENTBOOSTINGREGRESSOR WHERE A FLOAT BEING COMPARED TO 00 USINGCAUSED A DIVIDE BY ZERO ERROR 7970 BY HE CHEN
• FIX A BUG WHERE ENSEMBLEGRADIENTBOOSTINGCLASSIFIER ANDENSEMBLE GRADIENTBOOSTINGREGRESSOR IGNORED THE MINIMPURITYSPLIT PARAMETER 8006 BY SEBASTIAN PÖLSTERL
• FIXEDOOBSCORE INENSEMBLEBAGGINGCLASSIFIER 8936 BY MICHAEL LEWIS
• FIXED EXCESSIVE MEMORY USAGE IN PREDICTION FOR RANDOM FORESTS ESTIMATORS 8672 BY MIKE BENFIELD
• FIXED A BUG WHERE SAMPLEWEIGHT AS A LIST BROKE RANDOM FORESTS IN PYTHON 2 8068 BY XOR
• FIXED A BUG WHERE ENSEMBLEISOLATIONFOREST FAILS WHEN MAXFEATURES IS LESS THAN 1 5732 BY ISHANK GULATI
• FIX A BUG WHERE GRADIENT BOOSTING WITH LOSSQUANTILE COMPUTED NEGATIVE ERRORS FOR NEGATIVE VALUES OF YTRUE YPRED LEADING TO WRONG VALUES WHEN CALLING CALL 8087 BY ALEXIS MIGNON
• FIX A BUG WHERE ENSEMBLEVOTINGCLASSIFIER RAISES AN ERROR WHEN A NUMPY ARRAY IS PASSED IN FOR WEIGHTS 7983 BY VINCENT PHAM
• FIXED A BUG WHERE TREEEXPORTGRAPHVIZ RAISED AN ERROR WHEN THE LENGTH OF FEATURESNAMES DOES NOT MATCH NFEATURES IN THE DECISION TREE 8512 BY LI LI
LINEAR KERNELIZED AND RELATED MODELS
• FIXED A BUG WHERE LINEARMODELRANSACREGRESSORFIT MAY RUN UNTIL MAXITER IF IT FINDS A LARGE INLIER GROUP EARLY 8251 BY AIVISION2020
• FIXED A BUG WHERE NAIVEBAYESMULTINOMIALNB ANDNAIVEBAYESBERNOULLINB FAILED WHEN ALPHA0 5814 BY YICHUAN LIU AND HERILALAINA RAKOTOARISON

• FIXED A BUG WHERE LINEARMODELLASSOLARS DOES NOT GIVE THE SAME RESULT AS THE LASSOLARS IMPLEMEN
TATION AVAILABLE IN R LARS LIBRARY 7849 BY JAIR MONTOYA MARTINEZ
• FIXED A BUG IN LINEARMODELRANDOMIZEDLASSO LINEARMODELLARS LINEARMODEL
LASSOLARS LINEARMODELLARSCV ANDLINEARMODELLASSOLARSCV WHERE THE PARAMETER
PRECOMPUTE WAS NOT USED CONSISTENTLY ACROSS CLASSES AND SOME VALUES PROPOSED IN THE DOCSTRING COULD RAISE
ERRORS 5359 BY TOM DUPRE LA TOUR
• FIX INCONSISTENT RESULTS BETWEEN LINEARMODELRIDGECV ANDLINEARMODELRIDGE WHEN USING
NORMALIZETRUE 9302 BY ALEXANDRE GRAMFORT
• FIX A BUG WHERE LINEARMODELLASSOLARSFIT SOMETIMES LEFT COEF AS A LIST RATHER THAN AN NDARRAY
8160 BY CJ CAREY
• FIXLINEARMODELBAYESIANRIDGEFIT TO RETURN RIDGE PARAMETER ALPHA ANDLAMBDA CONSISTENT
WITH CALCULATED COEFFICIENTS COEF ANDINTERCEPT 8224 BY PETER GEDECK
• FIXED A BUG IN SVMONECLASSSVM WHERE IT RETURNED FLOATS INSTEAD OF INTEGER CLASSES 8676 BY VATHSALA
ACHAR
• FIX AICBIC CRITERION COMPUTATION IN LINEARMODELLASSOLARSIC 9022 BY ALEXANDRE GRAMFORT AND
MEHMET BASBUG
• FIXED A MEMORY LEAK IN OUR LIBLINEAR IMPLEMENTATION 9024 BY SERGEI LEBEDEV
• FIX BUG WHERE STRATIFIED CV SPLITTERS DID NOT WORK WITH LINEARMODELLASSOCV 8973 BY PAULO HADDAD
• FIXED A BUG IN GAUSSIANPROCESSGAUSSIANPROCESSREGRESSOR WHEN THE STANDARD DEVIATION AND
COVARIANCE PREDICTED WITHOUT FIT WOULD FAIL WITH A UNMEANINGFUL ERROR BY DEFAULT 6573 BY QUAZI MARUFUR
RAHMAN AND MANOJ KUMAR
OTHER PREDICTORS
• FIXSEMISUPERVISEDBASELABELPROPAGATION TO CORRECTLY IMPLEMENT LABELPROPAGATION AND
LABELSPREADING AS DONE IN THE REFERENCED PAPERS 9239 BY ANDRE AMBROSIO BOECHAT UTKARSH UPADHYAY
AND JOEL NOTHMAN
DECOMPOSITION MANIFOLD LEARNING AND CLUSTERING
• FIXED THE IMPLEMENTATION OF MANIFOLDTSNE
•EARLYEXAGERATION PARAMETER HAD NO EFFECT AND IS NOW USED FOR THE FIRST 250 OPTIMIZATION ITERATIONS
• FIXED THE ASSERTIONERROR TREE CONSISTENCY FAILED EXCEPTION REPORTED IN 8992
• IMPROVE THE LEARNING SCHEDULE TO MATCH THE ONE FROM THE REFERENCE IMPLEMENTATION LVDMAATENBHTSNE BY
THOMAS MOREAU AND OLIVIER GRISEL
• FIX A BUG IN DECOMPOSITIONLATENTDIRICHLETALLOCATION WHERE THEPERPLEXITY METHOD WAS
RETURNING INCORRECT RESULTS BECAUSE THE TRANSFORM METHOD RETURNS NORMALIZED DOCUMENT TOPIC DISTRIBUTIONS AS
OF VERSION 018 7954 BY GARY FOREMAN
• FIX OUTPUT SHAPE AND BUGS WITH NJOBS 1 IN DECOMPOSITIONSPARSECODER TRANSFORM AND
DECOMPOSITIONSPARSEENCODE FOR ONEDIMENSIONAL DATA AND ONE COMPONENT THIS ALSO IMPACTS THE
OUTPUT SHAPE OF DECOMPOSITIONDICTIONARYLEARNING 8086 BY ANDREAS MÜLLER
• FIXED THE IMPLEMENTATION OF EXPLAINEDVARIANCE INDECOMPOSITIONPCA DECOMPOSITION
RANDOMIZEDPCA ANDDECOMPOSITIONINCREMENTALPCA 9105 BY HANMIN QIN
• FIXED THE IMPLEMENTATION OF NOISEVARIANCE INDECOMPOSITIONPCA 9108 BY HANMIN QIN
• FIXED A BUG WHERE CLUSTERDBSCAN GIVES INCORRECT RESULT WHEN INPUT IS A PRECOMPUTED SPARSE MATRIX WITH
INITIAL ROWS ALL ZERO 8306 BY AKSHAY GUPTA

• FIX A BUG REGARDING FITTING CLUSTERKMEANS WITH A SPARSE ARRAY X AND INITIAL CENTROIDS WHERE X'S MEANS WERE UNNECESSARILY BEING SUBTRACTED FROM THE CENTROIDS 7872 BY JOSH KARNOFSKY
• FIXES TO THE INPUT VALIDATION IN COVARIANCEELLIPTICENVELOPE 8086 BY ANDREAS MÜLLER
• FIXED A BUG IN COVARIANCEMINCOVDET WHERE INPUTTING DATA THAT PRODUCED A SINGULAR COVARIANCE MATRIX WOULD CAUSE THE HELPER METHOD CSTEP TO THROW AN EXCEPTION 3367 BY JEREMY STEWARD
• FIXED A BUG IN MANIFOLDTSNE AFFECTING CONVERGENCE OF THE GRADIENT DESCENT 8768 BY DAVID DETOMASO
• FIXED A BUG IN MANIFOLDTSNE WHERE IT STORED THE INCORRECT KLDIVERGENCE 6507 BY SEBASTIAN SAEGER
• FIXED IMPROPER SCALING IN CROSSDECOMPOSITIONPLSREGRESSION WITHSCALETRUE 7819 BY JAYZED82
•CLUSTERBICLUSTERSPECTRALCOCLUSTERING AND CLUSTERBICLUSTER SPECTRALBICLUSTERING FIT METHOD CONFORMS WITH API BY ACCEPTING YAND RETURNING THE OBJECT 6126 7814 BY LAURENT DIRER AND MANITEJA NANDANA
• FIX BUG WHERE MIXTURESAMPLE METHODS DID NOT RETURN AS MANY SAMPLES AS REQUESTED 7702 BY LEVI JOHN WOLF
• FIXED THE SHRINKAGE IMPLEMENTATION IN NEIGHBORSNEARESTCENTROID 9219 BY HANMIN QIN

PREPROCESSING AND FEATURE SELECTION

• FOR SPARSE MATRICES PREPROCESSINGNORMALIZE WITHRETURNNORMTRUE WILL NOW RAISE A NOTIMPLEMENTEDERROR WITH 'L1' OR 'L2' NORM AND WITH NORM 'MAX' THE NORMS RETURNED WILL BE THE SAME AS FOR DENSE MATRICES 7771 BY ANG LU
• FIX A BUG WHERE FEATURESELECTIONSELECTFDR DID NOT EXACTLY IMPLEMENT BENJAMINIHOCHBERG PRO CEDURE IT FORMERLY MAY HAVE SELECTED FEWER FEATURES THAN IT SHOULD 7490 BY PENG MENG
• FIXED A BUG WHERE LINEARMODELRANDOMIZEDLASSO ANDLINEARMODEL RANDOMIZEDLOGISTICREGRESSION BREAKS FOR SPARSE INPUT 8259 BY AMAN DALMIA
• FIX A BUG WHERE FEATUREEXTRACTIONFEATUREHASHER MANDATORILY APPLIED A SPARSE RANDOM PROJEC TION TO THE HASHED FEATURES PREVENTING THE USE OF FEATUREEXTRACTIONTEXTHASHINGVECTORIZER IN A PIPELINE WITH FEATUREEXTRACTIONTEXTTFIDFTRANSFORMER 7565 BY ROMAN YURCHAK
• FIX A BUG WHERE FEATURESELECTIONMUTUALINFOREGRESSION DID NOT CORRECTLY USE NNEIGHBORS 8181 BY GUILLAUME LEMAITRE

MODEL EVALUATION AND METAESTIMATORS

• FIXED A BUG WHERE MODELSELECTIONBASESEARCHCVINVERSETRANSFORM RE TURNSSELFBESTESTIMATORTRANSFORM INSTEAD OF SELFBESTESTIMATOR INVERSETRANSFORM 8344 BY AKSHAY GUPTA AND RASMUS ERIKSSON
• ADDED CLASSES ATTRIBUTE TO MODELSELECTIONGRIDSEARCHCV MODELSELECTION RANDOMIZEDSEARCHCV GRIDSEARCHGRIDSEARCHCV AND GRIDSEARCH RANDOMIZEDSEARCHCV THAT MATCHES THE CLASSES ATTRIBUTE OF BESTESTIMATOR 7661 AND 8295 BY ALYSSA BATULA DYLAN WERNERMEIER AND STEPHEN HOOVER
• FIXED A BUG WHERE MODELSELECTIONVALIDATIONCURVE REUSED THE SAME ESTIMATOR FOR EACH PARAME TER VALUE 7365 BY ALEKSANDR SANDROVSKII
•MODELSELECTIONPERMUTATIONTESTSCORE NOW WORKS WITH PANDAS TYPES 5697 BY STIJN TONK
• SEVERAL FIXES TO INPUT VALIDATION IN MULTICLASSOUTPUTCODECLASSIFIER 8086 BY ANDREAS MÜLLER
•MULTICLASSONEVSONECLASSIFIER 'SPARTIALFIT NOW ENSURES ALL CLASSES ARE PROVIDED UPFRONT 6250 BY ASISH PANDA

• FIXMULTIOUTPUTMULTIOUTPUTCLASSIFIERPREDICTPROBA TO RETURN A LIST OF 2D ARRAYS RATHER THAN A 3D ARRAY IN THE CASE WHERE DIFFERENT TARGET COLUMNS HAD DIFFERENT NUMBERS OF CLASSES A VALUEERROR WOULD BE RAISED ON TRYING TO STACK MATRICES WITH DIFFERENT DIMENSIONS 8093 BY PETER BULL
• CROSS VALIDATION NOW WORKS WITH PANDAS DATATYPES THAT THAT HAVE A READONLY INDEX 9507 BY LOIC ESTEVE

METRICS

•METRICSAVERAGEPRECISIONSCORE NO LONGER LINEARLY INTERPOLATES BETWEEN OPERATING POINTS AND IN STEAD WEIGHS PRECISIONS BY THE CHANGE IN RECALL SINCE THE LAST OPERATING POINT AS PER THE WIKIPEDIA ENTRY 7356 BY NICK DINGWALL AND GAEL VAROQUAUX
• FIX A BUG IN METRICSCLASSIFICATIONCHECKTARGETS WHICH WOULD RETURN BINARY IFYTRUE ANDYPRED WERE BOTHBINARY BUT THE UNION OF YTRUE ANDYPRED WASMULTICLASS 8377 BY LOIC ESTEVE
• FIXED AN INTEGER OVERFLOW BUG IN METRICSCONFUSIONMATRIX AND HENCE METRICS COHENKAPPASCORE 8354 7929 BY JOEL NOTHMAN AND JON CRALL
• FIXED PASSING OF GAMMA PARAMETER TO THE CHI2 KERNEL INMETRICSPAIRWISEPAIRWISEKERNELS 5211 BY NICK RHINEHART SAURABH BANSOD AND ANDREAS MÜLLER

MISCELLANEOUS

• FIXED A BUG WHEN DATASETSMAKECLASSIFICATION FAILS WHEN GENERATING MORE THAN 30 FEATURES 8159 BY HERILALAINA RAKOTOARISON
• FIXED A BUG WHERE DATASETSMAKEMOONS GIVES AN INCORRECT RESULT WHEN NSAMPLES IS ODD 8198 BY JOSH LEVY
• SOMEFETCH FUNCTIONS IN DATASETS WERE IGNORING THE DOWNLOADIFMISSING KEYWORD 7944 BY RALF GOMMERS
• FIX ESTIMATORS TO ACCEPT A SAMPLEWEIGHT PARAMETER OF TYPE PANDASSERIES IN THEIRFIT FUNCTION 7825 BY KATHLEEN CHEN
• FIX A BUG IN CASES WHERE NUMPYCUMSUM MAY BE NUMERICALLY UNSTABLE RAISING AN EXCEPTION IF INSTABILITY IS IDENTIFIED 7376 AND 7331 BY JOEL NOTHMAN AND YANGARBITER
• FIX A BUG WHERE BASEBASEESTIMATORGETSTATE OBSTRUCTED PICKLING CUSTOMIZATIONS OF CHILD CLASSES WHEN USED IN A MULTIPLE INHERITANCE CONTEXT 8316 BY HOLGER PETERS
• UPDATE SPHINXGALLERY FROM 014 TO 017 FOR RESOLVING LINKS IN DOCUMENTATION BUILD WITH SPHINX15 8010 7986 BY OSCAR NAJERA
• ADDDATAHOME PARAMETER TO SKLEARNDATASETSFETCHKDDCUP99 9289 BY LOIC ESTEVE
• FIX DATASET LOADERS USING PYTHON 3 VERSION OF MAKEDIRS TO ALSO WORK IN PYTHON 2 9284 BY SEBASTIN SANTY
• SEVERAL MINOR ISSUES WERE FIXED WITH THANKS TO THE ALERTS OF LGTMCOMHTTPSLGTMCOM 9278 BY JEAN HELIE AMONG OTHERS

API CHANGES SUMMARY

TREES AND ENSEMBLES

• GRADIENT BOOSTING BASE MODELS ARE NO LONGER ESTIMATORS BY ANDREAS MÜLLER
• ALL TREE BASED ESTIMATORS NOW ACCEPT A MINIMPURITYDECREASE PARAMETER IN LIEU OF THE MINIMPURITYSPLIT WHICH IS NOW DEPRECATED THE MINIMPURITYDECREASE HELPS STOP SPLITTING THE NODES IN WHICH THE WEIGHTED IMPURITY DECREASE FROM SPLITTING IS NO LONGER AT LEAST MINIMPURITYDECREASE 8449 BY RAGHAV RV

LINEAR KERNELIZED AND RELATED MODELS
•NITER PARAMETER IS DEPRECATED IN LINEARMODELSGDCLASSIFIER LINEARMODEL
SGDREGRESSOR LINEARMODELPASSIVEAGGRESSIVECLASSIFIER LINEARMODEL
PASSIVEAGGRESSIVEREGRESSOR ANDLINEARMODELPERCEPTRON BY TOM DUPRE LA TOUR
OTHER PREDICTORS
•NEIGHBORSLSHFOREST HAS BEEN DEPRECATED AND WILL BE REMOVED IN 021 DUE TO POOR PERFORMANCE 9078
BY LAURENT DIRER
•NEIGHBORSNEARESTCENTROID NO LONGER PURPORTS TO SUPPORT METRICPRECOMPUTED WHICH NOW
RAISES AN ERROR 8515 BY SERGUL AYDORE
• THEALPHA PARAMETER OF SEMISUPERVISEDLABELPROPAGATION NOW HAS NO EFFECT AND IS DEPRECATED
TO BE REMOVED IN 021 9239 BY ANDRE AMBROSIO BOECHAT UTKARSH UPADHYAY AND JOEL NOTHMAN
DECOMPOSITION MANIFOLD LEARNING AND CLUSTERING
• DEPRECATE THE DOCTOPICDISTR ARGUMENT OF THE PERPLEXITY METHOD IN DECOMPOSITION
LATENTDIRICHLETALLOCATION BECAUSE THE USER NO LONGER HAS ACCESS TO THE UNNORMALIZED DOCUMENT TOPIC
DISTRIBUTION NEEDED FOR THE PERPLEXITY CALCULATION 7954 BY GARY FOREMAN
• THENTOPICS PARAMETER OF DECOMPOSITIONLATENTDIRICHLETALLOCATION HAS BEEN RENAMED TO
NCOMPONENTS AND WILL BE REMOVED IN VERSION 021 8922 BY ATTRACTADORE
•DECOMPOSITIONSPARSEPCATRANSFORM ’SRIDGEALPHA PARAMETER IS DEPRECATED IN PREFERENCE FOR
CLASS PARAMETER 8137 BY NAOYA KANAI
•CLUSTERDBSCAN NOW HAS AMETRICPARAMS PARAMETER 8139 BY NAOYA KANAI
PREPROCESSING AND FEATURE SELECTION
•FEATURESELECTIONSELECTFROMMODEL NOW HAS APARTIALFIT METHOD ONLY IF THE UNDERLYING ES
TIMATOR DOES BY ANDREAS MÜLLER
•FEATURESELECTIONSELECTFROMMODEL NOW VALIDATES THE THRESHOLD PARAMETER AND SETS THE
THRESHOLD ATTRIBUTE DURING THE CALL TO FIT AND NO LONGER DURING THE CALL TO TRANSFORM BY ANDREAS
MÜLLER
• THENONNEGATIVE PARAMETER IN FEATUREEXTRACTIONFEATUREHASHER HAS BEEN DEPRECATED AND
REPLACED WITH A MORE PRINCIPLED ALTERNATIVE ALTERNATESIGN 7565 BY ROMAN YURCHAK
•LINEARMODELRANDOMIZEDLOGISTICREGRESSION ANDLINEARMODELRANDOMIZEDLASSO
HAVE BEEN DEPRECATED AND WILL BE REMOVED IN VERSION 021 8995 BY RAMANAS
MODEL EVALUATION AND METAESTIMATORS
• DEPRECATE THE FITPARAMS CONSTRUCTOR INPUT TO THE MODELSELECTIONGRIDSEARCHCV AND
MODELSELECTIONRANDOMIZEDSEARCHCV IN FAVOR OF PASSING KEYWORD PARAMETERS TO THE FIT METHODS
OF THOSE CLASSES DATADEPENDENT PARAMETERS NEEDED FOR MODEL TRAINING SHOULD BE PASSED AS KEYWORD ARGUMENTS
TOFIT AND CONFORMING TO THIS CONVENTION WILL ALLOW THE HYPERPARAMETER SELECTION CLASSES TO BE USED WITH TOOLS
SUCH ASMODELSELECTIONCROSSVALPREDICT 2879 BY STEPHEN HOOVER
• IN VERSION 021 THE DEFAULT BEHAVIOR OF SPLITTERS THAT USE THE TESTSIZE ANDTRAINSIZE PARAMETER WILL
CHANGE SUCH THAT SPECIFYING TRAINSIZE ALONE WILL CAUSE TESTSIZE TO BE THE REMAINDER 7459 BY NELSON
LIU
•MULTICLASSONEVSRESTCLASSIFIER NOW HAS PARTIALFIT DECISIONFUNCTION AND
PREDICTPROBA METHODS ONLY WHEN THE UNDERLYING ESTIMATOR DOES 7812 BY ANDREAS MÜLLER AND MIKHAIL
KOROBOV
•MULTICLASSONEVSRESTCLASSIFIER NOW HAS APARTIALFIT METHOD ONLY IF THE UNDERLYING ESTIMA
TOR DOES BY ANDREAS MÜLLER

• THEDECISIONFUNCTION OUTPUT SHAPE FOR BINARY CLASSIFICATION IN MULTICLASS
ONEVSRESTCLASSIFIER ANDMULTICLASSONEVSONECLASSIFIER IS NOWNSAMPLES TO
CONFORM TO SCIKITLEARN CONVENTIONS 9100 BY ANDREAS MÜLLER
• THEMULTIOUTPUTMULTIOUTPUTCLASSIFIERPREDICTPROBA FUNCTION USED TO RETURN A 3D ARRAY
NSAMPLES NCLASSES NOUTPUTS IN THE CASE WHERE DIFFERENT TARGET COLUMNS HAD DIFFERENT NUMBERS
OF CLASSES A VALUEERROR WOULD BE RAISED ON TRYING TO STACK MATRICES WITH DIFFERENT DIMENSIONS THIS FUNC
TION NOW RETURNS A LIST OF ARRAYS WHERE THE LENGTH OF THE LIST IS NOUTPUTS AND EACH ARRAY IS NSAMPLES
NCLASSES FOR THAT PARTICULAR OUTPUT 8093 BY PETER BULL
• REPLACE ATTRIBUTE NAMEDSTEPS DICT TOUTILSBUNCH INPIPELINEPIPELINE TO ENABLE TAB COM
PLETION IN INTERACTIVE ENVIRONMENT IN THE CASE CONFLICT VALUE ON NAMEDSTEPS ANDDICT ATTRIBUTEDICT
BEHAVIOR WILL BE PRIORITIZED 8481 BY HERILALAINA RAKOTOARISON
MISCELLANEOUS
• DEPRECATE THE YPARAMETER IN TRANSFORM ANDINVERSETRANSFORM THE METHOD SHOULD NOT ACCEPT Y
PARAMETER AS IT’S USED AT THE PREDICTION TIME 8174 BY TAHAR ZANOUDA ALEXANDRE GRAMFORT AND RAGHAV RV
• SCIPY 0133 AND NUMPY 182 ARE NOW THE MINIMUM SUPPORTED VERSIONS FOR SCIKITLEARN THE FOLLOWING
BACKPORTED FUNCTIONS IN UTILS HAVE BEEN REMOVED OR DEPRECATED ACCORDINGLY 8854 AND 8874 BY NAOYA
KANAI
• THESTORECOVARIANCES ANDCOVARIANCES PARAMETERS OF DISCRIMINANTANALYSIS
QUADRATICDISCRIMINANTANALYSIS HAS BEEN RENAMED TO STORECOVARIANCE ANDCOVARIANCE
TO BE CONSISTENT WITH THE CORRESPONDING PARAMETER NAMES OF THE DISCRIMINANTANALYSIS
LINEARDISCRIMINANTANALYSIS THEY WILL BE REMOVED IN VERSION 021 7998 BY JIACHENG
REMOVED IN 019
–UTILSFIXESARGPARTITION
–UTILSFIXESARRAYEQUAL
–UTILSFIXESASTYPE
–UTILSFIXESBINCOUNT
–UTILSFIXESEXPIT
–UTILSFIXESFROMBUFFEREMPTY
–UTILSFIXESIN1D
–UTILSFIXESNORM
–UTILSFIXESRANKDATA
–UTILSFIXESSAFECOPY
DEPRECATED IN 019 TO BE REMOVED IN 021
–UTILSARPACKEIGS
–UTILSARPACKEIGSH
–UTILSARPACKSVDS
–UTILSEXTMATHFASTDOT
–UTILSEXTMATHLOGSUMEXP
–UTILSEXTMATHNORM
–UTILSEXTMATHPINVH
–UTILSGRAPHGRAPHLAPLACIAN

–UTILSRANDOMCHOICE
–UTILSSPARSETOOLSCONNECTEDCOMPONENTS
–UTILSSTATSRANKDATA
• ESTIMATORS WITH BOTH METHODS DECISIONFUNCTION ANDPREDICTPROBA ARE NOW REQUIRED TO HAVE A MONOTONIC RELATION BETWEEN THEM THE METHOD CHECKDECISIONPROBACONSISTENCY HAS BEEN ADDED INUTILSESTIMATORCHECKS TO CHECK THEIR CONSISTENCY 7578 BY SHUBHAM BHARDWAJ
• ALL CHECKS IN UTILSESTIMATORCHECKS IN PARTICULAR UTILSESTIMATORCHECKS CHECKESTIMATOR NOW ACCEPT ESTIMATOR INSTANCES MOST OTHER CHECKS DO NOT ACCEPT ESTIMATOR CLASSES ANY MORE 9019 BY ANDREAS MÜLLER
• ENSURE THAT ESTIMATORS' ATTRIBUTES ENDING WITH ARE NOT SET IN THE CONSTRUCTOR BUT ONLY IN THE FIT METHOD MOST NOTABLY ENSEMBLE ESTIMATORS DERIVING FROM ENSEMBLEBASEENSEMBLE NOW ONLY HAVE SELF ESTIMATORS AVAILABLE AFTER FIT 7464 BY LARS BUITINCK AND LOIC ESTEVE

CODE AND DOCUMENTATION CONTRIBUTORS

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JOEL NOTHMAN LOIC ESTEVE ANDREAS MUELLER GUILLAUME LEMAITRE OLIVIER GRISEL HANMIN QIN RAGHAV RV ALEXANDRE GRAMFORT THEMRMAX AMAN DALMIA GAEL VAROQUAUX NAOYA KANAI TOM DUPRÉ LA TOUR RISHIKESH NELSON LIU TAE HOON LEE NELLE VAROQUAUX AASHIL MIKHAIL KOROBOV SEBASTIN SANTY JOAN MASSICH ROMAN YURCHAK RAKOTOARI SON HERILALAINA THIERRY GUILLEMOT ALEXANDRE ABADIE CAROL WILLING BALAKUMARAN MANOHARAN JOSH KARNOFSKY VLAD NICULAE UTKARSH UPADHYAY DMITRY PETROV MINGHUI LIU SRIVATSAN VINCENT PHAM ALBERT THOMAS JAKE VAN DERPLAS ATTRACTADORE JC LIU ALEXANDERCBOOTH CHKOAR ÓSCAR NÁJERA AARSHAY JAIN KYLE GILLIAM RAMANA SUBRA MANYAM CJ CAREY CLEMENT JOUDET DAVID ROBLES HE CHEN JORIS VAN DEN BOSSCHE KARAN DESAI KATIE LUANGKOTE LELAND MCINNES MANITEJA NANDANA MICHELE LACCHIA SERGEI LEBEDEV SHUBHAM BHARDWAJ AKSHAY0724 OMTCYFZ RICKIEPARK WATERPONEY VATHSALA ACHAR JBDELAFOSSE RALF GOMMERS EKATERINA KRIVICH VIVEK KUMAR ISHANK GULATI DAVE ELLIOTT LDIRER REIICHIRO NAKANO LEVI JOHN WOLF MATHIEU BLONDEL SID KAPUR DOUGAL J SUTHERLAND MIDINAS MIKEBENFIELD SOURAV SINGH ASEEM BANSAL IBRAIM GANIEV STEPHEN HOOVER AISHWARYARK STEVEN C HOWELL GARY FOREMAN NEERAJ GANGWAR TAHAR JON CRALL DOKATO KATHY CHEN FERRIA THOMAS MOREAU CHARLIE BRUMMITT NICOLAS GOIX ADAM KLECZEWSKI SAM SHLEIFER NIKITA SINGH BASIL BEIROUTI GIORGIO PATRINI MANOJ KUMAR RAFAEL POSSAS JAMES BOURBEAU JAMES A BEDNAR JANINE HARPER JAYE JEAN HELIE JEREMY STEWARD ARTSIOM JOHN WEI JONATHAN LIGO JONATHAN RAHN SEANPWILLIAMS ARTHUR MENSCH JOSH LEVY JULIAN KUHLMANN JULIEN AUBERT JÖRN HEES KAI SHIVAMGARGSYA KAT HEMPSTALK KAUSHIK LAKSHMIKANTH KENNEDY KENNETH LYONS KENNETH MYERS KEVIN YAP KIR ILL BOBYREV KONSTANTIN PODSHUMOK ARTHUR IMBERT LEE MURRAY TOASTEDCORNFLAKES LERA LI LI ARTHUR DOUILLARD MAINAK JAS TOBYCHEESE MANRAJ SINGH MANVENDRA SINGH MARC MEKETON MARCOFALKE MATTHEW BRETT MATTHIAS GILCH MEHUL AHUJA MELANIE GOETZ MENG PENG MICHAEL DEZUBE MICHAL BAUMGARTNER VIBRANTABHI19 ARTEM GOLU BIN MILEN PASKOV ANTONIN CARETTE MORIKKO MRMJAUH NALEPA EMMANUEL NAMIYA ANTOINE WENDLINGER NARINE KOKHLIKYAN NARINEK NATE GUERIN ANGUS WILLIAMS ANG LU NICOLE VAVROVA NITISH PANDEY OKHLOPKOV DANIIL OLEGOVICH ANDY CRAZE OM PRAKASH PARMINDER SINGH PATRICK CARLSON PATRICK PEI PAUL GANSSLE PAULO HADDAD PAWEŁ LOREK PENG YU PETE BACHANT PETER BULL PETER CSIZSEK PETER WANG PIETER ARTHUR DE JONG PINGYAO CHANG PRESTON PARRY PUNEET MATHUR QUENTIN HIBON ANDREW SMITH ANDREW JACKSON 1KASTNER RAMESHWAR BHASKARAN RE BECCA BILBRO REMI RAMPIN ANDREA ESULI ROB HALL ROBERT BRADSHAW ROMAIN BRAULT AMAN PRATIK RUIFENG ZHENG RUSSELL SMITH SACHIN AGARWAL SAILESH CHOYAL SAMSON TAN SAMUËL WEBER SARAH BROWN SEBASTIAN PÖLSTERL SE BASTIAN RASCHKA SEBASTIAN SAEGER ALYSSA BATULA ABHYUDAY PRATAP SINGH SERGEY FELDMAN SERGUL AYDORE SHARAN YALBURGI WILLDUAN SIDDHARTH GUPTA SRI KRISHNA ALMER STIJN TONK ALLEN RIDDELL THEOFILOS PAPAPANAGIOTOU ALISON ALEXIS MIGNON TOMMY BOUCHER TOMMY LÖFSTEDT TOSHIHIRO KAMISHIMA TYLER FOLKMAN TYLER LANIGAN ALEXANDER JUNGE VARUN SHENOY VICTOR POUGHON VILHELM VON EHRENHEIM ALEKSANDR SANDROVSKII ALAN YEE VLASIOS VASILEIOU WARUT VIJITBENJARONK YANG ZHANG YAROSLAV HALCHENKO YICHUAN LIU YUICHI FUJIKAWA AFFANV14 AIVISION2020 XOR ANDREH7 BRADY SALZ CAMPUSTRAMPUS AGAMEMNON KRASOULIS DITENBERG ELENASHAROVA FILIPJ8 FUKATANI GEDECK GUIN IOL GUOCI HAKAA1 HONGKAHJUN IAMXHY JAKIRKHAM JAROSLAWWEBER JAYZED82 JEROKO JMONTOYAM JONATHANSTRIEBEL

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JOSEPHSALMON JSCHENDEL LEEREEVES MARTINHAHN MATHURINM MEHAKSACHDEVA MLEWIS1729 MLLIOU112 MTHORRELL NDINGWALL NUFFE YANGARBITER PLAGREE PLDTC325 BRENO FREITAS BRETT OLSEN BRIAN A ALFANO BRIAN BURNS POLMAURI BRANDON CARTER CHARLTON AUSTIN CHAYANT T15H CHINMAYA PANCHOLI CHRISTIAN DANIELSEN CHUNG YEN CHYIKWEI YAU PRAVARMAHAJAN DOHMATOB ELVIS DANIEL LEJEUNE DANIEL HNYK DARIUS MORAWIEC DAVID DETOMASO DAVID GASQUEZ DAVID HABERTHÜR DAVID HERYANTO DAVID KIRKBY DAVID NICHOLSON RASHCHEDRIN DEBORAH GERTRUDE DIGGES DENIS ENGEMANN DEVANSH D DICKSON BOB BAXLEY DON86 E LYNCHKLARUP ED ROGERS ELIZABETH FERRISS ELLEN CO2 FABIAN EGLI FANGCHIEH CHOU BING TIAN DAI GREG STUPP GRZEGORZ SZPAK BERTRAND THIRION HADRIEN BERTRAND HARIZO RAJAONA ZXCVBNIUS HENRY LIN HOLGER PETERS ICYBLADE DAI IGOR ANDRIUSHCHENKO ILYA ISAAC LAUGHLIN IVÁN VALLÉS AURÉLIEN BELLET JPFRANCOIA JACOB SCHREIBER ASISH MAHAPATRA
1174 VERSION 0182
JUNE 20 2017
LAST RELEASE WITH PYTHON 26 SUPPORT
SCIKITLEARN 018 IS THE LAST MAJOR RELEASE OF SCIKITLEARN TO SUPPORT PYTHON 26 LATER VERSIONS OF SCIKITLEARN WILL REQUIRE PYTHON 27 OR ABOVE
CHANGELOG
• FIXES FOR COMPATIBILITY WITH NUMPY 1130 7946 8355 BY LOIC ESTEVE
• MINOR COMPATIBILITY CHANGES IN THE EXAMPLES 9010 8040 9149
CODE CONTRIBUTORS
AMAN DALMIA LOIC ESTEVE NATE GUERIN SERGEI LEBEDEV
1175 VERSION 0181
NOVEMBER 11 2016
CHANGELOG
ENHANCEMENTS
• IMPROVED SAMPLEWITHOUTREPLACEMENT SPEED BY UTILIZING NUMPYRANDOMPERMUTATION FOR MOST CASES AS A RESULT SAMPLES MAY DIFFER IN THIS RELEASE FOR A FIXED RANDOM STATE AFFECTED ESTIMATORS
–ENSEMBLEBAGGINGCLASSIFIER
–ENSEMBLEBAGGINGREGRESSOR
–LINEARMODELRANSACREGRESSOR
–MODELSELECTIONRANDOMIZEDSEARCHCV
–RANDOMPROJECTIONSPARSERANDOMPROJECTION
THIS ALSO AFFECTS THE DATASETSMAKECLASSIFICATION METHOD
117 PREVIOUS RELEASES 77

BUG FIXES
• FIX ISSUE WHERE MINGRADNORM ANDNITERWITHOUTPROGRESS PARAMETERS WERE NOT BEING UTILISED BYMANIFOLDTSNE 6497 BY SEBASTIAN SÄGER
• FIX BUG FOR SVM'S DECISION VALUES WHEN DECISIONFUNCTIONSHAPE ISOVR INSVMSVC SVMSVC 'S DECISIONFUNCTION WAS INCORRECT FROM VERSIONS 0170 THROUGH 0180 7724 BY BING TIAN DAI
• ATTRIBUTE EXPLAINEDVARIANCERATIO OF DISCRIMINANTANALYSIS LINEARDISCRIMINANTANALYSIS CALCULATED WITH SVD AND EIGEN SOLVER ARE NOW OF THE SAME LENGTH 7632 BY JPFRANCOIA
• FIXES ISSUE IN UNIVARIATE FEATURE SELECTION WHERE SCORE FUNCTIONS WERE NOT ACCEPTING MULTILABEL TARGETS 7676 BY MOHAMMED AFFAN
• FIXED SETTING PARAMETERS WHEN CALLING FIT MULTIPLE TIMES ON FEATURESELECTIONSELECTFROMMODEL 7756 BY ANDREAS MÜLLER
• FIXES ISSUE IN PARTIALFIT METHOD OFMULTICLASSONEVSRESTCLASSIFIER WHEN NUMBER OF CLASSES USED INPARTIALFIT WAS LESS THAN THE TOTAL NUMBER OF CLASSES IN THE DATA 7786 BY SRIVATSAN RAMESH
• FIXES ISSUE IN CALIBRATIONCALIBRATEDCLASSIFIERCV WHERE THE SUM OF PROBABILITIES OF EACH CLASS FOR A DATA WAS NOT 1 AND CALIBRATEDCLASSIFIERCV NOW HANDLES THE CASE WHERE THE TRAINING SET HAS LESS NUMBER OF CLASSES THAN THE TOTAL DATA 7799 BY SRIVATSAN RAMESH
• FIX A BUG WHERE SKLEARNFEATURESELECTIONSELECTFDR DID NOT EXACTLY IMPLEMENT BENJAMINI HOCHBERG PROCEDURE IT FORMERLY MAY HAVE SELECTED FEWER FEATURES THAN IT SHOULD 7490 BY PENG MENG
•SKLEARNMANIFOLDLOCALLYLINEAREMBEDDING NOW CORRECTLY HANDLES INTEGER INPUTS 6282 BY JAKE VANDERPLAS
• THEMINWEIGHTFRACTIONLEAF PARAMETER OF TREEBASED CLASSIFIERS AND REGRESSORS NOW ASSUMES UNIFORM SAMPLE WEIGHTS BY DEFAULT IF THE SAMPLEWEIGHT ARGUMENT IS NOT PASSED TO THE FIT FUNCTION PREVIOUSLY THE PARAMETER WAS SILENTLY IGNORED 7301 BY NELSON LIU
• NUMERICAL ISSUE WITH LINEARMODELRIDGECV ON CENTERED DATA WHEN NFEATURES NSAMPLES 6178 BY BERTRAND THIRION
• TREE SPLITTING CRITERION CLASSES' CLONINGPICKLING IS NOW MEMORY SAFE 7680 BY IBRAIM GANIEV
• FIXED A BUG WHERE DECOMPOSITIONNMF SETS ITSNITERS ATTRIBUTE IN TRANSFORM 7553 BY EKATE RINA KRIVICH
•SKLEARNLINEARMODELLOGISTICREGRESSIONCV NOW CORRECTLY HANDLES STRING LABELS 5874 BY RAGHAV RV
• FIXED A BUG WHERE SKLEARNMODELSELECTIONTRAINTESTSPLIT RAISED AN ERROR WHEN STRATIFY IS A LIST OF STRING LABELS 7593 BY RAGHAV RV
• FIXED A BUG WHERE SKLEARNMODELSELECTIONGRIDSEARCHCV ANDSKLEARN MODELSELECTIONRANDOMIZEDSEARCHCV WERE NOT PICKLEABLE BECAUSE OF A PICKLING BUG IN NP MAMASKEDARRAY 7594 BY RAGHAV RV
• ALL CROSSVALIDATION UTILITIES IN SKLEARNMODELSELECTION NOW PERMIT ONE TIME CROSSVALIDATION SPLITTERS FOR THECVPARAMETER ALSO NONDETERMINISTIC CROSSVALIDATION SPLITTERS WHERE MULTIPLE CALLS TO SPLIT PRODUCE DISSIMILAR SPLITS CAN BE USED AS CVPARAMETER THE SKLEARNMODELSELECTIONGRIDSEARCHCV WILL CROSSVALIDATE EACH PARAMETER SETTING ON THE SPLIT PRODUCED BY THE FIRST SPLIT CALL TO THE CROSSVALIDATION SPLITTER 7660 BY RAGHAV RV
• FIX BUG WHERE PREPROCESSINGMULTILABELBINARIZERFITTRANSFORM RETURNED AN INVALID CSR MATRIX 7750 BY CJ CAREY

SCIKITLEARN USER GUIDE RELEASE 0213
• FIXED A BUG WHERE METRICSPAIRWISECOSINEDISTANCES COULD RETURN A SMALL NEGATIVE DISTANCE
7732 BY ARTSION
API CHANGES SUMMARY
TREES AND FORESTS
• THEMINWEIGHTFRACTIONLEAF PARAMETER OF TREEBASED CLASSIFIERS AND REGRESSORS NOW ASSUMES UNIFORM SAMPLE WEIGHTS BY DEFAULT IF THE SAMPLEWEIGHT ARGUMENT IS NOT PASSED TO THE FIT FUNCTION PREVIOUSLY THE PARAMETER WAS SILENTLY IGNORED 7301 BY NELSON LIU
• TREE SPLITTING CRITERION CLASSES' CLONINGPICKLING IS NOW MEMORY SAFE 7680 BY IBRAIM GANIEV
LINEAR KERNELIZED AND RELATED MODELS
• LENGTH OF EXPLAINEDVARIANCERATIO OFDISCRIMINANTANALYSIS
LINEARDISCRIMINANTANALYSIS CHANGED FOR BOTH EIGEN AND SVD SOLVERS THE ATTRIBUTE HAS NOW A LENGTH OF MINNCOMPONENTS NCLASSES 1 7632 BY JPFRANCOIA
• NUMERICAL ISSUE WITH LINEARMODELRIDGECV ON CENTERED DATA WHEN NFEATURES NSAMPLES 6178 BY BERTRAND THIRION
1176 VERSION 018
SEPTEMBER 28 2016
LAST RELEASE WITH PYTHON 26 SUPPORT
SCIKITLEARN 018 WILL BE THE LAST VERSION OF SCIKITLEARN TO SUPPORT PYTHON 26 LATER VERSIONS OF SCIKITLEARN WILL REQUIRE PYTHON 27 OR ABOVE
MODEL SELECTION ENHANCEMENTS AND API CHANGES
•THE MODELSELECTION MODULE
THE NEW MODULE SKLEARNMODELSELECTION WHICH GROUPS TOGETHER THE FUNCTIONALITIES OF FORMERLY SKLEARNCROSSVALIDATION SKLEARNGRIDSEARCH ANDSKLEARNLEARNINGCURVE INTRO DUCES NEW POSSIBILITIES SUCH AS NESTED CROSSVALIDATION AND BETTER MANIPULATION OF PARAMETER SEARCHES WITH PAN DAS
MANY THINGS WILL STAY THE SAME BUT THERE ARE SOME KEY DIFFERENCES READ BELOW TO KNOW MORE ABOUT THE CHANGES
•DATAINDEPENDENT CV SPLITTERS ENABLING NESTED CROSSVALIDATION
THE NEW CROSSVALIDATION SPLITTERS DEFINED IN THE SKLEARNMODELSELECTION ARE NO LONGER INITIALIZED WITH ANY DATADEPENDENT PARAMETERS SUCH AS Y INSTEAD THEY EXPOSE A SPLIT METHOD THAT TAKES IN THE DATA AND YIELDS A GENERATOR FOR THE DIFFERENT SPLITS
THIS CHANGE MAKES IT POSSIBLE TO USE THE CROSSVALIDATION SPLITTERS TO PERFORM NESTED CROSSVALIDATION FACILITATED BYMODELSELECTIONGRIDSEARCHCV ANDMODELSELECTIONRANDOMIZEDSEARCHCV UTILITIES
•THE ENHANCED CVRESULTS ATTRIBUTE
THE NEWCVRESULTS ATTRIBUTE OF MODELSELECTIONGRIDSEARCHCV ANDMODELSELECTION RANDOMIZEDSEARCHCV INTRODUCED IN LIEU OF THE GRIDSCORES ATTRIBUTE IS A DICT OF 1D ARRAYS WITH ELEMENTS IN EACH ARRAY CORRESPONDING TO THE PARAMETER SETTINGS IE SEARCH CANDIDATES

THECVRESULTS DICT CAN BE EASILY IMPORTED INTO PANDAS AS ADATAFRAME FOR EXPLORING THE SEARCH RESULTS
THECVRESULTS ARRAYS INCLUDE SCORES FOR EACH CROSSVALIDATION SPLIT WITH KEYS SUCH AS
SPLIT0TESTSCORE AS WELL AS THEIR MEAN MEANTESTSCORE AND STANDARD DEVIATION
STDTESTSCORE
THE RANKS FOR THE SEARCH CANDIDATES BASED ON THEIR MEAN CROSSVALIDATION SCORE IS AVAILABLE AT
CVRESULTSRANKTESTSCORE
THE PARAMETER VALUES FOR EACH PARAMETER IS STORED SEPARATELY AS NUMPY MASKED OBJECT ARRAYS THE VALUE FOR
THAT SEARCH CANDIDATE IS MASKED IF THE CORRESPONDING PARAMETER IS NOT APPLICABLE ADDITIONALLY A LIST OF ALL THE
PARAMETER DICTS ARE STORED AT CVRESULTSPARAMS
•PARAMETERS NFOLDS AND NITER RENAMED TO NSPLITS
SOME PARAMETER NAMES HAVE CHANGED THE NFOLDS PARAMETER IN NEW MODELSELECTIONKFOLD
MODELSELECTIONGROUPKFOLD SEE BELOW FOR THE NAME CHANGE AND MODELSELECTION
STRATIFIEDKFOLD IS NOW RENAMED TO NSPLITS THENITER PARAMETER IN MODELSELECTION
SHUFFLESPLIT THE NEW CLASS MODELSELECTIONGROUPSHUFFLESPLIT ANDMODELSELECTION
STRATIFIEDSHUFFLESPLIT IS NOW RENAMED TO NSPLITS
•RENAME OF SPLITTER CLASSES WHICH ACCEPTS GROUP LABELS ALONG WITH DATA
THE CROSSVALIDATION SPLITTERS LABELKFOLD LABELSHUFFLESPLIT LEAVEONELABELOUT AND
LEAVEPLABELOUT HAVE BEEN RENAMED TO MODELSELECTIONGROUPKFOLD MODELSELECTION
GROUPSHUFFLESPLIT MODELSELECTIONLEAVEONEGROUPOUT ANDMODELSELECTION
LEAVEPGROUPSOUT RESPECTIVELY
NOTE THE CHANGE FROM SINGULAR TO PLURAL FORM IN MODELSELECTIONLEAVEPGROUPSOUT
•FIT PARAMETER LABELS RENAMED TO GROUPS
THELABELS PARAMETER IN THE SPLIT METHOD OF THE NEWLY RENAMED SPLITTERS MODELSELECTION
GROUPKFOLD MODELSELECTIONLEAVEONEGROUPOUT MODELSELECTION
LEAVEPGROUPSOUT MODELSELECTIONGROUPSHUFFLESPLIT IS RENAMED TO GROUPS FOLLOWING THE
NEW NOMENCLATURE OF THEIR CLASS NAMES
•PARAMETER NLABELS RENAMED TO NGROUPS
THE PARAMETER NLABELS IN THE NEWLY RENAMED MODELSELECTIONLEAVEPGROUPSOUT IS CHANGED TO
NGROUPS
• TRAINING SCORES AND TIMING INFORMATION
CVRESULTS ALSO INCLUDES THE TRAINING SCORES FOR EACH CROSSVALIDATION SPLIT WITH KEYS SUCH
ASSPLIT0TRAINSCORE AS WELL AS THEIR MEAN MEANTRAINSCORE AND STAN
DARD DEVIATION STDTRAINSCORE TO AVOID THE COST OF EVALUATING TRAINING SCORE SET
RETURNTRAINSCOREFALSE
ADDITIONALLY THE MEAN AND STANDARD DEVIATION OF THE TIMES TAKEN TO SPLIT TRAIN AND SCORE THE MODEL ACROSS ALL THE
CROSSVALIDATION SPLITS IS AVAILABLE AT THE KEY MEANTIME ANDSTDTIME RESPECTIVELY
CHANGELOG
NEW FEATURES
CLASSIFIERS AND REGRESSORS
• THE GAUSSIAN PROCESS MODULE HAS BEEN REIMPLEMENTED AND NOW OFFERS CLASSIFICATION AND REGRESSION ESTI
MATORS THROUGH GAUSSIANPROCESSGAUSSIANPROCESSCLASSIFIER ANDGAUSSIANPROCESS
GAUSSIANPROCESSREGRESSOR AMONG OTHER THINGS THE NEW IMPLEMENTATION SUPPORTS KERNEL ENGINEERING

GRADIENTBASED HYPERPARAMETER OPTIMIZATION OR SAMPLING OF FUNCTIONS FROM GP PRIOR AND GP POSTERIOR EXTENSIVE DOCUMENTATION AND EXAMPLES ARE PROVIDED BY JAN HENDRIK METZEN

- ADDED NEW SUPERVISED LEARNING ALGORITHM MULTILAYER PERCEPTRON 3204 BY ISSAM H LARADJI
- ADDEDLINEARMODELHUBERREGRESSOR A LINEAR MODEL ROBUST TO OUTLIERS 5291 BY MANOJ KUMAR
- ADDED THE MULTIOUTPUTMULTIOUTPUTREGRESSOR METAESTIMATOR IT CONVERTS SINGLE OUTPUT REGRESSORS TO MULTIOUTPUT REGRESSORS BY FITTING ONE REGRESSOR PER OUTPUT BY TIM HEAD

OTHER ESTIMATORS

- NEWMIXTUREGAUSSIANMIXTURE ANDMIXTUREBAYESIANGAUSSIANMIXTURE REPLACE FORMER MIX TURE MODELS EMPLOYING FASTER INFERENCE FOR SOUNDER RESULTS 7295 BY WEI XUE AND THIERRY GUILLEMOT
- CLASSDECOMPOSITIONRANDOMIZEDPCA IS NOW FACTORED INTO DECOMPOSITIONPCA AND IT IS AVAIL ABLE CALLING WITH PARAMETER SVDSOLVERRANDOMIZED THE DEFAULT NUMBER OF NITER FOR RANDOMIZED HAS CHANGED TO 4 THE OLD BEHAVIOR OF PCA IS RECOVERED BY SVDSOLVERFULL AN ADDITIONAL SOLVER CALLS ARPACK AND PERFORMS TRUNCATED NONRANDOMIZED SVD BY DEFAULT THE BEST SOLVER IS SELECTED DEPENDING ON THE SIZE OF THE INPUT AND THE NUMBER OF COMPONENTS REQUESTED 5299 BY GIORGIO PATRINI
- ADDED TWO FUNCTIONS FOR MUTUAL INFORMATION ESTIMATION FEATURESELECTION MUTUALINFOCLASSIF ANDFEATURESELECTIONMUTUALINFOREGRESSION THESE FUNCTIONS CAN BE USED IN FEATURESELECTIONSELECTKBEST ANDFEATURESELECTION SELECTPERCENTILE AS SCORE FUNCTIONS BY ANDREA BRAVI AND NIKOLAY MAYOROV
- ADDED THE ENSEMBLEISOLATIONFOREST CLASS FOR ANOMALY DETECTION BASED ON RANDOM FORESTS BY NICOLAS GOIX
- ADDEDALGORITHMELKAN TOCLUSTERKMEANS IMPLEMENTING ELKAN'S FAST KMEANS ALGORITHM BY ANDREAS MÜLLER

MODEL SELECTION AND EVALUATION

- ADDEDMETRICSCLUSTERFOWLKESMALLOWSSCORE THE FOWLKES MALLOWS INDEX WHICH MEASURES THE SIMILARITY OF TWO CLUSTERINGS OF A SET OF POINTS BY ARNAUD FOUCHET AND THIERRY GUILLEMOT
- ADDEDMETRICSCALINSKIHARABAZSCORE WHICH COMPUTES THE CALINSKI AND HARABAZ SCORE TO EVALU ATE THE RESULTING CLUSTERING OF A SET OF POINTS BY ARNAUD FOUCHET AND THIERRY GUILLEMOT
- ADDED NEW CROSSVALIDATION SPLITTER MODELSELECTIONTIMESERIESSPLIT TO HANDLE TIME SERIES DATA 6586 BY YENCHEN LIN
- THE CROSSVALIDATION ITERATORS ARE REPLACED BY CROSSVALIDATION SPLITTERS AVAILABLE FROM SKLEARN MODELSELECTION ALLOWING FOR NESTED CROSSVALIDATION SEE MODEL SELECTION ENHANCEMENTS AND API CHANGES FOR MORE INFORMATION 4294 BY RAGHAV RV

ENHANCEMENTS

TREES AND ENSEMBLES

- ADDED A NEW SPLITTING CRITERION FOR TREEDECISIONTREEREGRESSOR THE MEAN ABSOLUTE ER ROR THIS CRITERION CAN ALSO BE USED IN ENSEMBLEEXTRATREESREGRESSOR ENSEMBLE RANDOMFORESTREGRESSOR AND THE GRADIENT BOOSTING ESTIMATORS 6667 BY NELSON LIU
- ADDED WEIGHTED IMPURITYBASED EARLY STOPPING CRITERION FOR DECISION TREE GROWTH 6954 BY NELSON LIU
- THE RANDOM FOREST EXTRA TREE AND DECISION TREE ESTIMATORS NOW HAS A METHOD DECISIONPATH WHICH RETURNS THE DECISION PATH OF SAMPLES IN THE TREE BY ARNAUD JOLY
- A NEW EXAMPLE HAS BEEN ADDED UNVEILING THE DECISION TREE STRUCTURE BY ARNAUD JOLY

• RANDOM FOREST EXTRA TREES DECISION TREES AND GRADIENT BOOSTING ESTIMATOR ACCEPT THE PARAMETER MINSAMPLESSPLIT ANDMINSAMPLESLEAF PROVIDED AS A PERCENTAGE OF THE TRAINING SAMPLES BY YELITE AND ARNAUD JOLY
• GRADIENT BOOSTING ESTIMATORS ACCEPT THE PARAMETER CRITERION TO SPECIFY TO SPLITTING CRITERION USED IN BUILT DECISION TREES 6667 BY NELSON LIU
• THE MEMORY FOOTPRINT IS REDUCED SOMETIMES GREATLY FOR ENSEMBLEBAGGINGBASEBAGGING AND CLASSES THAT INHERIT FROM IT IE ENSEMBLEBAGGINGCLASSIFIER ENSEMBLEBAGGINGREGRESSOR AND ENSEMBLEISOLATIONFOREST BY DYNAMICALLY GENERATING ATTRIBUTE ESTIMATORSSAMPLES ONLY WHEN IT IS NEEDED BY DAVID STAUB
• ADDEDNJOBS ANDSAMPLEWEIGHT PARAMETERS FOR ENSEMBLEVOTINGCLASSIFIER TO FIT UNDERLYING ESTIMATORS IN PARALLEL 5805 BY IBRAIM GANIEV

LINEAR KERNELIZED AND RELATED MODELS

• INLINEARMODELLOGISTICREGRESSION THE SAG SOLVER IS NOW AVAILABLE IN THE MULTINOMIAL CASE 5251 BY TOM DUPRE LA TOUR
•LINEARMODELRANSACREGRESSOR SVMLINEARSVC ANDSVMLINEARSVR NOW SUPPORT SAMPLEWEIGHT BY IMACULATE
• ADD PARAMETER LOSS TOLINEARMODELRANSACREGRESSOR TO MEASURE THE ERROR ON THE SAMPLES FOR EVERY TRIAL BY MANOJ KUMAR
• PREDICTION OF OUTOFSAMPLE EVENTS WITH ISOTONIC REGRESSION ISOTONICISOTONICREGRESSION IS NOW MUCH FASTER OVER 1000X IN TESTS WITH SYNTHETIC DATA BY JONATHAN ARFA
• ISOTONIC REGRESSION ISOTONICISOTONICREGRESSION NOW USES A BETTER ALGORITHM TO AVOID ON2 BEHAVIOR IN PATHOLOGICAL CASES AND IS ALSO GENERALLY FASTER 6691 BY ANTONY LEE
•NAIVEBAYESGAUSSIANNB NOW ACCEPTS DATAINDEPENDENT CLASSPRIORS THROUGH THE PARAMETER PRIORS BY GUILLAUME LEMAITRE
•LINEARMODELELASTICNET ANDLINEARMODELLASSO NOW WORKS WITH NPFLOAT32 INPUT DATA WITHOUT CONVERTING IT INTO NPFLOAT64 THIS ALLOWS TO REDUCE THE MEMORY CONSUMPTION 6913 BY YENCHEN LIN
•SEMISUPERVISEDLABELPROPAGATION ANDSEMISUPERVISEDLABELSPREADING NOW ACCEPT ARBITRARY KERNEL FUNCTIONS IN ADDITION TO STRINGS KNN ANDRBF 5762 BY UTKARSH UPADHYAY

DECOMPOSITION MANIFOLD LEARNING AND CLUSTERING

• ADDEDINVERSETRANSFORM FUNCTION TO DECOMPOSITIONNMF TO COMPUTE DATA MATRIX OF ORIGINAL SHAPE BY ANISH SHAH
•CLUSTERKMEANS ANDCLUSTERMINIBATCHKMEANS NOW WORKS WITH NPFLOAT32 ANDNP FLOAT64 INPUT DATA WITHOUT CONVERTING IT THIS ALLOWS TO REDUCE THE MEMORY CONSUMPTION BY USING NP FLOAT32 6846 BY SEBASTIAN SÄGER AND YENCHEN LIN

PREPROCESSING AND FEATURE SELECTION

•PREPROCESSINGROBUSTSCALER NOW ACCEPTS QUANTILERANGE PARAMETER 5929 BY KONSTANTIN POD SHUMOK
•FEATUREEXTRACTIONFEATUREHASHER NOW ACCEPTS STRING VALUES 6173 BY RYAD ZENINE AND DEVASHISH DESHPANDE
• KEYWORD ARGUMENTS CAN NOW BE SUPPLIED TO FUNC INPREPROCESSINGFUNCTIONTRANSFORMER BY MEANS OF THE KWARGS PARAMETER BY BRIAN MCFEE
•FEATURESELECTIONSELECTKBEST ANDFEATURESELECTIONSELECTPERCENTILE NOW ACCEPT SCORE FUNCTIONS THAT TAKE X Y AS INPUT AND RETURN ONLY THE SCORES BY NIKOLAY MAYOROV

MODEL EVALUATION AND METAESTIMATORS
•MULTICLASSONEVSONECLASSIFIER ANDMULTICLASSONEVSRESTCLASSIFIER NOW SUPPORT PARTIALFIT BY ASISH PANDA AND PHILIPP DOWLING
• ADDED SUPPORT FOR SUBSTITUTING OR DISABLING PIPELINEPIPELINE ANDPIPELINEFEATUREUNION COMPONENTS USING THE SETPARAMS INTERFACE THAT POWERS SKLEARNGRIDSEARCH SEE SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV BY JOEL NOTHMAN AND ROBERT MCGIBBON
• THE NEW CVRESULTS ATTRIBUTE OF MODELSELECTIONGRIDSEARCHCV ANDMODELSELECTION RANDOMIZEDSEARCHCV CAN BE EASILY IMPORTED INTO PANDAS AS A DATAFRAME REF MODEL SELECTION ENHANCEMENTS AND API CHANGES FOR MORE INFORMATION 6697 BY RAGHAV RV
• GENERALIZATION OF MODELSELECTIONCROSSVALPREDICT ONE CAN PASS METHOD NAMES SUCH AS PREDICTPROBA TO BE USED IN THE CROSS VALIDATION FRAMEWORK INSTEAD OF THE DEFAULT PREDICT BY ORI ZIV AND SEARS MERRITT
• THE TRAINING SCORES AND TIME TAKEN FOR TRAINING FOLLOWED BY SCORING FOR EACH SEARCH CANDIDATE ARE NOW AVAILABLE AT THECVRESULTS DICT SEE MODEL SELECTION ENHANCEMENTS AND API CHANGES FOR MORE INFORMATION 7325 BY EUGENE CHEN AND RAGHAV RV
METRICS
• ADDEDLABELS FLAG TOMETRICSLOGLOSS TO EXPLICITLY PROVIDE THE LABELS WHEN THE NUMBER OF CLASSES IN YTRUE ANDYPRED DIFFER 7239 BY HONG GUANGGUO WITH HELP FROM MADS JENSEN AND NELSON LIU
• SUPPORT SPARSE CONTINGENCY MATRICES IN CLUSTER EVALUATION METRICSCLUSTERSUPERVISED TO SCALE TO A LARGE NUMBER OF CLUSTERS 7419 BY GREGORY STUPP AND JOEL NOTHMAN
• ADDSAMPLEWEIGHT PARAMETER TO METRICSMATTHEWSCORRCOEF BY JATIN SHAH AND RAGHAV RV
• SPEED UP METRICSSILHOUETTESCORE BY USING VECTORIZED OPERATIONS BY MANOJ KUMAR
• ADDSAMPLEWEIGHT PARAMETER TO METRICSCONFUSIONMATRIX BY BERNARDO STEIN
MISCELLANEOUS
• ADDEDNJOBS PARAMETER TO FEATURESELECTIONRFECV TO COMPUTE THE SCORE ON THE TEST FOLDS IN PARALLEL BY MANOJ KUMAR
• CODEBASE DOES NOT CONTAIN CC CYTHON GENERATED FILES THEY ARE GENERATED DURING BUILD DISTRIBUTION PACKAGES WILL STILL CONTAIN GENERATED CC FILES BY ARTHUR MENSCH
• REDUCE THE MEMORY USAGE FOR 32BIT FLOAT INPUT ARRAYS OF UTILSSPARSEFUNCMEANVARIANCEAXIS ANDUTILSSPARSEFUNCINCRMEANVARIANCEAXIS BY SUPPORTING CYTHON FUSED TYPES BY YENCHEN LIN
• THEIGNOREWARNINGS NOW ACCEPT A CATEGORY ARGUMENT TO IGNORE ONLY THE WARNINGS OF A SPECIFIED TYPE BY THIERRY GUILLEMOT
• ADDED PARAMETER RETURNXY AND RETURN TYPE DATA TARGET TUPLE OPTION TOLOADIRIS DATASET 7049 LOADBREASTCANCER DATASET 7152 LOADDIGITS DATASETLOADDIABETES DATASET LOADLINNERUD DATASETLOADBOSTON DATASET 7154 BY MANVENDRA SINGH
• SIMPLIFICATION OF THE CLONE FUNCTION DEPRECATE SUPPORT FOR ESTIMATORS THAT MODIFY PARAMETERS IN INIT 5540 BY ANDREAS MÜLLER
• WHEN UNPICKLING A SCIKITLEARN ESTIMATOR IN A DIFFERENT VERSION THAN THE ONE THE ESTIMATOR WAS TRAINED WITH A USERWARNING IS RAISED SEE THE DOCUMENTATION ON MODEL PERSISTENCE FOR MORE DETAILS 7248 BY ANDREAS MÜLLER

SCIKITLEARN USER GUIDE RELEASE 0213

BUG FIXES

TREES AND ENSEMBLES

• RANDOM FOREST EXTRA TREES DECISION TREES AND GRADIENT BOOSTING WON'T ACCEPT ANYMORE MINSAMPLESSPLIT1 AS AT LEAST 2 SAMPLES ARE REQUIRED TO SPLIT A DECISION TREE NODE BY ARNAUD JOLY

•ENSEMBLEVOTINGCLASSIFIER NOW RAISES NOTFITTEDERROR IFPREDICT TRANSFORM OR PREDICTPROBA ARE CALLED ON THE NONFITTED ESTIMATOR BY SEBASTIAN RASCHKA

• FIX BUG WHERE ENSEMBLEADABOOSTCLASSIFIER ANDENSEMBLEADABOOSTREGRESSOR WOULD PER FORM POORLY IF THE RANDOMSTATE WAS FIXED 7411 BY JOEL NOTHMAN

• FIX BUG IN ENSEMBLES WITH RANDOMIZATION WHERE THE ENSEMBLE WOULD NOT SET RANDOMSTATE ON BASE ESTIMATORS IN A PIPELINE OR SIMILAR NESTING 7411 NOTE RESULTS FOR ENSEMBLE BAGGINGCLASSIFIER ENSEMBLEBAGGINGREGRESSOR ENSEMBLEADABOOSTCLASSIFIER AND ENSEMBLEADABOOSTREGRESSOR WILL NOW DIFFER FROM PREVIOUS VERSIONS BY JOEL NOTHMAN

LINEAR KERNELIZED AND RELATED MODELS

• FIXED INCORRECT GRADIENT COMPUTATION FOR LOSSSQUAREDEPSILONINSENSITIVE IN LINEARMODELSGDCLASSIFIER ANDLINEARMODELSGDREGRESSOR 6764 BY WENHUA YANG

• FIX BUG IN LINEARMODELLOGISTICREGRESSIONCV WHERESOLVERLIBLINEAR DID NOT ACCEPT CLASSWEIGHTSBALANCED 6817 BY TOM DUPRE LA TOUR

• FIX BUG IN NEIGHBORSRADIUSNEIGHBORSCLASSIFIER WHERE AN ERROR OCCURRED WHEN THERE WERE OUT LIERS BEING LABELLED AND A WEIGHT FUNCTION SPECIFIED 6902 BY LEONIEBORNE

• FIXLINEARMODELELASTICNET SPARSE DECISION FUNCTION TO MATCH OUTPUT WITH DENSE IN THE MULTIOUTPUT CASE

DECOMPOSITION MANIFOLD LEARNING AND CLUSTERING

•DECOMPOSITIONRANDOMIZEDPCA DEFAULT NUMBER OF ITERATEDPOWER IS 4 INSTEAD OF 3 5141 BY GIORGIO PATRINI

•UTILSEXTMATHRANDOMIZEDSVD PERFORMS 4 POWER ITERATIONS BY DEFAULT INSTEAD OR 0 IN PRACTICE THIS IS ENOUGH FOR OBTAINING A GOOD APPROXIMATION OF THE TRUE EIGENVALUESVECTORS IN THE PRESENCE OF NOISE WHEN NCOMPONENTS IS SMALL 1MINXSHAPE NITER IS SET TO 7 UNLESS THE USER SPECIFIES A HIGHER NUMBER THIS IMPROVES PRECISION WITH FEW COMPONENTS 5299 BY GIORGIO PATRINI

• WHITENNONWHITEN INCONSISTENCY BETWEEN COMPONENTS OF DECOMPOSITIONPCA ANDDECOMPOSITION RANDOMIZEDPCA NOW FACTORED INTO PCA SEE THE NEW FEATURES IS FIXED COMPONENTS ARE STORED WITH NO WHITENING 5299 BY GIORGIO PATRINI

• FIXED BUG IN MANIFOLDSPECTRALEMBEDDING WHERE DIAGONAL OF UNNORMALIZED LAPLACIAN MATRIX WAS INCORRECTLY SET TO 1 4995 BY PETER FISCHER

• FIXED INCORRECT INITIALIZATION OF UTILSARPACKEIGSH ON ALL OCCURRENCES AFFECTS CLUSTER BICLUSTERSPECTRALBICLUSTERING DECOMPOSITIONKERNELPCA MANIFOLD LOCALLYLINEAREMBEDDING ANDMANIFOLDSPECTRALEMBEDDING 5012 BY PETER FISCHER

• ATTRIBUTE EXPLAINEDVARIANCERATIO CALCULATED WITH THE SVD SOLVER OF DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS NOW RETURNS CORRECT RESULTS BY JPFRANCOIA

PREPROCESSING AND FEATURE SELECTION

•PREPROCESSINGDATATRANSFORMSELECTED NOW ALWAYS PASSES A COPY OF XTO TRANSFORM FUNCTION WHENCOPYTRUE 7194 BY CAIO OLIVEIRA

MODEL EVALUATION AND METAESTIMATORS
•MODELSELECTIONSTRATIFIEDKFOLD NOW RAISES ERROR IF ALL NLABELS FOR INDIVIDUAL CLASSES IS LESS THAN NFOLDS 6182 BY DEVASHISH DESHPANDE
• FIXED BUG IN MODELSELECTIONSTRATIFIEDSHUFFLESPLIT WHERE TRAIN AND TEST SAMPLE COULD OVERLAP IN SOME EDGE CASES SEE 6121 FOR MORE DETAILS BY LOIC ESTEVE
• FIX IN SKLEARNMODELSELECTIONSTRATIFIEDSHUFFLESPLIT TO RETURN SPLITS OF SIZE TRAINSIZE ANDTESTSIZE IN ALL CASES 6472 BY ANDREAS MÜLLER
• CROSSVALIDATION OF ONEVSONECLASSIFIER ANDONEVSRESTCLASSIFIER NOW WORKS WITH PRECOMPUTED KERNELS 7350 BY RUSSELL SMITH
• FIX INCOMPLETE PREDICTPROBA METHOD DELEGATION FROM MODELSELECTIONGRIDSEARCHCV TO LINEARMODELSGDCLASSIFIER 7159 BY YICHUAN LIU
METRICS
• FIX BUG IN METRICSSILHOUETTESCORE IN WHICH CLUSTERS OF SIZE 1 WERE INCORRECTLY SCORED THEY SHOULD GET A SCORE OF 0 BY JOEL NOTHMAN
• FIX BUG IN METRICSSILHOUETTESAMPLES SO THAT IT NOW WORKS WITH ARBITRARY LABELS NOT JUST THOSE RANGING FROM 0 TO NCLUSTERS 1
• FIX BUG WHERE EXPECTED AND ADJUSTED MUTUAL INFORMATION WERE INCORRECT IF CLUSTER CONTINGENCY CELLS EXCEEDED 216 BY JOEL NOTHMAN
•METRICSPAIRWISEPAIRWISEDISTANCES NOW CONVERTS ARRAYS TO BOOLEAN ARRAYS WHEN REQUIRED IN SCIPYSPATIALDISTANCE 5460 BY TOM DUPRE LA TOUR
• FIX SPARSE INPUT SUPPORT IN METRICSSILHOUETTESCORE AS WELL AS EXAMPLE EXAM PLESTEXTDOCUMENTCLUSTERINGPY BY YENCHEN LIN
•METRICSROCCURVE ANDMETRICSPRECISIONRECALLCURVE NO LONGER ROUND YSCORE VALUES WHEN CREATING ROC CURVES THIS WAS CAUSING PROBLEMS FOR USERS WITH VERY SMALL DIFFERENCES IN SCORES 7353
MISCELLANEOUS
•MODELSELECTIONTESTSSEARCHCHECKPARAMGRID NOW WORKS CORRECTLY WITH ALL TYPES THAT EXTENDSIMPLEMENTS SEQUENCE EXCEPT STRING INCLUDING RANGE PYTHON 3X AND XRANGE PYTHON 2X 7323 BY VIACHESLAV KOVALEVSKYI
•UTILSEXTMATHRANDOMIZEDRANGEFINDER IS MORE NUMERICALLY STABLE WHEN MANY POWER ITERATIONS ARE REQUESTED SINCE IT APPLIES LU NORMALIZATION BY DEFAULT IF NITER2 NUMERICAL ISSUES ARE UNLIKELY THUS NO NORMALIZATION IS APPLIED OTHER NORMALIZATION OPTIONS ARE AVAILABLE NONE LU ANDQR 5141 BY GIORGIO PATRINI
• FIX A BUG WHERE SOME FORMATS OF SCIPYSPARSE MATRIX AND ESTIMATORS WITH THEM AS PARAMETERS COULD NOT BE PASSED TO BASECLONE BY LOIC ESTEVE
•DATASETSLOADSVMLIGHTFILE NOW IS ABLE TO READ LONG INT QID VALUES 7101 BY IBRAIM GANIEV
API CHANGES SUMMARY
LINEAR KERNELIZED AND RELATED MODELS
•RESIDUALMETRIC HAS BEEN DEPRECATED IN LINEARMODELRANSACREGRESSOR USELOSS INSTEAD BY MANOJ KUMAR
• ACCESS TO PUBLIC ATTRIBUTES X ANDY HAS BEEN DEPRECATED IN ISOTONICISOTONICREGRESSION BY JONATHAN ARFA

DECOMPOSITION MANIFOLD LEARNING AND CLUSTERING

• THE OLDMIXTUREDPGMM IS DEPRECATED IN FAVOR OF THE NEW MIXTUREBAYESIANGAUSSIANMIXTURE WITH THE PARAMETER WEIGHTCONCENTRATIONPRIORTYPEDIRICHLETPROCESS THE NEW CLASS SOLVES THE COMPUTATIONAL PROBLEMS OF THE OLD CLASS AND COMPUTES THE GAUSSIAN MIXTURE WITH A DIRICH LET PROCESS PRIOR FASTER THAN BEFORE 7295 BY WEI XUE AND THIERRY GUILLEMOT

• THE OLDMIXTUREVBGMM IS DEPRECATED IN FAVOR OF THE NEW MIXTUREBAYESIANGAUSSIANMIXTURE WITH THE PARAMETER WEIGHTCONCENTRATIONPRIORTYPEDIRICHLETDISTRIBUTION THE NEW CLASS SOLVES THE COMPUTATIONAL PROBLEMS OF THE OLD CLASS AND COMPUTES THE VARIATIONAL BAYESIAN GAUSSIAN MIXTURE FASTER THAN BEFORE 6651 BY WEI XUE AND THIERRY GUILLEMOT

• THE OLDMIXTUREGMM IS DEPRECATED IN FAVOR OF THE NEW MIXTUREGAUSSIANMIXTURE THE NEW CLASS COMPUTES THE GAUSSIAN MIXTURE FASTER THAN BEFORE AND SOME OF COMPUTATIONAL PROBLEMS HAVE BEEN SOLVED 6666 BY WEI XUE AND THIERRY GUILLEMOT

MODEL EVALUATION AND METAESTIMATORS

• THESKLEARNCROSSVALIDATION SKLEARNGRIDSEARCH ANDSKLEARNLEARNINGCURVE HAVE BEEN DEPRECATED AND THE CLASSES AND FUNCTIONS HAVE BEEN REORGANIZED INTO THE SKLEARN MODELSELECTION MODULE REF MODEL SELECTION ENHANCEMENTS AND API CHANGES FOR MORE INFORMATION 4294 BY RAGHAV RV

• THEGRIDSCORES ATTRIBUTE OF MODELSELECTIONGRIDSEARCHCV ANDMODELSELECTION RANDOMIZEDSEARCHCV IS DEPRECATED IN FAVOR OF THE ATTRIBUTE CVRESULTS REF MODEL SELECTION EN HANCEMENTS AND API CHANGES FOR MORE INFORMATION 6697 BY RAGHAV RV

• THE PARAMETERS NITER ORNFOLDS IN OLD CV SPLITTERS ARE REPLACED BY THE NEW PARAMETER NSPLITS SINCE IT CAN PROVIDE A CONSISTENT AND UNAMBIGUOUS INTERFACE TO REPRESENT THE NUMBER OF TRAINTEST SPLITS 7187 BY YENCHEN LIN

•CLASSES PARAMETER WAS RENAMED TO LABELS INMETRICSHAMMINGLOSS 7260 BY SEBASTIÁN VANRELL

• THE SPLITTER CLASSES LABELKFOLD LABELSHUFFLESPLIT LEAVEONELABELOUT AND LEAVEPLABELSOUT ARE RENAMED TO MODELSELECTIONGROUPKFOLD MODELSELECTION GROUPSHUFFLESPLIT MODELSELECTIONLEAVEONEGROUPOUT ANDMODELSELECTION LEAVEPGROUPSOUT RESPECTIVELY ALSO THE PARAMETER LABELS IN THESPLIT METHOD OF THE NEWLY RENAMED SPLITTERSMODELSELECTIONLEAVEONEGROUPOUT ANDMODELSELECTIONLEAVEPGROUPSOUT IS RENAMED TO GROUPS ADDITIONALLY IN MODELSELECTIONLEAVEPGROUPSOUT THE PARAMETER NLABELS IS RENAMED TO NGROUPS 6660 BY RAGHAV RV

• ERROR AND LOSS NAMES FOR SCORING PARAMETERS ARE NOW PREFIXED BY NEG SUCH AS NEGMEANSQUAREDERROR THE UNPREFIXED VERSIONS ARE DEPRECATED AND WILL BE REMOVED IN VERSION 020 7261 BY TIM HEAD

CODE CONTRIBUTORS

ADITYA JOSHI ALEJANDRO ALEXANDER FABISCH ALEXANDER LOGINOV ALEXANDER MINYUSHKIN ALEXANDER RUDY ALEXAN DRE ABADIE ALEXANDRE ABRAHAM ALEXANDRE GRAMFORT ALEXANDRE SAINT ALEXFIELDS ALVARO ULLOA ALYSSAQ AMLAN KAR ANDREAS MUELLER ANDREW GIESSEL ANDREW JACKSON ANDREW MCCULLOH ANDREW MURRAY ANISH SHAH ARAFAT ARCHIT SHARMA ARIEL ROKEM ARNAUD JOLY ARNAUD RACHEZ ARTHUR MENSCH ASH HOOVER ASNT B0NOI BEHZAD TABIB IAN BERNARDO BERNHARD KRATZWALD BHARGAV MANGIPUDI BLAKEFLEI BOYUAN DENG BRANDON CARTER BRETT NAUL BRIAN MCFEE CAIO OLIVEIRA CAMILO LAMUS CAROL WILLING CASS CESHINE LEE CHARLES TRUONG CHYIKWEI YAU CJ CAREY CODEVIG COLIN NI DAN SHIEBLER DANIEL DANIEL HNYK DAVID ELLIS DAVID NICHOLSON DAVID STAUB DAVID THALER DAVID WARSHAW DAVIDE LASAGNA DEBORAH DEFINITELYUNCERTAIN DIDI BARZEV DJIPEY DSQUAREINDIA EDWINENSAE ELIAS KUTHE ELVIS DOHMATOB ETHAN WHITE FABIAN PEDREGOSA FABIO TICCONI FISACHE FLORIAN WILHELM FRANCIS FRANCIS O’DONOVAN GAEL VAROQUAUX GANIEV IBRAIM GHG GILLES LOUPPE GIORGIO PATRINI GIOVANNI CHERUBIN GIO VANNI LANZANI GLENN QIAN GORDON MOHR GOVINVATSAN GRAHAM CLENAGHAN GREG REDA GREG STUPP GUILLAUME

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1177 VERSION 0171

FEBRUARY 18 2016

CHANGELOG

BUG FIXES

• UPGRADE VENDORED JOBLIB TO VERSION 094 THAT FIXES AN IMPORTANT BUG IN JOBLIBPARALLEL THAT CAN SILENTLY YIELD TO WRONG RESULTS WHEN WORKING ON DATASETS LARGER THAN 1MB HTTPSGITHUBCOMJOBLIBJOBLIBBLOB094 CHANGESRST

• FIXED READING OF BUNCH PICKLES GENERATED WITH SCIKITLEARN VERSION 016 THIS CAN AFFECT USERS WHO HAVE ALREADY DOWNLOADED A DATASET WITH SCIKITLEARN 016 AND ARE LOADING IT WITH SCIKITLEARN 017 SEE 6196 FOR HOW THIS AFFECTED DATASETSFETCH20NEWSGROUPS BY LOIC ESTEVE

• FIXED A BUG THAT PREVENTED USING ROC AUC SCORE TO PERFORM GRID SEARCH ON SEVERAL CPU CORES ON LARGE ARRAYS SEE 6147 BY OLIVIER GRISEL

• FIXED A BUG THAT PREVENTED TO PROPERLY SET THE PRESORT PARAMETER IN ENSEMBLE GRADIENTBOOSTINGREGRESSOR SEE 5857 BY ANDREW MCCULLOH

• FIXED A JOBLIB ERROR WHEN EVALUATING THE PERPLEXITY OF A DECOMPOSITION LATENTDIRICHLETALLOCATION MODEL SEE 6258 BY CHYIKWEI YAU

SCIKITLEARN USER GUIDE RELEASE 0213
1178 VERSION 017
NOVEMBER 5 2015
CHANGELOG
NEW FEATURES
• ALL THE SCALER CLASSES BUT PREPROCESSINGROBUSTSCALER CAN BE FITTED ONLINE BY CALLING PARTIALFIT BY GIORGIO PATRINI
• THE NEW CLASS ENSEMBLEVOTINGCLASSIFIER IMPLEMENTS A “MAJORITY RULE” “SOFT VOTING” ENSEMBLE CLASSIFIER TO COMBINE ESTIMATORS FOR CLASSIFICATION BY SEBASTIAN RASCHKA
• THE NEW CLASS PREPROCESSINGROBUSTSCALER PROVIDES AN ALTERNATIVE TO PREPROCESSING STANDARDSCALER FOR FEATUREWISE CENTERING AND RANGE NORMALIZATION THAT IS ROBUST TO OUTLIERS BY THOMAS UNTERTHINER
• THE NEW CLASS PREPROCESSINGMAXABSSCALER PROVIDES AN ALTERNATIVE TO PREPROCESSING MINMAXSCALER FOR FEATUREWISE RANGE NORMALIZATION WHEN THE DATA IS ALREADY CENTERED OR SPARSE BY THOMAS UNTERTHINER
• THE NEW CLASS PREPROCESSINGFUNCTIONTRANSFORMER TURNS A PYTHON FUNCTION INTO A PIPELINE COMPATIBLE TRANSFORMER OBJECT BY JOE JEVNIK
• THE NEW CLASSES CROSSVALIDATIONLABELKFOLD ANDCROSSVALIDATION LABELSHUFFLESPLIT GENERATE TRAINTEST FOLDS RESPECTIVELY SIMILAR TO CROSSVALIDATIONKFOLD AND CROSSVALIDATIONSHUFFLESPLIT EXCEPT THAT THE FOLDS ARE CONDITIONED ON A LABEL ARRAY BY BRIAN MCFEE JEAN KOSSAIFI AND GILLES LOUPPE
•DECOMPOSITIONLATENTDIRICHLETALLOCATION IMPLEMENTS THE LATENT DIRICHLET ALLOCATION TOPIC MODEL WITH ONLINE VARIATIONAL INFERENCE BY CHYIKWEI YAU WITH CODE BASED ON AN IMPLEMENTATION BY MATT HOFFMAN 3659
• THE NEW SOLVER SAG IMPLEMENTS A STOCHASTIC AVERAGE GRADIENT DESCENT AND IS AVAILABLE IN BOTH LINEARMODELLOGISTICREGRESSION ANDLINEARMODELRIDGE THIS SOLVER IS VERY EFFICIENT FOR LARGE DATASETS BY DANNY SULLIVAN AND TOM DUPRE LA TOUR 4738
• THE NEW SOLVER CDIMPLEMENTS A COORDINATE DESCENT IN DECOMPOSITIONNMF PREVIOUS SOLVER BASED ON PROJECTED GRADIENT IS STILL AVAILABLE SETTING NEW PARAMETER SOLVER TOPG BUT IS DEPRECATED AND WILL BE REMOVED IN 019 ALONG WITH DECOMPOSITIONPROJECTEDGRADIENTNMF AND PARAMETERS SPARSENESS ETA BETA ANDNLSMAXITER NEW PARAMETERS ALPHA ANDL1RATIO CONTROL L1 AND L2 REGULARIZATION AND SHUFFLE ADDS A SHUFFLING STEP IN THE CDSOLVER BY TOM DUPRE LA TOUR AND MATHIEU BLONDEL
ENHANCEMENTS
•MANIFOLDTSNE NOW SUPPORTS APPROXIMATE OPTIMIZATION VIA THE BARNESHUT METHOD LEADING TO MUCH FASTER FITTING BY CHRISTOPHER ERICK MOODY 4025
•CLUSTERMEANSHIFTMEANSHIFT NOW SUPPORTS PARALLEL EXECUTION AS IMPLEMENTED IN THE MEANSHIFT FUNCTION BY MARTINO SORBARO
•NAIVEBAYESGAUSSIANNB NOW SUPPORTS FITTING WITH SAMPLEWEIGHT BY JAN HENDRIK METZEN
•DUMMYDUMMYCLASSIFIER NOW SUPPORTS A PRIOR FITTING STRATEGY BY ARNAUD JOLY
• ADDED AFITPREDICT METHOD FOR MIXTUREGMM AND SUBCLASSES BY CORY LORENZ

• ADDED THE METRICSLABELRANKINGLOSS METRIC BY ARNAUD JOLY
• ADDED THE METRICSCOHENKAPPASCORE METRIC
• ADDED A WARMSTART CONSTRUCTOR PARAMETER TO THE BAGGING ENSEMBLE MODELS TO INCREASE THE SIZE OF THE EN
SEMBLE BY TIM HEAD
• ADDED OPTION TO USE MULTIOUTPUT REGRESSION METRICS WITHOUT AVERAGING BY KONSTANTIN SHMELKOV AND MICHAEL
EICKENBERG
• ADDEDSTRATIFY OPTION TOCROSSVALIDATIONTRAINTESTSPLIT FOR STRATIFIED SPLITTING BY
MIROSLAV BATCHKAROV
• THETREEEXPORTGRAPHVIZ FUNCTION NOW SUPPORTS AESTHETIC IMPROVEMENTS FOR TREE
DECISIONTREECLASSIFIER ANDTREEDECISIONTREEREGRESSOR INCLUDING OPTIONS FOR COLORING
NODES BY THEIR MAJORITY CLASS OR IMPURITY SHOWING VARIABLE NAMES AND USING NODE PROPORTIONS INSTEAD OF RAW
SAMPLE COUNTS BY TREVOR STEPHENS
• IMPROVED SPEED OF NEWTONCG SOLVER INLINEARMODELLOGISTICREGRESSION BY AVOIDING LOSS COM
PUTATION BY MATHIEU BLONDEL AND TOM DUPRE LA TOUR
• THECLASSWEIGHTAUTO HEURISTIC IN CLASSIFIERS SUPPORTING CLASSWEIGHT WAS DEPRECATED AND RE
PLACED BY THE CLASSWEIGHTBALANCED OPTION WHICH HAS A SIMPLER FORMULA AND INTERPRETATION BY
HANNA WALLACH AND ANDREAS MÜLLER
• ADDCLASSWEIGHT PARAMETER TO AUTOMATICALLY WEIGHT SAMPLES BY CLASS FREQUENCY FOR LINEARMODEL
PASSIVEAGGRESSIVECLASSIFIER BY TREVOR STEPHENS
• ADDED BACKLINKS FROM THE API REFERENCE PAGES TO THE USER GUIDE BY ANDREAS MÜLLER
• THELABELS PARAMETER TO SKLEARNMETRICSF1SCORE SKLEARNMETRICSFBETASCORE
SKLEARNMETRICSRECALLSCORE ANDSKLEARNMETRICSPRECISIONSCORE HAS BEEN EX
TENDED IT IS NOW POSSIBLE TO IGNORE ONE OR MORE LABELS SUCH AS WHERE A MULTICLASS PROBLEM HAS A MAJORITY
CLASS TO IGNORE BY JOEL NOTHMAN
• ADDSAMPLEWEIGHT SUPPORT TOLINEARMODELRIDGECLASSIFIER BY TREVOR STEPHENS
• PROVIDE AN OPTION FOR SPARSE OUTPUT FROM SKLEARNMETRICSPAIRWISECOSINESIMILARITY BY
JAIDEV DESHPANDE
• ADDMINMAXSCALE TO PROVIDE A FUNCTION INTERFACE FOR MINMAXSCALER BY THOMAS UNTERTHINER
•DUMPSVMLIGHTFILE NOW HANDLES MULTILABEL DATASETS BY CHIHWEI CHANG
• RCV1 DATASET LOADER SKLEARNDATASETSFETCHRCV1 BY TOM DUPRE LA TOUR
• THE “WISCONSIN BREAST CANCER” CLASSICAL TWOCLASS CLASSIFICATION DATASET IS NOW INCLUDED IN SCIKITLEARN AVAIL
ABLE WITHSKLEARNDATASETLOADBREASTCANCER
• UPGRADED TO JOBLIB 093 TO BENEFIT FROM THE NEW AUTOMATIC BATCHING OF SHORT TASKS THIS MAKES IT POSSIBLE FOR
SCIKITLEARN TO BENEFIT FROM PARALLELISM WHEN MANY VERY SHORT TASKS ARE EXECUTED IN PARALLEL FOR INSTANCE BY THE
GRIDSEARCHGRIDSEARCHCV METAESTIMATOR WITH NJOBS 1 USED WITH A LARGE GRID OF PARAMETERS ON
A SMALL DATASET BY VLAD NICULAE OLIVIER GRISEL AND LOIC ESTEVE
• FOR MORE DETAILS ABOUT CHANGES IN JOBLIB 093 SEE THE RELEASE NOTES HTTPSGITHUBCOMJOBLIBJOBLIBBLOBMASTER
CHANGESRSTRELEASE093
• IMPROVED SPEED 3 TIMES PER ITERATION OF DECOMPOSITIONDICTLEARNING WITH COORDINATE DESCENT
METHOD FROM LINEARMODELLASSO BY ARTHUR MENSCH
• PARALLEL PROCESSING THREADED FOR QUERIES OF NEAREST NEIGHBORS USING THE BALLTREE BY NIKOLAY MAYOROV
• ALLOWDATASETSMAKEMULTILABELCLASSIFICATION TO OUTPUT A SPARSE Y BY KASHIF RASUL

•CLUSTERDBSCAN NOW ACCEPTS A SPARSE MATRIX OF PRECOMPUTED DISTANCES ALLOWING MEMORYEFFICIENT DISTANCE PRECOMPUTATION BY JOEL NOTHMAN
•TREEDECISIONTREECLASSIFIER NOW EXPOSES AN APPLY METHOD FOR RETRIEVING THE LEAF INDICES SAMPLES ARE PREDICTED AS BY DANIEL GALVEZ AND GILLES LOUPPE
• SPEED UP DECISION TREE REGRESSORS RANDOM FOREST REGRESSORS EXTRA TREES REGRESSORS AND GRADIENT BOOSTING ESTIMATORS BY COMPUTING A PROXY OF THE IMPURITY IMPROVEMENT DURING THE TREE GROWTH THE PROXY QUANTITY IS SUCH THAT THE SPLIT THAT MAXIMIZES THIS VALUE ALSO MAXIMIZES THE IMPURITY IMPROVEMENT BY ARNAUD JOLY JACOB SCHREIBER AND GILLES LOUPPE
• SPEED UP TREE BASED METHODS BY REDUCING THE NUMBER OF COMPUTATIONS NEEDED WHEN COMPUTING THE IMPURITY MEASURE TAKING INTO ACCOUNT LINEAR RELATIONSHIP OF THE COMPUTED STATISTICS THE EFFECT IS PARTICULARLY VISIBLE WITH EXTRA TREES AND ON DATASETS WITH CATEGORICAL OR SPARSE FEATURES BY ARNAUD JOLY
•ENSEMBLEGRADIENTBOOSTINGREGRESSOR ANDENSEMBLEGRADIENTBOOSTINGCLASSIFIER NOW EXPOSE AN APPLY METHOD FOR RETRIEVING THE LEAF INDICES EACH SAMPLE ENDS UP IN UNDER EACH TRY BY JACOB SCHREIBER
• ADDSAMPLEWEIGHT SUPPORT TOLINEARMODELLINEARREGRESSION BY SONNY HU 4881
• ADDNITERWITHOUTPROGRESS TOMANIFOLDTSNE TO CONTROL THE STOPPING CRITERION BY SANTI VILALBA 5186
• ADDED OPTIONAL PARAMETER RANDOMSTATE INLINEARMODELRIDGE TO SET THE SEED OF THE PSEUDO RANDOM GENERATOR USED IN SAG SOLVER BY TOM DUPRE LA TOUR
• ADDED OPTIONAL PARAMETER WARMSTART INLINEARMODELLOGISTICREGRESSION IF SET TO TRUE THE SOLVERSLBFGS NEWTONCG ANDSAG WILL BE INITIALIZED WITH THE COEFFICIENTS COMPUTED IN THE PREVIOUS FIT BY TOM DUPRE LA TOUR
• ADDEDSAMPLEWEIGHT SUPPORT TO LINEARMODELLOGISTICREGRESSION FOR THELBFGS NEWTONCG ANDSAG SOLVERS BY VALENTIN STOLBUNOV SUPPORT ADDED TO THE LIBLINEAR SOLVER BY MANOJ KUMAR
• ADDED OPTIONAL PARAMETER PRESORT TOENSEMBLEGRADIENTBOOSTINGREGRESSOR ANDENSEMBLEGRADIENTBOOSTINGCLASSIFIER KEEPING DEFAULT BEHAVIOR THE SAME THIS ALLOWS GRADIENT BOOSTERS TO TURN OFF PRESORTING WHEN BUILDING DEEP TREES OR USING SPARSE DATA BY JACOB SCHREIBER
• ALTEREDMETRICSROCCURVE TO DROP UNNECESSARY THRESHOLDS BY DEFAULT BY GRAHAM CLENAGHAN
• ADDEDFEATURESELECTIONSELECTFROMMODEL METATRANSFORMER WHICH CAN BE USED ALONG WITH ESTIMATORS THAT HAVE COEF ORFEATUREIMPORTANCES ATTRIBUTE TO SELECT IMPORTANT FEATURES OF THE INPUT DATA BY MAHESHAKYA WIJEWARDENA JOEL NOTHMAN AND MANOJ KUMAR
• ADDEDMETRICSPAIRWISELAPLACIANKERNEL BY CLYDE FARE
•COVARIANCEGRAPHLASSO ALLOWS SEPARATE CONTROL OF THE CONVERGENCE CRITERION FOR THE ELASTICNET SUBPROBLEM VIA THE ENETTOL PARAMETER
• IMPROVED VERBOSITY IN DECOMPOSITIONDICTIONARYLEARNING
•ENSEMBLERANDOMFORESTCLASSIFIER ANDENSEMBLERANDOMFORESTREGRESSOR NO LONGER EXPLICITLY STORE THE SAMPLES USED IN BAGGING RESULTING IN A MUCH REDUCED MEMORY FOOTPRINT FOR STORING RANDOM FOREST MODELS
• ADDEDPOSITIVE OPTION TOLINEARMODELLARS ANDLINEARMODELLARSPATH TO FORCE COEFFICIENTS TO BE POSITIVE 5131
• ADDED THE XNORMSQUARED PARAMETER TO METRICSPAIRWISEEUCLIDEANDISTANCES TO PROVIDE PRECOMPUTED SQUARED NORMS FOR X
• ADDED THE FITPREDICT METHOD TOPIPELINEPIPELINE

• ADDED THE PREPROCESSINGMINMAXSCALE FUNCTION

BUG FIXES

• FIXED NONDETERMINISM IN DUMMYDUMMYCLASSIFIER WITH SPARSE MULTILABEL OUTPUT BY ANDREAS MÜLLER
• FIXED THE OUTPUT SHAPE OF LINEARMODELRANSACREGRESSOR TONSAMPLES BY ANDREAS MÜLLER
• FIXED BUG IN DECOMPOSITIONDICTLEARNING WHENNJOBS 0 BY ANDREAS MÜLLER
• FIXED BUG WHERE GRIDSEARCHRANDOMIZEDSEARCHCV COULD CONSUME A LOT OF MEMORY FOR LARGE DISCRETE GRIDS BY JOEL NOTHMAN
• FIXED BUG IN LINEARMODELLOGISTICREGRESSIONCV WHEREPENALTY WAS IGNORED IN THE FINAL FIT BY MANOJ KUMAR
• FIXED BUG IN ENSEMBLEFORESTFORESTCLASSIFIER WHILE COMPUTING OOBSCORE AND X IS A SPARSECSCMATRIX BY ANKUR ANKAN
• ALL REGRESSORS NOW CONSISTENTLY HANDLE AND WARN WHEN GIVEN YTHAT IS OF SHAPE NSAMPLES 1 BY ANDREAS MÜLLER AND HENRY LIN 5431
• FIX INCLUSTERKMEANS CLUSTER REASSIGNMENT FOR SPARSE INPUT BY LARS BUITINCK
• FIXED A BUG IN LDALDA THAT COULD CAUSE ASYMMETRIC COVARIANCE MATRICES WHEN USING SHRINKAGE BY MARTIN BILLINGER
• FIXEDCROSSVALIDATIONCROSSVALPREDICT FOR ESTIMATORS WITH SPARSE PREDICTIONS BY BUDDHA PRAKASH
• FIXED THE PREDICTPROBA METHOD OFLINEARMODELLOGISTICREGRESSION TO USE SOFTMAX INSTEAD OF ONEVSREST NORMALIZATION BY MANOJ KUMAR 5182
• FIXED THE PARTIALFIT METHOD OF LINEARMODELSGDCLASSIFIER WHEN CALLED WITH AVERAGETRUE BY ANDREW LAMB 5282
• DATASET FETCHERS USE DIFFERENT FILENAMES UNDER PYTHON 2 AND PYTHON 3 TO AVOID PICKLING COMPATIBILITY ISSUES BY OLIVIER GRISEL 5355
• FIXED A BUG IN NAIVEBAYESGAUSSIANNB WHICH CAUSED CLASSIFICATION RESULTS TO DEPEND ON SCALE BY JAKE VANDERPLAS
• FIXED TEMPORARILY LINEARMODELRIDGE WHICH WAS INCORRECT WHEN FITTING THE INTERCEPT IN THE CASE OF SPARSE DATA THE FIX AUTOMATICALLY CHANGES THE SOLVER TO ‘SAG’ IN THIS CASE 5360 BY TOM DUPRE LA TOUR
• FIXED A PERFORMANCE BUG IN DECOMPOSITIONRANDOMIZEDPCA ON DATA WITH A LARGE NUMBER OF FEATURES AND FEWER SAMPLES 4478 BY ANDREAS MÜLLER LOIC ESTEVE AND GIORGIO PATRINI
• FIXED BUG IN CROSSDECOMPOSITIONPLS THAT YIELDED UNSTABLE AND PLATFORM DEPENDENT OUTPUT AND FAILED ONFITTRANSFORM BY ARTHUR MENSCH
• FIXES TO THE BUNCH CLASS USED TO STORE DATASETS
• FIXEDENSEMBLEPLOTPARTIALDEPENDENCE IGNORING THE PERCENTILES PARAMETER
• PROVIDING A SET AS VOCABULARY IN COUNTVECTORIZER NO LONGER LEADS TO INCONSISTENT RESULTS WHEN PICKLING
• FIXED THE CONDITIONS ON WHEN A PRECOMPUTED GRAM MATRIX NEEDS TO BE RECOMPUTED IN LINEARMODEL LINEARREGRESSION LINEARMODELORTHOGONALMATCHINGPURSUIT LINEARMODELLASSO ANDLINEARMODELELASTICNET
• FIXED INCONSISTENT MEMORY LAYOUT IN THE COORDINATE DESCENT SOLVER THAT AFFECTED LINEARMODEL DICTIONARYLEARNING ANDCOVARIANCEGRAPHLASSO 5337 BY OLIVIER GRISEL

•MANIFOLDLOCALLYLINEAREMBEDDING NO LONGER IGNORES THE REG PARAMETER
• NEAREST NEIGHBOR ESTIMATORS WITH CUSTOM DISTANCE METRICS CAN NOW BE PICKLED 4362
• FIXED A BUG IN PIPELINEFEATUREUNION WHERETRANSFORMERWEIGHTS WERE NOT PROPERLY HANDLED
WHEN PERFORMING GRIDSEARCHES
• FIXED A BUG IN LINEARMODELLOGISTICREGRESSION ANDLINEARMODEL
LOGISTICREGRESSIONCV WHEN USING CLASSWEIGHTBALANCED ORCLASSWEIGHTAUTO
BY TOM DUPRE LA TOUR
• FIXED BUG 5495 WHEN DOING OVRSVCDECISIONFUNCTIONSHAPE”OVR” FIXED BY ELVIS DOHMATOB
API CHANGES SUMMARY
• ATTRIBUTE DATAMIN DATAMAX ANDDATARANGE INPREPROCESSINGMINMAXSCALER ARE DEPRE
CATED AND WON’T BE AVAILABLE FROM 019 INSTEAD THE CLASS NOW EXPOSES DATAMIN DATAMAX AND
DATARANGE BY GIORGIO PATRINI
• ALL SCALER CLASSES NOW HAVE AN SCALE ATTRIBUTE THE FEATUREWISE RESCALING APPLIED BY THEIR TRANSFORM METHODS
THE OLD ATTRIBUTE STD INPREPROCESSINGSTANDARDSCALER IS DEPRECATED AND SUPERSEDED BY SCALE
IT WON’T BE AVAILABLE IN 019 BY GIORGIO PATRINI
•SVMSVC ANDSVMNUSVC NOW HAVE AN DECISIONFUNCTIONSHAPE PARAMETER TO MAKE THEIR DECISION
FUNCTION OF SHAPE NSAMPLES NCLASSES BY SETTINGDECISIONFUNCTIONSHAPEOVR THIS
WILL BE THE DEFAULT BEHAVIOR STARTING IN 019 BY ANDREAS MÜLLER
• PASSING 1D DATA ARRAYS AS INPUT TO ESTIMATORS IS NOW DEPRECATED AS IT CAUSED CONFUSION IN HOW THE ARRAY ELE
MENTS SHOULD BE INTERPRETED AS FEATURES OR AS SAMPLES ALL DATA ARRAYS ARE NOW EXPECTED TO BE EXPLICITLY SHAPED
NSAMPLES NFEATURES BY VIGHNESH BIRODKAR
•LDALDA ANDQDAQDA HAVE BEEN MOVED TO DISCRIMINANTANALYSIS
LINEARDISCRIMINANTANALYSIS AND DISCRIMINANTANALYSIS
QUADRATICDISCRIMINANTANALYSIS
• THESTORECOVARIANCE ANDTOL PARAMETERS HAVE BEEN MOVED FROM THE FIT METHOD TO THE CONSTRUCTOR IN
DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS AND THESTORECOVARIANCES AND
TOL PARAMETERS HAVE BEEN MOVED FROM THE FIT METHOD TO THE CONSTRUCTOR IN DISCRIMINANTANALYSIS
QUADRATICDISCRIMINANTANALYSIS
• MODELS INHERITING FROM LEARNTSELECTORMIXIN WILL NO LONGER SUPPORT THE TRANSFORM METHODS IE RAN
DOMFORESTS GRADIENTBOOSTING LOGISTICREGRESSION DECISIONTREES SVMS AND SGD RELATED MODELS WRAP
THESE MODELS AROUND THE METATRANSFOMER FEATURESELECTIONSELECTFROMMODEL TO REMOVE FEATURES
ACCORDING TO COEFS ORFEATUREIMPORTANCES WHICH ARE BELOW A CERTAIN THRESHOLD VALUE INSTEAD
•CLUSTERKMEANS RERUNS CLUSTERASSIGNMENTS IN CASE OF NONCONVERGENCE TO ENSURE CONSISTENCY OF
PREDICTX ANDLABELS BY VIGHNESH BIRODKAR
• CLASSIFIER AND REGRESSOR MODELS ARE NOW TAGGED AS SUCH USING THE ESTIMATORTYPE ATTRIBUTE
• CROSSVALIDATION ITERATORS ALWAYS PROVIDE INDICES INTO TRAINING AND TEST SET NOT BOOLEAN MASKS
• THEDECISIONFUNCTION ON ALL REGRESSORS WAS DEPRECATED AND WILL BE REMOVED IN 019 USE PREDICT
INSTEAD
•DATASETSLOADLFWPAIRS IS DEPRECATED AND WILL BE REMOVED IN 019 USE DATASETS
FETCHLFWPAIRS INSTEAD
• THE DEPRECATED HMM MODULE WAS REMOVED
• THE DEPRECATED BOOTSTRAP CROSSVALIDATION ITERATOR WAS REMOVED

SCIKITLEARN USER GUIDE RELEASE 0213

• THE DEPRECATED WARD ANDWARDAGGLOMERATIVE CLASSES HAVE BEEN REMOVED USE CLUSTERING AGGLOMERATIVECLUSTERING INSTEAD

•CROSSVALIDATIONCHECKCV IS NOW A PUBLIC FUNCTION

• THE PROPERTY RESIDUES OFLINEARMODELLINEARREGRESSION IS DEPRECATED AND WILL BE REMOVED IN 019

• THE DEPRECATED NJOBS PARAMETER OF LINEARMODELLINEARREGRESSION HAS BEEN MOVED TO THE CON STRUCTOR

• REMOVED DEPRECATED CLASSWEIGHT PARAMETER FROM LINEARMODELSGDCLASSIFIER 'SFIT METHOD USE THE CONSTRUCTION PARAMETER INSTEAD

• THE DEPRECATED SUPPORT FOR THE SEQUENCE OF SEQUENCES OR LIST OF LISTS MULTILABEL FORMAT WAS REMOVED TO CONVERT TO AND FROM THE SUPPORTED BINARY INDICATOR MATRIX FORMAT USE MULTILABELBINARIZER

• THE BEHAVIOR OF CALLING THE INVERSETRANSFORM METHOD OFPIPELINEPIPELINE WILL CHANGE IN 019 IT WILL NO LONGER RESHAPE ONEDIMENSIONAL INPUT TO TWODIMENSIONAL INPUT

• THE DEPRECATED ATTRIBUTES INDICATORMATRIX MULTILABEL ANDCLASSES OFPREPROCESSING LABELBINARIZER WERE REMOVED

• USINGGAMMA0 INSVMSVC ANDSVMSVR TO AUTOMATICALLY SET THE GAMMA TO 1 NFEATURES IS DEP RECATED AND WILL BE REMOVED IN 019 USE GAMMAAUTO INSTEAD

CODE CONTRIBUTORS

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1179 VERSION 0161

APRIL 14 2015

CHANGELOG
BUG FIXES
• ALLOW INPUT DATA LARGER THAN BLOCKSIZE INCOVARIANCEDOITWOLF BY ANDREAS MÜLLER
• FIX A BUG IN ISOTONICISOTONICREGRESSION DEDUPLICATION THAT CAUSED UNSTABLE RESULT IN CALIBRATIONCALIBRATEDCLASSIFIERCV BY JAN HENDRIK METZEN
• FIX SORTING OF LABELS IN FUNC PREPROCESSINGLABELBINARIZE BY MICHAEL HEILMAN
• FIX SEVERAL STABILITY AND CONVERGENCE ISSUES IN CROSSDECOMPOSITIONCCA AND CROSSDECOMPOSITIONPLSCANONICAL BY ANDREAS MÜLLER
• FIX A BUG IN CLUSTERKMEANS WHENPRECOMPUTEDISTANCESFALSE ON FORTRANORDERED DATA
• FIX A SPEED REGRESSION IN ENSEMBLERANDOMFORESTCLASSIFIER ’SPREDICT ANDPREDICTPROBA BY ANDREAS MÜLLER
• FIX A REGRESSION WHERE UTILSSHUFFLE CONVERTED LISTS AND DATAFRAMES TO ARRAYS BY OLIVIER GRISEL
11710 VERSION 016
MARCH 26 2015
HIGHLIGHTS
• SPEED IMPROVEMENTS NOTABLY IN CLUSTERDBSCAN REDUCED MEMORY REQUIREMENTS BUGFIXES AND BETTER DEFAULT SETTINGS
• MULTINOMIAL LOGISTIC REGRESSION AND A PATH ALGORITHM IN LINEARMODELLOGISTICREGRESSIONCV
• OUTOF CORE LEARNING OF PCA VIA DECOMPOSITIONINCREMENTALPCA
• PROBABILITY CALLIBRATION OF CLASSIFIERS USING CALIBRATIONCALIBRATEDCLASSIFIERCV
•CLUSTERBIRCH CLUSTERING METHOD FOR LARGESCALE DATASETS
• SCALABLE APPROXIMATE NEAREST NEIGHBORS SEARCH WITH LOCALITYSENSITIVE HASHING FORESTS IN NEIGHBORS LSHFOREST
• IMPROVED ERROR MESSAGES AND BETTER VALIDATION WHEN USING MALFORMED INPUT DATA
• MORE ROBUST INTEGRATION WITH PANDAS DATAFRAMES
CHANGELOG
NEW FEATURES
• THE NEW NEIGHBORSLSHFOREST IMPLEMENTS LOCALITYSENSITIVE HASHING FOR APPROXIMATE NEAREST NEIGHBORS SEARCH BY MAHESHAKYA WIJEWARDENA
• ADDEDSVMLINEARSVR THIS CLASS USES THE LIBLINEAR IMPLEMENTATION OF SUPPORT VECTOR REGRESSION WHICH IS MUCH FASTER FOR LARGE SAMPLE SIZES THAN SVMSVR WITH LINEAR KERNEL BY FABIAN PEDREGOSA AND QIANG LUO
• INCREMENTAL FIT FOR GAUSSIANNB
• ADDEDSAMPLEWEIGHT SUPPORT TODUMMYDUMMYCLASSIFIER ANDDUMMYDUMMYREGRESSOR BY ARNAUD JOLY

• ADDED THE METRICSLABELRANKINGAVERAGEPRECISIONSCORE METRICS BY ARNAUD JOLY
• ADD THEMETRICSCOVERAGEERROR METRICS BY ARNAUD JOLY
• ADDEDLINEARMODELLOGISTICREGRESSIONCV BY MANOJ KUMAR FABIAN PEDREGOSA GAEL VAROQUAUX AND ALEXANDRE GRAMFORT
• ADDEDWARMSTART CONSTRUCTOR PARAMETER TO MAKE IT POSSIBLE FOR ANY TRAINED FOREST MODEL TO GROW ADDITIONAL TREES INCREMENTALLY BY LAURENT DIRER
• ADDEDSAMPLEWEIGHT SUPPORT TO ENSEMBLEGRADIENTBOOSTINGCLASSIFIER ANDENSEMBLE GRADIENTBOOSTINGREGRESSOR BY PETER PRETTENHOFER
• ADDEDDECOMPOSITIONINCREMENTALPCA AN IMPLEMENTATION OF THE PCA ALGORITHM THAT SUPPORTS OUT OFCORE LEARNING WITH A PARTIALFIT METHOD BY KYLE KASTNER
• AVERAGED SGD FOR SGDCLASSIFIER ANDSGDREGRESSOR BY DANNY SULLIVAN
• ADDEDCROSSVALPREDICT FUNCTION WHICH COMPUTES CROSSVALIDATED ESTIMATES BY LUIS PEDRO COELHO
• ADDEDLINEARMODELTHEILSENREGRESSOR A ROBUST GENERALIZEDMEDIANBASED ESTIMATOR BY FLORIAN WILHELM
• ADDEDMETRICSMEDIANABSOLUTEERROR A ROBUST METRIC BY GAEL VAROQUAUX AND FLORIAN WILHELM
• ADDCLUSTERBIRCH AN ONLINE CLUSTERING ALGORITHM BY MANOJ KUMAR ALEXANDRE GRAMFORT AND JOEL NOTH MAN
• ADDED SHRINKAGE SUPPORT TO DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS USING TWO NEW SOLVERS BY CLEMENS BRUNNER AND MARTIN BILLINGER
• ADDEDKERNELRIDGEKERNELRIDGE AN IMPLEMENTATION OF KERNELIZED RIDGE REGRESSION BY MATHIEU BLONDEL AND JAN HENDRIK METZEN
• ALL SOLVERS IN LINEARMODELRIDGE NOW SUPPORT SAMPLEWEIGHT BY MATHIEU BLONDEL
• ADDEDCROSSVALIDATIONPREDEFINEDSPLIT CROSSVALIDATION FOR FIXED USERPROVIDED CROSSVALIDATION FOLDS BY THOMAS UNTERTHINER
• ADDEDCALIBRATIONCALIBRATEDCLASSIFIERCV AN APPROACH FOR CALIBRATING THE PREDICTED PROBABILI TIES OF A CLASSIFIER BY ALEXANDRE GRAMFORT JAN HENDRIK METZEN MATHIEU BLONDEL AND BALAZS KEGL
ENHANCEMENTS
• ADD OPTION RETURNDISTANCE INHIERARCHICALWARDTREE TO RETURN DISTANCES BETWEEN NODES FOR BOTH STRUCTURED AND UNSTRUCTURED VERSIONS OF THE ALGORITHM BY MATTEO VISCONTI DI OLEGGIO CASTELLO THE SAME OPTION WAS ADDED IN HIERARCHICALLINKAGETREE BY MANOJ KUMAR
• ADD SUPPORT FOR SAMPLE WEIGHTS IN SCORER OBJECTS METRICS WITH SAMPLE WEIGHT SUPPORT WILL AUTOMATICALLY BENEFIT FROM IT BY NOEL DAWE AND VLAD NICULAE
• ADDEDNEWTONCG ANDLBFGS SOLVER SUPPORT IN LINEARMODELLOGISTICREGRESSION BY MANOJ KUMAR
• ADDSELECTIONRANDOM PARAMETER TO IMPLEMENT STOCHASTIC COORDINATE DESCENT FOR LINEARMODEL LASSO LINEARMODELELASTICNET AND RELATED BY MANOJ KUMAR
• ADDSAMPLEWEIGHT PARAMETER TO METRICSJACCARDSIMILARITYSCORE ANDMETRICS LOGLOSS BY JATIN SHAH
• SUPPORT SPARSE MULTILABEL INDICATOR REPRESENTATION IN PREPROCESSINGLABELBINARIZER AND MULTICLASSONEVSRESTCLASSIFIER BY HAMZEH ALSALHI WITH THANKS TO ROHIT SIVAPRASAD AS WELL AS EVALUATION METRICS BY JOEL NOTHMAN

• ADDSAMPLEWEIGHT PARAMETER TO METRICSJACCARDSIMILARITYSCORE BYJATIN SHAH
• ADD SUPPORT FOR MULTICLASS IN METRICSHINGELOSS ADDEDLABELSNONE AS OPTIONAL PARAMETER BY SAURABH JHA
• ADDSAMPLEWEIGHT PARAMETER TO METRICSHINGELOSS BYSAURABH JHA
• ADDMULTICLASSMULTINOMIAL OPTION INLINEARMODELLOGISTICREGRESSION TO IMPLEMENT A LOGISTIC REGRESSION SOLVER THAT MINIMIZES THE CROSSENTROPY OR MULTINOMIAL LOSS INSTEAD OF THE DEFAULT ONEVSREST SETTING SUPPORTS LBFGS ANDNEWTONCG SOLVERS BY LARS BUITINCK AND MANOJ KUMAR SOLVER OPTIONNEWTONCG BY SIMON WU
•DICTVECTORIZER CAN NOW PERFORM FITTRANSFORM ON AN ITERABLE IN A SINGLE PASS WHEN GIVING THE OPTION SORTFALSE BY DAN BLANCHARD
•GRIDSEARCHCV ANDRANDOMIZEDSEARCHCV CAN NOW BE CONFIGURED TO WORK WITH ESTIMATORS THAT MAY FAIL AND RAISE ERRORS ON INDIVIDUAL FOLDS THIS OPTION IS CONTROLLED BY THE ERRORSCORE PARAMETER THIS DOES NOT AFFECT ERRORS RAISED ON REFIT BY MICHAL ROMANIUK
• ADDDIGITS PARAMETER TO METRICSCLASSIFICATIONREPORT TO ALLOW REPORT TO SHOW DIFFERENT PRECISION OF FLOATING POINT NUMBERS BY IAN GILMORE
• ADD A QUANTILE PREDICTION STRATEGY TO THE DUMMYDUMMYREGRESSOR BY AARON STAPLE
• ADDHANDLEUNKNOWN OPTION TOPREPROCESSINGONEHOTENCODER TO HANDLE UNKNOWN CATEGORICAL FEATURES MORE GRACEFULLY DURING TRANSFORM BY MANOJ KUMAR
• ADDED SUPPORT FOR SPARSE INPUT DATA TO DECISION TREES AND THEIR ENSEMBLES BY FARES HEDYATI AND ARNAUD JOLY
• OPTIMIZED CLUSTERAFFINITYPROPAGATION BY REDUCING THE NUMBER OF MEMORY ALLOCATIONS OF LARGE TEMPORARY DATASTRUCTURES BY ANTONY LEE
• PARELLIZATION OF THE COMPUTATION OF FEATURE IMPORTANCES IN RANDOM FOREST BY OLIVIER GRISEL AND ARNAUD JOLY
• ADDNITER ATTRIBUTE TO ESTIMATORS THAT ACCEPT A MAXITER ATTRIBUTE IN THEIR CONSTRUCTOR BY MANOJ KUMAR
• ADDED DECISION FUNCTION FOR MULTICLASSONEVSONECLASSIFIER BY RAGHAV RV AND KYLE BEAUCHAMP
•NEIGHBORSKNEIGHBORSGRAPH ANDRADIUSNEIGHBORSGRAPH SUPPORT NONEUCLIDEAN METRICS BY MANOJ KUMAR
• PARAMETER CONNECTIVITY INCLUSTERAGGLOMERATIVECLUSTERING AND FAMILY NOW ACCEPT CALLABLES THAT RETURN A CONNECTIVITY MATRIX BY MANOJ KUMAR
• SPARSE SUPPORT FOR PAIREDDISTANCES BY JOEL NOTHMAN
•CLUSTERDBSCAN NOW SUPPORTS SPARSE INPUT AND SAMPLE WEIGHTS AND HAS BEEN OPTIMIZED THE INNER LOOP HAS BEEN REWRITTEN IN CYTHON AND RADIUS NEIGHBORS QUERIES ARE NOW COMPUTED IN BATCH BY JOEL NOTHMAN AND LARS BUITINCK
• ADDCLASSWEIGHT PARAMETER TO AUTOMATICALLY WEIGHT SAMPLES BY CLASS FREQUENCY FOR ENSEMBLERANDOMFORESTCLASSIFIER TREEDECISIONTREECLASSIFIER ENSEMBLE EXTRATREESCLASSIFIER ANDTREEEXTRATREECLASSIFIER BY TREVOR STEPHENS
•GRIDSEARCHRANDOMIZEDSEARCHCV NOW DOES SAMPLING WITHOUT REPLACEMENT IF ALL PARAMETERS ARE GIVEN AS LISTS BY ANDREAS MÜLLER
• PARALLELIZED CALCULATION OF PAIRWISEDISTANCES IS NOW SUPPORTED FOR SCIPY METRICS AND CUSTOM CALLABLES BY JOEL NOTHMAN
• ALLOW THE FITTING AND SCORING OF ALL CLUSTERING ALGORITHMS IN PIPELINEPIPELINE BY ANDREAS MÜLLER
• MORE ROBUST SEEDING AND IMPROVED ERROR MESSAGES IN CLUSTERMEANSHIFT BY ANDREAS MÜLLER

• MAKE THE STOPPING CRITERION FOR MIXTUREGMM MIXTUREDPGMM ANDMIXTUREVBGMM LESS DEPENDENT ON THE NUMBER OF SAMPLES BY THRESHOLDING THE AVERAGE LOGLIKELIHOOD CHANGE INSTEAD OF ITS SUM OVER ALL SAMPLES BY HERVÉ BREDIN
• THE OUTCOME OF MANIFOLDSPECTRALEMBEDDING WAS MADE DETERMINISTIC BY FLIPPING THE SIGN OF EIGEN VECTORS BY HASIL SHARMA
• SIGNIFICANT PERFORMANCE AND MEMORY USAGE IMPROVEMENTS IN PREPROCESSINGPOLYNOMIALFEATURES BY ERIC MARTIN
• NUMERICAL STABILITY IMPROVEMENTS FOR PREPROCESSINGSTANDARDSCALER ANDPREPROCESSING SCALE BY NICOLAS GOIX
•SVMSVC FITTED ON SPARSE INPUT NOW IMPLEMENTS DECISIONFUNCTION BY ROB ZINKOV AND ANDREAS MÜLLER
•CROSSVALIDATIONTRAINTESTSPLIT NOW PRESERVES THE INPUT TYPE INSTEAD OF CONVERTING TO NUMPY ARRAYS

DOCUMENTATION IMPROVEMENTS

• ADDED EXAMPLE OF USING FEATUREUNION FOR HETEROGENEOUS INPUT BY MATT TERRY
• DOCUMENTATION ON SCORERS WAS IMPROVED TO HIGHLIGHT THE HANDLING OF LOSS FUNCTIONS BY MATT PICO
• A DISCREPANCY BETWEEN LIBLINEAR OUTPUT AND SCIKITLEARN'S WRAPPERS IS NOW NOTED BY MANOJ KUMAR
• IMPROVED DOCUMENTATION GENERATION EXAMPLES REFERRING TO A CLASS OR FUNCTION ARE NOW SHOWN IN A GALLERY ON THE CLASSFUNCTION'S API REFERENCE PAGE BY JOEL NOTHMAN
• MORE EXPLICIT DOCUMENTATION OF SAMPLE GENERATORS AND OF DATA TRANSFORMATION BY JOEL NOTHMAN
•SKLEARNNEIGHBORSBALLTREE ANDSKLEARNNEIGHBORSKDTREE USED TO POINT TO EMPTY PAGES STATING THAT THEY ARE ALIASES OF BINARYTREE THIS HAS BEEN FIXED TO SHOW THE CORRECT CLASS DOCS BY MANOJ KUMAR
• ADDED SILHOUETTE PLOTS FOR ANALYSIS OF KMEANS CLUSTERING USING METRICSSILHOUETTESAMPLES AND METRICSSILHOUETTESCORE SEE SELECTING THE NUMBER OF CLUSTERS WITH SILHOUETTE ANALYSIS ON KMEANS CLUSTERING

BUG FIXES

• METAESTIMATORS NOW SUPPORT DUCKTYPING FOR THE PRESENCE OF DECISIONFUNCTION PREDICTPROBA AND OTHER METHODS THIS FIXES BEHAVIOR OF GRIDSEARCHGRIDSEARCHCV GRIDSEARCHRANDOMIZEDSEARCHCV PIPELINEPIPELINE FEATURESELECTIONRFE FEATURESELECTIONRFECV WHEN NESTED BY JOEL NOTHMAN
• THESCORING ATTRIBUTE OF GRIDSEARCH AND CROSSVALIDATION METHODS IS NO LONGER IGNORED WHEN A GRIDSEARCHGRIDSEARCHCV IS GIVEN AS A BASE ESTIMATOR OR THE BASE ESTIMATOR DOESN'T HAVE PREDICT
• THE FUNCTION HIERARCHICALWARDTREE NOW RETURNS THE CHILDREN IN THE SAME ORDER FOR BOTH THE STRUCTURED AND UNSTRUCTURED VERSIONS BY MATTEO VISCONTI DI OLEGGIO CASTELLO
•FEATURESELECTIONRFECV NOW CORRECTLY HANDLES CASES WHEN STEP IS NOT EQUAL TO 1 BY NIKOLAY MAYOROV
• THEDECOMPOSITIONPCA NOW UNDOES WHITENING IN ITS INVERSETRANSFORM ALSO ITSCOMPONENTS NOW ALWAYS HAVE UNIT LENGTH BY MICHAEL EICKENBERG
• FIX INCOMPLETE DOWNLOAD OF THE DATASET WHEN DATASETSDOWNLOAD20NEWSGROUPS IS CALLED BY MANOJ KUMAR

• VARIOUS FIXES TO THE GAUSSIAN PROCESSES SUBPACKAGE BY VINCENT DUBOURG AND JAN HENDRIK METZEN
• CALLINGPARTIALFIT WITHCLASSWEIGHTAUTO THROWS AN APPROPRIATE ERROR MESSAGE AND SUGGESTS
A WORK AROUND BY DANNY SULLIVAN
•RBFSAMPLER WITHGAMMAG FORMERLY APPROXIMATED RBFKERNEL WITHGAMMAG2 THE DEFINITION OF
GAMMA IS NOW CONSISTENT WHICH MAY SUBSTANTIALLY CHANGE YOUR RESULTS IF YOU USE A FIXED VALUE IF YOU CROSS
VALIDATED OVER GAMMA IT PROBABLY DOESN'T MATTER TOO MUCH BY DOUGAL SUTHERLAND
• PIPELINE OBJECT DELEGATE THE CLASSES ATTRIBUTE TO THE UNDERLYING ESTIMATOR IT ALLOWS FOR INSTANCE TO MAKE
BAGGING OF A PIPELINE OBJECT BY ARNAUD JOLY
•NEIGHBORSNEARESTCENTROID NOW USES THE MEDIAN AS THE CENTROID WHEN METRIC IS SET TO MANHATTAN
IT WAS USING THE MEAN BEFORE BY MANOJ KUMAR
• FIX NUMERICAL STABILITY ISSUES IN LINEARMODELSGDCLASSIFIER ANDLINEARMODEL
SGDREGRESSOR BY CLIPPING LARGE GRADIENTS AND ENSURING THAT WEIGHT DECAY RESCALING IS ALWAYS POSITIVE FOR
LARGE L2 REGULARIZATION AND LARGE LEARNING RATE VALUES BY OLIVIER GRISEL
• WHENCOMPUTEFULLTREE IS SET TO "AUTO" THE FULL TREE IS BUILT WHEN NCLUSTERS IS HIGH AND
IS EARLY STOPPED WHEN NCLUSTERS IS LOW WHILE THE BEHAVIOR SHOULD BE VICEVERSA IN CLUSTER
AGGLOMERATIVECLUSTERING AND FRIENDS THIS HAS BEEN FIXED BY MANOJ KUMAR
• FIX LAZY CENTERING OF DATA IN LINEARMODELENETPATH ANDLINEARMODELLASSOPATH IT WAS
CENTERED AROUND ONE IT HAS BEEN CHANGED TO BE CENTERED AROUND THE ORIGIN BY MANOJ KUMAR
• FIX HANDLING OF PRECOMPUTED AFFINITY MATRICES IN CLUSTERAGGLOMERATIVECLUSTERING WHEN USING
CONNECTIVITY CONSTRAINTS BY CATHY DENG
• CORRECTPARTIALFIT HANDLING OF CLASSPRIOR FORSKLEARNNAIVEBAYESMULTINOMIALNB AND
SKLEARNNAIVEBAYESBERNOULLINB BY TREVOR STEPHENS
• FIXED A CRASH IN METRICSPRECISIONRECALLFSCORESUPPORT WHEN USING UNSORTED LABELS IN THE
MULTILABEL SETTING BY ANDREAS MÜLLER
• AVOID SKIPPING THE FIRST NEAREST NEIGHBOR IN THE METHODS RADIUSNEIGHBORS KNEIGHBORS
KNEIGHBORSGRAPH ANDRADIUSNEIGHBORSGRAPH INSKLEARNNEIGHBORS
NEARESTNEIGHBORS AND FAMILY WHEN THE QUERY DATA IS NOT THE SAME AS FIT DATA BY MANOJ KUMAR
• FIX LOGDENSITY CALCULATION IN THE MIXTUREGMM WITH TIED COVARIANCE BY WILL DAWSON
• FIXED A SCALING ERROR IN FEATURESELECTIONSELECTFDR WHERE A FACTOR NFEATURES WAS MISSING BY
ANDREW TULLOCH
• FIX ZERO DIVISION IN NEIGHBORSKNEIGHBORSREGRESSOR AND RELATED CLASSES WHEN USING DISTANCE WEIGHT
ING AND HAVING IDENTICAL DATA POINTS BY GARRETR
• FIXED ROUND OFF ERRORS WITH NON POSITIVEDEFINITE COVARIANCE MATRICES IN GMM BY ALEXIS MIGNON
• FIXED A ERROR IN THE COMPUTATION OF CONDITIONAL PROBABILITIES IN NAIVEBAYESBERNOULLINB BY HANNA
WALLACH
• MAKE THE METHOD RADIUSNEIGHBORS OFNEIGHBORSNEARESTNEIGHBORS RETURN THE SAMPLES LYING
ON THE BOUNDARY FOR ALGORITHMBRUTE BY YAN YI
• FLIP SIGN OF DUALCOEF OFSVMSVC TO MAKE IT CONSISTENT WITH THE DOCUMENTATION AND
DECISIONFUNCTION BY ARTEM SOBOLEV
• FIXED HANDLING OF TIES IN ISOTONICISOTONICREGRESSION WE NOW USE THE WEIGHTED AVERAGE OF TARGETS
SECONDARY METHOD BY ANDREAS MÜLLER AND MICHAEL BOMMARITO

API CHANGES SUMMARY

•GRIDSEARCHCV ANDCROSSVALSCORE AND OTHER METAESTIMATORS DON'T CONVERT PANDAS DATAFRAMES INTO ARRAYS ANY MORE ALLOWING DATAFRAME SPECIFIC OPERATIONS IN CUSTOM ESTIMATORS

•MULTICLASSFITOVR MULTICLASSPREDICTOVR PREDICTPROBAOVR MULTICLASSFITOVO MULTICLASSPREDICTOVO MULTICLASSFITECOC ANDMULTICLASSPREDICTECOC ARE DEPRECATED USE THE UNDERLYING ESTIMATORS INSTEAD

• NEAREST NEIGHBORS ESTIMATORS USED TO TAKE ARBITRARY KEYWORD ARGUMENTS AND PASS THESE TO THEIR DISTANCE METRIC THIS WILL NO LONGER BE SUPPORTED IN SCIKITLEARN 018 USE THE METRICPARAMS ARGUMENT INSTEAD

•NJOBS PARAMETER OF THE FIT METHOD SHIFTED TO THE CONSTRUCTOR OF THE LINEARREGRESSION CLASS

• THEPREDICTPROBA METHOD OFMULTICLASSONEVSRESTCLASSIFIER NOW RETURNS TWO PROBABILITIES PER SAMPLE IN THE MULTICLASS CASE THIS IS CONSISTENT WITH OTHER ESTIMATORS AND WITH THE METHOD'S DOCUMENTATION BUT PREVIOUS VERSIONS ACCIDENTALLY RETURNED ONLY THE POSITIVE PROBABILITY FIXED BY WILL LAMOND AND LARS BUITINCK

• CHANGE DEFAULT VALUE OF PRECOMPUTE IN ELASTICNET ANDLASSO TO FALSE SETTING PRECOMPUTE TO "AUTO" WAS FOUND TO BE SLOWER WHEN NSAMPLES NFEATURES SINCE THE COMPUTATION OF THE GRAM MATRIX IS COMPUTATIONALLY EXPENSIVE AND OUTWEIGHS THE BENEFIT OF FITTING THE GRAM FOR JUST ONE ALPHA PRECOMPUTEAUTO IS NOW DEPRECATED AND WILL BE REMOVED IN 018 BY MANOJ KUMAR

• EXPOSEPOSITIVE OPTION INLINEARMODELENETPATH ANDLINEARMODELENETPATH WHICH CONSTRAINS COEFFICIENTS TO BE POSITIVE BY MANOJ KUMAR

• USERS SHOULD NOW SUPPLY AN EXPLICIT AVERAGE PARAMETER TO SKLEARNMETRICSF1SCORE SKLEARNMETRICSFBETASCORE SKLEARNMETRICSRECALLSCORE ANDSKLEARNMETRICSPRECISIONSCORE WHEN PERFORMING MULTICLASS OR MULTILABEL IE NOT BINARY CLASSIFICATION BY JOEL NOTHMAN

•SCORING PARAMETER FOR CROSS VALIDATION NOW ACCEPTS F1MICRO F1MACRO ORF1WEIGHTED F1 IS NOW FOR BINARY CLASSIFICATION ONLY SIMILAR CHANGES APPLY TO PRECISION ANDRECALL BY JOEL NOTHMAN

• THEFITINTERCEPT NORMALIZE ANDRETURNMODELS PARAMETERS IN LINEARMODELENETPATH ANDLINEARMODELLASSOPATH HAVE BEEN REMOVED THEY WERE DEPRECATED SINCE 014

• FROM NOW ONWARDS ALL ESTIMATORS WILL UNIFORMLY RAISE NOTFITTEDERROR UTILSVALIDATION NOTFITTEDERROR WHEN ANY OF THE PREDICT LIKE METHODS ARE CALLED BEFORE THE MODEL IS FIT BY RAGHAV RV

• INPUT DATA VALIDATION WAS REFACTORED FOR MORE CONSISTENT INPUT VALIDATION THE CHECKARRAYS FUNCTION WAS REPLACED BY CHECKARRAY ANDCHECKXY BY ANDREAS MÜLLER

• ALLOWXNONE IN THE METHODS RADIUSNEIGHBORS KNEIGHBORS KNEIGHBORSGRAPH AND RADIUSNEIGHBORSGRAPH INSKLEARNNEIGHBORSNEARESTNEIGHBORS AND FAMILY IF SET TO NONE THEN FOR EVERY SAMPLE THIS AVOIDS SETTING THE SAMPLE ITSELF AS THE FIRST NEAREST NEIGHBOR BY MANOJ KUMAR

• ADD PARAMETER INCLUDESELF INNEIGHBORSKNEIGHBORSGRAPH ANDNEIGHBORSRADIUSNEIGHBORSGRAPH WHICH HAS TO BE EXPLICITLY SET BY THE USER IF SET TO TRUE THEN THE SAMPLE ITSELF IS CONSIDERED AS THE FIRST NEAREST NEIGHBOR

•THRESH PARAMETER IS DEPRECATED IN FAVOR OF NEW TOL PARAMETER IN GMMDPGMM ANDVBGMM SEE ENHANCEMENTS SECTION FOR DETAILS BY HERVÉ BREDIN

• ESTIMATORS WILL TREAT INPUT WITH DTYPE OBJECT AS NUMERIC WHEN POSSIBLE BY ANDREAS MÜLLER

• ESTIMATORS NOW RAISE VALUEERROR CONSISTENTLY WHEN FITTED ON EMPTY DATA LESS THAN 1 SAMPLE OR LESS THAN 1 FEATURE FOR 2D INPUT BY OLIVIER GRISEL

SCIKITLEARN USER GUIDE RELEASE 0213

• THESHUFFLE OPTION OF LINEARMODELSGDCLASSIFIER LINEARMODELSGDREGRESSOR LINEARMODELPERCEPTRON LINEARMODELPASSIVEAGGRESSIVECLASSIFIER AND LINEARMODELPASSIVEAGGRESSIVEREGRESSOR NOW DEFAULTS TO TRUE

•CLUSTERDBSCAN NOW USES A DETERMINISTIC INITIALIZATION THE RANDOMSTATE PARAMETER IS DEPRECATED BY ERICH SCHUBERT

CODE CONTRIBUTORS

A FLAXMAN AARON SCHUMACHER AARON STAPLE ABHISHEK THAKUR AKSHAY AKSHAYAH3 ALDRIAN OBAJA ALEXANDER FABISCH ALEXANDRE GRAMFORT ALEXIS MIGNON ANDERS AAGAARD ANDREAS MUELLER ANDREAS VAN CRANENBURGH AN DREW TULLOCH ANDREW WALKER ANTONY LEE ARNAUD JOLY BANILO BARMALEYEXE BEN DAVIES BENEDIKT KOEHLER BHSU BORIS FELD BORJA AYERDI BOYUAN DENG BRENT PEDERSEN BRIAN WIGNALL BROOKE OSBORN CALVIN GILES CATHY DENG CELEO CGOHLKE CHEBEE7I CHRISTIAN STADESCHULDT CHRISTOF ANGERMUELLER CHYIKWEI YAU CJ CAREY CLEMENS BRUN NER DAIKI AMINAKA DAN BLANCHARD DANFRANKJ DANNY SULLIVAN DAVID FLETCHER DMITRIJS MILAJEVS DOUGAL J SUTHER LAND ERICH SCHUBERT FABIAN PEDREGOSA FLORIAN WILHELM FLOYDSOFT FÉLIXANTOINE FORTIN GAEL VAROQUAUX GARRETTR GILLES LOUPPE GPASSINO GWULFS HAMPUS BENGTSSON HAMZEH ALSALHI HANNA WALLACH HARRY MAVROFORAKIS HASIL SHARMA HELDER HERVE BREDIN HSIANGFU YU HUGUES SALAMIN IAN GILMORE ILAMBHARATHI KANNIAH IMRAN HAQUE ISMS JAKE VANDERPLAS JAN DLABAL JAN HENDRIK METZEN JATIN SHAH JAVIER LÓPEZ PEÑA JDCABALLERO JEAN KOSSAIFI JEFF HAMMERBACHER JOEL NOTHMAN JONATHAN HELMUS JOSEPH KAICHENG ZHANG KEVIN MARKHAM KYLE BEAUCHAMP KYLE KASTNER LAGACHERIE MATTHIEU LARS BUITINCK LAURENT DIRER LEEPEI LOIC ESTEVE LUIS PEDRO COELHO LUKAS MICHEL BACHER MAHESHAKYA MANOJ KUMAR MANUEL MARIO MICHAEL KRELL MARTIN MARTIN BILLINGER MARTIN KU MATEUSZ SUSIK MATHIEU BLONDEL MATT PICO MATT TERRY MATTEO VISCONTI DOC MATTI LYRA MAX LINKE MEHDI CHERTI MICHAEL BOMMARITO MICHAEL EICKENBERG MICHAL ROMANIUK MLG MRSHU NELLE VAROQUAUX NICOLA MONTECCHIO NICOLAS NIKOLAY MAYOROV NOEL DAWE OKAL BILLY OLIVIER GRISEL ÓSCAR NÁJERA PAOLO PUGGIONI PETER PRETTENHOFER PRATAP VARDHAN PVNGUYEN QUEQICHAO RAFAEL CARRASCOSA RAGHAV R V RAHIEL KASIM RANDALL MASON ROB ZINKOV ROBERT BRADSHAW SAKET CHOUDHARY SAM NICHOLLS SAMUEL CHARRON SAURABH JHA SETHDANDRIDGE SINHRKS SNUDERL STEFAN OTTE STEFAN VAN DER WALT STEVE TJOA SWU SYLVAIN ZIMMER TEJESH95 TERRYCOJONES THOMAS DELTEIL THOMAS UN TERTHINER TOMAS KAZMAR TREVORSTEPHENS TTTTHOMASSSSS TZUMING KUO UGURCALISKAN UGURTHEMASTER VINAYAK MEHTA VINCENT DUBOURG VJACHESLAV MURASHKIN VLAD NICULAE WADAWSON WEI XUE WILL LAMOND WU JIANG X0L XINFAN MENG YAN YI YUCHIN

11711 VERSION 0152

SEPTEMBER 4 2014

BUG FIXES

• FIXED HANDLING OF THE PPARAMETER OF THE MINKOWSKI DISTANCE THAT WAS PREVIOUSLY IGNORED IN NEAREST NEIGHBORS MODELS BY NIKOLAY MAYOROV

• FIXED DUPLICATED ALPHAS IN LINEARMODELLASSOLARS WITH EARLY STOPPING ON 32 BIT PYTHON BY OLIVIER GRISEL AND FABIAN PEDREGOSA

• FIXED THE BUILD UNDER WINDOWS WHEN SCIKITLEARN IS BUILT WITH MSVC WHILE NUMPY IS BUILT WITH MINGW BY OLIVIER GRISEL AND FEDERICO VAGGI

• FIXED AN ARRAY INDEX OVERFLOW BUG IN THE COORDINATE DESCENT SOLVER BY GAEL VAROQUAUX

• BETTER HANDLING OF NUMPY 19 DEPRECATION WARNINGS BY GAEL VAROQUAUX

• REMOVED UNNECESSARY DATA COPY IN CLUSTERKMEANS BY GAEL VAROQUAUX

• EXPLICITLY CLOSE OPEN FILES TO AVOID RESOURCEWARNINGS UNDER PYTHON 3 BY CALVIN GILES

SCIKITLEARN USER GUIDE RELEASE 0213
• THETRANSFORM OFDISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS NOW PROJECTS THE INPUT ON THE MOST DISCRIMINANT DIRECTIONS BY MARTIN BILLINGER
• FIXED POTENTIAL OVERFLOW IN TREESAFEREALLOC BY LARS BUITINCK
• PERFORMANCE OPTIMIZATION IN ISOTONICISOTONICREGRESSION BY ROBERT BRADSHAW
•NOSE IS NONLONGER A RUNTIME DEPENDENCY TO IMPORT SKLEARN ONLY FOR RUNNING THE TESTS BY JOEL NOTHMAN
• MANY DOCUMENTATION AND WEBSITE FIXES BY JOEL NOTHMAN LARS BUITINCK MATT PICO AND OTHERS

11712 VERSION 0151

AUGUST 1 2014

BUG FIXES

• MADECROSSVALIDATIONCROSSVALSCORE USECROSSVALIDATIONKFOLD INSTEAD OF CROSSVALIDATIONSTRATIFIEDKFOLD ON MULTIOUTPUT CLASSIFICATION PROBLEMS BY NIKOLAY MAYOROV
• SUPPORT UNSEEN LABELS PREPROCESSINGLABELBINARIZER TO RESTORE THE DEFAULT BEHAVIOR OF 0141 FOR BACKWARD COMPATIBILITY BY HAMZEH ALSALHI
• FIXED THE CLUSTERKMEANS STOPPING CRITERION THAT PREVENTED EARLY CONVERGENCE DETECTION BY EDWARD RAFF AND GAEL VAROQUAUX
• FIXED THE BEHAVIOR OF MULTICLASSONEVSONECLASSIFIER IN CASE OF TIES AT THE PERCLASS VOTE LEVEL BY COMPUTING THE CORRECT PERCLASS SUM OF PREDICTION SCORES BY ANDREAS MÜLLER
• MADECROSSVALIDATIONCROSSVALSCORE ANDGRIDSEARCHGRIDSEARCHCV ACCEPT PYTHON LISTS AS INPUT DATA THIS IS ESPECIALLY USEFUL FOR CROSSVALIDATION AND MODEL SELECTION OF TEXT PROCESSING PIPELINES BY ANDREAS MÜLLER
• FIXED DATA INPUT CHECKS OF MOST ESTIMATORS TO ACCEPT INPUT DATA THAT IMPLEMENTS THE NUMPY ARRAY PROTOCOL THIS IS THE CASE FOR FOR PANDASSERIES ANDPANDASDATAFRAME IN RECENT VERSIONS OF PANDAS BY GAEL VAROQUAUX
• FIXED A REGRESSION FOR LINEARMODELSGDCLASSIFIER WITHCLASSWEIGHTAUTO ON DATA WITH NONCONTIGUOUS LABELS BY OLIVIER GRISEL

11713 VERSION 015

JULY 15 2014

HIGHLIGHTS

• MANY SPEED AND MEMORY IMPROVEMENTS ALL ACROSS THE CODE
• HUGE SPEED AND MEMORY IMPROVEMENTS TO RANDOM FORESTS AND EXTRA TREES THAT ALSO BENEFIT BETTER FROM PARALLEL COMPUTING
• INCREMENTAL FIT TO BERNOULLIRBM
• ADDEDCLUSTERAGGLOMERATIVECLUSTERING FOR HIERARCHICAL AGGLOMERATIVE CLUSTERING WITH AVERAGE LINKAGE COMPLETE LINKAGE AND WARD STRATEGIES
• ADDEDLINEARMODELRANSACREGRESSOR FOR ROBUST REGRESSION MODELS

• ADDED DIMENSIONALITY REDUCTION WITH MANIFOLDTSNE WHICH CAN BE USED TO VISUALIZE HIGHDIMENSIONAL DATA

CHANGELOG

NEW FEATURES

• ADDEDENSEMBLEBAGGINGCLASSIFIER ANDENSEMBLEBAGGINGREGRESSOR METAESTIMATORS FOR ENSEMBLING ANY KIND OF BASE ESTIMATOR SEE THE BAGGING SECTION OF THE USER GUIDE FOR DETAILS AND EXAMPLES BY GILLES LOUPPE
• NEW UNSUPERVISED FEATURE SELECTION ALGORITHM FEATURESELECTIONVARIANCETHRESHOLD BY LARS BUITINCK
• ADDEDLINEARMODELRANSACREGRESSOR METAESTIMATOR FOR THE ROBUST FITTING OF REGRESSION MODELS BY JOHANNES SCHÖNBERGER
• ADDEDCLUSTERAGGLOMERATIVECLUSTERING FOR HIERARCHICAL AGGLOMERATIVE CLUSTERING WITH AVERAGE LINKAGE COMPLETE LINKAGE AND WARD STRATEGIES BY NELLE VAROQUAUX AND GAEL VAROQUAUX
• SHORTHAND CONSTRUCTORS PIPELINEMAKEPIPELINE ANDPIPELINEMAKEUNION WERE ADDED BY LARS BUITINCK
• SHUFFLE OPTION FOR CROSSVALIDATIONSTRATIFIEDKFOLD BY JEFFREY BLACKBURNE
• INCREMENTAL LEARNING PARTIALFIT FOR GAUSSIAN NAIVE BAYES BY IMRAN HAQUE
• ADDEDPARTIALFIT TOBERNOULLIRBM BY DANNY SULLIVAN
• ADDEDLEARNINGCURVE UTILITY TO CHART PERFORMANCE WITH RESPECT TO TRAINING SIZE SEE PLOTTING LEARNING CURVES BY ALEXANDER FABISCH
• ADD POSITIVE OPTION IN LASSOCV ANDELASTICNETCV BY BRIAN WIGNALL AND ALEXANDRE GRAMFORT
• ADDEDLINEARMODELMULTITASKELASTICNETCV ANDLINEARMODELMULTITASKLASSOCV BY MANOJ KUMAR
• ADDEDMANIFOLDTSNE BY ALEXANDER FABISCH

ENHANCEMENTS

• ADD SPARSE INPUT SUPPORT TO ENSEMBLEADABOOSTCLASSIFIER ANDENSEMBLE ADABOOSTREGRESSOR METAESTIMATORS BY HAMZEH ALSALHI
• MEMORY IMPROVEMENTS OF DECISION TREES BY ARNAUD JOLY
• DECISION TREES CAN NOW BE BUILT IN BESTFIRST MANNER BY USING MAXLEAFNODES AS THE STOPPING CRITERIA REFACTORED THE TREE CODE TO USE EITHER A STACK OR A PRIORITY QUEUE FOR TREE BUILDING BY PETER PRETTENHOFER AND GILLES LOUPPE
• DECISION TREES CAN NOW BE FITTED ON FORTRAN AND CSTYLE ARRAYS AND NONCONTINUOUS ARRAYS WITHOUT THE NEED TO MAKE A COPY IF THE INPUT ARRAY HAS A DIFFERENT DTYPE THAN NPFLOAT32 A FORTRAN STYLE COPY WILL BE MADE SINCE FORTRANSTYLE MEMORY LAYOUT HAS SPEED ADVANTAGES BY PETER PRETTENHOFER AND GILLES LOUPPE
• SPEED IMPROVEMENT OF REGRESSION TREES BY OPTIMIZING THE THE COMPUTATION OF THE MEAN SQUARE ERROR CRITERION THIS LEAD TO SPEED IMPROVEMENT OF THE TREE FOREST AND GRADIENT BOOSTING TREE MODULES BY ARNAUD JOLY
• THEIMGTOGRAPH ANDGRIDTOGRAPH FUNCTIONS IN SKLEARNFEATUREEXTRACTIONIMAGE NOW RETURNNPNDARRAY INSTEAD OFNPMATRIX WHENRETURNASNPNDARRAY SEE THE NOTES SECTION FOR MORE INFORMATION ON COMPATIBILITY

• CHANGED THE INTERNAL STORAGE OF DECISION TREES TO USE A STRUCT ARRAY THIS FIXED SOME SMALL BUGS WHILE IMPROVING CODE AND PROVIDING A SMALL SPEED GAIN BY JOEL NOTHMAN
• REDUCE MEMORY USAGE AND OVERHEAD WHEN FITTING AND PREDICTING WITH FORESTS OF RANDOMIZED TREES IN PARALLEL WITHNJOBS 1 BY LEVERAGING NEW THREADING BACKEND OF JOBLIB 08 AND RELEASING THE GIL IN THE TREE FITTING CYTHON CODE BY OLIVIER GRISEL AND GILLES LOUPPE
• SPEED IMPROVEMENT OF THE SKLEARNENSEMBLEGRADIENTBOOSTING MODULE BY GILLES LOUPPE AND PETER PRETTENHOFER
• VARIOUS ENHANCEMENTS TO THE SKLEARNENSEMBLEGRADIENTBOOSTING MODULE AWARMSTART AR GUMENT TO FIT ADDITIONAL TREES A MAXLEAFNODES ARGUMENT TO FIT GBM STYLE TREES A MONITOR FIT ARGUMENT TO INSPECT THE ESTIMATOR DURING TRAINING AND REFACTORING OF THE VERBOSE CODE BY PETER PRETTENHOFER
• FASTERSKLEARNENSEMBLEEXTRATREES BY CACHING FEATURE VALUES BY ARNAUD JOLY
• FASTER DEPTHBASED TREE BUILDING ALGORITHM SUCH AS DECISION TREE RANDOM FOREST EXTRA TREES OR GRADIENT TREE BOOSTING WITH DEPTH BASED GROWING STRATEGY BY AVOIDING TRYING TO SPLIT ON FOUND CONSTANT FEATURES IN THE SAMPLE SUBSET BY ARNAUD JOLY
• ADDMINWEIGHTFRACTIONLEAF PREPRUNING PARAMETER TO TREEBASED METHODS THE MINIMUM WEIGHTED FRACTION OF THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE BY NOEL DAWE
• ADDEDMETRICSPAIRWISEDISTANCESARGMINMIN BY PHILIPPE GERVAIS
• ADDED PREDICT METHOD TO CLUSTERAFFINITYPROPAGATION ANDCLUSTERMEANSHIFT BY MATHIEU BLONDEL
• VECTOR AND MATRIX MULTIPLICATIONS HAVE BEEN OPTIMISED THROUGHOUT THE LIBRARY BY DENIS ENGEMANN AND ALEXAN DRE GRAMFORT IN PARTICULAR THEY SHOULD TAKE LESS MEMORY WITH OLDER NUMPY VERSIONS PRIOR TO 172
• PRECISIONRECALL AND ROC EXAMPLES NOW USE TRAINTESTSPLIT AND HAVE MORE EXPLANATION OF WHY THESE METRICS ARE USEFUL BY KYLE KASTNER
• THE TRAINING ALGORITHM FOR DECOMPOSITIONNMF IS FASTER FOR SPARSE MATRICES AND HAS MUCH LOWER MEMORY COMPLEXITY MEANING IT WILL SCALE UP GRACEFULLY TO LARGE DATASETS BY LARS BUITINCK
• ADDED SVDMETHOD OPTION WITH DEFAULT VALUE TO “RANDOMIZED” TO DECOMPOSITIONFACTORANALYSIS TO SAVE MEMORY AND SIGNIFICANTLY SPEEDUP COMPUTATION BY DENIS ENGEMANN AND ALEXANDRE GRAMFORT
• CHANGED CROSSVALIDATIONSTRATIFIEDKFOLD TO TRY AND PRESERVE AS MUCH OF THE ORIGINAL ORDERING OF SAMPLES AS POSSIBLE SO AS NOT TO HIDE OVERFITTING ON DATASETS WITH A NONNEGLIGIBLE LEVEL OF SAMPLES DEPENDENCY BY DANIEL NOURI AND OLIVIER GRISEL
• ADD MULTIOUTPUT SUPPORT TO GAUSSIANPROCESSGAUSSIANPROCESS BY JOHN NOVAK
• SUPPORT FOR PRECOMPUTED DISTANCE MATRICES IN NEAREST NEIGHBOR ESTIMATORS BY ROBERT LAYTON AND JOEL NOTHMAN
• NORM COMPUTATIONS OPTIMIZED FOR NUMPY 16 AND LATER VERSIONS BY LARS BUITINCK IN PARTICULAR THE KMEANS ALGORITHM NO LONGER NEEDS A TEMPORARY DATA STRUCTURE THE SIZE OF ITS INPUT
•DUMMYDUMMYCLASSIFIER CAN NOW BE USED TO PREDICT A CONSTANT OUTPUT VALUE BY MANOJ KUMAR
•DUMMYDUMMYREGRESSOR HAS NOW A STRATEGY PARAMETER WHICH ALLOWS TO PREDICT THE MEAN THE MEDIAN OF THE TRAINING SET OR A CONSTANT OUTPUT VALUE BY MAHESHAKYA WIJEWARDENA
• MULTILABEL CLASSIFICATION OUTPUT IN MULTILABEL INDICATOR FORMAT IS NOW SUPPORTED BY METRICS ROCAUCSCORE ANDMETRICSAVERAGEPRECISIONSCORE BY ARNAUD JOLY
• SIGNIFICANT PERFORMANCE IMPROVEMENTS MORE THAN 100X SPEEDUP FOR LARGE PROBLEMS IN ISOTONIC ISOTONICREGRESSION BY ANDREW TULLOCH
• SPEED AND MEMORY USAGE IMPROVEMENTS TO THE SGD ALGORITHM FOR LINEAR MODELS IT NOW USES THREADS NOT SEPARATE PROCESSES WHEN NJOBS1 BY LARS BUITINCK

• GRID SEARCH AND CROSS VALIDATION ALLOW NANS IN THE INPUT ARRAYS SO THAT PREPROCESSORS SUCH AS PREPROCESSINGIMPUTER CAN BE TRAINED WITHIN THE CROSS VALIDATION LOOP AVOIDING POTENTIALLY SKEWED RESULTS
• RIDGE REGRESSION CAN NOW DEAL WITH SAMPLE WEIGHTS IN FEATURE SPACE ONLY SAMPLE SPACE UNTIL THEN BY MICHAEL EICKENBERG BOTH SOLUTIONS ARE PROVIDED BY THE CHOLESKY SOLVER
• SEVERAL CLASSIFICATION AND REGRESSION METRICS NOW SUPPORT WEIGHTED SAMPLES WITH THE NEW SAMPLEWEIGHT ARGUMENT METRICSACCURACYSCORE METRICSZEROONELOSS METRICSPRECISIONSCORE METRICSAVERAGEPRECISIONSCORE METRICS F1SCORE METRICSFBETASCORE METRICSRECALLSCORE METRICSROCAUCSCORE METRICSEXPLAINEDVARIANCESCORE METRICSMEANSQUAREDERROR METRICS MEANABSOLUTEERROR METRICSR2SCORE BY NOEL DAWE
• SPEED UP OF THE SAMPLE GENERATOR DATASETSMAKEMULTILABELCLASSIFICATION BY JOEL NOTHMAN

DOCUMENTATION IMPROVEMENTS

• THE WORKING WITH TEXT DATA TUTORIAL HAS NOW BEEN WORKED IN TO THE MAIN DOCUMENTATION'S TUTORIAL SECTION INCLUDES EXERCISES AND SKELETONS FOR TUTORIAL PRESENTATION ORIGINAL TUTORIAL CREATED BY SEVERAL AUTHORS INCLUDING OLIVIER GRISEL LARS BUITINCK AND MANY OTHERS TUTORIAL INTEGRATION INTO THE SCIKITLEARN DOCUMENTATION BY JAQUES GROBLER
• ADDED COMPUTATIONAL PERFORMANCE DOCUMENTATION DISCUSSION AND EXAMPLES OF PREDICTION LATENCY THROUGHPUT AND DIFFERENT FACTORS THAT HAVE INFLUENCE OVER SPEED ADDITIONAL TIPS FOR BUILDING FASTER MODELS AND CHOOSING A RELEVANT COMPROMISE BETWEEN SPEED AND PREDICTIVE POWER BY EUSTACHE DIEMERT

BUG FIXES

• FIXED BUG IN DECOMPOSITIONMINIBATCHDICTIONARYLEARNING PARTIALFIT WAS NOT WORKING PROPERLY
• FIXED BUG IN LINEARMODELSTOCHASTICGRADIENT L1RATIO WAS USED AS 10 L1RATIO

• FIXED BUG IN MULTICLASSONEVSONECLASSIFIER WITH STRING LABELS
• FIXED A BUG IN LASSOCV ANDELASTICNETCV THEY WOULD NOT PRECOMPUTE THE GRAM MATRIX WITH PRECOMPUTETRUE ORPRECOMPUTEAUTO ANDNSAMPLES NFEATURES BY MANOJ KUMAR
• FIXED INCORRECT ESTIMATION OF THE DEGREES OF FREEDOM IN FEATURESELECTIONFREGRESSION WHEN VARI ATES ARE NOT CENTERED BY VIRGILE FRITSCH
• FIXED A RACE CONDITION IN PARALLEL PROCESSING WITH PREDISPATCH ALL FOR INSTANCE IN CROSSVALSCORE BY OLIVIER GRISEL
• RAISE ERROR IN CLUSTERFEATUREAGGLOMERATION ANDCLUSTERWARDAGGLOMERATION WHEN NO SAMPLES ARE GIVEN RATHER THAN RETURNING MEANINGLESS CLUSTERING
• FIXED BUG IN GRADIENTBOOSTINGGRADIENTBOOSTINGREGRESSOR WITHLOSSHUBER GAMMA MIGHT HAVE NOT BEEN INITIALIZED
• FIXED FEATURE IMPORTANCES AS COMPUTED WITH A FOREST OF RANDOMIZED TREES WHEN FIT WITH SAMPLEWEIGHT NONE ANDOR WITH BOOTSTRAPTRUE BY GILLES LOUPPE

API CHANGES SUMMARY
•SKLEARNHMM IS DEPRECATED ITS REMOVAL IS PLANNED FOR THE 017 RELEASE
• USE OF COVARIANCEELLIPTICENVELOP HAS NOW BEEN REMOVED AFTER DEPRECATION PLEASE USE COVARIANCEELLIPTICENVELOPE INSTEAD
•CLUSTERWARD IS DEPRECATED USE CLUSTERAGGLOMERATIVECLUSTERING INSTEAD
•CLUSTERWARDCLUSTERING IS DEPRECATED USE
•CLUSTERAGGLOMERATIVECLUSTERING INSTEAD
•CROSSVALIDATIONBOOTSTRAP IS DEPRECATED CROSSVALIDATIONKFOLD OR CROSSVALIDATIONSHUFFLESPLIT ARE RECOMMENDED INSTEAD
• DIRECT SUPPORT FOR THE SEQUENCE OF SEQUENCES OR LIST OF LISTS MULTILABEL FORMAT IS DEPRECATED TO CONVERT TO AND FROM THE SUPPORTED BINARY INDICATOR MATRIX FORMAT USE MULTILABELBINARIZER BY JOEL NOTHMAN
• ADD SCORE METHOD TO PCA FOLLOWING THE MODEL OF PROBABILISTIC PCA AND DEPRECATE PROBABILISTICPCA MODEL WHOSE SCORE IMPLEMENTATION IS NOT CORRECT THE COMPUTATION NOW ALSO EXPLOITS THE MATRIX INVERSION LEMMA FOR FASTER COMPUTATION BY ALEXANDRE GRAMFORT
• THE SCORE METHOD OF FACTORANALYSIS NOW RETURNS THE AVERAGE LOGLIKELIHOOD OF THE SAMPLES USE SCORESAMPLES TO GET LOGLIKELIHOOD OF EACH SAMPLE BY ALEXANDRE GRAMFORT
• GENERATING BOOLEAN MASKS THE SETTING INDICESFALSE FROM CROSSVALIDATION GENERATORS IS DEPRECATED SUP PORT FOR MASKS WILL BE REMOVED IN 017 THE GENERATORS HAVE PRODUCED ARRAYS OF INDICES BY DEFAULT SINCE 010 BY JOEL NOTHMAN
• 1D ARRAYS CONTAINING STRINGS WITH DTYPEOBJECT AS USED IN PANDAS ARE NOW CONSIDERED VALID CLASSIFICATION TARGETS THIS FIXES A REGRESSION FROM VERSION 013 IN SOME CLASSIFIERS BY JOEL NOTHMAN
• FIX WRONG EXPLAINEDVARIANCERATIO ATTRIBUTE IN RANDOMIZEDPCA BY ALEXANDRE GRAMFORT
• FIT ALPHAS FOR EACH L1RATIO INSTEAD OF MEANL1RATIO INLINEARMODELELASTICNETCV AND LINEARMODELLASSOCV THIS CHANGES THE SHAPE OF ALPHAS FROMNALPHAS TONL1RATIO NALPHAS IF THEL1RATIO PROVIDED IS A 1D ARRAY LIKE OBJECT OF LENGTH GREATER THAN ONE BY MANOJ KUMAR
• FIXLINEARMODELELASTICNETCV ANDLINEARMODELLASSOCV WHEN FITTING INTERCEPT AND INPUT DATA IS SPARSE THE AUTOMATIC GRID OF ALPHAS WAS NOT COMPUTED CORRECTLY AND THE SCALING WITH NORMALIZE WAS WRONG BY MANOJ KUMAR
• FIX WRONG MAXIMAL NUMBER OF FEATURES DRAWN MAXFEATURES AT EACH SPLIT FOR DECISION TREES RANDOM FORESTS AND GRADIENT TREE BOOSTING PREVIOUSLY THE COUNT FOR THE NUMBER OF DRAWN FEATURES STARTED ONLY AFTER ONE NON CONSTANT FEATURES IN THE SPLIT THIS BUG FIX WILL AFFECT COMPUTATIONAL AND GENERALIZATION PERFORMANCE OF THOSE ALGORITHMS IN THE PRESENCE OF CONSTANT FEATURES TO GET BACK PREVIOUS GENERALIZATION PERFORMANCE YOU SHOULD MODIFY THE VALUE OF MAXFEATURES BY ARNAUD JOLY
• FIX WRONG MAXIMAL NUMBER OF FEATURES DRAWN MAXFEATURES AT EACH SPLIT FOR ENSEMBLE EXTRATREESCLASSIFIER ANDENSEMBLEEXTRATREESREGRESSOR PREVIOUSLY ONLY NON CONSTANT FEATURES IN THE SPLIT WAS COUNTED AS DRAWN NOW CONSTANT FEATURES ARE COUNTED AS DRAWN FURTHERMORE AT LEAST ONE FEATURE MUST BE NON CONSTANT IN ORDER TO MAKE A VALID SPLIT THIS BUG FIX WILL AFFECT COMPUTATIONAL AND GEN ERALIZATION PERFORMANCE OF EXTRA TREES IN THE PRESENCE OF CONSTANT FEATURES TO GET BACK PREVIOUS GENERALIZATION PERFORMANCE YOU SHOULD MODIFY THE VALUE OF MAXFEATURES BY ARNAUD JOLY
• FIXUTILSCOMPUTECLASSWEIGHT WHENCLASSWEIGHTAUTO PREVIOUSLY IT WAS BROKEN FOR INPUT OF NONINTEGER DTYPE AND THE WEIGHTED ARRAY THAT WAS RETURNED WAS WRONG BY MANOJ KUMAR
• FIXCROSSVALIDATIONBOOTSTRAP TO RETURNVALUEERROR WHENNTRAIN NTEST N BY RONALD PHLYPO

PEOPLE
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• 312 OLIVIER GRISEL
• 275 LARS BUITINCK
• 221 GAEL VAROQUAUX
• 148 ARNAUD JOLY
• 134 JOHANNES SCHÖNBERGER
• 119 GILLES LOUPPE
• 113 JOEL NOTHMAN
• 111 ALEXANDRE GRAMFORT
• 95 JAQUES GROBLER
• 89 DENIS ENGEMANN
• 83 PETER PRETTENHOFER
• 83 ALEXANDER FABISCH
• 62 MATHIEU BLONDEL
• 60 EUSTACHE DIEMERT
• 60 NELLE VAROQUAUX
• 49 MICHAEL BOMMARITO
• 45 MANOJKUMARS
• 28 KYLE KASTNER
• 26 ANDREAS MUELLER
• 22 NOEL DAWE
• 21 MAHESHAKYA WIJEWARDENA
• 21 BROOKE OSBORN
• 21 HAMZEH ALSALHI
• 21 JAKE VANDERPLAS
• 21 PHILIPPE GERVAIS
• 19 BALA SUBRAHMANYAM VARANASI
• 12 RONALD PHLYPO
• 10 MIKHAIL KOROBOV
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• 8 JEFFREY BLACKBURNE
• 8 ELTERMANN
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• 7 CJ CAREY

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• 3 JOHN COLLINS
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• 3 ERWIN MARSI
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• 2 LAURENT DIRER
• 2 ERIK SHILTS

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• 2 YOSHIKI VÁZQUEZ BAEZA
• 2 YUNG SIANG LIAU
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• 1 FABIAN PEDREGOSA
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• 1 STEPHAN HOYER
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• 1 VALENTIN HAENEL
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• 1 WILL MYERS
• 1 YAROSLAV HALCHENKO
• 1 YONI BENMESHULAM
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• 1 ALEX
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• 1 DZIKIE DRO ˙ZD˙ZE
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• 1 FRANÇOIS BOULOGNE
• 1 ALEXANDER MEASURE
• 1 ETHAN WHITE
• 1 GUILHERME TREIN
• 1 HENDRIK HEUER
• 1 IVICAJOVIC
• 1 JAN HENDRIK METZEN
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• 1 EDUARDO ARIÑO DE LA RUBIA
• 1 JELLE ZIJLSTRA
• 1 EDDY L O JANSSON
• 1 DENIS
• 1 JOHN
• 1 JOHN SCHMIDT
• 1 JORGE CAÑARDO ALASTUEY
• 1 JOSEPH PERLA
• 1 JOSHUA VREDEVOOGD
• 1 JOSÉ RICARDO
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• 1 KEMAL EREN
• 1 KENTA SATO
• 1 DAVID COURNAPEAU
• 1 KYLE KELLEY
• 1 DANIELE MEDRI
• 1 LAURENT LUCE

SCIKITLEARN USER GUIDE RELEASE 0213
• 1 LAURENT PIERRON
• 1 LUIS PEDRO COELHO
• 1 DANIELWEITZENFELD
• 1 CRAIG THOMPSON
• 1 CHYIKWEI YAU
• 1 MATTHEW BRETT
• 1 MATTHIAS FEURER
• 1 MAX LINKE
• 1 CHRIS FILO GORGOLEWSKI
• 1 CHARLES EARL
• 1 MICHAEL HANKE
• 1 MICHELE ORRÙ
• 1 BRYAN LUNT
• 1 BRIAN KEARNS
• 1 PAUL BUTLER
• 1 PAWEŁ MANDERA
• 1 PETER
• 1 ANDREW ASH
• 1 PIETRO ZAMBELLI
• 1 STAUBDA
11714 VERSION 014
AUGUST 7 2013
CHANGELOG
• MISSING VALUES WITH SPARSE AND DENSE MATRICES CAN BE IMPUTED WITH THE TRANSFORMER PREPROCESSING
IMPUTER BY NICOLAS TRÉSEGNIE
• THE CORE IMPLEMENTATION OF DECISIONS TREES HAS BEEN REWRITTEN FROM SCRATCH ALLOWING FOR FASTER TREE INDUCTION
AND LOWER MEMORY CONSUMPTION IN ALL TREEBASED ESTIMATORS BY GILLES LOUPPE
• ADDEDENSEMBLEADABOOSTCLASSIFIER ANDENSEMBLEADABOOSTREGRESSOR BY NOEL DAWE AND
GILLES LOUPPE SEE THE ADABOOST SECTION OF THE USER GUIDE FOR DETAILS AND EXAMPLES
• ADDEDGRIDSEARCHRANDOMIZEDSEARCHCV ANDGRIDSEARCHPARAMETERSAMPLER FOR RANDOM
IZED HYPERPARAMETER OPTIMIZATION BY ANDREAS MÜLLER
• ADDED BICLUSTERING ALGORITHMS SKLEARNCLUSTERBICLUSTERSPECTRALCOCLUSTERING AND
SKLEARNCLUSTERBICLUSTERSPECTRALBICLUSTERING DATA GENERATION METHODS SKLEARN
DATASETSMAKEBICLUSTERS ANDSKLEARNDATASETSMAKECHECKERBOARD AND SCORING MET
RICS SKLEARNMETRICSCONSENSUSSCORE BY KEMAL EREN
• ADDED RESTRICTED BOLTZMANN MACHINES NEURALNETWORKBERNOULLIRBM BY YANN DAUPHIN
110 CHAPTER 1 WELCOME TO SCIKITLEARN

• PYTHON 3 SUPPORT BY JUSTIN VINCENT LARS BUITINCK SUBHODEEP MOITRA AND OLIVIER GRISEL ALL TESTS NOW PASS UNDER PYTHON 33
• ABILITY TO PASS ONE PENALTY ALPHA VALUE PER TARGET IN LINEARMODELRIDGE BY EICKENBERG AND MATHIEU BLONDEL
• FIXEDSKLEARNLINEARMODELSTOCHASTICGRADIENTPY L2 REGULARIZATION ISSUE MINOR PRACTICAL SIGNIFICANCE BY NORBERT CROMBACH AND MATHIEU BLONDEL
• ADDED AN INTERACTIVE VERSION OF ANDREAS MÜLLER'S MACHINE LEARNING CHEAT SHEET FOR SCIKITLEARN TO THE DOCU MENTATION SEE CHOOSING THE RIGHT ESTIMATOR BY JAQUES GROBLER
•GRIDSEARCHGRIDSEARCHCV ANDCROSSVALIDATIONCROSSVALSCORE NOW SUPPORT THE USE OF ADVANCED SCORING FUNCTION SUCH AS AREA UNDER THE ROC CURVE AND FBETA SCORES SEE THE SCORING PARAMETER DEFINING MODEL EVALUATION RULES FOR DETAILS BY ANDREAS MÜLLER AND LARS BUITINCK PASSING A FUNCTION FROM SKLEARNMETRICS ASSCOREFUNC IS DEPRECATED
• MULTILABEL CLASSIFICATION OUTPUT IS NOW SUPPORTED BY METRICSACCURACYSCORE METRICSZEROONELOSS METRICSF1SCORE METRICSFBETASCORE METRICS CLASSIFICATIONREPORT METRICSPRECISIONSCORE ANDMETRICSRECALLSCORE BY ARNAUD JOLY
• TWO NEW METRICS METRICSHAMMINGLOSS ANDMETRICSJACCARDSIMILARITYSCORE ARE ADDED WITH MULTILABEL SUPPORT BY ARNAUD JOLY
• SPEED AND MEMORY USAGE IMPROVEMENTS IN FEATUREEXTRACTIONTEXTCOUNTVECTORIZER AND FEATUREEXTRACTIONTEXTTFIDFVECTORIZER BY JOCHEN WERSDÖRFER AND ROMAN SINAYEV
• THEMINDF PARAMETER IN FEATUREEXTRACTIONTEXTCOUNTVECTORIZER AND FEATUREEXTRACTIONTEXTTFIDFVECTORIZER WHICH USED TO BE 2 HAS BEEN RESET TO 1 TO AVOID UNPLEASANT SURPRISES EMPTY VOCABULARIES FOR NOVICE USERS WHO TRY IT OUT ON TINY DOCUMENT COLLECTIONS A VALUE OF AT LEAST 2 IS STILL RECOMMENDED FOR PRACTICAL USE
•SVMLINEARSVC LINEARMODELSGDCLASSIFIER ANDLINEARMODELSGDREGRESSOR NOW HAVE ASPARSIFY METHOD THAT CONVERTS THEIR COEF INTO A SPARSE MATRIX MEANING STORED MODELS TRAINED USING THESE ESTIMATORS CAN BE MADE MUCH MORE COMPACT
•LINEARMODELSGDCLASSIFIER NOW PRODUCES MULTICLASS PROBABILITY ESTIMATES WHEN TRAINED UNDER LOG LOSS OR MODIFIED HUBER LOSS
• HYPERLINKS TO DOCUMENTATION IN EXAMPLE CODE ON THE WEBSITE BY MARTIN LUESSI
• FIXED BUG IN PREPROCESSINGMINMAXSCALER CAUSING INCORRECT SCALING OF THE FEATURES FOR NONDEFAULT FEATURERANGE SETTINGS BY ANDREAS MÜLLER
•MAXFEATURES INTREEDECISIONTREECLASSIFIER TREEDECISIONTREEREGRESSOR AND ALL DERIVED ENSEMBLE ESTIMATORS NOW SUPPORTS PERCENTAGE VALUES BY GILLES LOUPPE
• PERFORMANCE IMPROVEMENTS IN ISOTONICISOTONICREGRESSION BY NELLE VAROQUAUX
•METRICSACCURACYSCORE HAS AN OPTION NORMALIZE TO RETURN THE FRACTION OR THE NUMBER OF CORRECTLY CLAS SIFIED SAMPLE BY ARNAUD JOLY
• ADDEDMETRICSLOGLOSS THAT COMPUTES LOG LOSS AKA CROSSENTROPY LOSS BY JOCHEN WERSDÖRFER AND LARS BUITINCK
• A BUG THAT CAUSED ENSEMBLEADABOOSTCLASSIFIER 'S TO OUTPUT INCORRECT PROBABILITIES HAS BEEN FIXED
• FEATURE SELECTORS NOW SHARE A MIXIN PROVIDING CONSISTENT TRANSFORM INVERSETRANSFORM AND GETSUPPORT METHODS BY JOEL NOTHMAN
• A FITTEDGRIDSEARCHGRIDSEARCHCV ORGRIDSEARCHRANDOMIZEDSEARCHCV CAN NOW GENERALLY BE PICKLED BY JOEL NOTHMAN

• REFACTORED AND VECTORIZED IMPLEMENTATION OF METRICSROCCURVE ANDMETRICS
PRECISIONRECALLCURVE BY JOEL NOTHMAN
• THE NEW ESTIMATOR SKLEARNDECOMPOSITIONTRUNCATEDSVD PERFORMS DIMENSIONALITY REDUCTION USING
SVD ON SPARSE MATRICES AND CAN BE USED FOR LATENT SEMANTIC ANALYSIS LSA BY LARS BUITINCK
• ADDED SELFCONTAINED EXAMPLE OF OUTOFCORE LEARNING ON TEXT DATA OUTOFCORE CLASSIFICATION OF TEXT DOCUMENTS
BY EUSTACHE DIEMERT
• THE DEFAULT NUMBER OF COMPONENTS FOR SKLEARNDECOMPOSITIONRANDOMIZEDPCA IS NOW CORRECTLY
DOCUMENTED TO BE NFEATURES THIS WAS THE DEFAULT BEHAVIOR SO PROGRAMS USING IT WILL CONTINUE TO WORK AS
THEY DID
•SKLEARNCLUSTERKMEANS NOW FITS SEVERAL ORDERS OF MAGNITUDE FASTER ON SPARSE DATA THE SPEEDUP DEPENDS
ON THE SPARSITY BY LARS BUITINCK
• REDUCE MEMORY FOOTPRINT OF FASTICA BY DENIS ENGEMANN AND ALEXANDRE GRAMFORT
• VERBOSE OUTPUT IN SKLEARNENSEMBLEGRADIENTBOOSTING NOW USES A COLUMN FORMAT AND PRINTS
PROGRESS IN DECREASING FREQUENCY IT ALSO SHOWS THE REMAINING TIME BY PETER PRETTENHOFER
•SKLEARNENSEMBLEGRADIENTBOOSTING PROVIDES OUTOFBAG IMPROVEMENT OOBIMPROVEMENT
RATHER THAN THE OOB SCORE FOR MODEL SELECTION AN EXAMPLE THAT SHOWS HOW TO USE OOB ESTIMATES TO SELECT THE
NUMBER OF TREES WAS ADDED BY PETER PRETTENHOFER
• MOST METRICS NOW SUPPORT STRING LABELS FOR MULTICLASS CLASSIFICATION BY ARNAUD JOLY AND LARS BUITINCK
• NEW ORTHOGONALMATCHINGPURSUITCV CLASS BY ALEXANDRE GRAMFORT AND VLAD NICULAE
• FIXED A BUG IN SKLEARNCOVARIANCEGRAPHLASSOCV THE ‘ALPHAS’ PARAMETER NOW WORKS AS EXPECTED
WHEN GIVEN A LIST OF VALUES BY PHILIPPE GERVAIS
• FIXED AN IMPORTANT BUG IN SKLEARNCOVARIANCEGRAPHLASSOCV THAT PREVENTED ALL FOLDS PROVIDED BY
A CV OBJECT TO BE USED ONLY THE FIRST 3 WERE USED WHEN PROVIDING A CV OBJECT EXECUTION TIME MAY THUS
INCREASE SIGNIFICANTLY COMPARED TO THE PREVIOUS VERSION BUG RESULTS ARE CORRECT NOW BY PHILIPPE GERVAIS
•CROSSVALIDATIONCROSSVALSCORE AND THEGRIDSEARCH MODULE IS NOW TESTED WITH MULTI
OUTPUT DATA BY ARNAUD JOLY
•DATASETSMAKEMULTILABELCLASSIFICATION CAN NOW RETURN THE OUTPUT IN LABEL INDICATOR MULTIL
ABEL FORMAT BY ARNAUD JOLY
• KNEAREST NEIGHBORS NEIGHBORSKNEIGHBORSREGRESSOR ANDNEIGHBORS
RADIUSNEIGHBORSREGRESSOR AND RADIUS NEIGHBORS NEIGHBORSRADIUSNEIGHBORSREGRESSOR
ANDNEIGHBORSRADIUSNEIGHBORSCLASSIFIER SUPPORT MULTIOUTPUT DATA BY ARNAUD JOLY
• RANDOM STATE IN LIBSVMBASED ESTIMATORS SVMSVC NUSVC ONECLASSSVM SVMSVR SVMNUSVR
CAN NOW BE CONTROLLED THIS IS USEFUL TO ENSURE CONSISTENCY IN THE PROBABILITY ESTIMATES FOR THE CLASSIFIERS TRAINED
WITHPROBABILITYTRUE BY VLAD NICULAE
• OUTOFCORE LEARNING SUPPORT FOR DISCRETE NAIVE BAYES CLASSIFIERS SKLEARNNAIVEBAYES
MULTINOMIALNB ANDSKLEARNNAIVEBAYESBERNOULLINB BY ADDING THE PARTIALFIT
METHOD BY OLIVIER GRISEL
• NEW WEBSITE DESIGN AND NAVIGATION BY GILLES LOUPPE NELLE VAROQUAUX VINCENT MICHEL AND ANDREAS MÜLLER
• IMPROVED DOCUMENTATION ON MULTICLASS MULTILABEL AND MULTIOUTPUT CLASSIFICATION BY YANNICK SCHWARTZ AND
ARNAUD JOLY
• BETTER INPUT AND ERROR HANDLING IN THE METRICS MODULE BY ARNAUD JOLY AND JOEL NOTHMAN
• SPEED OPTIMIZATION OF THE HMM MODULE BY MIKHAIL KOROBOV
• SIGNIFICANT SPEED IMPROVEMENTS FOR SKLEARNCLUSTERDBSCAN BY CLEVERLESS

API CHANGES SUMMARY
• THEAUCSCORE WAS RENAMED ROCAUCSCORE
• TESTING SCIKITLEARN WITH SKLEARNTEST IS DEPRECATED USE NOSETESTS SKLEARN FROM THE COMMAND LINE
• FEATURE IMPORTANCES IN TREEDECISIONTREECLASSIFIER TREEDECISIONTREEREGRESSOR AND ALL DERIVED ENSEMBLE ESTIMATORS ARE NOW COMPUTED ON THE FLY WHEN ACCESSING THE FEATUREIMPORTANCES ATTRIBUTE SETTING COMPUTEIMPORTANCESTRUE IS NO LONGER REQUIRED BY GILLES LOUPPE
•LINEARMODELLASSOPATH ANDLINEARMODELENETPATH CAN RETURN ITS RESULTS IN THE SAME FORMAT AS THAT OFLINEARMODELLARSPATH THIS IS DONE BY SETTING THE RETURNMODELS PARAMETER TO FALSE BY JAQUES GROBLER AND ALEXANDRE GRAMFORT
•GRIDSEARCHITERGRID WAS RENAMED TO GRIDSEARCHPARAMETERGRID
• FIXED BUG IN KFOLD CAUSING IMPERFECT CLASS BALANCE IN SOME CASES BY ALEXANDRE GRAMFORT AND TADEJ JANEŽ
•SKLEARNNEIGHBORSBALLTREE HAS BEEN REFACTORED AND A SKLEARNNEIGHBORSKDTREE HAS BEEN ADDED WHICH SHARES THE SAME INTERFACE THE BALL TREE NOW WORKS WITH A WIDE VARIETY OF DISTANCE METRICS BOTH CLASSES HAVE MANY NEW METHODS INCLUDING SINGLETREE AND DUALTREE QUERIES BREADTHFIRST AND DEPTHFIRST SEARCHING AND MORE ADVANCED QUERIES SUCH AS KERNEL DENSITY ESTIMATION AND 2POINT CORRELATION FUNCTIONS BY JAKE VANDERPLAS
• SUPPORT FOR SCIPYSPATIALCKDTREE WITHIN NEIGHBORS QUERIES HAS BEEN REMOVED AND THE FUNCTIONALITY REPLACED WITH THE NEW KDTREE CLASS
•SKLEARNNEIGHBORSKERNELDENSITY HAS BEEN ADDED WHICH PERFORMS EFFICIENT KERNEL DENSITY ESTIMATION WITH A VARIETY OF KERNELS
•SKLEARNDECOMPOSITIONKERNELPCA NOW ALWAYS RETURNS OUTPUT WITH NCOMPONENTS COMPONENTS UNLESS THE NEW PARAMETER REMOVEZEROEIG IS SET TOTRUE THIS NEW BEHAVIOR IS CONSISTENT WITH THE WAY KERNEL PCA WAS ALWAYS DOCUMENTED PREVIOUSLY THE REMOVAL OF COMPONENTS WITH ZERO EIGENVALUES WAS TACITLY PERFORMED ON ALL DATA
•GCVMODEAUTO NO LONGER TRIES TO PERFORM SVD ON A DENSIFIED SPARSE MATRIX IN SKLEARN LINEARMODELRIDGECV
• SPARSE MATRIX SUPPORT IN SKLEARNDECOMPOSITIONRANDOMIZEDPCA IS NOW DEPRECATED IN FAVOR OF THE NEWTRUNCATEDSVD
•CROSSVALIDATIONKFOLD ANDCROSSVALIDATIONSTRATIFIEDKFOLD NOW ENFORCE NFOLDS 2 OTHERWISE A VALUEERROR IS RAISED BY OLIVIER GRISEL
•DATASETSLOADFILES ’SCHARSET ANDCHARSETERRORS PARAMETERS WERE RENAMED ENCODING AND DECODEERRORS
• ATTRIBUTE OOBSCORE INSKLEARNENSEMBLEGRADIENTBOOSTINGREGRESSOR AND SKLEARNENSEMBLEGRADIENTBOOSTINGCLASSIFIER IS DEPRECATED AND HAS BEEN REPLACED BY OOBIMPROVEMENT
• ATTRIBUTES IN ORTHOGONALMATCHINGPURSUIT HAVE BEEN DEPRECATED COPYX GRAM AND PRECOMPUTEGRAM RENAMED PRECOMPUTE FOR CONSISTENCY SEE 2224
•SKLEARNPREPROCESSINGSTANDARDSCALER NOW CONVERTS INTEGER INPUT TO FLOAT AND RAISES A WARNING PREVIOUSLY IT ROUNDED FOR DENSE INTEGER INPUT
•SKLEARNMULTICLASSONEVSRESTCLASSIFIER NOW HAS A DECISIONFUNCTION METHOD THIS WILL RETURN THE DISTANCE OF EACH SAMPLE FROM THE DECISION BOUNDARY FOR EACH CLASS AS LONG AS THE UNDERLYING ESTIMATORS IMPLEMENT THE DECISIONFUNCTION METHOD BY KYLE KASTNER
• BETTER INPUT VALIDATION WARNING ON UNEXPECTED SHAPES FOR Y

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• 109 GAEL VAROQUAUX
• 107 OLIVIER GRISEL
• 102 NOEL DAWE
• 99 KEMAL EREN
• 79 JOEL NOTHMAN
• 75 JAKE VANDERPLAS
• 73 NELLE VAROQUAUX
• 71 VLAD NICULAE
• 65 PETER PRETTENHOFER
• 64 ALEXANDRE GRAMFORT
• 54 MATHIEU BLONDEL
• 38 NICOLAS TRÉSEGNIE
• 35 EUSTACHE
• 27 DENIS ENGEMANN
• 25 YANN N DAUPHIN
• 19 JUSTIN VINCENT
• 17 ROBERT LAYTON
• 15 DOUG COLEMAN
• 14 MICHAEL EICKENBERG
• 13 ROBERT MARCHMAN
• 11 FABIAN PEDREGOSA
• 11 PHILIPPE GERVAIS
• 10 JIM HOLMSTRÖM
• 10 TADEJ JANEŽ
• 10 SYHW
• 9 MIKHAIL KOROBOV
• 9 STEVEN DE GRYZE
• 8 SERGEYF
• 7 BEN ROOT

• 7 HRISHIKESH HUILGOLKAR
• 6 KYLE KASTNER
• 6 MARTIN LUESSI
• 6 ROB SPEER
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• 5 RAUL GARRETA
• 5 ROB ZINKOV
• 4 KEN GEIS
• 3 A FLAXMAN
• 3 DENTON COCKBURN
• 3 DOUGAL SUTHERLAND
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• 1 ABHIJEET KOLHE
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• 1 FAZLUL SHAHRIAR
• 1 FELIX BROCKHERDE
• 1 FÉLIXANTOINE FORTIN
• 1 HARIKRISHNAN S
• 1 JACK HALE
• 1 JAKEMICK
• 1 JAMES MCDERMOTT
• 1 JOHN BENEDIKTSSON
• 1 JOHN ZWINCK

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• 1 JUSTIN PATI
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• 1 KYLE KELLEY
• 1 MATTHIAS EKMAN
• 1 MIROSLAV SHUBERNETSKIY
• 1 NAOKI ORII
• 1 NORBERT CROMBACH
• 1 RAFAEL CUNHA DE ALMEIDA
• 1 ROLANDO ESPINOZA LA FUENTE
• 1 SEAMUS ABSHERE
• 1 SERGEY FELDMAN
• 1 SERGIO MEDINA
• 1 STEFANO LATTARINI
• 1 STEVE KOCH
• 1 STURLA MOLDEN
• 1 THOMAS JAROSCH
• 1 YAROSLAV HALCHENKO

11715 VERSION 0131

FEBRUARY 23 2013

THE 0131 RELEASE ONLY FIXES SOME BUGS AND DOES NOT ADD ANY NEW FUNCTIONALITY

CHANGELOG

• FIXED A TESTING ERROR CAUSED BY THE FUNCTION CROSSVALIDATIONTRAINTESTSPLIT BEING INTERPRETED AS A TEST BY YAROSLAV HALCHENKO
• FIXED A BUG IN THE REASSIGNMENT OF SMALL CLUSTERS IN THE CLUSTERMINIBATCHKMEANS BY GAEL VAROQUAUX
• FIXED DEFAULT VALUE OF GAMMA INDECOMPOSITIONKERNELPCA BY LARS BUITINCK
• UPDATED JOBLIB TO 070D BY GAEL VAROQUAUX
• FIXED SCALING OF THE DEVIANCE IN ENSEMBLEGRADIENTBOOSTINGCLASSIFIER BY PETER PRETTENHOFER
• BETTER TIEBREAKING IN MULTICLASSONEVSONECLASSIFIER BY ANDREAS MÜLLER
• OTHER SMALL IMPROVEMENTS TO TESTS AND DOCUMENTATION

SCIKITLEARN USER GUIDE RELEASE 0213

PEOPLE

LIST OF CONTRIBUTORS FOR RELEASE 0131 BY NUMBER OF COMMITS

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- 3 PETER PRETTENHOFER
- 2 HRISHIKESH HUILGOLKAR
- 1 BASTIAAN VAN DEN BERG
- 1 DIEGO MOLLA
- 1 GILLES LOUPPE
- 1 MATHIEU BLONDEL
- 1 NELLE VAROQUAUX
- 1 RAFAEL CUNHA DE ALMEIDA
- 1 ROLANDO ESPINOZA LA FUENTE
- 1 VLAD NICULAE
- 1 YAROSLAV HALCHENKO

11716 VERSION 013

JANUARY 21 2013

NEW ESTIMATOR CLASSES

•DUMMYDUMMYCLASSIFIER ANDDUMMYDUMMYREGRESSOR TWO DATAINDEPENDENT PREDICTORS BY MATHIEU BLONDEL USEFUL TO SANITYCHECK YOUR ESTIMATORS SEE DUMMY ESTIMATORS IN THE USER GUIDE MULTIOUTPUT SUPPORT ADDED BY ARNAUD JOLY

•DECOMPOSITIONFACTORANALYSIS A TRANSFORMER IMPLEMENTING THE CLASSICAL FACTOR ANALYSIS BY CHRISTIAN OSENDORFER AND ALEXANDRE GRAMFORT SEE FACTOR ANALYSIS IN THE USER GUIDE

•FEATUREEXTRACTIONFEATUREHASHER A TRANSFORMER IMPLEMENTING THE “HASHING TRICK” FOR FAST LOWMEMORY FEATURE EXTRACTION FROM STRING FIELDS BY LARS BUITINCK AND FEATUREEXTRACTIONTEXT HASHINGVECTORIZER FOR TEXT DOCUMENTS BY OLIVIER GRISEL SEE FEATURE HASHING ANDVECTORIZING A LARGE TEXT CORPUS WITH THE HASHING TRICK FOR THE DOCUMENTATION AND SAMPLE USAGE

•PIPELINEFEATUREUNION A TRANSFORMER THAT CONCATENATES RESULTS OF SEVERAL OTHER TRANSFORMERS BY ANDREAS MÜLLER SEE FEATUREUNION COMPOSITE FEATURE SPACES IN THE USER GUIDE

•RANDOMPROJECTIONGAUSSIANRANDOMPROJECTION RANDOMPROJECTION SPARSERANDOMPROJECTION AND THE FUNCTION RANDOMPROJECTION JOHNSONLINDENSTRAUSSMINDIM THE FIRST TWO ARE TRANSFORMERS IMPLEMENTING GAUSSIAN AND SPARSE RANDOM PROJECTION MATRIX BY OLIVIER GRISEL AND ARNAUD JOLY SEE RANDOM PROJECTION IN THE USER GUIDE

•KERNELAPPROXIMATIONNYSTROEM A TRANSFORMER FOR APPROXIMATING ARBITRARY KERNELS BY ANDREAS MÜLLER SEE NYSTROEM METHOD FOR KERNEL APPROXIMATION IN THE USER GUIDE

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•PREPROCESSINGONEHOTENCODER A TRANSFORMER THAT COMPUTES BINARY ENCODINGS OF CATEGORICAL FEATURES
BY ANDREAS MÜLLER SEE ENCODING CATEGORICAL FEATURES IN THE USER GUIDE
•LINEARMODELPASSIVEAGGRESSIVECLASSIFIER AND LINEARMODEL
PASSIVEAGGRESSIVEREGRESSOR PREDICTORS IMPLEMENTING AN EFFICIENT STOCHASTIC OPTIMIZATION FOR
LINEAR MODELS BY ROB ZINKOV AND MATHIEU BLONDEL SEE PASSIVE AGGRESSIVE ALGORITHMS IN THE USER GUIDE
•ENSEMBLERANDOMTREESEMBEDDING A TRANSFORMER FOR CREATING HIGHDIMENSIONAL SPARSE REPRESENTATIONS
USING ENSEMBLES OF TOTALLY RANDOM TREES BY ANDREAS MÜLLER SEE TOTALLY RANDOM TREES EMBEDDING IN THE USER
GUIDE
•MANIFOLDSPECTRALEMBEDDING AND FUNCTION MANIFOLDSPECTRALEMBEDDING IMPLEMENTING
THE “LAPLACIAN EIGENMAPS” TRANSFORMATION FOR NONLINEAR DIMENSIONALITY REDUCTION BY WEI LI SEE SPECTRAL
EMBEDDING IN THE USER GUIDE
•ISOTONICISOTONICREGRESSION BY FABIAN PEDREGOSA ALEXANDRE GRAMFORT AND NELLE VAROQUAUX
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•TREEDECISIONTREECLASSIFIER AND ALL DERIVED ENSEMBLE MODELS NOW SUPPORT SAMPLE WEIGHTING BY
NOEL DAWE AND GILLES LOUPPE
• SPEEDUP IMPROVEMENT WHEN USING BOOTSTRAP SAMPLES IN FORESTS OF RANDOMIZED TREES BY PETER PRETTENHOFER AND
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• PARTIAL DEPENDENCE PLOTS FOR GRADIENT TREE BOOSTING INENSEMBLE
PARTIALDEPENDENCEPARTIALDEPENDENCE BY PETER PRETTENHOFER SEE
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• THE TABLE OF CONTENTS ON THE WEBSITE HAS NOW BEEN MADE EXPANDABLE BY JAQUES GROBLER
•FEATURESELECTIONSELECTPERCENTILE NOW BREAKS TIES DETERMINISTICALLY INSTEAD OF RETURNING ALL
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•FEATURESELECTIONSELECTKBEST ANDFEATURESELECTIONSELECTPERCENTILE ARE MORE
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SOMETIMES SELECT DIFFERENT FEATURES THAN THEY DID PREVIOUSLY
• RIDGE REGRESSION AND RIDGE CLASSIFICATION FITTING WITH SPARSECG SOLVER NO LONGER HAS QUADRATIC MEMORY COM
PLEXITY BY LARS BUITINCK AND FABIAN PEDREGOSA
• RIDGE REGRESSION AND RIDGE CLASSIFICATION NOW SUPPORT A NEW FAST SOLVER CALLED LSQR BY MATHIEU BLONDEL
• SPEED UP OF METRICSPRECISIONRECALLCURVE BY CONRAD LEE
• ADDED SUPPORT FOR READINGWRITING SVMLIGHT FILES WITH PAIRWISE PREFERENCE ATTRIBUTE QID IN SVMLIGHT FILE FORMAT
INDATASETSDUMPSVMLIGHTFILE ANDDATASETSLOADSVMLIGHTFILE BY FABIAN PEDREGOSA
• FASTER AND MORE ROBUST METRICSCONFUSIONMATRIX ANDCLUSTERING PERFORMANCE EVALUATION BY WEI LI
•CROSSVALIDATIONCROSSVALSCORE NOW WORKS WITH PRECOMPUTED KERNELS AND AFFINITY MATRICES BY
ANDREAS MÜLLER
• LARS ALGORITHM MADE MORE NUMERICALLY STABLE WITH HEURISTICS TO DROP REGRESSORS TOO CORRELATED AS WELL AS TO
STOP THE PATH WHEN NUMERICAL NOISE BECOMES PREDOMINANT BY GAEL VAROQUAUX
• FASTER IMPLEMENTATION OF METRICSPRECISIONRECALLCURVE BY CONRAD LEE
• NEW KERNEL METRICSCHI2KERNEL BY ANDREAS MÜLLER OFTEN USED IN COMPUTER VISION APPLICATIONS

• FIX OF LONGSTANDING BUG IN NAIVEBAYESBERNOULLINB FIXED BY SHAUN JACKMAN
• IMPLEMENTED PREDICTPROBA INMULTICLASSONEVSRESTCLASSIFIER BY ANDREW WINTERMAN
• IMPROVE CONSISTENCY IN GRADIENT BOOSTING ESTIMATORS ENSEMBLEGRADIENTBOOSTINGREGRESSOR AND ENSEMBLEGRADIENTBOOSTINGCLASSIFIER USE THE ESTIMATOR TREEDECISIONTREEREGRESSOR INSTEAD OF THE TREETREETREE DATA STRUCTURE BY ARNAUD JOLY
• FIXED A FLOATING POINT EXCEPTION IN THE DECISION TREES MODULE BY SEBERG
• FIXMETRICSROCCURVE FAILS WHEN YTRUE HAS ONLY ONE CLASS BY WEI LI
• ADD THE METRICSMEANABSOLUTEERROR FUNCTION WHICH COMPUTES THE MEAN ABSOLUTE ERROR THE METRICSMEANSQUAREDERROR METRICSMEANABSOLUTEERROR ANDMETRICSR2SCORE METRICS SUPPORT MULTIOUTPUT BY ARNAUD JOLY
• FIXEDCLASSWEIGHT SUPPORT INSVMLINEARSVC ANDLINEARMODELLOGISTICREGRESSION BY ANDREAS MÜLLER THE MEANING OF CLASSWEIGHT WAS REVERSED AS ERRONEOUSLY HIGHER WEIGHT MEANT LESS POSITIVES OF A GIVEN CLASS IN EARLIER RELEASES
• IMPROVE NARRATIVE DOCUMENTATION AND CONSISTENCY IN SKLEARNMETRICS FOR REGRESSION AND CLASSIFICATION METRICS BY ARNAUD JOLY
• FIXED A BUG IN SKLEARNSVMSVC WHEN USING CSRMATRICES WITH UNSORTED INDICES BY XINFAN MENG AND AN DREAS MÜLLER
•MINIBATCHKMEANS ADD RANDOM REASSIGNMENT OF CLUSTER CENTERS WITH LITTLE OBSERVATIONS ATTACHED TO THEM BY GAEL VAROQUAUX

API CHANGES SUMMARY

• RENAMED ALL OCCURRENCES OF NATOMS TONCOMPONENTS FOR CONSISTENCY THIS APPLIES TO DECOMPOSITIONDICTIONARYLEARNING DECOMPOSITION MINIBATCHDICTIONARYLEARNING DECOMPOSITIONDICTLEARNING DECOMPOSITION DICTLEARNINGONLINE
• RENAMED ALL OCCURRENCES OF MAXITERS TOMAXITER FOR CONSISTENCY THIS APPLIES TO SEMISUPERVISEDLABELPROPAGATION ANDSEMISUPERVISEDLABELPROPAGATION LABELSPREADING
• RENAMED ALL OCCURRENCES OF LEARNRATE TOLEARNINGRATE FOR CONSISTENCY IN ENSEMBLE BASEGRADIENTBOOSTING ANDENSEMBLEGRADIENTBOOSTINGREGRESSOR
• THE MODULE SKLEARNLINEARMODELSPARSE IS GONE SPARSE MATRIX SUPPORT WAS ALREADY INTEGRATED INTO THE “REGULAR” LINEAR MODELS
•SKLEARNMETRICSMEANSQUAREERROR WHICH INCORRECTLY RETURNED THE ACCUMULATED ERROR WAS RE MOVED USE MEANSQUAREDERROR INSTEAD
• PASSINGCLASSWEIGHT PARAMETERS TO FIT METHODS IS NO LONGER SUPPORTED PASS THEM TO ESTIMATOR CONSTRUC TORS INSTEAD
• GMMS NO LONGER HAVE DECODE ANDRVS METHODS USE THE SCORE PREDICT ORSAMPLE METHODS INSTEAD
• THESOLVER FIT OPTION IN RIDGE REGRESSION AND CLASSIFICATION IS NOW DEPRECATED AND WILL BE REMOVED IN V014 USE THE CONSTRUCTOR OPTION INSTEAD
•FEATUREEXTRACTIONTEXTDICTVECTORIZER NOW RETURNS SPARSE MATRICES IN THE CSR FORMAT IN STEAD OF COO
• RENAMED KINCROSSVALIDATIONKFOLD ANDCROSSVALIDATIONSTRATIFIEDKFOLD TO NFOLDS RENAMEDNBOOTSTRAPS TONITER INCROSSVALIDATIONBOOTSTRAP

• RENAMED ALL OCCURRENCES OF NITERATIONS TONITER FOR CONSISTENCY THIS APPLIES TO CROSSVALIDATIONSHUFFLESPLIT CROSSVALIDATIONSTRATIFIEDSHUFFLESPLIT UTILSRANDOMIZEDRANGEFINDER ANDUTILSRANDOMIZEDSVD
• REPLACED RHO INLINEARMODELELASTICNET ANDLINEARMODELSGDCLASSIFIER BY L1RATIO THERHO PARAMETER HAD DIFFERENT MEANINGS L1RATIO WAS INTRODUCED TO AVOID CONFU SION IT HAS THE SAME MEANING AS PREVIOUSLY RHO INLINEARMODELELASTICNET AND1RHO IN LINEARMODELSGDCLASSIFIER
•LINEARMODELLASSOLARS ANDLINEARMODELLARS NOW STORE A LIST OF PATHS IN THE CASE OF MULTIPLE TARGETS RATHER THAN AN ARRAY OF PATHS
• THE ATTRIBUTE GMM OFHMMGMMHMM WAS RENAMED TO GMM TO ADHERE MORE STRICTLY WITH THE API
•CLUSTERSPECTRALEMBEDDING WAS MOVED TO MANIFOLDSPECTRALEMBEDDING
• RENAMED EIGTOL INMANIFOLDSPECTRALEMBEDDING CLUSTERSPECTRALCLUSTERING TO EIGENTOL RENAMEDMODE TOEIGENSOLVER
• RENAMED MODE INMANIFOLDSPECTRALEMBEDDING ANDCLUSTERSPECTRALCLUSTERING TO EIGENSOLVER
•CLASSES ANDNCLASSES ATTRIBUTES OF TREEDECISIONTREECLASSIFIER AND ALL DERIVED ENSEMBLE MODELS ARE NOW FLAT IN CASE OF SINGLE OUTPUT PROBLEMS AND NESTED IN CASE OF MULTIOUTPUT PROBLEMS
• THEESTIMATORS ATTRIBUTE OF ENSEMBLEGRADIENTBOOSTINGGRADIENTBOOSTINGREGRESSOR ANDENSEMBLEGRADIENTBOOSTINGGRADIENTBOOSTINGCLASSIFIER IS NOW AN ARRAY OF CLASS'TREEDECISIONTREEREGRESSOR'
• RENAMED CHUNKSIZE TOBATCHSIZE INDECOMPOSITIONMINIBATCHDICTIONARYLEARNING ANDDECOMPOSITIONMINIBATCHSPARSEPCA FOR CONSISTENCY
•SVMSVC ANDSVMNUSVC NOW PROVIDE A CLASSES ATTRIBUTE AND SUPPORT ARBITRARY DTYPES FOR LABELS Y ALSO THE DTYPE RETURNED BY PREDICT NOW REFLECTS THE DTYPE OF YDURINGFIT USED TO BE NPFLOAT
• CHANGED DEFAULT TESTSIZE IN CROSSVALIDATIONTRAINTESTSPLIT TO NONE ADDED POS SIBILITY TO INFER TESTSIZE FROMTRAINSIZE INCROSSVALIDATIONSHUFFLESPLIT AND CROSSVALIDATIONSTRATIFIEDSHUFFLESPLIT
• RENAMED FUNCTION SKLEARNMETRICSZEROONE TOSKLEARNMETRICSZEROONELOSS BE AWARE THAT THE DEFAULT BEHAVIOR IN SKLEARNMETRICSZEROONELOSS IS DIFFERENT FROM SKLEARN METRICSZEROONE NORMALIZEFALSE IS CHANGED TO NORMALIZETRUE
• RENAMED FUNCTION METRICSZEROONESCORE TOMETRICSACCURACYSCORE
•DATASETSMAKECIRCLES NOW HAS THE SAME NUMBER OF INNER AND OUTER POINTS
• IN THE NAIVE BAYES CLASSIFIERS THE CLASSPRIOR PARAMETER WAS MOVED FROM FIT TOINIT

PEOPLE

LIST OF CONTRIBUTORS FOR RELEASE 013 BY NUMBER OF COMMITS
• 364 ANDREAS MÜLLER
• 143 ARNAUD JOLY
• 137 PETER PRETTENHOFER
• 131 GAEL VAROQUAUX
• 117 MATHIEU BLONDEL
• 108 LARS BUITINCK

• 106 WEI LI
• 101 OLIVIER GRISEL
• 65 VLAD NICULAE
• 54 GILLES LOUPPE
• 40 JAQUES GROBLER
• 38 ALEXANDRE GRAMFORT
• 30 ROB ZINKOV
• 19 AYMERIC MASURELLE
• 18 ANDREW WINTERMAN
• 17 FABIAN PEDREGOSA
• 17 NELLE VAROQUAUX
• 16 CHRISTIAN OSENDORFER
• 14 DANIEL NOURI
• 13 VIRGILE FRITSCH
• 13 SYHW
• 12 SATRAJIT GHOSH
• 10 COREY LYNCH
• 10 KYLE BEAUCHAMP
• 9 BRIAN CHEUNG
• 9 IMMANUEL BAYER
• 9 MRSHU
• 8 CONRAD LEE
• 8 JAMES BERGSTRA
• 7 TADEJ JANEŽ
• 6 BRIAN CAJES
• 6 JAKE VANDERPLAS
• 6 MICHAEL
• 6 NOEL DAWE
• 6 TIAGO NUNES
• 6 COW
• 5 ANZE
• 5 SHIQIAO DU
• 4 CHRISTIAN JAUVIN
• 4 JACQUES KVAM
• 4 RICHARD T GUY
• 4 ROBERT LAYTON

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SCIKITLEARN USER GUIDE RELEASE 0213
• 3 ALEXANDRE ABRAHAM
• 3 DOUG COLEMAN
• 3 SCOTT DICKERSON
• 2 APPROXIMATEIDENTITY
• 2 JOHN BENEDIKTSSON
• 2 MARK VERONDA
• 2 MATTI LYRA
• 2 MIKHAIL KOROBOV
• 2 XINFAN MENG
• 1 ALEJANDRO WEINSTEIN
• 1 ALEXANDRE PASSOS
• 1 CHRISTOPH DEIL
• 1 EUGENE NIZHIBITSKY
• 1 KENNETH C ARNOLD
• 1 LUIS PEDRO COELHO
• 1 MIROSLAV BATCHKAROV
• 1 PAVEL
• 1 SEBASTIAN BERG
• 1 SHAUN JACKMAN
• 1 SUBHODEEP MOITRA
• 1 BOB
• 1 DENGEMANN
• 1 EMANUELE
• 1 X006

11717 VERSION 0121

OCTOBER 8 2012

THE 0121 RELEASE IS A BUGFIX RELEASE WITH NO ADDITIONAL FEATURES BUT IS INSTEAD A SET OF BUG FIXES

CHANGELOG

• IMPROVED NUMERICAL STABILITY IN SPECTRAL EMBEDDING BY GAEL VAROQUAUX
• DOCTEST UNDER WINDOWS 64BIT BY GAEL VAROQUAUX
• DOCUMENTATION FIXES FOR ELASTIC NET BY ANDREAS MÜLLER AND ALEXANDRE GRAMFORT
• PROPER BEHAVIOR WITH FORTRANORDERED NUMPY ARRAYS BY GAEL VAROQUAUX
• MAKE GRIDSEARCHCV WORK WITH NONCSR SPARSE MATRIX BY LARS BUITINCK
• FIX PARALLEL COMPUTING IN MDS BY GAEL VAROQUAUX

SCIKITLEARN USER GUIDE RELEASE 0213
• FIX UNICODE SUPPORT IN COUNT VECTORIZER BY ANDREAS MÜLLER
• FIX MINCOVDET BREAKING WITH XSHAPE 3 1 BY VIRGILE FRITSCH
• FIX CLONE OF SGD OBJECTS BY PETER PRETTENHOFER
• STABILIZE GMM BY VIRGILE FRITSCH
PEOPLE
• 14 PETER PRETTENHOFER
• 12 GAEL VAROQUAUX
• 10 ANDREAS MÜLLER
• 5 LARS BUITINCK
• 3 VIRGILE FRITSCH
• 1 ALEXANDRE GRAMFORT
• 1 GILLES LOUPPE
• 1 MATHIEU BLONDEL
11718 VERSION 012
SEPTEMBER 4 2012
CHANGELOG
• VARIOUS SPEED IMPROVEMENTS OF THE DECISION TREES MODULE BY GILLES LOUPPE
•ENSEMBLEGRADIENTBOOSTINGREGRESSOR ANDENSEMBLEGRADIENTBOOSTINGCLASSIFIER
NOW SUPPORT FEATURE SUBSAMPLING VIA THE MAXFEATURES ARGUMENT BY PETER PRETTENHOFER
• ADDED HUBER AND QUANTILE LOSS FUNCTIONS TO ENSEMBLEGRADIENTBOOSTINGREGRESSOR BY PETER PRET
TENHOFER
•DECISION TREES ANDFORESTS OF RANDOMIZED TREES NOW SUPPORT MULTIOUTPUT CLASSIFICATION AND REGRESSION PROBLEMS
BY GILLES LOUPPE
• ADDEDPREPROCESSINGLABELENCODER A SIMPLE UTILITY CLASS TO NORMALIZE LABELS OR TRANSFORM NON
NUMERICAL LABELS BY MATHIEU BLONDEL
• ADDED THE EPSILONINSENSITIVE LOSS AND THE ABILITY TO MAKE PROBABILISTIC PREDICTIONS WITH THE MODIFIED HUBER LOSS
INSTOCHASTIC GRADIENT DESCENT BY MATHIEU BLONDEL
• ADDED MULTIDIMENSIONAL SCALING MDS BY NELLE VAROQUAUX
• SVMLIGHT FILE FORMAT LOADER NOW DETECTS COMPRESSED GZIPBZIP2 FILES AND DECOMPRESSES THEM ON THE FLY BY
LARS BUITINCK
• SVMLIGHT FILE FORMAT SERIALIZER NOW PRESERVES DOUBLE PRECISION FLOATING POINT VALUES BY OLIVIER GRISEL
• A COMMON TESTING FRAMEWORK FOR ALL ESTIMATORS WAS ADDED BY ANDREAS MÜLLER
• UNDERSTANDABLE ERROR MESSAGES FOR ESTIMATORS THAT DO NOT ACCEPT SPARSE INPUT BY GAEL VAROQUAUX
• SPEEDUPS IN HIERARCHICAL CLUSTERING BY GAEL VAROQUAUX IN PARTICULAR BUILDING THE TREE NOW SUPPORTS EARLY
STOPPING THIS IS USEFUL WHEN THE NUMBER OF CLUSTERS IS NOT SMALL COMPARED TO THE NUMBER OF SAMPLES

• ADD MULTITASKLASSO AND MULTITASKELASTICNET FOR JOINT FEATURE SELECTION BY ALEXANDRE GRAMFORT
• ADDEDMETRICSAUCSCORE ANDMETRICSAVERAGEPRECISIONSCORE CONVENIENCE FUNCTIONS BY ANDREAS MÜLLER
• IMPROVED SPARSE MATRIX SUPPORT IN THE FEATURE SELECTION MODULE BY ANDREAS MÜLLER
• NEW WORD BOUNDARIESAWARE CHARACTER NGRAM ANALYZER FOR THE TEXT FEATURE EXTRACTION MODULE BY KERNC
• FIXED BUG IN SPECTRAL CLUSTERING THAT LED TO SINGLE POINT CLUSTERS BY ANDREAS MÜLLER
• INFEATUREEXTRACTIONTEXTCOUNTVECTORIZER ADDED AN OPTION TO IGNORE INFREQUENT WORDS MINDF BY ANDREAS MÜLLER
• ADD SUPPORT FOR MULTIPLE TARGETS IN SOME LINEAR MODELS ELASTICNET LASSO AND ORTHOGONALMATCHINGPURSUIT BY VLAD NICULAE AND ALEXANDRE GRAMFORT
• FIXES INDECOMPOSITIONPROBABILISTICPCA SCORE FUNCTION BY WEI LI
• FIXED FEATURE IMPORTANCE COMPUTATION IN GRADIENT TREE BOOSTING

API CHANGES SUMMARY

• THE OLDSCIKITSLEARN PACKAGE HAS DISAPPEARED ALL CODE SHOULD IMPORT FROM SKLEARN INSTEAD WHICH WAS INTRODUCED IN 09
• INMETRICSROCCURVE THETHRESHOLDS ARRAY IS NOW RETURNED WITH IT'S ORDER REVERSED IN ORDER TO KEEP IT CONSISTENT WITH THE ORDER OF THE RETURNED FPR ANDTPR
• INHMM OBJECTS LIKE HMMGAUSSIANHMM HMMMULTINOMIALHMM ETC ALL PARAMETERS MUST BE PASSED TO THE OBJECT WHEN INITIALISING IT AND NOT THROUGH FIT NOWFIT WILL ONLY ACCEPT THE DATA AS AN INPUT PARAMETER
• FOR ALL SVM CLASSES A FAULTY BEHAVIOR OF GAMMA WAS FIXED PREVIOUSLY THE DEFAULT GAMMA VALUE WAS ONLY COMPUTED THE FIRST TIME FIT WAS CALLED AND THEN STORED IT IS NOW RECALCULATED ON EVERY CALL TO FIT
• ALLBASE CLASSES ARE NOW ABSTRACT META CLASSES SO THAT THEY CAN NOT BE INSTANTIATED
•CLUSTERWARDTREE NOW ALSO RETURNS THE PARENT ARRAY THIS IS NECESSARY FOR EARLYSTOPPING IN WHICH CASE THE TREE IS NOT COMPLETELY BUILT
• INFEATUREEXTRACTIONTEXTCOUNTVECTORIZER THE PARAMETERS MINN ANDMAXN WERE JOINED TO THE PARAMETER NGRAMRANGE TO ENABLE GRIDSEARCHING BOTH AT ONCE
• INFEATUREEXTRACTIONTEXTCOUNTVECTORIZER WORDS THAT APPEAR ONLY IN ONE DOCUMENT ARE NOW IGNORED BY DEFAULT TO REPRODUCE THE PREVIOUS BEHAVIOR SET MINDF1
• FIXED API INCONSISTENCY LINEARMODELSGDCLASSIFIERPREDICTPROBA NOW RETURNS 2D ARRAY WHEN FIT ON TWO CLASSES
• FIXED API INCONSISTENCY DISCRIMINANTANALYSISQUADRATICDISCRIMINANTANALYSIS DECISIONFUNCTION ANDDISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS DECISIONFUNCTION NOW RETURN 1D ARRAYS WHEN FIT ON TWO CLASSES
• GRID OF ALPHAS USED FOR FITTING LINEARMODELLASSOCV ANDLINEARMODELELASTICNETCV IS NOW STORED IN THE ATTRIBUTE ALPHAS RATHER THAN OVERRIDING THE INIT PARAMETER ALPHAS
• LINEAR MODELS WHEN ALPHA IS ESTIMATED BY CROSSVALIDATION STORE THE ESTIMATED VALUE IN THE ALPHA ATTRIBUTE RATHER THAN JUST ALPHA ORBESTALPHA
•ENSEMBLEGRADIENTBOOSTINGCLASSIFIER NOW SUPPORTS ENSEMBLE GRADIENTBOOSTINGCLASSIFIERSTAGEDPREDICTPROBA AND ENSEMBLE GRADIENTBOOSTINGCLASSIFIERSTAGEDPREDICT

•SVMSPARSESVC AND OTHER SPARSE SVM CLASSES ARE NOW DEPRECATED THE ALL CLASSES IN THE SUPPORT VECTOR MACHINES MODULE NOW AUTOMATICALLY SELECT THE SPARSE OR DENSE REPRESENTATION BASE ON THE INPUT
• ALL CLUSTERING ALGORITHMS NOW INTERPRET THE ARRAY XGIVEN TOFIT AS INPUT DATA IN PARTICULAR CLUSTER SPECTRALCLUSTERING ANDCLUSTERAFFINITYPROPAGATION WHICH PREVIOUSLY EXPECTED AFFINITY MA TRICES
• FOR CLUSTERING ALGORITHMS THAT TAKE THE DESIRED NUMBER OF CLUSTERS AS A PARAMETER THIS PARAMETER IS NOW CALLED NCLUSTERS
PEOPLE
• 267 ANDREAS MÜLLER
• 94 GILLES LOUPPE
• 89 GAEL VAROQUAUX
• 79 PETER PRETTENHOFER
• 60 MATHIEU BLONDEL
• 57 ALEXANDRE GRAMFORT
• 52 VLAD NICULAE
• 45 LARS BUITINCK
• 44 NELLE VAROQUAUX
• 37 JAQUES GROBLER
• 30 ALEXIS MIGNON
• 30 IMMANUEL BAYER
• 27 OLIVIER GRISEL
• 16 SUBHODEEP MOITRA
• 13 YANNICK SCHWARTZ
• 12 KERNC
• 11 VIRGILE FRITSCH
• 9 DANIEL DUCKWORTH
• 9 FABIAN PEDREGOSA
• 9 ROBERT LAYTON
• 8 JOHN BENEDIKTSSON
• 7 MARKO BURJEK
• 5 NICOLAS PINTO
• 4 ALEXANDRE ABRAHAM
• 4 JAKE VANDERPLAS
• 3 BRIAN HOLT
• 3 EDOUARD DUCHESNAY
• 3 FLORIAN HOENIG

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• 3 FLYINGIMMIDEV
• 2 FRANCOIS SAVARD
• 2 HANNES SCHULZ
• 2 PETER WELINDER
• 2 YAROSLAV HALCHENKO
• 2 WEI LI
• 1 ALEX COMPANIONI
• 1 BRANDYN A WHITE
• 1 BUSSONNIER MATTHIAS
• 1 CHARLESPIERRE ASTOLFI
• 1 DAN O'HUIGINN
• 1 DAVID COURNAPEAU
• 1 KEITH GOODMAN
• 1 LUDWIG SCHWARDT
• 1 OLIVIER HERVIEU
• 1 SERGIO MEDINA
• 1 SHIQIAO DU
• 1 TIM SHEERMANCHASE
• 1 BUGUEN
11719 VERSION 011
MAY 7 2012
CHANGELOG
HIGHLIGHTS
• GRADIENT BOOSTED REGRESSION TREES GRADIENT TREE BOOSTING FOR CLASSIFICATION AND REGRESSION BY PETER PRETTEN
HOFER AND SCOTT WHITE
• SIMPLE DICTBASED FEATURE LOADER WITH SUPPORT FOR CATEGORICAL VARIABLES FEATUREEXTRACTION
DICTVECTORIZER BY LARS BUITINCK
• ADDED MATTHEWS CORRELATION COEFFICIENT METRICSMATTHEWSCORRCOEF AND ADDED MACRO AND MICRO AV
ERAGE OPTIONS TO METRICSPRECISIONSCORE METRICSRECALLSCORE ANDMETRICSF1SCORE
BY SATRAJIT GHOSH
•OUT OF BAG ESTIMATES OF GENERALIZATION ERROR FOR ENSEMBLE METHODS BY ANDREAS MÜLLER
• RANDOMIZED SPARSE LINEAR MODELS FOR FEATURE SELECTION BY ALEXANDRE GRAMFORT AND GAEL VAROQUAUX
•LABEL PROPAGATION FOR SEMISUPERVISED LEARNING BY CLAY WOOLAM NOTE THE SEMISUPERVISED API IS STILL WORK
IN PROGRESS AND MAY CHANGE

• ADDED BICAIC MODEL SELECTION TO CLASSICAL GAUSSIAN MIXTURE MODELS AND UNIFIED THE API WITH THE REMAINDER OF SCIKITLEARN BY BERTRAND THIRION
• ADDEDSKLEARNCROSSVALIDATIONSTRATIFIEDSHUFFLESPLIT WHICH IS A SKLEARN CROSSVALIDATIONSHUFFLESPLIT WITH BALANCED SPLITS BY YANNICK SCHWARTZ
•SKLEARNNEIGHBORSNEARESTCENTROID CLASSIFIER ADDED ALONG WITH A SHRINKTHRESHOLD PARAM ETER WHICH IMPLEMENTS SHRUNKEN CENTROID CLASSIFICATION BY ROBERT LAYTON

OTHER CHANGES

• MERGED DENSE AND SPARSE IMPLEMENTATIONS OF STOCHASTIC GRADIENT DESCENT MODULE AND EXPOSED UTILITY EXTENSION TYPES FOR SEQUENTIAL DATASETS SEQDATASET AND WEIGHT VECTORS WEIGHTVECTOR BY PETER PRETTENHOFER
• ADDEDPARTIALFIT SUPPORT FOR ONLINEMINIBATCH LEARNING AND WARMSTART TO THE STOCHASTIC GRADIENT DE SCENT MODULE BY MATHIEU BLONDEL
• DENSE AND SPARSE IMPLEMENTATIONS OF SUPPORT VECTOR MACHINES CLASSES AND LINEARMODEL LOGISTICREGRESSION MERGED BY LARS BUITINCK
• REGRESSORS CAN NOW BE USED AS BASE ESTIMATOR IN THE MULTICLASS AND MULTILABEL ALGORITHMS MODULE BY MATHIEU BLONDEL
• ADDED NJOBS OPTION TO METRICSPAIRWISEPAIRWISEDISTANCES ANDMETRICSPAIRWISE PAIRWISEKERNELS FOR PARALLEL COMPUTATION BY MATHIEU BLONDEL
•KMEANS CAN NOW BE RUN IN PARALLEL USING THE NJOBS ARGUMENT TO EITHER KMEANS ORKMEANS BY ROBERT LAYTON
• IMPROVED CROSSVALIDATION EVALUATING ESTIMATOR PERFORMANCE ANDTUNING THE HYPERPARAMETERS OF AN ESTIMA TORDOCUMENTATION AND INTRODUCED THE NEW CROSSVALIDATIONTRAINTESTSPLIT HELPER FUNCTION BY OLIVIER GRISEL
•SVMSVC MEMBERSCOEF ANDINTERCEPT CHANGED SIGN FOR CONSISTENCY WITH DECISIONFUNCTION FORKERNELLINEAR COEF WAS FIXED IN THE ONEVSONE CASE BY ANDREAS MÜLLER
• PERFORMANCE IMPROVEMENTS TO EFFICIENT LEAVEONEOUT CROSSVALIDATED RIDGE REGRESSION ESP FOR THE NSAMPLES NFEATURES CASE INLINEARMODELRIDGECV BY REUBEN FLETCHERCOSTIN
• REFACTORING AND SIMPLIFICATION OF THE TEXT FEATURE EXTRACTION API AND FIXED A BUG THAT CAUSED POSSIBLE NEGATIVE IDF BY OLIVIER GRISEL
• BEAM PRUNING OPTION IN BASEHMM MODULE HAS BEEN REMOVED SINCE IT IS DIFFICULT TO CYTHONIZE IF YOU ARE INTERESTED IN CONTRIBUTING A CYTHON VERSION YOU CAN USE THE PYTHON VERSION IN THE GIT HISTORY AS A REFERENCE
• CLASSES IN NEAREST NEIGHBORS NOW SUPPORT ARBITRARY MINKOWSKI METRIC FOR NEAREST NEIGHBORS SEARCHES THE METRIC CAN BE SPECIFIED BY ARGUMENT P

API CHANGES SUMMARY

•COVARIANCEELLIPTICENVELOP IS NOW DEPRECATED PLEASE USE COVARIANCEELLIPTICENVELOPE INSTEAD
•NEIGHBORSCLASSIFIER ANDNEIGHBORSREGRESSOR ARE GONE IN THE MODULE NEAREST NEIGHBORS USE THE CLASSES KNEIGHBORSCLASSIFIER RADIUSNEIGHBORSCLASSIFIER KNEIGHBORSREGRESSOR ANDORRADIUSNEIGHBORSREGRESSOR INSTEAD
• SPARSE CLASSES IN THE STOCHASTIC GRADIENT DESCENT MODULE ARE NOW DEPRECATED

• INMIXTUREGMM MIXTUREDPGMM ANDMIXTUREVBGMM PARAMETERS MUST BE PASSED TO AN OBJECT WHEN INITIALISING IT AND NOT THROUGH FIT NOWFIT WILL ONLY ACCEPT THE DATA AS AN INPUT PARAMETER
• METHODS RVS ANDDECODE INGMM MODULE ARE NOW DEPRECATED SAMPLE ANDSCORE ORPREDICT SHOULD BE USED INSTEAD
• ATTRIBUTESCORES ANDPVALUES IN UNIVARIATE FEATURE SELECTION OBJECTS ARE NOW DEPRECATED SCORES OR PVALUES SHOULD BE USED INSTEAD
• INLOGISTICREGRESSION LINEARSVC SVC ANDNUSVC THECLASSWEIGHT PARAMETER IS NOW AN INI TIALIZATION PARAMETER NOT A PARAMETER TO FIT THIS MAKES GRID SEARCHES OVER THIS PARAMETER POSSIBLE
• LFWDATA IS NOW ALWAYS SHAPE NSAMPLES NFEATURES TO BE CONSISTENT WITH THE OLIVETTI FACES DATASET USE IMAGES ANDPAIRS ATTRIBUTE TO ACCESS THE NATURAL IMAGES SHAPES INSTEAD
• INSVMLINEARSVC THE MEANING OF THE MULTICLASS PARAMETER CHANGED OPTIONS NOW ARE OVR AND CRAMMERSINGER WITHOVR BEING THE DEFAULT THIS DOES NOT CHANGE THE DEFAULT BEHAVIOR BUT HOPEFULLY IS LESS CONFUSING
• CLASS FEATURESELECTIONTEXTVECTORIZER IS DEPRECATED AND REPLACED BY FEATURESELECTIONTEXTTFIDFVECTORIZER
• THE PREPROCESSOR ANALYZER NESTED STRUCTURE FOR TEXT FEATURE EXTRACTION HAS BEEN REMOVED ALL THOSE FEATURES ARE NOW DIRECTLY PASSED AS FLAT CONSTRUCTOR ARGUMENTS TO FEATURESELECTIONTEXTTFIDFVECTORIZER ANDFEATURESELECTIONTEXTCOUNTVECTORIZER IN PARTICULAR THE FOLLOWING PARAMETERS ARE NOW USED
•ANALYZER CAN BEWORD ORCHAR TO SWITCH THE DEFAULT ANALYSIS SCHEME OR USE A SPECIFIC PYTHON CALLABLE AS PREVIOUSLY
•TOKENIZER ANDPREPROCESSOR HAVE BEEN INTRODUCED TO MAKE IT STILL POSSIBLE TO CUSTOMIZE THOSE STEPS WITH THE NEW API
•INPUT EXPLICITLY CONTROL HOW TO INTERPRET THE SEQUENCE PASSED TO FIT ANDPREDICT FILENAMES FILE OBJECTS OR DIRECT BYTE OR UNICODE STRINGS
• CHARSET DECODING IS EXPLICIT AND STRICT BY DEFAULT
• THEVOCABULARY FITTED OR NOT IS NOW STORED IN THE VOCABULARY ATTRIBUTE TO BE CONSISTENT WITH THE PROJECT CONVENTIONS
• CLASS FEATURESELECTIONTEXTTFIDFVECTORIZER NOW DERIVES DIRECTLY FROM FEATURESELECTIONTEXTCOUNTVECTORIZER TO MAKE GRID SEARCH TRIVIAL
• METHODSRVS INBASEHMM MODULE ARE NOW DEPRECATED SAMPLE SHOULD BE USED INSTEAD
• BEAM PRUNING OPTION IN BASEHMM MODULE IS REMOVED SINCE IT IS DIFFICULT TO BE CYTHONIZED IF YOU ARE INTER ESTED YOU CAN LOOK IN THE HISTORY CODES BY GIT
• THE SVMLIGHT FORMAT LOADER NOW SUPPORTS FILES WITH BOTH ZEROBASED AND ONEBASED COLUMN INDICES SINCE BOTH OCCUR “IN THE WILD”
• ARGUMENTS IN CLASS SHUFFLESPLIT ARE NOW CONSISTENT WITH STRATIFIEDSHUFFLESPLIT ARGUMENTS TESTFRACTION ANDTRAINFRACTION ARE DEPRECATED AND RENAMED TO TESTSIZE ANDTRAINSIZE AND CAN ACCEPT BOTH FLOAT ANDINT
• ARGUMENTS IN CLASS BOOTSTRAP ARE NOW CONSISTENT WITH STRATIFIEDSHUFFLESPLIT ARGUMENTS NTEST ANDNTRAIN ARE DEPRECATED AND RENAMED TO TESTSIZE ANDTRAINSIZE AND CAN ACCEPT BOTH FLOAT ANDINT
• ARGUMENT PADDED TO CLASSES IN NEAREST NEIGHBORS TO SPECIFY AN ARBITRARY MINKOWSKI METRIC FOR NEAREST NEIGH BORS SEARCHES

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PEOPLE
• 282 ANDREAS MÜLLER
• 239 PETER PRETTENHOFER
• 198 GAEL VAROQUAUX
• 129 OLIVIER GRISEL
• 114 MATHIEU BLONDEL
• 103 CLAY WOOLAM
• 96 LARS BUITINCK
• 88 JAQUES GROBLER
• 82 ALEXANDRE GRAMFORT
• 50 BERTRAND THIRION
• 42 ROBERT LAYTON
• 28 FLYINGIMMIDEV
• 26 JAKE VANDERPLAS
• 26 SHIQIAO DU
• 21 SATRAJIT GHOSH
• 17 DAVID MAREK
• 17 GILLES LOUPPE
• 14 VLAD NICULAE
• 11 YANNICK SCHWARTZ
• 10 FABIAN PEDREGOSA
• 9 FCOSTIN
• 7 NICK WILSON
• 5 ADRIEN GAIDON
• 5 NICOLAS PINTO
• 4 DAVID WARDEFARLEY
• 5 NELLE VAROQUAUX
• 5 EMMANUELLE GOUILLART
• 3 JOONAS SILLANPÄÄ
• 3 PAOLO LOSI
• 2 CHARLES MCCARTHY
• 2 ROY HYUNJIN HAN
• 2 SCOTT WHITE
• 2 IBAYER
• 1 BRANDYN WHITE
• 1 CARLOS SCHEIDEGGER

SCIKITLEARN USER GUIDE RELEASE 0213
• 1 CLAIRE REVILLET
• 1 CONRAD LEE
• 1 EDOUARD DUCHESNAY
• 1 JAN HENDRIK METZEN
• 1 MENG XINFAN
• 1 ROB ZINKOV
• 1 SHIQIAO
• 1 UDI WEINSBERG
• 1 VIRGILE FRITSCH
• 1 XINFAN MENG
• 1 YAROSLAV HALCHENKO
• 1 JANSOE
• 1 LEON PALAFOX
11720 VERSION 010
JANUARY 11 2012
CHANGELOG
• PYTHON 25 COMPATIBILITY WAS DROPPED THE MINIMUM PYTHON VERSION NEEDED TO USE SCIKITLEARN IS NOW 26
•SPARSE INVERSE COVARIANCE ESTIMATION USING THE GRAPH LASSO WITH ASSOCIATED CROSSVALIDATED ESTIMATOR BY GAEL VAROQUAUX
• NEW TREE MODULE BY BRIAN HOLT PETER PRETTENHOFER SATRAJIT GHOSH AND GILLES LOUPPE THE MODULE COMES WITH COMPLETE DOCUMENTATION AND EXAMPLES
• FIXED A BUG IN THE RFE MODULE BY GILLES LOUPPE ISSUE 378
• FIXED A MEMORY LEAK IN SUPPORT VECTOR MACHINES MODULE BY BRIAN HOLT ISSUE 367
• FASTER TESTS BY FABIAN PEDREGOSA AND OTHERS
• SILHOUETTE COEFFICIENT CLUSTER ANALYSIS EVALUATION METRIC ADDED AS SKLEARNMETRICS SILHOUETTESCORE BY ROBERT LAYTON
• FIXED A BUG IN KMEANS IN THE HANDLING OF THE NINIT PARAMETER THE CLUSTERING ALGORITHM USED TO BE RUN NINIT TIMES BUT THE LAST SOLUTION WAS RETAINED INSTEAD OF THE BEST SOLUTION BY OLIVIER GRISEL
• MINOR REFACTORING IN STOCHASTIC GRADIENT DESCENT MODULE CONSOLIDATED DENSE AND SPARSE PREDICT METHODS EN HANCED TEST TIME PERFORMANCE BY CONVERTING MODEL PARAMETERS TO FORTRANSTYLE ARRAYS AFTER FITTING ONLY MULTI CLASS
• ADJUSTED MUTUAL INFORMATION METRIC ADDED AS SKLEARNMETRICSADJUSTEDMUTUALINFOSCORE BY ROBERT LAYTON
• MODELS LIKE SVCSVRLINEARSVCLOGISTICREGRESSION FROM LIBSVMLIBLINEAR NOW SUPPORT SCALING OF C REGULAR IZATION PARAMETER BY THE NUMBER OF SAMPLES BY ALEXANDRE GRAMFORT
• NEW ENSEMBLE METHODS MODULE BY GILLES LOUPPE AND BRIAN HOLT THE MODULE COMES WITH THE RANDOM FOREST ALGORITHM AND THE EXTRATREES METHOD ALONG WITH DOCUMENTATION AND EXAMPLES

•NOVELTY AND OUTLIER DETECTION OUTLIER AND NOVELTY DETECTION BY VIRGILE FRITSCH
•KERNEL APPROXIMATION A TRANSFORM IMPLEMENTING KERNEL APPROXIMATION FOR FAST SGD ON NONLINEAR KERNELS BY ANDREAS MÜLLER
• FIXED A BUG DUE TO ATOM SWAPPING IN ORTHOGONAL MATCHING PURSUIT OMP BY VLAD NICULAE
•SPARSE CODING WITH A PRECOMPUTED DICTIONARY BY VLAD NICULAE
•MINI BATCH KMEANS PERFORMANCE IMPROVEMENTS BY OLIVIER GRISEL
•KMEANS SUPPORT FOR SPARSE MATRICES BY MATHIEU BLONDEL
• IMPROVED DOCUMENTATION FOR DEVELOPERS AND FOR THE SKLEARNUTILS MODULE BY JAKE VANDERPLAS
• VECTORIZED 20NEWSGROUPS DATASET LOADER SKLEARNDATASETSFETCH20NEWSGROUPSVECTORIZED BY MATHIEU BLONDEL
•MULTICLASS AND MULTILABEL ALGORITHMS BY LARS BUITINCK
• UTILITIES FOR FAST COMPUTATION OF MEAN AND VARIANCE FOR SPARSE MATRICES BY MATHIEU BLONDEL
• MAKESKLEARNPREPROCESSINGSCALE ANDSKLEARNPREPROCESSINGSCALER WORK ON SPARSE MATRICES BY OLIVIER GRISEL
• FEATURE IMPORTANCES USING DECISION TREES ANDOR FOREST OF TREES BY GILLES LOUPPE
• PARALLEL IMPLEMENTATION OF FORESTS OF RANDOMIZED TREES BY GILLES LOUPPE
•SKLEARNCROSSVALIDATIONSHUFFLESPLIT CAN SUBSAMPLE THE TRAIN SETS AS WELL AS THE TEST SETS BY OLIVIER GRISEL
• ERRORS IN THE BUILD OF THE DOCUMENTATION FIXED BY ANDREAS MÜLLER

API CHANGES SUMMARY

HERE ARE THE CODE MIGRATION INSTRUCTIONS WHEN UPGRADING FROM SCIKITLEARN VERSION 09
• SOME ESTIMATORS THAT MAY OVERWRITE THEIR INPUTS TO SAVE MEMORY PREVIOUSLY HAD OVERWRITE PARAMETERS THESE HAVE BEEN REPLACED WITH COPY PARAMETERS WITH EXACTLY THE OPPOSITE MEANING
THIS PARTICULARLY AFFECTS SOME OF THE ESTIMATORS IN LINEARMODEL THE DEFAULT BEHAVIOR IS STILL TO COPY EVERYTHING PASSED IN
• THE SVMLIGHT DATASET LOADER SKLEARNDATASETSLOADSVMLIGHTFILE NO LONGER SUPPORTS LOADING TWO FILES AT ONCE USE LOADSVMLIGHTFILES INSTEAD ALSO THE UNUSED BUFFERMB PARAMETER IS GONE
• SPARSE ESTIMATORS IN THE STOCHASTIC GRADIENT DESCENT MODULE USE DENSE PARAMETER VECTOR COEF INSTEAD OF SPARSECOEF THIS SIGNIFICANTLY IMPROVES TEST TIME PERFORMANCE
• THE COVARIANCE ESTIMATION MODULE NOW HAS A ROBUST ESTIMATOR OF COVARIANCE THE MINIMUM COVARIANCE DETER MINANT ESTIMATOR
• CLUSTER EVALUATION METRICS IN METRICSCLUSTER HAVE BEEN REFACTORED BUT THE CHANGES ARE BACKWARDS COMPAT IBLE THEY HAVE BEEN MOVED TO THE METRICSCLUSTERSUPERVISED ALONG WITH METRICSCLUSTER UNSUPERVISED WHICH CONTAINS THE SILHOUETTE COEFFICIENT
• THEPERMUTATIONTESTSCORE FUNCTION NOW BEHAVES THE SAME WAY AS CROSSVALSCORE IE USES THE MEAN SCORE ACROSS THE FOLDS
• CROSS VALIDATION GENERATORS NOW USE INTEGER INDICES INDICESTRUE BY DEFAULT INSTEAD OF BOOLEAN MASKS THIS MAKE IT MORE INTUITIVE TO USE WITH SPARSE MATRIX DATA

• THE FUNCTIONS USED FOR SPARSE CODING SPARSEENCODE ANDSPARSEENCODEPARALLEL HAVE BEEN COM
BINED INTOSKLEARNDECOMPOSITIONSPARSEENCODE AND THE SHAPES OF THE ARRAYS HAVE BEEN TRANS
POSED FOR CONSISTENCY WITH THE MATRIX FACTORIZATION SETTING AS OPPOSED TO THE REGRESSION SETTING
• FIXED AN OFFBYONE ERROR IN THE SVMLIGHTLIBSVM FILE FORMAT HANDLING FILES GENERATED USING SKLEARN
DATASETSDUMPSVMLIGHTFILE SHOULD BE REGENERATED THEY SHOULD CONTINUE TO WORK BUT ACCIDEN
TALLY HAD ONE EXTRA COLUMN OF ZEROS PREPENDED
•BASEDICTIONARYLEARNING CLASS REPLACED BY SPARSECODINGMIXIN
•SKLEARNUTILSEXTMATHFASTSVD HAS BEEN RENAMED SKLEARNUTILSEXTMATH
RANDOMIZEDSVD AND THE DEFAULT OVERSAMPLING IS NOW FIXED TO 10 ADDITIONAL RANDOM VECTORS INSTEAD
OF DOUBLING THE NUMBER OF COMPONENTS TO EXTRACT THE NEW BEHAVIOR FOLLOWS THE REFERENCE PAPER
PEOPLE
THE FOLLOWING PEOPLE CONTRIBUTED TO SCIKITLEARN SINCE LAST RELEASE
• 246 ANDREAS MÜLLER
• 242 OLIVIER GRISEL
• 220 GILLES LOUPPE
• 183 BRIAN HOLT
• 166 GAEL VAROQUAUX
• 144 LARS BUITINCK
• 73 VLAD NICULAE
• 65 PETER PRETTENHOFER
• 64 FABIAN PEDREGOSA
• 60 ROBERT LAYTON
• 55 MATHIEU BLONDEL
• 52 JAKE VANDERPLAS
• 44 NOEL DAWE
• 38 ALEXANDRE GRAMFORT
• 24 VIRGILE FRITSCH
• 23 SATRAJIT GHOSH
• 3 JAN HENDRIK METZEN
• 3 KENNETH C ARNOLD
• 3 SHIQIAO DU
• 3 TIM SHEERMANCHASE
• 3 YAROSLAV HALCHENKO
• 2 BALA SUBRAHMANYAM VARANASI
• 2 DRAXUS
• 2 MICHAEL EICKENBERG
• 1 BOGDAN TRACH

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• 1 FÉLIXANTOINE FORTIN
• 1 JUAN MANUEL CAICEDO CARVAJAL
• 1 NELLE VAROQUAUX
• 1 NICOLAS PINTO
• 1 TIZIANO ZITO
• 1 XINFAN MENG
11721 VERSION 09
SEPTEMBER 21 2011
SCIKITLEARN 09 WAS RELEASED ON SEPTEMBER 2011 THREE MONTHS AFTER THE 08 RELEASE AND INCLUDES THE NEW MODULES MANIFOLD LEARNING THE DIRICHLET PROCESS AS WELL AS SEVERAL NEW ALGORITHMS AND DOCUMENTATION IMPROVEMENTS THIS RELEASE ALSO INCLUDES THE DICTIONARYLEARNING WORK DEVELOPED BY VLAD NICULAE AS PART OF THE GOOGLE SUMMER OF CODE PROGRAM
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CHANGELOG
• NEW MANIFOLD LEARNING MODULE BY JAKE VANDERPLAS AND FABIAN PEDREGOSA
• NEW DIRICHLET PROCESS GAUSSIAN MIXTURE MODEL BY ALEXANDRE PASSOS

•NEAREST NEIGHBORS MODULE REFACTORING BY JAKE VANDERPLAS GENERAL REFACTORING SUPPORT FOR SPARSE MATRICES IN INPUT SPEED AND DOCUMENTATION IMPROVEMENTS SEE THE NEXT SECTION FOR A FULL LIST OF API CHANGES
• IMPROVEMENTS ON THE FEATURE SELECTION MODULE BY GILLES LOUPPE REFACTORING OF THE RFE CLASSES DOCUMENTATION REWRITE INCREASED EFFICIENCY AND MINOR API CHANGES
•SPARSE PRINCIPAL COMPONENTS ANALYSIS SPARSEPCA AND MINIBATCHSPARSEPCA BY VLAD NICULAE GAEL VAROQUAUX AND ALEXANDRE GRAMFORT
• PRINTING AN ESTIMATOR NOW BEHAVES INDEPENDENTLY OF ARCHITECTURES AND PYTHON VERSION THANKS TO JEAN KOSSAIFI
•LOADER FOR LIBSVMSVMLIGHT FORMAT BY MATHIEU BLONDEL AND LARS BUITINCK
• DOCUMENTATION IMPROVEMENTS THUMBNAILS IN EXAMPLE GALLERY BY FABIAN PEDREGOSA
• IMPORTANT BUGFIXES IN SUPPORT VECTOR MACHINES MODULE SEGFAULTS BAD PERFORMANCE BY FABIAN PEDREGOSA
• ADDED MULTINOMIAL NAIVE BAYES ANDBERNOULLI NAIVE BAYES BY LARS BUITINCK
• TEXT FEATURE EXTRACTION OPTIMIZATIONS BY LARS BUITINCK
• CHISQUARE FEATURE SELECTION FEATURESELECTIONUNIVARIATESELECTIONCHI2 BY LARS BUITINCK
•GENERATED DATASETS MODULE REFACTORING BY GILLES LOUPPE
•MULTICLASS AND MULTILABEL ALGORITHMS BY MATHIEU BLONDEL
• BALL TREE REWRITE BY JAKE VANDERPLAS
• IMPLEMENTATION OF DBSCAN ALGORITHM BY ROBERT LAYTON
• KMEANS PREDICT AND TRANSFORM BY ROBERT LAYTON
• PREPROCESSING MODULE REFACTORING BY OLIVIER GRISEL
• FASTER MEAN SHIFT BY CONRAD LEE
• NEWBOOTSTRAP RANDOM PERMUTATIONS CROSSVALIDATION AKA SHUFFLE SPLIT AND VARIOUS OTHER IMPROVEMENTS IN CROSS VALIDATION SCHEMES BY OLIVIER GRISEL AND GAEL VAROQUAUX
• ADJUSTED RAND INDEX AND VMEASURE CLUSTERING EVALUATION METRICS BY OLIVIER GRISEL
• ADDEDORTHOGONAL MATCHING PURSUIT BY VLAD NICULAE
• ADDED 2DPATCH EXTRACTOR UTILITIES IN THE FEATURE EXTRACTION MODULE BY VLAD NICULAE
• IMPLEMENTATION OF LINEARMODELLASSOLARSCV CROSSVALIDATED LASSO SOLVER USING THE LARS ALGORITHM ANDLINEARMODELLASSOLARSIC BICAIC MODEL SELECTION IN LARS BY GAEL VAROQUAUX AND ALEXANDRE GRAMFORT
• SCALABILITY IMPROVEMENTS TO METRICSROCCURVE BY OLIVIER HERVIEU
• DISTANCE HELPER FUNCTIONS METRICSPAIRWISEPAIRWISEDISTANCES ANDMETRICSPAIRWISE PAIRWISEKERNELS BY ROBERT LAYTON
•MINIBATCH KMEANS BY NELLE VAROQUAUX AND PETER PRETTENHOFER
• MLDATA UTILITIES BY PIETRO BERKES
• OLIVETTIFACES BY DAVID WARDEFARLEY

API CHANGES SUMMARY

HERE ARE THE CODE MIGRATION INSTRUCTIONS WHEN UPGRADING FROM SCIKITLEARN VERSION 08

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• THESCIKITSLEARN PACKAGE WAS RENAMED SKLEARN THERE IS STILL A SCIKITSLEARN PACKAGE ALIAS FOR
BACKWARD COMPATIBILITY
THIRDPARTY PROJECTS WITH A DEPENDENCY ON SCIKITLEARN 09 SHOULD UPGRADE THEIR CODEBASE FOR INSTANCE UNDER
LINUX MACOSX JUST RUN MAKE A BACKUP FIRST
FIND NAME PY XARGS SED I S BSCIKITSLEARN BSKLEARNG
• ESTIMATORS NO LONGER ACCEPT MODEL PARAMETERS AS FIT ARGUMENTS INSTEAD ALL PARAMETERS MUST BE ONLY
BE PASSED AS CONSTRUCTOR ARGUMENTS OR USING THE NOW PUBLIC SETPARAMS METHOD INHERITED FROM BASE
BASEESTIMATOR
SOME ESTIMATORS CAN STILL ACCEPT KEYWORD ARGUMENTS ON THE FIT BUT THIS IS RESTRICTED TO DATADEPENDENT VALUES
EG A GRAM MATRIX OR AN AFFINITY MATRIX THAT ARE PRECOMPUTED FROM THE XDATA MATRIX
• THECROSSVAL PACKAGE HAS BEEN RENAMED TO CROSSVALIDATION ALTHOUGH THERE IS ALSO A CROSSVAL
PACKAGE ALIAS IN PLACE FOR BACKWARD COMPATIBILITY
THIRDPARTY PROJECTS WITH A DEPENDENCY ON SCIKITLEARN 09 SHOULD UPGRADE THEIR CODEBASE FOR INSTANCE UNDER
LINUX MACOSX JUST RUN MAKE A BACKUP FIRST
FIND NAME PY XARGS SED I S BCROSSVAL BCROSSVALIDATIONG
• THESCOREFUNC ARGUMENT OF THE SKLEARNCROSSVALIDATIONCROSSVALSCORE FUNCTION IS
NOW EXPECTED TO ACCEPT YTEST ANDYPREDICTED AS ONLY ARGUMENTS FOR CLASSIFICATION AND REGRESSION TASKS
ORXTEST FOR UNSUPERVISED ESTIMATORS
•GAMMA PARAMETER FOR SUPPORT VECTOR MACHINE ALGORITHMS IS SET TO 1 NFEATURES BY DEFAULT INSTEAD OF 1
 NSAMPLES
• THESKLEARNHMM HAS BEEN MARKED AS ORPHANED IT WILL BE REMOVED FROM SCIKITLEARN IN VERSION 011 UNLESS
SOMEONE STEPS UP TO CONTRIBUTE DOCUMENTATION EXAMPLES AND FIX LURKING NUMERICAL STABILITY ISSUES
•SKLEARNNEIGHBORS HAS BEEN MADE INTO A SUBMODULE THE TWO PREVIOUSLY AVAILABLE ESTIMATORS
NEIGHBORSCLASSIFIER ANDNEIGHBORSREGRESSOR HAVE BEEN MARKED AS DEPRECATED THEIR FUNCTION
ALITY HAS BEEN DIVIDED AMONG FIVE NEW CLASSES NEARESTNEIGHBORS FOR UNSUPERVISED NEIGHBORS SEARCHES
KNEIGHBORSCLASSIFIER RADIUSNEIGHBORSCLASSIFIER FOR SUPERVISED CLASSIFICATION PROBLEMS
ANDKNEIGHBORSREGRESSOR RADIUSNEIGHBORSREGRESSOR FOR SUPERVISED REGRESSION PROBLEMS
•SKLEARNBALLTREEBALLTREE HAS BEEN MOVED TO SKLEARNNEIGHBORSBALLTREE USING THE
FORMER WILL GENERATE A WARNING
•SKLEARNLINEARMODELLARS AND RELATED CLASSES LASSOLARS LASSOLARSCV ETC HAVE BEEN RE
NAMED TOSKLEARNLINEARMODELLARS
• ALL DISTANCE METRICS AND KERNELS IN SKLEARNMETRICSPAIRWISE NOW HAVE A Y PARAMETER WHICH BY
DEFAULT IS NONE IF NOT GIVEN THE RESULT IS THE DISTANCE OR KERNEL SIMILARITY BETWEEN EACH SAMPLE IN Y IF GIVEN
THE RESULT IS THE PAIRWISE DISTANCE OR KERNEL SIMILARITY BETWEEN SAMPLES IN X TO Y
•SKLEARNMETRICSPAIRWISEL1DISTANCE IS NOW CALLED MANHATTANDISTANCE AND BY DEFAULT
RETURNS THE PAIRWISE DISTANCE FOR THE COMPONENT WISE DISTANCE SET THE PARAMETER SUMOVERFEATURES TO
FALSE
BACKWARD COMPATIBILITY PACKAGE ALIASES AND OTHER DEPRECATED CLASSES AND FUNCTIONS WILL BE REMOVED IN VERSION 011
PEOPLE
38 PEOPLE CONTRIBUTED TO THIS RELEASE
• 387 VLAD NICULAE

• 320 OLIVIER GRISEL
• 192 LARS BUITINCK
• 179 GAEL VAROQUAUX
• 168 FABIAN PEDREGOSA INRIA PARIETAL TEAM
• 127 JAKE VANDERPLAS
• 120 MATHIEU BLONDEL
• 85 ALEXANDRE PASSOS
• 67 ALEXANDRE GRAMFORT
• 57 PETER PRETTENHOFER
• 56 GILLES LOUPPE
• 42 ROBERT LAYTON
• 38 NELLE VAROQUAUX
• 32 JEAN KOSSAIFI
• 30 CONRAD LEE
• 22 PIETRO BERKES
• 18 ANDY
• 17 DAVID WARDEFARLEY
• 12 BRIAN HOLT
• 11 ROBERT
• 8 AMIT AIDES
• 8 VIRGILE FRITSCH
• 7 YAROSLAV HALCHENKO
• 6 SALVATORE MASECCHIA
• 5 PAOLO LOSI
• 4 VINCENT SCHUT
• 3 ALEXIS METAIREAU
• 3 BRYAN SILVERTHORN
• 3 ANDREAS MÜLLER
• 2 MINWOO JAKE LEE
• 1 EMMANUELLE GOUILLART
• 1 KEITH GOODMAN
• 1 LUCAS WIMAN
• 1 NICOLAS PINTO
• 1 THOUIS RAY JONES
• 1 TIM SHEERMANCHASE

SCIKITLEARN USER GUIDE RELEASE 0213
11722 VERSION 08
MAY 11 2011
SCIKITLEARN 08 WAS RELEASED ON MAY 2011 ONE MONTH AFTER THE FIRST “INTERNATIONAL” SCIKITLEARN CODING SPRINT AND IS MARKED BY THE INCLUSION OF IMPORTANT MODULES HIERARCHICAL CLUSTERING CROSS DECOMPOSITION NONNEGATIVE MATRIX FACTORIZATION NMF OR NNMF INITIAL SUPPORT FOR PYTHON 3 AND BY IMPORTANT ENHANCEMENTS AND BUG FIXES
CHANGELOG
SEVERAL NEW MODULES WHERE INTRODUCED DURING THIS RELEASE
• NEW HIERARCHICAL CLUSTERING MODULE BY VINCENT MICHEL BERTRAND THIRION ALEXANDRE GRAMFORT AND GAEL VARO QUAUX
•KERNEL PCA IMPLEMENTATION BY MATHIEU BLONDEL
• LABELEDFACESINTHEWILD BY OLIVIER GRISEL
• NEW CROSS DECOMPOSITION MODULE BY EDOUARD DUCHESNAY
•NONNEGATIVE MATRIX FACTORIZATION NMF OR NNMF MODULE VLAD NICULAE
• IMPLEMENTATION OF THE ORACLE APPROXIMATING SHRINKAGE ALGORITHM BY VIRGILE FRITSCH IN THE COVARIANCE ESTIMA TIONMODULE
SOME OTHER MODULES BENEFITED FROM SIGNIFICANT IMPROVEMENTS OR CLEANUPS
• INITIAL SUPPORT FOR PYTHON 3 BUILDS AND IMPORTS CLEANLY SOME MODULES ARE USABLE WHILE OTHERS HAVE FAILING TESTS BY FABIAN PEDREGOSA
•DECOMPOSITIONPCA IS NOW USABLE FROM THE PIPELINE OBJECT BY OLIVIER GRISEL
• GUIDE HOW TO OPTIMIZE FOR SPEED BY OLIVIER GRISEL
• FIXES FOR MEMORY LEAKS IN LIBSVM BINDINGS 64BIT SAFER BALLTREE BY LARS BUITINCK
• BUG AND STYLE FIXING IN KMEANS ALGORITHM BY JAN SCHLÜTER
• ADD ATTRIBUTE CONVERGED TO GAUSSIAN MIXTURE MODELS BY VINCENT SCHUT
• IMPLEMENTED TRANSFORM PREDICTLOGPROBA INDISCRIMINANTANALYSIS LINEARDISCRIMINANTANALYSIS BY MATHIEU BLONDEL
• REFACTORING IN THE SUPPORT VECTOR MACHINES MODULE AND BUG FIXES BY FABIAN PEDREGOSA GAEL VAROQUAUX AND AMIT AIDES
• REFACTORED SGD MODULE REMOVED CODE DUPLICATION BETTER VARIABLE NAMING ADDED INTERFACE FOR SAMPLE WEIGHT BY PETER PRETTENHOFER
• WRAPPED BALLTREE WITH CYTHON BY THOUIS RAY JONES
• ADDED FUNCTION SVML1MINC BY PAOLO LOSI
• TYPOS DOC STYLE ETC BY YAROSLAV HALCHENKO GAEL VAROQUAUX OLIVIER GRISEL YANN MALET NICOLAS PINTO LARS BUITINCK AND FABIAN PEDREGOSA
PEOPLE
PEOPLE THAT MADE THIS RELEASE POSSIBLE PRECEDED BY NUMBER OF COMMITS
• 159 OLIVIER GRISEL

SCIKITLEARN USER GUIDE RELEASE 0213
• 96 GAEL VAROQUAUX
• 96 VLAD NICULAE
• 94 FABIAN PEDREGOSA
• 36 ALEXANDRE GRAMFORT
• 32 PAOLO LOSI
• 31 EDOUARD DUCHESNAY
• 30 MATHIEU BLONDEL
• 25 PETER PRETTENHOFER
• 22 NICOLAS PINTO
•11 VIRGILE FRITSCH
–7 LARS BUITINCK
–6 VINCENT MICHEL
–5 BERTRAND THIRION
–4 THOUIS RAY JONES
–4 VINCENT SCHUT
–3 JAN SCHLÜTER
–2 JULIEN MIOTTE
–2 MATTHIEU PERROT
–2 YANN MALET
–2 YAROSLAV HALCHENKO
–1 AMIT AIDES
–1 ANDREAS MÜLLER
–1 FETH AREZKI
–1 MENG XINFAN
11723 VERSION 07
MARCH 2 2011
SCIKITLEARN 07 WAS RELEASED IN MARCH 2011 ROUGHLY THREE MONTHS AFTER THE 06 RELEASE THIS RELEASE IS MARKED BY THE SPEED IMPROVEMENTS IN EXISTING ALGORITHMS LIKE KNEAREST NEIGHBORS AND KMEANS ALGORITHM AND BY THE INCLUSION OF AN EFFICIENT ALGORITHM FOR COMPUTING THE RIDGE GENERALIZED CROSS VALIDATION SOLUTION UNLIKE THE PRECEDING RELEASE NO NEW MODULES WHERE ADDED TO THIS RELEASE
CHANGELOG
• PERFORMANCE IMPROVEMENTS FOR GAUSSIAN MIXTURE MODEL SAMPLING JAN SCHLÜTER
• IMPLEMENTATION OF EFFICIENT LEAVEONEOUT CROSSVALIDATED RIDGE IN LINEARMODELRIDGECV MATHIEU BLONDEL
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• BETTER HANDLING OF COLLINEARITY AND EARLY STOPPING IN LINEARMODELLARSPATH ALEXANDRE GRAMFORT AND FABIAN PEDREGOSA
• FIXES FOR LIBLINEAR ORDERING OF LABELS AND SIGN OF COEFFICIENTS DAN YAMINS PAOLO LOSI MATHIEU BLONDEL AND FABIAN PEDREGOSA
• PERFORMANCE IMPROVEMENTS FOR NEAREST NEIGHBORS ALGORITHM IN HIGHDIMENSIONAL SPACES FABIAN PEDREGOSA
• PERFORMANCE IMPROVEMENTS FOR CLUSTERKMEANS GAEL VAROQUAUX AND JAMES BERGSTRA
• SANITY CHECKS FOR SVMBASED CLASSES MATHIEU BLONDEL
• REFACTORING OF NEIGHBORSNEIGHBORSCLASSIFIER ANDNEIGHBORSKNEIGHBORSGRAPH ADDED DIFFERENT ALGORITHMS FOR THE KNEAREST NEIGHBOR SEARCH AND IMPLEMENTED A MORE STABLE ALGORITHM FOR FINDING BARYCENTER WEIGHTS ALSO ADDED SOME DEVELOPER DOCUMENTATION FOR THIS MODULE SEE NOTESNEIGHBORS FOR MORE INFORMATION FABIAN PEDREGOSA
• DOCUMENTATION IMPROVEMENTS ADDED PCARANDOMIZEDPCA ANDLINEARMODEL LOGISTICREGRESSION TO THE CLASS REFERENCE ALSO ADDED REFERENCES OF MATRICES USED FOR CLUSTERING AND OTHER FIXES GAEL VAROQUAUX FABIAN PEDREGOSA MATHIEU BLONDEL OLIVIER GRISEL VIRGILE FRITSCH EMMANUELLE GOUILLART
• BINDED DECISIONFUNCTION IN CLASSES THAT MAKE USE OF LIBLINEAR DENSE AND SPARSE VARIANTS LIKE SVM LINEARSVC ORLINEARMODELLOGISTICREGRESSION FABIAN PEDREGOSA
• PERFORMANCE AND API IMPROVEMENTS TO METRICSEUCLIDEANDISTANCES AND TOPCA RANDOMIZEDPCA JAMES BERGSTRA
• FIX COMPILATION ISSUES UNDER NETBSD KAMEL IBN HASSEN DEROUICHE
• ALLOW INPUT SEQUENCES OF DIFFERENT LENGTHS IN HMMGAUSSIANHMM RON WEISS
• FIX BUG IN AFFINITY PROPAGATION CAUSED BY INCORRECT INDEXING XINFAN MENG

PEOPLE

PEOPLE THAT MADE THIS RELEASE POSSIBLE PRECEDED BY NUMBER OF COMMITS
• 85 FABIAN PEDREGOSA
• 67 MATHIEU BLONDEL
• 20 ALEXANDRE GRAMFORT
• 19 JAMES BERGSTRA
• 14 DAN YAMINS
• 13 OLIVIER GRISEL
• 12 GAEL VAROQUAUX
• 4 EDOUARD DUCHESNAY
• 4 RON WEISS
• 2 SATRAJIT GHOSH
• 2 VINCENT DUBOURG
• 1 EMMANUELLE GOUILLART
• 1 KAMEL IBN HASSEN DEROUICHE
• 1 PAOLO LOSI

SCIKITLEARN USER GUIDE RELEASE 0213

• 1 VIRGILEFRITSCH
• 1 YAROSLAV HALCHENKO
• 1 XINFAN MENG

11724 VERSION 06

DECEMBER 21 2010

SCIKITLEARN 06 WAS RELEASED ON DECEMBER 2010 IT IS MARKED BY THE INCLUSION OF SEVERAL NEW MODULES AND A GENERAL RENAMING OF OLD ONES IT IS ALSO MARKED BY THE INCLUSION OF NEW EXAMPLE INCLUDING APPLICATIONS TO REALWORLD DATASETS

CHANGELOG

• NEW STOCHASTIC GRADIENT DESCENT MODULE BY PETER PRETTENHOFER THE MODULE COMES WITH COMPLETE DOCUMENTATION AND EXAMPLES
• IMPROVED SVM MODULE MEMORY CONSUMPTION HAS BEEN REDUCED BY 50 HEURISTIC TO AUTOMATICALLY SET CLASS WEIGHTS POSSIBILITY TO ASSIGN WEIGHTS TO SAMPLES SEE SVM WEIGHTED SAMPLES FOR AN EXAMPLE
• NEW GAUSSIAN PROCESSES MODULE BY VINCENT DUBOURG THIS MODULE ALSO HAS GREAT DOCUMENTA TION AND SOME VERY NEAT EXAMPLES SEE EXAMPLEGAUSSIANPROCESSPLOTGPREGRESSIONPY OR EXAM PLEGAUSSIANPROCESSPLOTGPPROBABILISTICCLASSIFICATIONAFTERREGRESSIONPY FOR A TASTE OF WHAT CAN BE DONE
• IT IS NOW POSSIBLE TO USE LIBLINEAR'S MULTICLASS SVC OPTION MULTICLASS IN SVMLINEARSVC
• NEW FEATURES AND PERFORMANCE IMPROVEMENTS OF TEXT FEATURE EXTRACTION
• IMPROVED SPARSE MATRIX SUPPORT BOTH IN MAIN CLASSES GRIDSEARCHGRIDSEARCHCV AS IN MODULES SKLEARNSVMSPARSE AND SKLEARNLINEARMODELSPARSE
• LOTS OF COOL NEW EXAMPLES AND A NEW SECTION THAT USES REALWORLD DATASETS WAS CREATED THESE INCLUDE FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS SPECIES DISTRIBUTION MODELING LIBSVM GUI WIKIPEDIA PRINCI PAL EIGENVECTOR AND OTHERS
• FASTER LEAST ANGLE REGRESSION ALGORITHM IT IS NOW 2X FASTER THAN THE R VERSION ON WORST CASE AND UP TO 10X TIMES FASTER ON SOME CASES
• FASTER COORDINATE DESCENT ALGORITHM IN PARTICULAR THE FULL PATH VERSION OF LASSO LINEARMODEL LASSOPATH IS MORE THAN 200X TIMES FASTER THAN BEFORE
• IT IS NOW POSSIBLE TO GET PROBABILITY ESTIMATES FROM A LINEARMODELLOGISTICREGRESSION MODEL
• MODULE RENAMING THE GLM MODULE HAS BEEN RENAMED TO LINEARMODEL THE GMM MODULE HAS BEEN INCLUDED INTO THE MORE GENERAL MIXTURE MODEL AND THE SGD MODULE HAS BEEN INCLUDED IN LINEARMODEL
• LOTS OF BUG FIXES AND DOCUMENTATION IMPROVEMENTS

PEOPLE

PEOPLE THAT MADE THIS RELEASE POSSIBLE PRECEDED BY NUMBER OF COMMITS

• 207 OLIVIER GRISEL
• 167 FABIAN PEDREGOSA
• 97 PETER PRETTENHOFER
• 68 ALEXANDRE GRAMFORT

117 PREVIOUS RELEASES 141

SCIKITLEARN USER GUIDE RELEASE 0213
• 59 MATHIEU BLONDEL
• 55 GAEL VAROQUAUX
• 33 VINCENT DUBOURG
• 21 RON WEISS
• 9 BERTRAND THIRION
• 3 ALEXANDRE PASSOS
• 3 ANNELAURE FOUQUE
• 2 RONAN AMICEL
• 1 CHRISTIAN OSENDORFER
11725 VERSION 05
OCTOBER 11 2010
CHANGELOG
NEW CLASSES
• SUPPORT FOR SPARSE MATRICES IN SOME CLASSIFIERS OF MODULES SVM ANDLINEARMODEL SEESVM
SPARSESVC SVMSPARSESVR SVMSPARSELINEARSVC LINEARMODELSPARSELASSO
LINEARMODELSPARSEELASTICNET
• NEWPIPELINEPIPELINE OBJECT TO COMPOSE DIFFERENT ESTIMATORS
• RECURSIVE FEATURE ELIMINATION ROUTINES IN MODULE FEATURE SELECTION
• ADDITION OF VARIOUS CLASSES CAPABLE OF CROSS VALIDATION IN THE LINEARMODEL MODULE LINEARMODEL
LASSOCV LINEARMODELELASTICNETCV ETC
• NEW MORE EFFICIENT LARS ALGORITHM IMPLEMENTATION THE LASSO VARIANT OF THE ALGORITHM IS ALSO IMPLEMENTED
SEELINEARMODELLARSPATH LINEARMODELLARS ANDLINEARMODELLASSOLARS
• NEW HIDDEN MARKOV MODELS MODULE SEE CLASSES HMMGAUSSIANHMM HMMMULTINOMIALHMM HMM
GMMHMM
• NEW MODULE FEATUREEXTRACTION SEE CLASS REFERENCE
• NEW FASTICA ALGORITHM IN MODULE SKLEARNFASTICA
DOCUMENTATION
• IMPROVED DOCUMENTATION FOR MANY MODULES NOW SEPARATING NARRATIVE DOCUMENTATION FROM THE CLASS REFERENCE
AS AN EXAMPLE SEE DOCUMENTATION FOR THE SVM MODULE AND THE COMPLETE CLASS REFERENCE
FIXES
• API CHANGES ADHERE VARIABLE NAMES TO PEP8 GIVE MORE MEANINGFUL NAMES
• FIXES FOR SVM MODULE TO RUN ON A SHARED MEMORY CONTEXT MULTIPROCESSING
• IT IS AGAIN POSSIBLE TO GENERATE LATEX AND THUS PDF FROM THE SPHINX DOCS

EXAMPLES

• NEW EXAMPLES USING SOME OF THE MLCOMP DATASETS SPHXGLRAUTOEXAMPLESMLCOMPSPARSEDOCUMENTCLASSIFICATION PYSINCE REMOVED AND CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
• MANY MORE EXAMPLES SEE HERE THE FULL LIST OF EXAMPLES

EXTERNAL DEPENDENCIES

• JOBLIB IS NOW A DEPENDENCY OF THIS PACKAGE ALTHOUGH IT IS SHIPPED WITH SKLEARNEXTERNALSJOBLIB

REMOVED MODULES

• MODULE ANN ARTIFICIAL NEURAL NETWORKS HAS BEEN REMOVED FROM THE DISTRIBUTION USERS WANTING THIS SORT OF ALGORITHMS SHOULD TAKE A LOOK INTO PYBRAIN

MISC

• NEW SPHINX THEME FOR THE WEB PAGE

AUTHORS

THE FOLLOWING IS A LIST OF AUTHORS FOR THIS RELEASE PRECEDED BY NUMBER OF COMMITS

• 262 FABIAN PEDREGOSA
• 240 GAEL VAROQUAUX
• 149 ALEXANDRE GRAMFORT
• 116 OLIVIER GRISEL
• 40 VINCENT MICHEL
• 38 RON WEISS
• 23 MATTHIEU PERROT
• 10 BERTRAND THIRION
• 7 YAROSLAV HALCHENKO
• 9 VIRGILEFRITSCH
• 6 EDOUARD DUCHESNAY
• 4 MATHIEU BLONDEL
• 1 ARIEL ROKEM
• 1 MATTHIEU BRUCHER

11726 VERSION 04

AUGUST 26 2010

CHANGELOG

MAJOR CHANGES IN THIS RELEASE INCLUDE

- COORDINATE DESCENT ALGORITHM LASSO ELASTICNET REFACTORING SPEED IMPROVEMENTS ROUGHLY 100X TIMES FASTER
- COORDINATE DESCENT REFACTORING AND BUG FIXING FOR CONSISTENCY WITH R'S PACKAGE GLMNET
- NEW METRICS MODULE
- NEW GMM MODULE CONTRIBUTED BY RON WEISS
- IMPLEMENTATION OF THE LARS ALGORITHM WITHOUT LASSO VARIANT FOR NOW
- FEATURESELECTION MODULE REDESIGN
- MIGRATION TO GIT AS VERSION CONTROL SYSTEM
- REMOVAL OF OBSOLETE ATTRSELECT MODULE
- RENAME OF PRIVATE COMPILED EXTENSIONS ADDED UNDERSCORE
- REMOVAL OF LEGACY UNMAINTAINED CODE
- DOCUMENTATION IMPROVEMENTS BOTH DOCSTRING AND RST
- IMPROVEMENT OF THE BUILD SYSTEM TO OPTIONALLY LINK WITH MKL ALSO PROVIDE A LITE BLAS IMPLEMENTATION IN CASE NO SYSTEMWIDE BLAS IS FOUND
- LOTS OF NEW EXAMPLES
- MANY MANY BUG FIXES

AUTHORS

THE COMMITTER LIST FOR THIS RELEASE IS THE FOLLOWING PRECEDED BY NUMBER OF COMMITS

- 143 FABIAN PEDREGOSA
- 35 ALEXANDRE GRAMFORT
- 34 OLIVIER GRISEL
- 11 GAEL VAROQUAUX
- 5 YAROSLAV HALCHENKO
- 2 VINCENT MICHEL
- 1 CHRIS FILO GORGOLEWSKI

11727 EARLIER VERSIONS

EARLIER VERSIONS INCLUDED CONTRIBUTIONS BY FRED MAILHOT DAVID COOKE DAVID HUARD DAVE MORRILL ED SCHOFIELD TRAVIS OLIPHANT PEARU PETERSON

118 ROADMAP

1181 PURPOSE OF THIS DOCUMENT

THIS DOCUMENT LIST GENERAL DIRECTIONS THAT CORE CONTRIBUTORS ARE INTERESTED TO SEE DEVELOPED IN SCIKITLEARN THE FACT THAT AN ITEM IS LISTED HERE IS IN NO WAY A PROMISE THAT IT WILL HAPPEN AS RESOURCES ARE LIMITED RATHER IT IS AN INDICATION THAT HELP IS WELCOMED ON THIS TOPIC

1182 STATEMENT OF PURPOSE SCIKITLEARN IN 2018

ELEVEN YEARS AFTER THE INCEPTION OF SCIKITLEARN MUCH HAS CHANGED IN THE WORLD OF MACHINE LEARNING KEY CHANGES INCLUDE

• COMPUTATIONAL TOOLS THE EXPLOITATION OF GPUS DISTRIBUTED PROGRAMMING FRAMEWORKS LIKE SCALASPARK ETC

• HIGHLEVEL PYTHON LIBRARIES FOR EXPERIMENTATION PROCESSING AND DATA MANAGEMENT JUPYTER NOTEBOOK CYTHON PANDAS DASK NUMBA

• CHANGES IN THE FOCUS OF MACHINE LEARNING RESEARCH ARTIFICIAL INTELLIGENCE APPLICATIONS WHERE INPUT STRUCTURE IS KEY WITH DEEP LEARNING REPRESENTATION LEARNING REINFORCEMENT LEARNING DOMAIN TRANSFER ETC

A MORE SUBTLE CHANGE OVER THE LAST DECADE IS THAT DUE TO CHANGING INTERESTS IN ML PHD STUDENTS IN MACHINE LEARNING ARE MORE LIKELY TO CONTRIBUTE TO PYTORCH DASK ETC THAN TO SCIKITLEARN SO OUR CONTRIBUTOR POOL IS VERY DIFFERENT TO A DECADE AGO

SCIKITLEARN REMAINS VERY POPULAR IN PRACTICE FOR TRYING OUT CANONICAL MACHINE LEARNING TECHNIQUES PARTICULARLY FOR APPLICATIONS IN EXPERIMENTAL SCIENCE AND IN DATA SCIENCE A LOT OF WHAT WE PROVIDE IS NOW VERY MATURE BUT IT CAN BE COSTLY TO MAINTAIN AND WE CANNOT THEREFORE INCLUDE ARBITRARY NEW IMPLEMENTATIONS YET SCIKITLEARN IS ALSO ESSENTIAL IN DEFINING AN API FRAMEWORK FOR THE DEVELOPMENT OF INTEROPERABLE MACHINE LEARNING COMPONENTS EXTERNAL TO THE CORE LIBRARY

THUS OUR MAIN GOALS IN THIS ERA ARE TO

• CONTINUE MAINTAINING A HIGHQUALITY WELLDOCUMENTED COLLECTION OF CANONICAL TOOLS FOR DATA PROCESSING AND MACHINE LEARNING WITHIN THE CURRENT SCOPE IE RECTANGULAR DATA LARGELY INVARIANT TO COLUMN AND ROW ORDER PREDICTING TARGETS WITH SIMPLE STRUCTURE

• IMPROVE THE EASE FOR USERS TO DEVELOP AND PUBLISH EXTERNAL COMPONENTS

• IMPROVE INTEROPERABILITY WITH MODERN DATA SCIENCE TOOLS EG PANDAS DASK AND INFRASTRUCTURES EG DISTRIBUTED PROCESSING

MANY OF THE MORE FINEGRAINED GOALS CAN BE FOUND UNDER THE API TAG ON THE ISSUE TRACKER

1183 ARCHITECTURAL GENERAL GOALS

THE LIST IS NUMBERED NOT AS AN INDICATION OF THE ORDER OF PRIORITY BUT TO MAKE REFERRING TO SPECIFIC POINTS EASIER PLEASE ADD NEW ENTRIES ONLY AT THE BOTTOM

1 EVERYTHING IN SCIKITLEARN SHOULD CONFORM TO OUR API CONTRACT

•PIPELINE ANDFEATUREUNION MODIFY THEIR INPUT PARAMETERS IN FIT FIXING THIS REQUIRES MAKING SURE WE HAVE A GOOD GRASP OF THEIR USE CASES TO MAKE SURE ALL CURRENT FUNCTIONALITY IS MAINTAINED 8157 7382

2 IMPROVED HANDLING OF PANDAS DATAFRAMES AND SPARSEDATAFRAMES

• DOCUMENT CURRENT HANDLING

• COLUMN REORDERING ISSUE 7242

• AVOIDING UNNECESSARY CONVERSION TO NDARRAY
• RETURNING DATAFRAMES FROM TRANSFORMERS 5523
• GETTING DATAFRAMES FROM DATASET LOADERS
• SPARSE CURRENTLY NOT CONSIDERED
3 IMPROVED HANDLING OF CATEGORICAL FEATURES
• TREEBASED MODELS SHOULD BE ABLE TO HANDLE BOTH CONTINUOUS AND CATEGORICAL FEATURES 4899
• IN DATASET LOADERS
• AS GENERIC TRANSFORMERS TO BE USED WITH COLUMNTRANSFORMS EG ORDINAL ENCODING SUPERVISED BY CORRELA
TION WITH TARGET VARIABLE
4 IMPROVED HANDLING OF MISSING DATA
• MAKING SURE METAESTIMATORS ARE LENIENT TOWARDS MISSING DATA
• NONTRIVIAL IMPUTERS
• LEARNERS DIRECTLY HANDLING MISSING DATA
• AN AMPUTATION SAMPLE GENERATOR TO MAKE PARTS OF A DATASET GO MISSING
• HANDLING MIXTURES OF CATEGORICAL AND CONTINUOUS VARIABLES
5 PASSING AROUND INFORMATION THAT IS NOT X Y SAMPLE PROPERTIES
• WE NEED TO BE ABLE TO PASS SAMPLE WEIGHTS TO SCORERS IN CROSS VALIDATION
• WE SHOULD HAVE STANDARDGENERALISED WAYS OF PASSING SAMPLEWISE PROPERTIES AROUND IN METAESTIMATORS
4497 7646
6 PASSING AROUND INFORMATION THAT IS NOT X Y FEATURE PROPERTIES
• FEATURE NAMES OR DESCRIPTIONS SHOULD IDEALLY BE AVAILABLE TO FIT FOR EG 6425 6424
• PERFEATURE HANDLING EG “IS THIS A NOMINAL ORDINAL ENGLISH LANGUAGE TEXT” SHOULD ALSO NOT NEED TO BE
PROVIDED TO ESTIMATOR CONSTRUCTORS IDEALLY BUT SHOULD BE AVAILABLE AS METADATA ALONGSIDE X 8480
7 PASSING AROUND INFORMATION THAT IS NOT X Y TARGET INFORMATION
• WE HAVE PROBLEMS GETTING THE FULL SET OF CLASSES TO ALL COMPONENTS WHEN THE DATA IS SPLITSAMPLED 6231
8100
• WE HAVE NO WAY TO HANDLE A MIXTURE OF CATEGORICAL AND CONTINUOUS TARGETS
8 MAKE IT EASIER FOR EXTERNAL USERS TO WRITE SCIKITLEARNCOMPATIBLE COMPONENTS
• MORE FLEXIBLE ESTIMATOR CHECKS THAT DO NOT SELECT BY ESTIMATOR NAME 6599 6715
• EXAMPLE OF HOW TO DEVELOP A METAESTIMATOR
• MORE SELFSUFFICIENT RUNNING OF SCIKITLEARNCONTRIB OR A SIMILAR RESOURCE
9 SUPPORT RESAMPLING AND SAMPLE REDUCTION
• ALLOW SUBSAMPLING OF MAJORITY CLASSES IN A PIPELINE 3855
• IMPLEMENT RANDOM FORESTS WITH RESAMPLING 8732
10 BETTER INTERFACES FOR INTERACTIVE DEVELOPMENT
• REPR AND HTML VISUALISATIONS OF ESTIMATORS 6323
• INCLUDE PLOTTING TOOLS NOT JUST AS EXAMPLES 9173

11 IMPROVED TOOLS FOR MODEL DIAGNOSTICS AND BASIC INFERENCE
• ALTERNATIVE FEATURE IMPORTANCES IMPLEMENTATIONS EG METHODS OR WRAPPERS
• BETTER WAYS TO HANDLE VALIDATION SETS WHEN FITTING
• BETTER WAYS TO FIND THRESHOLDS CREATE DECISION RULES 8614
12 BETTER TOOLS FOR SELECTING HYPERPARAMETERS WITH TRANSDUCTIVE ESTIMATORS
• GRID SEARCH AND CROSS VALIDATION ARE NOT APPLICABLE TO MOST CLUSTERING TASKS STABILITYBASED SELECTION IS MORE RELEVANT
13 IMPROVED TRACKING OF FITTING
• VERBOSE IS NOT VERY FRIENDLY AND SHOULD USE A STANDARD LOGGING LIBRARY 6929
• CALLBACKS OR A SIMILAR SYSTEM WOULD FACILITATE LOGGING AND EARLY STOPPING
14 DISTRIBUTED PARALLELISM
• JOBLIB CAN NOW PLUG ONTO SEVERAL BACKENDS SOME OF THEM CAN DISTRIBUTE THE COMPUTATION ACROSS COMPUTERS
• HOWEVER WE WANT TO STAY HIGH LEVEL IN SCIKITLEARN
15 A WAY FORWARD FOR MORE OUT OF CORE
• DASK ENABLES EASY OUTOFCORE COMPUTATION WHILE THE DASK MODEL PROBABLY CANNOT BE ADAPTABLE TO ALL MACHINELEARNING ALGORITHMS MOST MACHINE LEARNING IS ON SMALLER DATA THAN ETL HENCE WE CAN MAYBE ADAPT TO VERY LARGE SCALE WHILE SUPPORTING ONLY A FRACTION OF THE PATTERNS
16 BETTER SUPPORT FOR MANUAL AND AUTOMATIC PIPELINE BUILDING
• EASIER WAY TO CONSTRUCT COMPLEX PIPELINES AND VALID SEARCH SPACES 7608 5082 8243
• PROVIDE SEARCH RANGES FOR COMMON ESTIMATORS
• CF SEARCHGRID
17 SUPPORT FOR WORKING WITH PRETRAINED MODELS
• ESTIMATOR “FREEZING” IN PARTICULAR RIGHT NOW IT’S IMPOSSIBLE TO CLONE A CALIBRATEDCLASSIFIERCV WITH PREFIT 8370 6451
18 BACKWARDSCOMPATIBLE DESERIALIZATION OF SOME ESTIMATORS
• CURRENTLY SERIALIZATION WITH PICKLE BREAKS ACROSS VERSIONS WHILE WE MAY NOT BE ABLE TO GET AROUND OTHER LIMITATIONS OF PICKLE RE SECURITY ETC IT WOULD BE GREAT TO OFFER CROSSVERSION SAFETY FROM VERSION 10 NOTE GAEL AND OLIVIER THINK THAT THIS CAN CAUSE HEAVY MAINTENANCE BURDEN AND WE SHOULD MANAGE THE TRADEOFFS A POSSIBLE ALTERNATIVE IS PRESENTED IN THE FOLLOWING POINT
19 DOCUMENTATION AND TOOLING FOR MODEL LIFECYCLE MANAGEMENT
• DOCUMENT GOOD PRACTICES FOR MODEL DEPLOYMENTS AND LIFECYCLE BEFORE DEPLOYING A MODEL SNAPSHOT THE CODE VERSIONS NUMPY SCIPY SCIKITLEARN CUSTOM CODE REPO THE TRAINING SCRIPT AND AN ALIAS ON HOW TO RETRIEVE HISTORICAL TRAINING DATA SNAPSHOT A COPY OF A SMALL VALIDATION SET SNAPSHOT OF THE PREDICTIONS PREDICTED PROBABILITIES FOR CLASSIFIERS ON THAT VALIDATION SET
• DOCUMENT AND TOOLS TO MAKE IT EASY TO MANAGE UPGRADE OF SCIKITLEARN VERSIONS
–TRY TO LOAD THE OLD PICKLE IF IT WORKS USE THE VALIDATION SET PREDICTION SNAPSHOT TO DETECT THAT THE SERIALIZED MODEL STILL BEHAVE THE SAME
–IF JOBLIBLOAD PICKLELOAD NOT WORK USE THE VERSIONED CONTROL TRAINING SCRIPT HISTORICAL TRAINING SET TO RETRAIN THE MODEL AND USE THE VALIDATION SET PREDICTION SNAPSHOT TO ASSERT THAT IT IS POSSIBLE TO RECOVER THE PREVIOUS PREDICTIVE PERFORMANCE IF THIS IS NOT THE CASE THERE IS PROBABLY A BUG IN SCIKITLEARN THAT NEEDS TO BE REPORTED
118 ROADMAP 147

20 OPTIONAL IMPROVE SCIKITLEARN COMMON TESTS SUITE TO MAKE SURE THAT AT LEAST FOR FREQUENTLY USED MODELS HAVE STABLE PREDICTIONS ACROSSVERSIONS TO BE DISCUSSED
• EXTEND DOCUMENTATION TO MENTION HOW TO DEPLOY MODELS IN PYTHONFREE ENVIRONMENTS FOR INSTANCE ONNX AND USE THE ABOVE BEST PRACTICES TO ASSESS PREDICTIVE CONSISTENCY BETWEEN SCIKITLEARN AND ONNX PREDICTION FUNCTIONS ON VALIDATION SET
• DOCUMENT GOOD PRACTICES TO DETECT TEMPORAL DISTRIBUTION DRIFT FOR DEPLOYED MODEL AND GOOD PRACTICES FOR RETRAINING ON FRESH DATA WITHOUT CAUSING CATASTROPHIC PREDICTIVE PERFORMANCE REGRESSIONS
21 MORE DIDACTIC DOCUMENTATION
• MORE AND MORE OPTIONS HAVE BEEN ADDED TO SCIKITLEARN AS A RESULT THE DOCUMENTATION IS CROWDED WHICH MAKES IT HARD FOR BEGINNERS TO GET THE BIG PICTURE SOME WORK COULD BE DONE IN PRIORITIZING THE INFORMATION
1184 SUBPACKAGESPECIFIC GOALS
SKLEARNCLUSTER
• KMEANS VARIANTS FOR NONEUCLIDEAN DISTANCES IF WE CAN SHOW THESE HAVE BENEFITS BEYOND HIERARCHICAL CLUSTERING
SKLEARNENSEMBLE
• A STACKING IMPLEMENTATION
SKLEARNMODELSELECTION
• MULTIMETRIC SCORING IS SLOW 9326
• PERHAPS WE WANT TO BE ABLE TO GET BACK MORE THAN MULTIPLE METRICS
• THE HANDLING OF RANDOM STATES IN CV SPLITTERS IS A POOR DESIGN AND CONTRADICTS THE VALIDATION OF SIMILAR PARAMETERS IN ESTIMATORS
• EXPLOIT WARMSTARTING AND PATH ALGORITHMS SO THE BENEFITS OF ESTIMATORCV OBJECTS CAN BE ACCESSED VIA GRIDSEARCHCV AND USED IN PIPELINES 1626
• CROSSVALIDATION SHOULD BE ABLE TO BE REPLACED BY OOB ESTIMATES WHENEVER A CROSSVALIDATION ITERATOR IS USED
• REDUNDANT COMPUTATIONS IN PIPELINES SHOULD BE AVOIDED RELATED TO POINT ABOVE CF DASKML
SKLEARNNEIGHBORS
• ABILITY TO SUBSTITUTE A CUSTOMAPPROXIMATEPRECOMPUTED NEAREST NEIGHBORS IMPLEMENTATION FOR OURS IN ALLMOST CONTEXTS THAT NEAREST NEIGHBORS ARE USED FOR LEARNING 10463
SKLEARNPIPELINE
• PERFORMANCE ISSUES WITH PIPELINEMEMORY
• SEE “EVERYTHING IN SCIKITLEARN SHOULD CONFORM TO OUR API CONTRACT” ABOVE
119 SCIKITLEARN GOVERNANCE AND DECISIONMAKING
THE PURPOSE OF THIS DOCUMENT IS TO FORMALIZE THE GOVERNANCE PROCESS USED BY THE SCIKITLEARN PROJECT TO CLARIFY HOW DECISIONS ARE MADE AND HOW THE VARIOUS ELEMENTS OF OUR COMMUNITY INTERACT THIS DOCUMENT ESTABLISHES A DECISION MAKING STRUCTURE THAT TAKES INTO ACCOUNT FEEDBACK FROM ALL MEMBERS OF THE COMMUNITY AND STRIVES TO FIND CONSENSUS WHILE AVOIDING ANY DEADLOCKS

THIS IS A MERITOCRATIC CONSENSUSBASED COMMUNITY PROJECT ANYONE WITH AN INTEREST IN THE PROJECT CAN JOIN THE COM MUNITY CONTRIBUTE TO THE PROJECT DESIGN AND PARTICIPATE IN THE DECISION MAKING PROCESS THIS DOCUMENT DESCRIBES HOW THAT PARTICIPATION TAKES PLACE AND HOW TO SET ABOUT EARNING MERIT WITHIN THE PROJECT COMMUNITY

1191 ROLES AND RESPONSIBILITIES

CONTRIBUTORS

CONTRIBUTORS ARE COMMUNITY MEMBERS WHO CONTRIBUTE IN CONCRETE WAYS TO THE PROJECT ANYONE CAN BECOME A CONTRIB UTOR AND CONTRIBUTIONS CAN TAKE MANY FORMS – NOT ONLY CODE – AS DETAILED IN THE CONTRIBUTORS GUIDE

CORE DEVELOPERS

CORE DEVELOPERS ARE COMMUNITY MEMBERS WHO HAVE SHOWN THAT THEY ARE DEDICATED TO THE CONTINUED DEVELOPMENT OF THE PROJECT THROUGH ONGOING ENGAGEMENT WITH THE COMMUNITY THEY HAVE SHOWN THEY CAN BE TRUSTED TO MAINTAIN SCIKIT LEARN WITH CARE BEING A CORE DEVELOPER ALLOWS CONTRIBUTORS TO MORE EASILY CARRY ON WITH THEIR PROJECT RELATED ACTIVITIES BY GIVING THEM DIRECT ACCESS TO THE PROJECT'S REPOSITORY AND IS REPRESENTED AS BEING AN ORGANIZATION MEMBER ON THE SCIKITLEARN GITHUB ORGANIZATION CORE DEVELOPERS ARE EXPECTED TO REVIEW CODE CONTRIBUTIONS CAN MERGE APPROVED PULL REQUESTS CAN CAST VOTES FOR AND AGAINST MERGING A PULLREQUEST AND CAN BE INVOLVED IN DECIDING MAJOR CHANGES TO THE API

NEW CORE DEVELOPERS CAN BE NOMINATED BY ANY EXISTING CORE DEVELOPERS ONCE THEY HAVE BEEN NOMINATED THERE WILL BE A VOTE BY THE CURRENT CORE DEVELOPERS V OTING ON NEW CORE DEVELOPERS IS ONE OF THE FEW ACTIVITIES THAT TAKES PLACE ON THE PROJECT'S PRIVATE MANAGEMENT LIST WHILE IT IS EXPECTED THAT MOST VOTES WILL BE UNANIMOUS A TWOTHIRDS MAJORITY OF THE CAST VOTES IS ENOUGH THE VOTE NEEDS TO BE OPEN FOR AT LEAST 1 WEEK

CORE DEVELOPERS THAT HAVE NOT CONTRIBUTED TO THE PROJECT COMMITS OR GITHUB COMMENTS IN THE PAST 12 MONTHS WILL BE ASKED IF THEY WANT TO BECOME EMERITUS CORE DEVELOPERS AND RECANT THEIR COMMIT AND VOTING RIGHTS UNTIL THEY BECOME ACTIVE AGAIN THE LIST OF CORE DEVELOPERS ACTIVE AND EMERITUS WITH DATES AT WHICH THEY BECAME ACTIVE IS PUBLIC ON THE SCIKITLEARN WEBSITE

TECHNICAL COMMITTEE

THE TECHNICAL COMMITTEE TC MEMBERS ARE CORE DEVELOPERS WHO HAVE ADDITIONAL RESPONSIBILITIES TO ENSURE THE SMOOTH RUNNING OF THE PROJECT TC MEMBERS ARE EXPECTED TO PARTICIPATE IN STRATEGIC PLANNING AND APPROVE CHANGES TO THE GOVERNANCE MODEL THE PURPOSE OF THE TC IS TO ENSURE A SMOOTH PROGRESS FROM THE BIGPICTURE PERSPECTIVE INDEED CHANGES THAT IMPACT THE FULL PROJECT REQUIRE A SYNTHETIC ANALYSIS AND A CONSENSUS THAT IS BOTH EXPLICIT AND INFORMED IN CASES THAT THE CORE DEVELOPER COMMUNITY WHICH INCLUDES THE TC MEMBERS FAILS TO REACH SUCH A CONSENSUS IN THE REQUIRED TIME FRAME THE TC IS THE ENTITY TO RESOLVE THE ISSUE MEMBERSHIP OF THE TC IS BY NOMINATION BY A CORE DEVELOPER A NOMINATION WILL RESULT IN DISCUSSION WHICH CANNOT TAKE MORE THAN A MONTH AND THEN A VOTE BY THE CORE DEVELOPERS WHICH WILL STAY OPEN FOR A WEEK TC MEMBERSHIP VOTES ARE SUBJECT TO A TWOTHIRD MAJORITY OF ALL CAST VOTES AS WELL AS A SIMPLE MAJORITY APPROVAL OF ALL THE CURRENT TC MEMBERS TC MEMBERS WHO DO NOT ACTIVELY ENGAGE WITH THE TC DUTIES ARE EXPECTED TO RESIGN

THE INITIAL TECHNICAL COMMITTEE OF SCIKITLEARN CONSISTS OF ALEXANDRE GRAMFORT OLIVIER GRISEL ANDREAS MÜLLER JOEL NOTHMAN HANMIN QIN GAËL VAROQUAUX AND ROMAN YURCHAK

1192 DECISION MAKING PROCESS

DECISIONS ABOUT THE FUTURE OF THE PROJECT ARE MADE THROUGH DISCUSSION WITH ALL MEMBERS OF THE COMMUNITY ALL NON SENSITIVE PROJECT MANAGEMENT DISCUSSION TAKES PLACE ON THE PROJECT CONTRIBUTORS' MAILING LIST AND THE ISSUE TRACKER OCCASIONALLY SENSITIVE DISCUSSION OCCURS ON A PRIVATE LIST

SCIKITLEARN USES A “CONSENSUS SEEKING” PROCESS FOR MAKING DECISIONS THE GROUP TRIES TO FIND A RESOLUTION THAT HAS NO OPEN OBJECTIONS AMONG CORE DEVELOPERS AT ANY POINT DURING THE DISCUSSION ANY COREDEVELOPER CAN CALL FOR A VOTE WHICH WILL CONCLUDE ONE MONTH FROM THE CALL FOR THE VOTE ANY VOTE MUST BE BACKED BY A SLEP IF NO OPTION CAN GATHER TWO THIRDS OF THE VOTES CAST THE DECISION IS ESCALATED TO THE TC WHICH IN TURN WILL USE CONSENSUS SEEKING WITH THE FALLBACK OPTION OF A SIMPLE MAJORITY VOTE IF NO CONSENSUS CAN BE FOUND WITHIN A MONTH THIS IS WHAT WE HEREAFTER MAY REFER TO AS “THE DECISION MAKING PROCESS”

DECISIONS IN ADDITION TO ADDING CORE DEVELOPERS AND TC MEMBERSHIP AS ABOVE ARE MADE ACCORDING TO THE FOLLOWING RULES

•MINOR DOCUMENTATION CHANGES SUCH AS TYPO FIXES OR ADDITION CORRECTION OF A SENTENCE BUT NO CHANGE OF THE SCIKITLEARNORG LANDING PAGE OR THE “ABOUT” PAGE REQUIRES 1 BY A CORE DEVELOPER NO 1 BY A CORE DEVELOPER LAZY CONSENSUS HAPPENS ON THE ISSUE OR PULL REQUEST PAGE CORE DEVELOPERS ARE EXPECTED TO GIVE “REASONABLE TIME” TO OTHERS TO GIVE THEIR OPINION ON THE PULL REQUEST IF THEY’RE NOT CONFIDENT OTHERS WOULD AGREE

•CODE CHANGES AND MAJOR DOCUMENTATION CHANGES REQUIRE 1 BY TWO CORE DEVELOPERS NO 1 BY A CORE DEVELOPER LAZY CONSENSUS HAPPENS ON THE ISSUE OF PULLREQUEST PAGE

•CHANGES TO THE API PRINCIPLES AND CHANGES TO DEPENDENCIES OR SUPPORTED VERSIONS HAPPEN VIA A ENHANCE MENT PROPOSALS SLEPS AND FOLLOWS THE DECISIONMAKING PROCESS OUTLINED ABOVE

•CHANGES TO THE GOVERNANCE MODEL USE THE SAME DECISION PROCESS OUTLINED ABOVE

IF A VETO 1 VOTE IS CAST ON A LAZY CONSENSUS THE PROPOSER CAN APPEAL TO THE COMMUNITY AND CORE DEVELOPERS AND THE CHANGE CAN BE APPROVED OR REJECTED USING THE DECISION MAKING PROCEDURE OUTLINED ABOVE

1193 ENHANCEMENT PROPOSALS SLEPS

FOR ALL VOTES A PROPOSAL MUST HAVE BEEN MADE PUBLIC AND DISCUSSED BEFORE THE VOTE SUCH PROPOSAL MUST BE A CONSOL IDATED DOCUMENT IN THE FORM OF A ‘SCIKITLEARN ENHANCEMENT PROPOSAL’ SLEP RATHER THAN A LONG DISCUSSION ON AN ISSUE A SLEP MUST BE SUBMITTED AS A PULLREQUEST TO ENHANCEMENT PROPOSALS USING THE SLEP TEMPLATE

CHAPTER
TWO
SCIKITLEARN TUTORIALS
21 AN INTRODUCTION TO MACHINE LEARNING WITH SCIKITLEARN
SECTION CONTENTS
IN THIS SECTION WE INTRODUCE THE MACHINE LEARNING VOCABULARY THAT WE USE THROUGHOUT SCIKITLEARN AND GIVE A SIMPLE LEARNING EXAMPLE
211 MACHINE LEARNING THE PROBLEM SETTING
IN GENERAL A LEARNING PROBLEM CONSIDERS A SET OF N SAMPLES OF DATA AND THEN TRIES TO PREDICT PROPERTIES OF UNKNOWN DATA IF EACH SAMPLE IS MORE THAN A SINGLE NUMBER AND FOR INSTANCE A MULTIDIMENSIONAL ENTRY AKA MULTIVARIATE DATA IT IS SAID TO HAVE SEVERAL ATTRIBUTES OR FEATURES
LEARNING PROBLEMS FALL INTO A FEW CATEGORIES
• SUPERVISED LEARNING IN WHICH THE DATA COMES WITH ADDITIONAL ATTRIBUTES THAT WE WANT TO PREDICT CLICK HERE TO GO TO THE SCIKITLEARN SUPERVISED LEARNING PAGETHIS PROBLEM CAN BE EITHER
–CLASSIFICATION SAMPLES BELONG TO TWO OR MORE CLASSES AND WE WANT TO LEARN FROM ALREADY LABELED DATA HOW TO PREDICT THE CLASS OF UNLABELED DATA AN EXAMPLE OF A CLASSIFICATION PROBLEM WOULD BE HANDWRITTEN DIGIT RECOGNITION IN WHICH THE AIM IS TO ASSIGN EACH INPUT VECTOR TO ONE OF A FINITE NUMBER OF DISCRETE CATEGORIES ANOTHER WAY TO THINK OF CLASSIFICATION IS AS A DISCRETE AS OPPOSED TO CONTINUOUS FORM OF SUPERVISED LEARNING WHERE ONE HAS A LIMITED NUMBER OF CATEGORIES AND FOR EACH OF THE N SAMPLES PROVIDED ONE IS TO TRY TO LABEL THEM WITH THE CORRECT CATEGORY OR CLASS
–REGRESSION IF THE DESIRED OUTPUT CONSISTS OF ONE OR MORE CONTINUOUS VARIABLES THEN THE TASK IS CALLED REGRESSION AN EXAMPLE OF A REGRESSION PROBLEM WOULD BE THE PREDICTION OF THE LENGTH OF A SALMON AS A FUNCTION OF ITS AGE AND WEIGHT
• UNSUPERVISED LEARNING IN WHICH THE TRAINING DATA CONSISTS OF A SET OF INPUT VECTORS X WITHOUT ANY CORRESPONDING TARGET VALUES THE GOAL IN SUCH PROBLEMS MAY BE TO DISCOVER GROUPS OF SIMILAR EXAMPLES WITHIN THE DATA WHERE IT IS CALLED CLUSTERING OR TO DETERMINE THE DISTRIBUTION OF DATA WITHIN THE INPUT SPACE KNOWN AS DENSITY ESTIMA TION OR TO PROJECT THE DATA FROM A HIGHDIMENSIONAL SPACE DOWN TO TWO OR THREE DIMENSIONS FOR THE PURPOSE OF VISUALIZATION CLICK HERE TO GO TO THE SCIKITLEARN UNSUPERVISED LEARNING PAGE

TRAINING SET AND TESTING SET

MACHINE LEARNING IS ABOUT LEARNING SOME PROPERTIES OF A DATA SET AND THEN TESTING THOSE PROPERTIES AGAINST ANOTHER DATA SET A COMMON PRACTICE IN MACHINE LEARNING IS TO EVALUATE AN ALGORITHM BY SPLITTING A DATA SET INTO TWO WE CALL ONE OF THOSE SETS THE TRAINING SET ON WHICH WE LEARN SOME PROPERTIES WE CALL THE OTHER SET THE TESTING SET ON WHICH WE TEST THE LEARNED PROPERTIES

212 LOADING AN EXAMPLE DATASET

SCIKITLEARN COMES WITH A FEW STANDARD DATASETS FOR INSTANCE THE IRIS AND DIGITS DATASETS FOR CLASSIFICATION AND THE BOSTON HOUSE PRICES DATASET FOR REGRESSION

IN THE FOLLOWING WE START A PYTHON INTERPRETER FROM OUR SHELL AND THEN LOAD THE IRIS ANDDIGITS DATASETS OUR NOTATIONAL CONVENTION IS THAT DENOTES THE SHELL PROMPT WHILE DENOTES THE PYTHON INTERPRETER PROMPT

```
 PYTHON
 FROM SKLEARN IMPORT DATASETS
 IRIS  DATASETSLOADIRIS
 DIGITS  DATASETSLOADDIGITS
```

A DATASET IS A DICTIONARYLIKE OBJECT THAT HOLDS ALL THE DATA AND SOME METADATA ABOUT THE DATA THIS DATA IS STORED IN THEDATA MEMBER WHICH IS A NSAMPLES NFEATURES ARRAY IN THE CASE OF SUPERVISED PROBLEM ONE OR MORE RESPONSE VARIABLES ARE STORED IN THE TARGET MEMBER MORE DETAILS ON THE DIFFERENT DATASETS CAN BE FOUND IN THE DEDICATED SECTION

FOR INSTANCE IN THE CASE OF THE DIGITS DATASET DIGITSDATA GIVES ACCESS TO THE FEATURES THAT CAN BE USED TO CLASSIFY THE DIGITS SAMPLES

```
PRINTDIGITSDATA
 0 0 5  0 0 0
 0 0 0  10 0 0
 0 0 0  16 9 0

 0 0 1  6 0 0
 0 0 2  12 0 0
 0 0 10  12 1 0
```

ANDDIGITSTARGET GIVES THE GROUND TRUTH FOR THE DIGIT DATASET THAT IS THE NUMBER CORRESPONDING TO EACH DIGIT IMAGE THAT WE ARE TRYING TO LEARN

```
DIGITSTARGET
ARRAY0 1 2  8 9 8
```

SHAPE OF THE DATA ARRAYS

THE DATA IS ALWAYS A 2D ARRAY SHAPE NSAMPLES NFEATURES ALTHOUGH THE ORIGINAL DATA MAY HAVE HAD A DIFFERENT SHAPE IN THE CASE OF THE DIGITS EACH ORIGINAL SAMPLE IS AN IMAGE OF SHAPE 8 8 AND CAN BE ACCESSED USING

```
DIGITSIMAGES0
ARRAY 0 0 5 13 9 1 0 0
 0 0 13 15 10 15 5 0
 0 3 15 2 0 11 8 0
 0 4 12 0 0 8 8 0
 0 5 8 0 0 9 8 0
 0 4 11 0 1 12 7 0
 0 2 14 5 10 12 0 0
 0 0 6 13 10 0 0 0
```

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THESIMPLE EXAMPLE ON THIS DATASET ILLUSTRATES HOW STARTING FROM THE ORIGINAL PROBLEM ONE CAN SHAPE THE DATA FOR CONSUMPTION IN SCIKITLEARN
LOADING FROM EXTERNAL DATASETS
TO LOAD FROM AN EXTERNAL DATASET PLEASE REFER TO LOADING EXTERNAL DATASETS
213 LEARNING AND PREDICTING
IN THE CASE OF THE DIGITS DATASET THE TASK IS TO PREDICT GIVEN AN IMAGE WHICH DIGIT IT REPRESENTS WE ARE GIVEN SAMPLES OF EACH OF THE 10 POSSIBLE CLASSES THE DIGITS ZERO THROUGH NINE ON WHICH WE FITAN ESTIMATOR TO BE ABLE TO PREDICT THE CLASSES TO WHICH UNSEEN SAMPLES BELONG
IN SCIKITLEARN AN ESTIMATOR FOR CLASSIFICATION IS A PYTHON OBJECT THAT IMPLEMENTS THE METHODS FITX Y AND PREDICTT
AN EXAMPLE OF AN ESTIMATOR IS THE CLASS SKLEARNSVMSVC WHICH IMPLEMENTS SUPPORT VECTOR CLASSIFICATION THE ESTIMATOR’S CONSTRUCTOR TAKES AS ARGUMENTS THE MODEL’S PARAMETERS
FOR NOW WE WILL CONSIDER THE ESTIMATOR AS A BLACK BOX
 FROM SKLEARN IMPORT SVM
CLF SVMSVCGAMMA0001 C100
CHOOSING THE PARAMETERS OF THE MODEL
IN THIS EXAMPLE WE SET THE VALUE OF GAMMA MANUALLY TO FIND GOOD VALUES FOR THESE PARAMETERS WE CAN USE TOOLS SUCH AS GRID SEARCH ANDCROSS VALIDATION
THECLF FOR CLASSIFIER ESTIMATOR INSTANCE IS FIRST FITTED TO THE MODEL THAT IS IT MUST LEARN FROM THE MODEL THIS IS DONE BY PASSING OUR TRAINING SET TO THE FIT METHOD FOR THE TRAINING SET WE’LL USE ALL THE IMAGES FROM OUR DATASET EXCEPT FOR THE LAST IMAGE WHICH WE’LL RESERVE FOR OUR PREDICTING WE SELECT THE TRAINING SET WITH THE 1 PYTHON SYNTAX WHICH PRODUCES A NEW ARRAY THAT CONTAINS ALL BUT THE LAST ITEM FROM DIGITSDATA
CLFFITDIGITSDATA1 DIGITSTARGET1
SVCC1000 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMA0001 KERNELRBF
MAXITER1 PROBABILITYFALSE RANDOMSTATENONE SHRINKINGTRUE
TOL0001 VERBOSEFALSE
NOW YOU CAN PREDICT NEW VALUES IN THIS CASE YOU’LL PREDICT USING THE LAST IMAGE FROM DIGITSDATA BY PREDICTING YOU’LL DETERMINE THE IMAGE FROM THE TRAINING SET THAT BEST MATCHES THE LAST IMAGE
CLFPREDICTDIGITSDATA1
ARRAY8
21 AN INTRODUCTION TO MACHINE LEARNING WITH SCIKITLEARN 153

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THE CORRESPONDING IMAGE IS
AS YOU CAN SEE IT IS A CHALLENGING TASK AFTER ALL THE IMAGES
ARE OF POOR RESOLUTION DO YOU AGREE WITH THE CLASSIFIER
A COMPLETE EXAMPLE OF THIS CLASSIFICATION PROBLEM IS AVAILABLE AS AN EXAMPLE THAT YOU CAN RUN AND STUDY RECOGNIZING
HANDWRITTEN DIGITS
214 MODEL PERSISTENCE
IT IS POSSIBLE TO SAVE A MODEL IN SCIKITLEARN BY USING PYTHON'S BUILTIN PERSISTENCE MODEL PICKLE
FROM SKLEARN IMPORT SVM
FROM SKLEARN IMPORT DATASETS
CLF SVMSVCGAMMASCALE
IRIS DATASETSLOADIRIS
X Y IRISDATA IRISTARGET
CLFFITX Y
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMASCALE KERNELRBF
MAXITER1 PROBABILITYFALSE RANDOMSTATENONE SHRINKINGTRUE
TOL0001 VERBOSEFALSE
IMPORT PICKLE
S PICKLEDUMPSCLF
CLF2 PICKLELOADSS
CLF2PREDICTX01
ARRAY0
Y0
0
IN THE SPECIFIC CASE OF SCIKITLEARN IT MAY BE MORE INTERESTING TO USE JOBLIB'S REPLACEMENT FOR PICKLE JOBLIBDUMP
JOBLIBLOAD WHICH IS MORE EFFICIENT ON BIG DATA BUT IT CAN ONLY PICKLE TO THE DISK AND NOT TO A STRING
FROM JOBLIB IMPORT DUMP LOAD
DUMPCLF FILENAMEJOBLIB
LATER YOU CAN RELOAD THE PICKLED MODEL POSSIBLY IN ANOTHER PYTHON PROCESS WITH
CLF LOADFILENAMEJOBLIB
NOTEJOBLIBDUMP ANDJOBLIBLOAD FUNCTIONS ALSO ACCEPT FILELIKE OBJECT INSTEAD OF FILENAMES MORE INFOR
MATION ON DATA PERSISTENCE WITH JOBLIB IS AVAILABLE HERE
NOTE THAT PICKLE HAS SOME SECURITY AND MAINTAINABILITY ISSUES PLEASE REFER TO SECTION MODEL PERSISTENCE FOR MORE
DETAILED INFORMATION ABOUT MODEL PERSISTENCE WITH SCIKITLEARN
154 CHAPTER 2 SCIKITLEARN TUTORIALS

215 CONVENTIONS
SCIKITLEARN ESTIMATORS FOLLOW CERTAIN RULES TO MAKE THEIR BEHAVIOR MORE PREDICTIVE THESE ARE DESCRIBED IN MORE DETAIL IN THE GLOSSARY OF COMMON TERMS AND API ELEMENTS
TYPE CASTING
UNLESS OTHERWISE SPECIFIED INPUT WILL BE CAST TO FLOAT64
```
 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT RANDOMPROJECTION
RNG  NPRANDOMRANDOMSTATE0
X  RNGRAND10 2000
X  NPARRAYX DTYPEFLOAT32
XDTYPE
DTYPEFLOAT32
TRANSFORMER  RANDOMPROJECTIONGAUSSIANRANDOMPROJECTION
XNEW  TRANSFORMERFITTRANSFORMX
XNEWDTYPE
DTYPEFLOAT64
```
IN THIS EXAMPLE XISFLOAT32 WHICH IS CAST TO FLOAT64 BYFITTRANSFORMX
REGRESSION TARGETS ARE CAST TO FLOAT64 AND CLASSIFICATION TARGETS ARE MAINTAINED
```
 FROM SKLEARN IMPORT DATASETS
 FROM SKLEARNSVM IMPORT SVC
IRIS  DATASETSLOADIRIS
CLF  SVCGAMMASCALE
CLFFITIRISDATA IRISTARGET
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMASCALE KERNELRBF
MAXITER1 PROBABILITYFALSE RANDOMSTATENONE SHRINKINGTRUE
TOL0001 VERBOSEFALSE
LISTCLFPREDICTIRISDATA3
0 0 0
CLFFITIRISDATA IRISTARGETNAMESIRISTARGET
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMASCALE KERNELRBF
MAXITER1 PROBABILITYFALSE RANDOMSTATENONE SHRINKINGTRUE
TOL0001 VERBOSEFALSE
LISTCLFPREDICTIRISDATA3
SETOSA SETOSA SETOSA
```
HERE THE FIRST PREDICT RETURNS AN INTEGER ARRAY SINCE IRISTARGET AN INTEGER ARRAY WAS USED IN FIT THE SECONDPREDICT RETURNS A STRING ARRAY SINCE IRISTARGETNAMES WAS FOR FITTING
REFITTING AND UPDATING PARAMETERS
HYPERPARAMETERS OF AN ESTIMATOR CAN BE UPDATED AFTER IT HAS BEEN CONSTRUCTED VIA THE SETPARAMS METHOD CALLING FIT MORE THAN ONCE WILL OVERWRITE WHAT WAS LEARNED BY ANY PREVIOUS FIT

```
 IMPORT NUMPY AS NP
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNSVM IMPORT SVC
X Y  LOADIRISRETURNXY TRUE
CLF  SVC
CLFSETPARAMSKERNELLINEARFITX Y
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMAAUTODEPRECATED
KERNELLINEAR MAXITER1 PROBABILITYFALSE RANDOMSTATENONE
SHRINKINGTRUE TOL0001 VERBOSEFALSE
CLFPREDICTX5
ARRAY0 0 0 0 0
CLFSETPARAMSKERNELRBF GAMMASCALEFITX Y
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMASCALE KERNELRBF
MAXITER1 PROBABILITYFALSE RANDOMSTATENONE SHRINKINGTRUE
TOL0001 VERBOSEFALSE
CLFPREDICTX5
ARRAY0 0 0 0 0
```

HERE THE DEFAULT KERNEL RBF IS FIRST CHANGED TO LINEAR VIASVCSETPARAMS AFTER THE ESTIMATOR HAS BEEN CONSTRUCTED AND CHANGED BACK TO RBF TO REFIT THE ESTIMATOR AND TO MAKE A SECOND PREDICTION

MULTICLASS VS MULTILABEL FITTING

WHEN USING MULTICLASS CLASSIFIERS THE LEARNING AND PREDICTION TASK THAT IS PERFORMED IS DEPENDENT ON THE FORMAT OF THE TARGET DATA FIT UPON

```
 FROM SKLEARNSVM IMPORT SVC
 FROM SKLEARNMULTICLASS IMPORT ONEVSRESTCLASSIFIER
 FROM SKLEARNPREPROCESSING IMPORT LABELBINARIZER
X  1 2 2 4 4 5 3 2 3 1
Y  0 0 1 1 2
CLASSIF  ONEVSRESTCLASSIFIERESTIMATORSVCGAMMASCALE
 RANDOMSTATE0
CLASSIFFITX YPREDICTX
ARRAY0 0 1 1 2
```

IN THE ABOVE CASE THE CLASSIFIER IS FIT ON A 1D ARRAY OF MULTICLASS LABELS AND THE PREDICT METHOD THEREFORE PROVIDES CORRESPONDING MULTICLASS PREDICTIONS IT IS ALSO POSSIBLE TO FIT UPON A 2D ARRAY OF BINARY LABEL INDICATORS

```
Y  LABELBINARIZERFITTRANSFORMY
CLASSIFFITX YPREDICTX
ARRAY1 0 0
1 0 0
0 1 0
0 0 0
0 0 0
```

HERE THE CLASSIFIER IS FIT ON A 2D BINARY LABEL REPRESENTATION OF Y USING THE LABELBINARIZER IN THIS CASE PREDICT RETURNS A 2D ARRAY REPRESENTING THE CORRESPONDING MULTILABEL PREDICTIONS

NOTE THAT THE FOURTH AND FIFTH INSTANCES RETURNED ALL ZEROES INDICATING THAT THEY MATCHED NONE OF THE THREE LABELS FIT UPON WITH MULTILABEL OUTPUTS IT IS SIMILARLY POSSIBLE FOR AN INSTANCE TO BE ASSIGNED MULTIPLE LABELS

```
 FROM SKLEARNPREPROCESSING IMPORT MULTILABELBINARIZER
Y  0 1 0 2 1 3 0 2 3 2 4
Y  MULTILABELBINARIZERFITTRANSFORMY
CLASSIFFITX YPREDICTX
ARRAY1 1 0 0 0
1 0 1 0 0
0 1 0 1 0
1 0 1 0 0
1 0 1 0 0
```

IN THIS CASE THE CLASSIFIER IS FIT UPON INSTANCES EACH ASSIGNED MULTIPLE LABELS THE MULTILABELBINARIZER IS USED TO BINARIZE THE 2D ARRAY OF MULTILABELS TO FIT UPON AS A RESULT PREDICT RETURNS A 2D ARRAY WITH MULTIPLE PREDICTED LABELS FOR EACH INSTANCE

22 A TUTORIAL ON STATISTICALLEARNING FOR SCIENTIFIC DATA PROCESSING

STATISTICAL LEARNING

MACHINE LEARNING IS A TECHNIQUE WITH A GROWING IMPORTANCE AS THE SIZE OF THE DATASETS EXPERIMENTAL SCIENCES ARE FAC ING IS RAPIDLY GROWING PROBLEMS IT TACKLES RANGE FROM BUILDING A PREDICTION FUNCTION LINKING DIFFERENT OBSERVATIONS TO CLASSIFYING OBSERVATIONS OR LEARNING THE STRUCTURE IN AN UNLABELED DATASET

THIS TUTORIAL WILL EXPLORE STATISTICAL LEARNING THE USE OF MACHINE LEARNING TECHNIQUES WITH THE GOAL OF STATISTICAL INFERENCE DRAWING CONCLUSIONS ON THE DATA AT HAND

SCIKITLEARN IS A PYTHON MODULE INTEGRATING CLASSIC MACHINE LEARNING ALGORITHMS IN THE TIGHTLYKNIT WORLD OF SCIENTIFIC PYTHON PACKAGES NUMPY SCIPY MATPLOTLIB

221 STATISTICAL LEARNING THE SETTING AND THE ESTIMATOR OBJECT IN SCIKITLEARN

DATASETS

SCIKITLEARN DEALS WITH LEARNING INFORMATION FROM ONE OR MORE DATASETS THAT ARE REPRESENTED AS 2D ARRAYS THEY CAN BE UNDERSTOOD AS A LIST OF MULTIDIMENSIONAL OBSERVATIONS WE SAY THAT THE FIRST AXIS OF THESE ARRAYS IS THE SAMPLES AXIS WHILE THE SECOND IS THE FEATURES AXIS

A SIMPLE EXAMPLE SHIPPED WITH SCIKITLEARN IRIS DATASET

```
 FROM SKLEARN IMPORT DATASETS
IRIS  DATASETSLOADIRIS
DATA  IRISDATA
DATASHAPE
150 4
```

IT IS MADE OF 150 OBSERVATIONS OF IRISES EACH DESCRIBED BY 4 FEATURES THEIR SEPAL AND PETAL LENGTH AND WIDTH AS DETAILED ININIRISDESCR

WHEN THE DATA IS NOT INITIALLY IN THE NSAMPLES NFEATURES SHAPE IT NEEDS TO BE PREPROCESSED IN ORDER TO
BE USED BY SCIKITLEARN
AN EXAMPLE OF RESHAPING DATA WOULD BE THE DIGITS DATASET
THE DIGITS DATASET IS MADE OF 1797 8X8 IMAGES OF HANDWRITTEN DIGITS
DIGITS DATASETSLOADDIGITS
DIGITSIMAGESSHAPE
1797 8 8
 IMPORT MATPLOTLIBPYPLOT AS PLT
PLTIMSHOWDIGITSIMAGES1 CMAPPLTCMGRAYR
MATPLOTLIBIMAGEAXESIMAGE OBJECT AT
TO USE THIS DATASET WITH SCIKITLEARN WE TRANSFORM EACH 8X8 IMAGE INTO A FEATURE VECTOR OF LENGTH 64
DATA DIGITSIMAGESRESHAPEDIGITSIMAGESSHAPE0 1
ESTIMATORS OBJECTS
FITTING DATA THE MAIN API IMPLEMENTED BY SCIKITLEARN IS THAT OF THE ESTIMATOR AN ESTIMATOR IS ANY OBJECT THAT LEARNS
FROM DATA IT MAY BE A CLASSIFICATION REGRESSION OR CLUSTERING ALGORITHM OR A TRANSFORMER THAT EXTRACTSFILTERS USEFUL
FEATURES FROM RAW DATA
ALL ESTIMATOR OBJECTS EXPOSE A FIT METHOD THAT TAKES A DATASET USUALLY A 2D ARRAY
ESTIMATORFITDATA
ESTIMATOR PARAMETERS ALL THE PARAMETERS OF AN ESTIMATOR CAN BE SET WHEN IT IS INSTANTIATED OR BY MODIFYING THE
CORRESPONDING ATTRIBUTE
ESTIMATOR ESTIMATORPARAM11 PARAM22
ESTIMATORPARAM1
1
ESTIMATED PARAMETERS WHEN DATA IS FITTED WITH AN ESTIMATOR PARAMETERS ARE ESTIMATED FROM THE DATA AT HAND ALL THE
ESTIMATED PARAMETERS ARE ATTRIBUTES OF THE ESTIMATOR OBJECT ENDING BY AN UNDERSCORE
ESTIMATORESTIMATEDPARAM

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222 SUPERVISED LEARNING PREDICTING AN OUTPUT VARIABLE FROM HIGHDIMENSIONAL OB
SERVATIONS
THE PROBLEM SOLVED IN SUPERVISED LEARNING
SUPERVISED LEARNING CONSISTS IN LEARNING THE LINK BETWEEN TWO DATASETS THE OBSERVED DATA XAND AN EXTERNAL VARIABLE
YTHAT WE ARE TRYING TO PREDICT USUALLY CALLED “TARGET” OR “LABELS” MOST OFTEN YIS A 1D ARRAY OF LENGTH NSAMPLES
ALL SUPERVISED ESTIMATORS IN SCIKITLEARN IMPLEMENT A FITX Y METHOD TO FIT THE MODEL AND A PREDICTX
METHOD THAT GIVEN UNLABELED OBSERVATIONS X RETURNS THE PREDICTED LABELS Y
VOCABULARY CLASSIFICATION AND REGRESSION
IF THE PREDICTION TASK IS TO CLASSIFY THE OBSERVATIONS IN A SET OF FINITE LABELS IN OTHER WORDS TO “NAME” THE OBJECTS
OBSERVED THE TASK IS SAID TO BE A CLASSIFICATION TASK ON THE OTHER HAND IF THE GOAL IS TO PREDICT A CONTINUOUS TARGET
VARIABLE IT IS SAID TO BE A REGRESSION TASK
WHEN DOING CLASSIFICATION IN SCIKITLEARN YIS A VECTOR OF INTEGERS OR STRINGS
NOTE SEE THE INTRODUCTION TO MACHINE LEARNING WITH SCIKITLEARN TUTORIAL FOR A QUICK RUNTHROUGH ON THE BASIC
MACHINE LEARNING VOCABULARY USED WITHIN SCIKITLEARN
NEAREST NEIGHBOR AND THE CURSE OF DIMENSIONALITY
CLASSIFYING IRISES
22 A TUTORIAL ON STATISTICALLEARNING FOR SCIENTIFIC DATA PROCESSING 159

THE IRIS DATASET IS A
CLASSIFICATION TASK CONSISTING IN IDENTIFYING 3 DIFFERENT TYPES OF IRISES SETOSA VERSICOLOUR AND VIRGINICA FROM THEIR PETAL AND SEPAL LENGTH AND WIDTH

```
 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT DATASETS
IRIS  DATASETSLOADIRIS
IRISX  IRISDATA
IRISY  IRISTARGET
NPUNIQUEIRISY
ARRAY0 1 2
```

KNEAREST NEIGHBORS CLASSIFIER
THE SIMPLEST POSSIBLE CLASSIFIER IS THE NEAREST NEIGHBOR GIVEN A NEW OBSERVATION XTEST FIND IN THE TRAINING SET IE THE DATA USED TO TRAIN THE ESTIMATOR THE OBSERVATION WITH THE CLOSEST FEATURE VECTOR PLEASE SEE THE NEAREST NEIGHBORS SECTION OF THE ONLINE SCIKITLEARN DOCUMENTATION FOR MORE INFORMATION ABOUT THIS TYPE OF CLASSIFIER
TRAINING SET AND TESTING SET
WHILE EXPERIMENTING WITH ANY LEARNING ALGORITHM IT IS IMPORTANT NOT TO TEST THE PREDICTION OF AN ESTIMATOR ON THE DATA USED TO FIT THE ESTIMATOR AS THIS WOULD NOT BE EVALUATING THE PERFORMANCE OF THE ESTIMATOR ON NEW DATA THIS IS WHY DATASETS ARE OFTEN SPLIT INTO TRAIN ANDTESTDATA

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KNN K NEAREST NEIGHBORS CLASSIFICATION EXAMPLE
SPLIT IRIS DATA IN TRAIN AND TEST DATA
A RANDOM PERMUTATION TO SPLIT THE DATA RANDOMLY
NPRANDOMSEED0
INDICES NPRANDOMPERMUTATIONLENIRISX
IRISXTRAIN IRISXINDICES10
IRISYTRAIN IRISYINDICES10
IRISXTEST IRISXINDICES10
IRISYTEST IRISYINDICES10
CREATE AND FIT A NEARESTNEIGHBOR CLASSIFIER
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSCLASSIFIER
KNN KNEIGHBORSCLASSIFIER
KNNFITIRISXTRAIN IRISYTRAIN
KNEIGHBORSCLASSIFIERALGORITHMAUTO LEAFSIZE30 METRICMINKOWSKI
METRICPARAMSNONE NJOBSNONE NNEIGHBORS5 P2
WEIGHTSUNIFORM
KNNPREDICTIRISXTEST
ARRAY1 2 1 0 0 0 2 1 2 0
IRISYTEST
ARRAY1 1 1 0 0 0 2 1 2 0
THE CURSE OF DIMENSIONALITY
FOR AN ESTIMATOR TO BE EFFECTIVE YOU NEED THE DISTANCE BETWEEN NEIGHBORING POINTS TO BE LESS THAN SOME VALUE WHICH DEPENDS ON THE PROBLEM IN ONE DIMENSION THIS REQUIRES ON AVERAGE ~1POINTS IN THE CONTEXT OF THE ABOVE NN EXAMPLE IF THE DATA IS DESCRIBED BY JUST ONE FEATURE WITH VALUES RANGING FROM 0 TO 1 AND WITH TRAINING OBSERVATIONS THEN NEW DATA WILL BE NO FURTHER AWAY THAN 1 THEREFORE THE NEAREST NEIGHBOR DECISION RULE WILL BE EFFICIENT AS SOON AS1IS SMALL COMPARED TO THE SCALE OF BETWEENCLASS FEATURE VARIATIONS
IF THE NUMBER OF FEATURES IS YOU NOW REQUIRE ~1POINTS LET'S SAY THAT WE REQUIRE 10 POINTS IN ONE DIMENSION NOW10POINTS ARE REQUIRED IN DIMENSIONS TO PAVE THE 01SPACE AS BECOMES LARGE THE NUMBER OF TRAINING POINTS REQUIRED FOR A GOOD ESTIMATOR GROWS EXPONENTIALLY
FOR EXAMPLE IF EACH POINT IS JUST A SINGLE NUMBER 8 BYTES THEN AN EFFECTIVE NN ESTIMATOR IN A PALTRY ~20 DIMENSIONS WOULD REQUIRE MORE TRAINING DATA THAN THE CURRENT ESTIMATED SIZE OF THE ENTIRE INTERNET ±1000 EXABYTES OR 22 A TUTORIAL ON STATISTICALLEARNING FOR SCIENTIFIC DATA PROCESSING 161

SO
THIS IS CALLED THE CURSE OF DIMENSIONALITY AND IS A CORE PROBLEM THAT MACHINE LEARNING ADDRESSES
LINEAR MODEL FROM REGRESSION TO SPARSITY
DIABETES DATASET
THE DIABETES DATASET CONSISTS OF 10 PHYSIOLOGICAL VARIABLES AGE SEX WEIGHT BLOOD PRESSURE MEASURE ON 442
PATIENTS AND AN INDICATION OF DISEASE PROGRESSION AFTER ONE YEAR
DIABETES DATASETSLOADDIABETES
DIABETESXTRAIN DIABETESDATA20
DIABETESXTEST DIABETESDATA20
DIABETESYTRAIN DIABETESTARGET20
DIABETESYTEST DIABETESTARGET20
THE TASK AT HAND IS TO PREDICT DISEASE PROGRESSION FROM PHYSIOLOGICAL VARIABLES
LINEAR REGRESSION
LINEARREGRESSION IN ITS SIMPLEST FORM FITS A LINEAR MODEL TO THE DATA SET BY ADJUSTING A SET
OF PARAMETERS IN ORDER TO MAKE THE SUM OF THE SQUARED RESIDUALS OF THE MODEL AS SMALL AS POSSIBLE
LINEAR MODELS □□□□
•□ DATA
•□ TARGET VARIABLE
•□ COEFFICIENTS
•□ OBSERVATION NOISE
 FROM SKLEARN IMPORT LINEARMODEL
REGR LINEARMODELLINEARREGRESSION
REGRFITDIABETESXTRAIN DIABETESYTRAIN

LINEARREGRESSIONCOPYXTRUE FITINTERCEPTTRUE NJOBSNONE
NORMALIZEFALSE
PRINTREGRCOEF
 030349955 23763931533 51053060544 32773698041 81413170937
49281458798 10284845219 18460648906 74351961675 7609517222

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 THE MEAN SQUARE ERROR
NPMEANREGRPREDICTDIABETESXTEST DIABETESYTEST 2

200456760268
 EXPLAINED VARIANCE SCORE 1 IS PERFECT PREDICTION
 AND 0 MEANS THAT THERE IS NO LINEAR RELATIONSHIP
 BETWEEN X AND Y
REGRSCOREDIABETESXTEST DIABETESYTEST
05850753022690
SHRINKAGE
IF THERE ARE FEW DATA POINTS PER DIMENSION NOISE IN THE OBSERVATIONS INDUCES HIGH VARIANCE
X NPC 5 1T
Y 5 1
TEST NPC 0 2T
REGR LINEARMODELLINEARREGRESSION
 IMPORT MATPLOTLIBPYPLOT AS PLT
PLTFIGURE
NPRANDOMSEED0
 FOR INRANGE6
 THISX 1 NPRANDOMNORMALSIZE2 1 X
 REGRFITTHISX Y
 PLTPLOTTEST REGRPREDICTTEST
 PLTSCATTERTHISX Y S3
A SOLUTION IN HIGHDIMENSIONAL STATISTICAL LEARNING IS TO SHRINK THE REGRESSION COEFFICIENTS TO ZERO ANY
TWO RANDOMLY CHOSEN SET OF OBSERVATIONS ARE LIKELY TO BE UNCORRELATED THIS IS CALLED RIDGE REGRESSION

SCIKITLEARN USER GUIDE RELEASE 0213
REGR LINEARMODELRIDGEALPHA1
PLTFIGURE
NPRANDOMSEED0
 FOR INRANGE6
 THISX 1 NPRANDOMNORMALSIZE2 1 X
 REGRFITTHISX Y
 PLTPLOTTEST REGRPREDICTTEST
 PLTSCATTERTHISX Y S3
THIS IS AN EXAMPLE OF BIASVARIANCE TRADEOFF THE LARGER THE RIDGE ALPHA PARAMETER THE HIGHER THE BIAS AND THE LOWER THE VARIANCE
WE CAN CHOOSE ALPHA TO MINIMIZE LEFT OUT ERROR THIS TIME USING THE DIABETES DATASET RATHER THAN OUR SYNTHETIC DATA
ALPHAS NPLOGSPACE4 1 6
PRINTREGRSETPARAMSALPHAALPHA
 FITDIABETESXTRAIN DIABETESYTRAIN
 SCOREDIABETESXTEST DIABETESYTEST
 FOR ALPHAINALPHAS

05851110683883 05852073015444 05854677540698
05855512036503 05830717085554 057058999437
NOTE CAPTURING IN THE FITTED PARAMETERS NOISE THAT PREVENTS THE MODEL TO GENERALIZE TO NEW DATA IS CALLED OVERFITTING
THE BIAS INTRODUCED BY THE RIDGE REGRESSION IS CALLED A REGULARIZATION
SPARSITY
FITTING ONLY FEATURES 1 AND 2

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NOTE A REPRESENTATION OF THE FULL DIABETES DATASET WOULD INVOLVE 11 DIMENSIONS 10 FEATURE DIMENSIONS AND ONE OF THE TARGET VARIABLE IT IS HARD TO DEVELOP AN INTUITION ON SUCH REPRESENTATION BUT IT MAY BE USEFUL TO KEEP IN MIND THAT IT WOULD BE A FAIRLY EMPTY SPACE
WE CAN SEE THAT ALTHOUGH FEATURE 2 HAS A STRONG COEFFICIENT ON THE FULL MODEL IT CONVEYS LITTLE INFORMATION ON YWHEN CONSIDERED WITH FEATURE 1
TO IMPROVE THE CONDITIONING OF THE PROBLEM IE MITIGATING THE THE CURSE OF DIMENSIONALITY IT WOULD BE INTERESTING TO SELECT ONLY THE INFORMATIVE FEATURES AND SET NONINFORMATIVE ONES LIKE FEATURE 2 TO 0 RIDGE REGRESSION WILL DECREASE THEIR CONTRIBUTION BUT NOT SET THEM TO ZERO ANOTHER PENALIZATION APPROACH CALLED LASSO LEAST ABSOLUTE SHRINKAGE AND SELECTION OPERATOR CAN SET SOME COEFFICIENTS TO ZERO SUCH METHODS ARE CALLED SPARSE METHOD AND SPARSITY CAN BE SEEN AS AN APPLICATION OF OCCAM'S RAZOR PREFER SIMPLER MODELS
REGR LINEARMODELLASSO
SCORES REGRSETPARAMSALPHAALPHA
FITDIABETESXTRAIN DIABETESYTRAIN
SCOREDIABETESXTEST DIABETESYTEST
FOR ALPHAINALPHAS
BESTALPHA ALPHASSCORESINDEXMAXSCORES
REGRALPHA BESTALPHA
REGRFITDIABETESXTRAIN DIABETESYTRAIN

LASSOALPHA0025118864315095794 COPYXTRUE FITINTERCEPTTRUE
MAXITER1000 NORMALIZEFALSE POSITIVEFALSE PRECOMPUTEFALSE
RANDOMSTATENONE SELECTIONCYCLIC TOL00001 WARMSTARTFALSE
PRINTREGRCOEF
0 21243764548 51719478111 31377959962 1608303982 0
18719554705 6938229038 50866011217 7184239008
22 A TUTORIAL ON STATISTICALLEARNING FOR SCIENTIFIC DATA PROCESSING 165

DIFFERENT ALGORITHMS FOR THE SAME PROBLEM
DIFFERENT ALGORITHMS CAN BE USED TO SOLVE THE SAME MATHEMATICAL PROBLEM FOR INSTANCE THE LASSO OBJECT IN SCIKIT LEARN SOLVES THE LASSO REGRESSION PROBLEM USING A COORDINATE DESCENT METHOD THAT IS EFFICIENT ON LARGE DATASETS HOWEVER SCIKITLEARN ALSO PROVIDES THE LASSOLARS OBJECT USING THE LARS ALGORITHM WHICH IS VERY EFFICIENT FOR PROBLEMS IN WHICH THE WEIGHT VECTOR ESTIMATED IS VERY SPARSE IE PROBLEMS WITH VERY FEW OBSERVATIONS
CLASSIFICATION
FOR CLASSIFICATION AS IN THE LABELING IRIS TASK LINEAR REGRESSION IS NOT
THE RIGHT APPROACH AS IT WILL GIVE TOO MUCH WEIGHT TO DATA FAR FROM THE DECISION FRONTIER A LINEAR APPROACH IS TO FIT A SIGMOID FUNCTION OR LOGISTIC FUNCTION
□SIGMOID □□−OFFSET □1
1 EXP−□□OFFSET □
LOG LINEARMODELLOGISTICREGRESSIONSOLVERLBFGS C1E5
MULTICLASSMULTINOMIAL
LOGFITIRISXTRAIN IRISYTRAIN
LOGISTICREGRESSIONC1000000 CLASSWEIGHTNONE DUALFALSE
FITINTERCEPTTRUE INTERCEPTSCALING1 L1RATIONONE MAXITER100
MULTICLASSMULTINOMIAL NJOBSNONE PENALTYL2 RANDOMSTATENONE
SOLVERLBFGS TOL00001 VERBOSE0 WARMSTARTFALSE
THIS IS KNOWN AS LOGISTICREGRESSION

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MULTICLASS CLASSIFICATION
IF YOU HAVE SEVERAL CLASSES TO PREDICT AN OPTION OFTEN USED IS TO FIT ONEVERSUSALL CLASSIFIERS AND THEN USE A VOTING HEURISTIC FOR THE FINAL DECISION
SHRINKAGE AND SPARSITY WITH LOGISTIC REGRESSION
THECPARAMETER CONTROLS THE AMOUNT OF REGULARIZATION IN THE LOGISTICREGRESSION OBJECT A LARGE VALUE FORCRESULTS IN LESS REGULARIZATION PENALTYL2 GIVES SHRINKAGE IE NONSPARSE COEFFICIENTS WHILE PENALTYL1 GIVES SPARSITY
EXERCISE
TRY CLASSIFYING THE DIGITS DATASET WITH NEAREST NEIGHBORS AND A LINEAR MODEL LEAVE OUT THE LAST 10 AND TEST PREDICTION PERFORMANCE ON THESE OBSERVATIONS
FROM SKLEARN IMPORT DATASETS NEIGHBORS LINEARMODEL
DIGITS DATASETSLOADDIGITS
XDIGITS DIGITSDATA DIGITSDATAMAX
YDIGITS DIGITSTARGET
SOLUTIONAUTOEXAMPLESEXERCISESPLOTDIGITSCLASSIFICATIONEXERCISEPY
SUPPORT VECTOR MACHINES SVMS
LINEAR SVMS
SUPPORT VECTOR MACHINES BELONG TO THE DISCRIMINANT MODEL FAMILY THEY TRY TO FIND A COMBINATION OF SAMPLES TO BUILD A PLANE MAXIMIZING THE MARGIN BETWEEN THE TWO CLASSES REGULARIZATION IS SET BY THE CPARAMETER A SMALL VALUE FOR C MEANS THE MARGIN IS CALCULATED USING MANY OR ALL OF THE OBSERVATIONS AROUND THE SEPARATING LINE MORE REGULARIZATION A LARGE VALUE FOR CMEANS THE MARGIN IS CALCULATED ON OBSERVATIONS CLOSE TO THE SEPARATING LINE LESS REGULARIZATION UNREGULARIZED SVM REGULARIZED SVM DEFAULT

EXAMPLE
•PLOT DIFFERENT SVM CLASSIFIERS IN THE IRIS DATASET
SVMS CAN BE USED IN REGRESSION – SVR SUPPORT VECTOR REGRESSION– OR IN CLASSIFICATION – SVC SUPPORT VECTOR CLAS
SIFICATION
```
 FROM SKLEARN IMPORT SVM
SVC  SVMSVCKERNELLINEAR
SVCFITIRISXTRAIN IRISYTRAIN
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMAAUTODEPRECATED
KERNELLINEAR MAXITER1 PROBABILITYFALSE RANDOMSTATENONE
SHRINKINGTRUE TOL0001 VERBOSEFALSE
```
WARNING NORMALIZING DATA
FOR MANY ESTIMATORS INCLUDING THE SVMS HAVING DATASETS WITH UNIT STANDARD DEVIATION FOR EACH FEATURE IS IMPORTANT
TO GET GOOD PREDICTION
USING KERNELS
CLASSES ARE NOT ALWAYS LINEARLY SEPARABLE IN FEATURE SPACE THE SOLUTION IS TO BUILD A DECISION FUNCTION THAT IS NOT LINEAR
BUT MAY BE POLYNOMIAL INSTEAD THIS IS DONE USING THE KERNEL TRICK THAT CAN BE SEEN AS CREATING A DECISION ENERGY BY
POSITIONING KERNELS ON OBSERVATIONS
LINEAR KERNEL POLYNOMIAL KERNEL
```
SVC  SVMSVCKERNELLINEAR SVC  SVMSVCKERNELPOLY
 DEGREE3
 DEGREE POLYNOMIAL DEGREE
```

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RBF KERNEL RADIAL BASIS FUNCTION
SVC SVMSVCKERNELRBF
 GAMMA INVERSE OF SIZE OF
 RADIAL KERNEL
INTERACTIVE EXAMPLE
SEE THE SVM GUI TO DOWNLOAD SVMGUIPY ADD DATA POINTS OF BOTH CLASSES WITH RIGHT AND LEFT BUTTON FIT THE MODEL AND CHANGE PARAMETERS AND DATA
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EXERCISE
TRY CLASSIFYING CLASSES 1 AND 2 FROM THE IRIS DATASET WITH SVMS WITH THE 2 FIRST FEATURES LEAVE OUT 10 OF EACH CLASS AND TEST PREDICTION PERFORMANCE ON THESE OBSERVATIONS
WARNING THE CLASSES ARE ORDERED DO NOT LEAVE OUT THE LAST 10 YOU WOULD BE TESTING ON ONLY ONE CLASS
HINT YOU CAN USE THE DECISIONFUNCTION METHOD ON A GRID TO GET INTUITIONS
IRIS DATASETSLOADIRIS
X IRISDATA
Y IRISTARGET
X XY 0 2
Y YY 0
SOLUTIONAUTOEXAMPLESEXERCISESPLOTIRISEXERCISEPY
223 MODEL SELECTION CHOOSING ESTIMATORS AND THEIR PARAMETERS
SCORE AND CROSSVALIDATED SCORES
AS WE HAVE SEEN EVERY ESTIMATOR EXPOSES A SCORE METHOD THAT CAN JUDGE THE QUALITY OF THE FIT OR THE PREDICTION ON NEW DATA BIGGER IS BETTER
```
 FROM SKLEARN IMPORT DATASETS SVM
DIGITS  DATASETSLOADDIGITS
XDIGITS  DIGITSDATA
YDIGITS  DIGITSTARGET
SVC  SVMSVCC1 KERNELLINEAR
SVCFITXDIGITS100 YDIGITS100SCOREXDIGITS100 YDIGITS100
```
098
TO GET A BETTER MEASURE OF PREDICTION ACCURACY WHICH WE CAN USE AS A PROXY FOR GOODNESS OF FIT OF THE MODEL WE CAN SUCCESSIVELY SPLIT THE DATA IN FOLDS THAT WE USE FOR TRAINING AND TESTING
```
 IMPORT NUMPY AS NP
XFOLDS  NPARRAYSPLITXDIGITS 3
YFOLDS  NPARRAYSPLITYDIGITS 3
SCORES  LIST
 FOR KINRANGE3
  WE USE LIST TO COPY IN ORDER TO POP LATER ON
 XTRAIN  LISTXFOLDS
 XTEST  XTRAINPOPK
 XTRAIN  NPCONCATENATEXTRAIN
 YTRAIN  LISTYFOLDS
 YTEST  YTRAINPOPK
 YTRAIN  NPCONCATENATEYTRAIN
 SCORESAPPENDSVCFITXTRAIN YTRAINSCOREXTEST YTEST
PRINTSCORES
```
0934 0956 0939
THIS IS CALLED A KFOLD CROSSVALIDATION

CROSSVALIDATION GENERATORS

SCIKITLEARN HAS A COLLECTION OF CLASSES WHICH CAN BE USED TO GENERATE LISTS OF TRAINTEST INDICES FOR POPULAR CROSS VALIDATION STRATEGIES

THEY EXPOSE A SPLIT METHOD WHICH ACCEPTS THE INPUT DATASET TO BE SPLIT AND YIELDS THE TRAINTEST SET INDICES FOR EACH ITERATION OF THE CHOSEN CROSSVALIDATION STRATEGY

THIS EXAMPLE SHOWS AN EXAMPLE USAGE OF THE SPLIT METHOD

```
 FROM SKLEARNMODELSELECTION IMPORT KFOLD CROSSVALSCORE
X  A A A B B C C C C C
KFOLD  KFOLDNSPLITS5
 FOR TRAININDICES TESTINDICES INKFOLDSPLITX
 PRINTTRAIN S TEST S  TRAININDICES TESTINDICES
TRAIN 2 3 4 5 6 7 8 9  TEST 0 1
TRAIN 0 1 4 5 6 7 8 9  TEST 2 3
TRAIN 0 1 2 3 6 7 8 9  TEST 4 5
TRAIN 0 1 2 3 4 5 8 9  TEST 6 7
TRAIN 0 1 2 3 4 5 6 7  TEST 8 9
```

THE CROSSVALIDATION CAN THEN BE PERFORMED EASILY

```
SVCFITXDIGITSTRAIN YDIGITSTRAINSCOREXDIGITSTEST YDIGITSTEST
 FOR TRAIN TEST INKFOLDSPLITXDIGITS
0963 0922 0963 0963 0930
```

THE CROSSVALIDATION SCORE CAN BE DIRECTLY CALCULATED USING THE CROSSVALSCORE HELPER GIVEN AN ESTIMATOR THE CROSSVALIDATION OBJECT AND THE INPUT DATASET THE CROSSVALSCORE SPLITS THE DATA REPEATEDLY INTO A TRAINING AND A TESTING SET TRAINS THE ESTIMATOR USING THE TRAINING SET AND COMPUTES THE SCORES BASED ON THE TESTING SET FOR EACH ITERATION OF CROSSVALIDATION

BY DEFAULT THE ESTIMATOR’S SCORE METHOD IS USED TO COMPUTE THE INDIVIDUAL SCORES

REFER THE METRICS MODULE TO LEARN MORE ON THE AVAILABLE SCORING METHODS

```
CROSSVALSCORESVC XDIGITS YDIGITS CVKFOLD NJOBS1
ARRAY096388889 092222222 09637883  09637883  093036212
```

NJOBS1 MEANS THAT THE COMPUTATION WILL BE DISPATCHED ON ALL THE CPUS OF THE COMPUTER

ALTERNATIVELY THE SCORING ARGUMENT CAN BE PROVIDED TO SPECIFY AN ALTERNATIVE SCORING METHOD

```
CROSSVALSCORESVC XDIGITS YDIGITS CVKFOLD
 SCORINGPRECISIONMACRO
ARRAY096578289 092708922 096681476 096362897 093192644
```

CROSSVALIDATION GENERATORS

KFOLD NSPLITS SHUFFLE RAN

DOMSTATESTRATIFIEDKFOLD NSPLITS

SHUFFLE RANDOMSTATEGROUPKFOLD NSPLITS

SPLITS IT INTO K FOLDS TRAINS ON K1

AND THEN TESTS ON THE LEFTOUTSAME AS KFOLD BUT PRESERVES THE

CLASS DISTRIBUTION WITHIN EACH FOLDENSURES THAT THE SAME GROUP IS NOT IN

BOTH TESTING AND TRAINING SETS

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SHUFFLESPLIT NSPLITS
TESTSIZE TRAINSIZE RAN
DOMSTATESTRATIFIEDSHUFFLESPLIT GROUPSHUFFLESPLIT
GENERATES TRAINTEST INDICES BASED
ON RANDOM PERMUTATIONSAME AS SHUFFLE SPLIT BUT PRESERVES THE
CLASS DISTRIBUTION WITHIN EACH ITERATIONENSURES THAT THE SAME GROUP IS NOT
IN BOTH TESTING AND TRAINING SETS
LEAVEONEGROUPOUT LEAVEPGROUPSOUT NGROUPS LEAVEONEOUT
TAKES A GROUP ARRAY TO GROUP OBSERVATIONS LEAVE P GROUPS OUT LEAVE ONE OBSERVATION OUT
LEAVEPOUT P PREDEFINEDSPLIT
LEAVE P OBSERVATIONS OUT GENERATES TRAINTEST INDICES BASED ON PREDEFINED SPLITS
EXERCISE
ON THE
DIGITS DATASET PLOT THE CROSSVALIDATION SCORE OF A SVC ESTIMATOR WITH AN LINEAR KERNEL AS A FUNCTION OF PARAMETER C
USE A LOGARITHMIC GRID OF POINTS FROM 1 TO 10
IMPORT NUMPY AS NP
FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
FROM SKLEARN IMPORT DATASETS SVM
DIGITS DATASETSLOADDIGITS
X DIGITSDATA
Y DIGITSTARGET
SVC SVMSVCKERNELLINEAR
CS NPLOGSPACE10 0 10

SOLUTION CROSSVALIDATION ON DIGITS DATASET EXERCISE
GRIDSEARCH AND CROSSVALIDATED ESTIMATORS
GRIDSEARCH
SCIKITLEARN PROVIDES AN OBJECT THAT GIVEN DATA COMPUTES THE SCORE DURING THE FIT OF AN ESTIMATOR ON A PARAMETER GRID AND CHOOSES THE PARAMETERS TO MAXIMIZE THE CROSSVALIDATION SCORE THIS OBJECT TAKES AN ESTIMATOR DURING THE CONSTRUCTION AND EXPOSES AN ESTIMATOR API

```
 FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV CROSSVALSCORE
CS  NPLOGSPACE6 1 10
CLF  GRIDSEARCHCVESTIMATORSVC PARAMGRIDDICTCCS
 NJOBS1
CLFFITXDIGITS1000 YDIGITS1000
GRIDSEARCHCVCVNONE
CLFBESTSCORE
0925
CLFBESTESTIMATORC
00077
 PREDICTION PERFORMANCE ON TEST SET IS NOT AS GOOD AS ON TRAIN SET
CLFSCOREXDIGITS1000 YDIGITS1000
0943
```

BY DEFAULT THE GRIDSEARCHCV USES A 3FOLD CROSSVALIDATION HOWEVER IF IT DETECTS THAT A CLASSIFIER IS PASSED RATHER THAN A REGRESSOR IT USES A STRATIFIED 3FOLD THE DEFAULT WILL CHANGE TO A 5FOLD CROSSVALIDATION IN VERSION 022
NESTED CROSSVALIDATION

```
CROSSVALSCORECLF XDIGITS YDIGITS
ARRAY0938 0963 0944
```

TWO CROSSVALIDATION LOOPS ARE PERFORMED IN PARALLEL ONE BY THE GRIDSEARCHCV ESTIMATOR TO SET GAMMA AND THE OTHER ONE BY CROSSVALSCORE TO MEASURE THE PREDICTION PERFORMANCE OF THE ESTIMATOR THE RESULTING SCORES ARE UNBIASED ESTIMATES OF THE PREDICTION SCORE ON NEW DATA
WARNING YOU CANNOT NEST OBJECTS WITH PARALLEL COMPUTING NJOBS DIFFERENT THAN 1
CROSSVALIDATED ESTIMATORS
CROSSVALIDATION TO SET A PARAMETER CAN BE DONE MORE EFFICIENTLY ON AN ALGORITHMBYALGORITHM BASIS THIS IS WHY FOR CERTAIN ESTIMATORS SCIKITLEARN EXPOSES CROSSVALIDATION EVALUATING ESTIMATOR PERFORMANCE ESTIMATORS THAT SET THEIR PARAMETER AUTOMATICALLY BY CROSSVALIDATION

```
 FROM SKLEARN IMPORT LINEARMODEL DATASETS
LASSO  LINEARMODELLASSOCVCV3
DIABETES  DATASETSLOADDIABETES
XDIABETES  DIABETESDATA
YDIABETES  DIABETESTARGET
```

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LASSOFITXDIABETES YDIABETES
LASSOCVALPHASNONE COPYXTRUE CV3 EPS0001 FITINTERCEPTTRUE
MAXITER1000 NALPHAS100 NJOBSNONE NORMALIZEFALSE
POSITIVEFALSE PRECOMPUTEAUTO RANDOMSTATENONE
SELECTIONCYCLIC TOL00001 VERBOSEFALSE
 THE ESTIMATOR CHOSE AUTOMATICALLY ITS LAMBDA
LASSOALPHA
001229
THESE ESTIMATORS ARE CALLED SIMILARLY TO THEIR COUNTERPARTS WITH ‘CV’ APPENDED TO THEIR NAME
EXERCISE
ON THE DIABETES DATASET FIND THE OPTIMAL REGULARIZATION PARAMETER ALPHA
BONUS HOW MUCH CAN YOU TRUST THE SELECTION OF ALPHA
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNLINEARMODEL IMPORT LASSOCV
FROM SKLEARNLINEARMODEL IMPORT LASSO
FROM SKLEARNMODELSELECTION IMPORT KFOLD
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
DIABETES DATASETSLOADDIABETES
X DIABETESDATA150
SOLUTION CROSSVALIDATION ON DIABETES DATASET EXERCISE
224 UNSUPERVISED LEARNING SEEKING REPRESENTATIONS OF THE DATA
CLUSTERING GROUPING OBSERVATIONS TOGETHER
THE PROBLEM SOLVED IN CLUSTERING
GIVEN THE IRIS DATASET IF WE KNEW THAT THERE WERE 3 TYPES OF IRIS BUT DID NOT HAVE ACCESS TO A TAXONOMIST TO LABEL
THEM WE COULD TRY A CLUSTERING TASK SPLIT THE OBSERVATIONS INTO WELLSEPARATED GROUP CALLED CLUSTERS

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KMEANS CLUSTERING
NOTE THAT THERE EXIST A LOT OF DIFFERENT CLUSTERING CRITERIA AND ASSOCIATED ALGORITHMS THE SIMPLEST CLUSTERING ALGORITHM
ISKMEANS
FROM SKLEARN IMPORT CLUSTER DATASETS
IRIS DATASETSLOADIRIS
XIRIS IRISDATA
YIRIS IRISTARGET
KMEANS CLUSTERKMEANSNCLUSTERS3
KMEANSFITXIRIS
KMEANSALGORITHMAUTO COPYXTRUE INITKMEANS
PRINTKMEANSLABELS10
1 1 1 1 1 0 0 0 0 0 2 2 2 2 2
PRINTYIRIS10
0 0 0 0 0 1 1 1 1 1 2 2 2 2 2
WARNING THERE IS ABSOLUTELY NO GUARANTEE OF RECOVERING A GROUND TRUTH FIRST CHOOSING THE RIGHT NUMBER OF CLUSTERS IS HARD SECOND THE ALGORITHM IS SENSITIVE TO INITIALIZATION AND CAN FALL INTO LOCAL MINIMA ALTHOUGH SCIKIT LEARN EMPLOYS SEVERAL TRICKS TO MITIGATE THIS ISSUE
BAD INITIALIZATION 8 CLUSTERS GROUND TRUTH
DON’T OVERINTERPRET CLUSTERING RESULTS
APPLICATION EXAMPLE VECTOR QUANTIZATION
CLUSTERING IN GENERAL AND KMEANS IN PARTICULAR CAN BE SEEN AS A WAY OF CHOOSING A SMALL NUMBER OF EXEMPLARS TO COMPRESS THE INFORMATION THE PROBLEM IS SOMETIMES KNOWN AS VECTOR QUANTIZATION FOR INSTANCE THIS CAN BE USED
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TO POSTERIZE AN IMAGE
```
 IMPORT SCIPY AS SP
 TRY
FACE  SPFACEGRAY TRUE
 EXCEPT ATTRIBUTEERROR
 FROM SCIPY IMPORT MISC
FACE  MISCFACEGRAY TRUE
X  FACERESHAPE1 1  WE NEED AN NSAMPLE NFEATURE ARRAY
KMEANS  CLUSTERKMEANSNCLUSTERS5 NINIT1
KMEANSFITX
KMEANSALGORITHMAUTO COPYXTRUE INITKMEANS
VALUES  KMEANSCLUSTERCENTERSSQUEEZE
LABELS  KMEANSLABELS
FACECOMPRESSED  NPCHOOSELABELS VALUES
FACECOMPRESSEDSHAPE  FACESHAPE
```
RAW IMAGE KMEANS QUANTIZATION EQUAL BINS IMAGE HISTOGRAM
HIERARCHICAL AGGLOMERATIVE CLUSTERING WARD
AHIERARCHICAL CLUSTERING METHOD IS A TYPE OF CLUSTER ANALYSIS THAT AIMS TO BUILD A HIERARCHY OF CLUSTERS IN GENERAL THE VARIOUS APPROACHES OF THIS TECHNIQUE ARE EITHER
•AGGLOMERATIVE BOTTOMUP APPROACHES EACH OBSERVATION STARTS IN ITS OWN CLUSTER AND CLUSTERS ARE ITERATIVELY MERGED IN SUCH A WAY TO MINIMIZE A LINKAGE CRITERION THIS APPROACH IS PARTICULARLY INTERESTING WHEN THE CLUS TERS OF INTEREST ARE MADE OF ONLY A FEW OBSERVATIONS WHEN THE NUMBER OF CLUSTERS IS LARGE IT IS MUCH MORE COMPUTATIONALLY EFFICIENT THAN KMEANS
•DIVISIVE TOPDOWN APPROACHES ALL OBSERVATIONS START IN ONE CLUSTER WHICH IS ITERATIVELY SPLIT AS ONE MOVES DOWN THE HIERARCHY FOR ESTIMATING LARGE NUMBERS OF CLUSTERS THIS APPROACH IS BOTH SLOW DUE TO ALL OBSERVATIONS STARTING AS ONE CLUSTER WHICH IT SPLITS RECURSIVELY AND STATISTICALLY ILLPOSED
CONNECTIVITYCONSTRAINED CLUSTERING
WITH AGGLOMERATIVE CLUSTERING IT IS POSSIBLE TO SPECIFY WHICH SAMPLES CAN BE CLUSTERED TOGETHER BY GIVING A CONNEC TIVITY GRAPH GRAPHS IN SCIKITLEARN ARE REPRESENTED BY THEIR ADJACENCY MATRIX OFTEN A SPARSE MATRIX IS USED THIS CAN BE USEFUL FOR INSTANCE TO RETRIEVE CONNECTED REGIONS SOMETIMES ALSO REFERRED TO AS CONNECTED COMPONENTS WHEN

CLUSTERING AN IMAGE
FROM SCIPYNDIMAGEFILTERS IMPORT GAUSSIANFILTER
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT SKIMAGE
FROM SKIMAGEDATA IMPORT COINS
FROM SKIMAGETRANSFORM IMPORT RESCALE
FROM SKLEARNFEATUREEXTRACTIONIMAGE IMPORT GRIDTOGRAPH
FROM SKLEARNCLUSTER IMPORT AGGLOMERATIVECLUSTERING
 THESE WERE INTRODUCED IN SKIMAGE014
IFLOOSEVERSIONSKIMAGEVERSION 014
RESCALEPARAMS ANTIALIASING FALSE MULTICHANNEL FALSE
ELSE
RESCALEPARAMS

 GENERATE DATA
ORIGCOINS COINS
 RESIZE IT TO 20 OF THE ORIGINAL SIZE TO SPEED UP THE PROCESSING
 APPLYING A GAUSSIAN FILTER FOR SMOOTHING PRIOR TO DOWNSCALING
 REDUCES ALIASING ARTIFACTS
SMOOTHENEDCOINS GAUSSIANFILTERORIGCOINS SIGMA2
FEATURE AGGLOMERATION
WE HAVE SEEN THAT SPARSITY COULD BE USED TO MITIGATE THE CURSE OF DIMENSIONALITY IEAN INSUFFICIENT AMOUNT OF OB SERVATIONS COMPARED TO THE NUMBER OF FEATURES ANOTHER APPROACH IS TO MERGE TOGETHER SIMILAR FEATURES FEATURE AGGLOMERATION THIS APPROACH CAN BE IMPLEMENTED BY CLUSTERING IN THE FEATURE DIRECTION IN OTHER WORDS CLUSTERING

THE TRANSPOSED DATA
DIGITS DATASETSLOADDIGITS
IMAGES DIGITSIMAGES
X NPRESHAPEIMAGES LENIMAGES 1
CONNECTIVITY GRIDTOGRAPH IMAGES0SHAPE
AGGLO CLUSTERFEATUREAGGLOMERATIONCONNECTIVITYCONNECTIVITY
 NCLUSTERS32
AGGLOFITX
FEATUREAGGLOMERATIONAFFINITYEUCLIDEAN COMPUTEFULLTREEAUTO
XREDUCED AGGLOTRANSFORMX
XAPPROX AGGLOINVERSETRANSFORMXREDUCED
IMAGESAPPROX NPRESHAPEXAPPROX IMAGESSHAPE
TRANSFORM ANDINVERSETRANSFORM METHODS
SOME ESTIMATORS EXPOSE A TRANSFORM METHOD FOR INSTANCE TO REDUCE THE DIMENSIONALITY OF THE DATASET
DECOMPOSITIONS FROM A SIGNAL TO COMPONENTS AND LOADINGS
COMPONENTS AND LOADINGS
IF X IS OUR MULTIVARIATE DATA THEN THE PROBLEM THAT WE ARE TRYING TO SOLVE IS TO REWRITE IT ON A DIFFERENT OBSERVATIONAL BASIS WE WANT TO LEARN LOADINGS L AND A SET OF COMPONENTS C SUCH THAT X L C DIFFERENT CRITERIA EXIST TO CHOOSE THE COMPONENTS
PRINCIPAL COMPONENT ANALYSIS PCA
PRINCIPAL COMPONENT ANALYSIS PCA SELECTS THE SUCCESSIVE COMPONENTS THAT EXPLAIN THE MAXIMUM VARIANCE IN THE SIGNAL

THE POINT CLOUD SPANNED BY THE OBSERVATIONS ABOVE IS VERY FLAT IN ONE DIRECTION ONE OF THE THREE UNIVARIATE FEATURES
CAN ALMOST BE EXACTLY COMPUTED USING THE OTHER TWO PCA FINDS THE DIRECTIONS IN WHICH THE DATA IS NOT FLAT
WHEN USED TO TRANSFORM DATA PCA CAN REDUCE THE DIMENSIONALITY OF THE DATA BY PROJECTING ON A PRINCIPAL SUBSPACE
```
 CREATE A SIGNAL WITH ONLY 2 USEFUL DIMENSIONS
X1  NPRANDOMNORMALSIZE100
X2  NPRANDOMNORMALSIZE100
X3  X1  X2
X  NPCX1 X2 X3
 FROM SKLEARN IMPORT DECOMPOSITION
PCA  DECOMPOSITIONPCA
PCAFITX
PCACOPYTRUE ITERATEDPOWERAUTO NCOMPONENTSNONE RANDOMSTATENONE
SVDSOLVERAUTO TOL00 WHITENFALSE
PRINTPCAEXPLAINEDVARIANCE
 218565811E00 119346747E00 843026679E32
 AS WE CAN SEE ONLY THE 2 FIRST COMPONENTS ARE USEFUL
PCANCOMPONENTS  2
XREDUCED  PCAFITTRANSFORMX
XREDUCEDSHAPE
100 2
```
INDEPENDENT COMPONENT ANALYSIS ICA
INDEPENDENT COMPONENT ANALYSIS ICA SELECTS COMPONENTS SO THAT THE DISTRIBUTION OF THEIR LOADINGS CARRIES
A MAXIMUM AMOUNT OF INDEPENDENT INFORMATION IT IS ABLE TO RECOVER NONGAUSSIAN INDEPENDENT SIGNALS

```
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 GENERATE SAMPLE DATA
 IMPORT NUMPY AS NP
 FROM SCIPY IMPORT SIGNAL
TIME  NPLINSPACE0 10 2000
S1  NPSIN2 TIME SIGNAL 1  SINUSOIDAL SIGNAL
S2  NPSIGNNPSIN3 TIME  SIGNAL 2  SQUARE SIGNAL
S3  SIGNALSAWTOOTH2 NPPITIME SIGNAL 3 SAW TOOTH SIGNAL
S  NPCS1 S2 S3
S  02 NPRANDOMNORMALSIZESSHAPE  ADD NOISE
S  SSTDAXIS0  STANDARDIZE DATA
 MIX DATA
A  NPARRAY1 1 1 05 2 1 15 1 2  MIXING MATRIX
X  NPDOTS AT  GENERATE OBSERVATIONS
 COMPUTE ICA
ICA  DECOMPOSITIONFASTICA
S  ICAFITTRANSFORMX  GET THE ESTIMATED SOURCES
A  ICAMIXINGT
NPALLCLOSEX NPDOTS A  ICAMEAN
TRUE
225 PUTTING IT ALL TOGETHER
180 CHAPTER 2 SCIKITLEARN TUTORIALS
```

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PIPELINING
WE HAVE SEEN THAT SOME ESTIMATORS CAN TRANSFORM DATA AND THAT SOME ESTIMATORS CAN PREDICT VARIABLES WE CAN ALSO CREATE COMBINED ESTIMATORS

```
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT PANDAS AS PD
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
FROM SKLEARNPIPELINE IMPORT PIPELINE
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
 DEFINE A PIPELINE TO SEARCH FOR THE BEST COMBINATION OF PCA TRUNCATION
 AND CLASSIFIER REGULARIZATION
LOGISTIC  SGDCLASSIFIERLOSSLOG PENALTYL2 EARLYSTOPPING TRUE
MAXITER10000 TOL1E5 RANDOMSTATE0
PCA  PCA
PIPE  PIPELINESTEPSPCA PCA LOGISTIC LOGISTIC
DIGITS  DATASETSLOADDIGITS
XDIGITS  DIGITSDATA
YDIGITS  DIGITSTARGET
 PARAMETERS OF PIPELINES CAN BE SET USING ‘’ SEPARATED PARAMETER NAMES
PARAMGRID
PCANCOMPONENTS 5 20 30 40 50 64
LOGISTICALPHA NPLOGSPACE4 4 5

SEARCH  GRIDSEARCHCVPIPE PARAMGRID IID FALSE CV5
SEARCHFITXDIGITS YDIGITS
```

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PRINTBEST PARAMETER CV SCORE 03F SEARCHBESTSCORE
PRINTSEARCHBESTPARAMS
 PLOT THE PCA SPECTRUM
PCAFITXDIGITS
FIG AX0 AX1 PLTSUBPLOTSNROWS2 SHAREX TRUE FIGSIZE6 6
AX0PLOTPCAEXPLAINEDVARIANCERATIO LINEWIDTH2
AX0SETYLABELPCA EXPLAINED VARIANCE
AX0AXVLINESEARCHBESTESTIMATORNAMEDSTEPSPCANCOMPONENTS
LINESTYLE LABELNCOMPONENTS CHOSEN
FACE RECOGNITION WITH EIGENFACES
THE DATASET USED IN THIS EXAMPLE IS A PREPROCESSED EXCERPT OF THE “LABELED FACES IN THE WILD” ALSO KNOWN AS LFW
HTTPVISWWWCSUMASSEDULFWLFWFUNNELEDTGZ 233MB

FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS

THE DATASET USED IN THIS EXAMPLE IS A PREPROCESSED EXCERPT OF THE
LABELED FACES IN THE WILD AKA LFW
HTTPVISWWWCSUMASSEDULFWLFWFUNNELEDTGZ 233MB
 LFW HTTPVISWWWCSUMASSEDULFW
EXPECTED RESULTS FOR THE TOP 5 MOST REPRESENTED PEOPLE IN THE DATASET

PRECISION RECALL F1SCORE SUPPORT

ARIEL SHARON 067 092 077 13
COLIN POWELL 075 078 076 60
DONALD RUMSFELD 078 067 072 27
GEORGE W BUSH 086 086 086 146
GERHARD SCHROEDER 076 076 076 25
HUGO CHAVEZ 067 067 067 15
TONY BLAIR 081 069 075 36
AVG TOTAL 080 080 080 322

FROM TIME IMPORT TIME
IMPORT LOGGING
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNDATASETS IMPORT FETCHLFWPEOPLE
FROM SKLEARNMETRICS IMPORT CLASSIFICATIONREPORT
FROM SKLEARNMETRICS IMPORT CONFUSIONMATRIX

SCIKITLEARN USER GUIDE RELEASE 0213
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNSVM IMPORT SVC
PRINTDOC
 DISPLAY PROGRESS LOGS ON STDOUT
LOGGINGBASICCONFIGLEVELLOGGINGINFO FORMAT ASCTIMES MESSAGES

 DOWNLOAD THE DATA IF NOT ALREADY ON DISK AND LOAD IT AS NUMPY ARRAYS
LFWPEOPLE FETCHLFWPEOPLEMINFACESPERPERSON70 RESIZE04
 INTROSPECT THE IMAGES ARRAYS TO FIND THE SHAPES FOR PLOTTING
NSAMPLES H W LFWPEOPLEIMAGESSHAPE
 FOR MACHINE LEARNING WE USE THE 2 DATA DIRECTLY AS RELATIVE PIXEL
 POSITIONS INFO IS IGNORED BY THIS MODEL
X LFWPEOPLEDATA
NFEATURES XSHAPE1
 THE LABEL TO PREDICT IS THE ID OF THE PERSON
Y LFWPEOPLETARGET
TARGETNAMES LFWPEOPLETARGETNAMES
NCLASSES TARGETNAMESSHAPE0
PRINTTOTAL DATASET SIZE
PRINTNSAMPLES D NSAMPLES
PRINTNFEATURES D NFEATURES
PRINTNCLASSES D NCLASSES

 SPLIT INTO A TRAINING SET AND A TEST SET USING A STRATIFIED K FOLD
 SPLIT INTO A TRAINING AND TESTING SET
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLIT
X Y TESTSIZE025 RANDOMSTATE42

 COMPUTE A PCA EIGENFACES ON THE FACE DATASET TREATED AS UNLABELED
 DATASET UNSUPERVISED FEATURE EXTRACTION DIMENSIONALITY REDUCTION
NCOMPONENTS 150
PRINTEXTRACTING THE TOP DEIGENFACES FROM DFACES
 NCOMPONENTS XTRAINSHAPE0
T0 TIME
PCA PCANCOMPONENTSNCOMPONENTS SVDSOLVERRANDOMIZED
WHITENTRUEFITXTRAIN
PRINTDONE IN 03FS TIME T0
EIGENFACES PCACOMPONENTSRESHAPENCOMPONENTS H W
PRINTPROJECTING THE INPUT DATA ON THE EIGENFACES ORTHONORMAL BASIS
T0 TIME

```
SCIKITLEARN USER GUIDE RELEASE 0213
XTRAINPCA  PCATRANSFORMXTRAIN
XTESTPCA  PCATRANSFORMXTEST
PRINTDONE IN 03FS  TIME  T0

 TRAIN A SVM CLASSIFICATION MODEL
PRINTFITTING THE CLASSIFIER TO THE TRAINING SET
T0  TIME
PARAMGRID  C 1E3 5E3 1E4 5E4 1E5
GAMMA 00001 00005 0001 0005 001 01
CLF  GRIDSEARCHCVSVCKERNELRBF CLASSWEIGHTBALANCED
PARAMGRID CV5 IID FALSE
CLF  CLFFITXTRAINPCA YTRAIN
PRINTDONE IN 03FS  TIME  T0
PRINTBEST ESTIMATOR FOUND BY GRID SEARCH
PRINTCLFBESTESTIMATOR

 QUANTITATIVE EVALUATION OF THE MODEL QUALITY ON THE TEST SET
PRINTPREDICTING PEOPLES NAMES ON THE TEST SET
T0  TIME
YPRED  CLFPREDICTXTESTPCA
PRINTDONE IN 03FS  TIME  T0
PRINTCLASSIFICATIONREPORTYTEST YPRED TARGETNAMESTARGETNAMES
PRINTCONFUSIONMATRIXYTEST YPRED LABELSRANGENCLASSES

 QUALITATIVE EVALUATION OF THE PREDICTIONS USING MATPLOTLIB
DEFPLOTGALLERYIMAGES TITLES H W NROW3 NCOL4
HELPER FUNCTION TO PLOT A GALLERY OF PORTRAITS
PLTFIGUREFIGSIZE18 NCOL 24 NROW
PLTSUBPLOTSADJUSTBOTTOM0 LEFT01 RIGHT99 TOP90 HSPACE35
FORIINRANGENROW NCOL
PLTSUBPLOTNROW NCOL I  1
PLTIMSHOWIMAGESIRESHAPEH W CMAPPLTCMGRAY
PLTTITLETITLESI SIZE12
PLTXTICKS
PLTYTICKS
 PLOT THE RESULT OF THE PREDICTION ON A PORTION OF THE TEST SET
DEFTITLEYPRED YTEST TARGETNAMES I
PREDNAME  TARGETNAMESYPREDIRSPLIT  11
TRUENAME  TARGETNAMESYTESTIRSPLIT  11
RETURNPREDICTED SNTRUE S  PREDNAME TRUENAME
PREDICTIONTITLES  TITLEYPRED YTEST TARGETNAMES I
FORIINRANGEYPREDSHAPE0
PLOTGALLERYXTEST PREDICTIONTITLES H W
184 CHAPTER 2 SCIKITLEARN TUTORIALS
```

SCIKITLEARN USER GUIDE RELEASE 0213
PLOT THE GALLERY OF THE MOST SIGNIFICATIVE EIGENFACES
EIGENFACETITLES EIGENFACE D IFORIINRANGEEIGENFACESSHAPE0
PLOTGALLERYEIGENFACES EIGENFACETITLES H W
PLTSHOW
PREDICTION EIGENFACES
EXPECTED RESULTS FOR THE TOP 5 MOST REPRESENTED PEOPLE IN THE DATASET
PRECISION RECALL F1SCORE SUPPORT
GERHARDSCHROEDER 091 075 082 28
DONALDRUMSFELD 084 082 083 33
TONYBLAIR 065 082 073 34
COLINPOWELL 078 088 083 58
GEORGEWBUSH 093 086 090 129
AVG TOTAL 086 084 085 282
OPEN PROBLEM STOCK MARKET STRUCTURE
CAN WE PREDICT THE VARIATION IN STOCK PRICES FOR GOOGLE OVER A GIVEN TIME FRAME
LEARNING A GRAPH STRUCTURE
226 FINDING HELP
THE PROJECT MAILING LIST
IF YOU ENCOUNTER A BUG WITH SCIKITLEARN OR SOMETHING THAT NEEDS CLARIFICATION IN THE DOCSTRING OR THE ONLINE DOCUMENTATION PLEASE FEEL FREE TO ASK ON THE MAILING LIST
22 A TUTORIAL ON STATISTICALLEARNING FOR SCIENTIFIC DATA PROCESSING 185

SCIKITLEARN USER GUIDE RELEASE 0213
QA COMMUNITIES WITH MACHINE LEARNING PRACTITIONERS
QUORACOM QUORA HAS A TOPIC FOR MACHINE LEARNING RELATED QUESTIONS THAT ALSO FEATURES SOME INTERESTING DISCUSSIONS HTTPSWWWQUORACOMTOPICMACHINELEARNING
STACK EXCHANGE THE STACK EXCHANGE FAMILY OF SITES HOSTS MULTIPLE SUBDOMAINS FOR MACHINE LEARNING QUESTIONS
– 'AN EXCELLENT FREE ONLINE COURSE FOR MACHINE LEARNING TAUGHT BY PROFESSOR ANDREW NG OF STANFORD' HTTPSWWW COURSERAORGLEARNMACHINELEARNING
– 'ANOTHER EXCELLENT FREE ONLINE COURSE THAT TAKES A MORE GENERAL APPROACH TO ARTIFICIAL INTELLIGENCE' HTTPSWWWUDACITYCOMCOURSEINTROTOARTIFICIALINTELLIGENCE–CS271
23 WORKING WITH TEXT DATA
THE GOAL OF THIS GUIDE IS TO EXPLORE SOME OF THE MAIN SCIKITLEARN TOOLS ON A SINGLE PRACTICAL TASK ANALYZING A COLLECTION OF TEXT DOCUMENTS NEWSGROUPS POSTS ON TWENTY DIFFERENT TOPICS
IN THIS SECTION WE WILL SEE HOW TO
• LOAD THE FILE CONTENTS AND THE CATEGORIES
• EXTRACT FEATURE VECTORS SUITABLE FOR MACHINE LEARNING
• TRAIN A LINEAR MODEL TO PERFORM CATEGORIZATION
• USE A GRID SEARCH STRATEGY TO FIND A GOOD CONFIGURATION OF BOTH THE FEATURE EXTRACTION COMPONENTS AND THE CLASSIFIER
231 TUTORIAL SETUP
TO GET STARTED WITH THIS TUTORIAL YOU MUST FIRST INSTALL SCIKITLEARN AND ALL OF ITS REQUIRED DEPENDENCIES
PLEASE REFER TO THE INSTALLATION INSTRUCTIONS PAGE FOR MORE INFORMATION AND FOR SYSTEMSPECIFIC INSTRUCTIONS
THE SOURCE OF THIS TUTORIAL CAN BE FOUND WITHIN YOUR SCIKITLEARN FOLDER
SCIKITLEARNDOCTUTORIALTEXTANALYTICS
THE SOURCE CAN ALSO BE FOUND ON GITHUB
THE TUTORIAL FOLDER SHOULD CONTAIN THE FOLLOWING SUBFOLDERS
•RST FILES THE SOURCE OF THE TUTORIAL DOCUMENT WRITTEN WITH SPHINX
•DATA FOLDER TO PUT THE DATASETS USED DURING THE TUTORIAL
•SKELETONS SAMPLE INCOMPLETE SCRIPTS FOR THE EXERCISES
•SOLUTIONS SOLUTIONS OF THE EXERCISES
YOU CAN ALREADY COPY THE SKELETONS INTO A NEW FOLDER SOMEWHERE ON YOUR HARDDRIVE NAMED SKLEARNTUTWORKSPACE WHERE YOU WILL EDIT YOUR OWN FILES FOR THE EXERCISES WHILE KEEPING THE ORIGINAL SKELETONS INTACT
 CP R SKELETONS WORKDIRECTORYSKLEARNTUTWORKSPACE

SCIKITLEARN USER GUIDE RELEASE 0213
MACHINE LEARNING ALGORITHMS NEED DATA GO TO EACH TUTORIALHOMEDATA SUBFOLDER AND RUN THE
FETCHDATAPY SCRIPT FROM THERE AFTER HAVING READ THEM FIRST
FOR INSTANCE
```
 CD TUTORIALHOMEDATALANGUAGES
 LESS FETCHDATAPY
 PYTHON FETCHDATAPY
```
232 LOADING THE 20 NEWSGROUPS DATASET
THE DATASET IS CALLED “TWENTY NEWSGROUPS” HERE IS THE OFFICIAL DESCRIPTION QUOTED FROM THE WEBSITE
THE 20 NEWSGROUPS DATA SET IS A COLLECTION OF APPROXIMATELY 20000 NEWSGROUP DOCUMENTS PARTITIONED
NEARLY EVENLY ACROSS 20 DIFFERENT NEWSGROUPS TO THE BEST OF OUR KNOWLEDGE IT WAS ORIGINALLY COLLECTED
BY KEN LANG PROBABLY FOR HIS PAPER “NEWSWEEDER LEARNING TO FILTER NETNEWS” THOUGH HE DOES NOT EXPLIC
ITLY MENTION THIS COLLECTION THE 20 NEWSGROUPS COLLECTION HAS BECOME A POPULAR DATA SET FOR EXPERIMENTS
IN TEXT APPLICATIONS OF MACHINE LEARNING TECHNIQUES SUCH AS TEXT CLASSIFICATION AND TEXT CLUSTERING
IN THE FOLLOWING WE WILL USE THE BUILTIN DATASET LOADER FOR 20 NEWSGROUPS FROM SCIKITLEARN ALTERNATIVELY IT IS POSSIBLE
TO DOWNLOAD THE DATASET MANUALLY FROM THE WEBSITE AND USE THE SKLEARNDATASETSLOADFILES FUNCTION BY
POINTING IT TO THE 20NEWSBYDATETRAIN SUBFOLDER OF THE UNCOMPRESSED ARCHIVE FOLDER
IN ORDER TO GET FASTER EXECUTION TIMES FOR THIS FIRST EXAMPLE WE WILL WORK ON A PARTIAL DATASET WITH ONLY 4 CATEGORIES OUT
OF THE 20 AVAILABLE IN THE DATASET
```
CATEGORIES  ALTATHEISM SOCRELIGIONCHRISTIAN
 COMPGRAPHICS SCIMED
```
WE CAN NOW LOAD THE LIST OF FILES MATCHING THOSE CATEGORIES AS FOLLOWS
```
 FROM SKLEARNDATASETS IMPORT FETCH20NEWSGROUPS
TWENTYTRAIN  FETCH20NEWSGROUPSSUBSETTRAIN
 CATEGORIESCATEGORIES SHUFFLE TRUE RANDOMSTATE42
```
THE RETURNED DATASET IS A SCIKITLEARN “BUNCH” A SIMPLE HOLDER OBJECT WITH FIELDS THAT CAN BE BOTH ACCESSED
AS PYTHONDICT KEYS OROBJECT ATTRIBUTES FOR CONVENIENCE FOR INSTANCE THE TARGETNAMES HOLDS THE LIST OF THE
REQUESTED CATEGORY NAMES
```
TWENTYTRAINTARGETNAMES
```
ALTATHEISM COMPGRAPHICS SCIMED SOCRELIGIONCHRISTIAN
THE FILES THEMSELVES ARE LOADED IN MEMORY IN THE DATA ATTRIBUTE FOR REFERENCE THE FILENAMES ARE ALSO AVAILABLE
```
LENTWENTYTRAINDATA
```
2257
```
LENTWENTYTRAINFILENAMES
```
2257
LET’S PRINT THE FIRST LINES OF THE FIRST LOADED FILE
```
PRINTNJOINTWENTYTRAINDATA0SPLIT N3
```
FROM SD345CITYACUK MICHAEL COLLIER
SUBJECT CONVERTING IMAGES TO HP LASERJET III
NNTPPOSTINGHOST HAMPTON
```
PRINTTWENTYTRAINTARGETNAMESTWENTYTRAINTARGET0
```
COMPGRAPHICS

SUPERVISED LEARNING ALGORITHMS WILL REQUIRE A CATEGORY LABEL FOR EACH DOCUMENT IN THE TRAINING SET IN THIS CASE THE CAT EGORY IS THE NAME OF THE NEWSGROUP WHICH ALSO HAPPENS TO BE THE NAME OF THE FOLDER HOLDING THE INDIVIDUAL DOCUMENTS FOR SPEED AND SPACE EFFICIENCY REASONS SCIKITLEARN LOADS THE TARGET ATTRIBUTE AS AN ARRAY OF INTEGERS THAT CORRE SPONDS TO THE INDEX OF THE CATEGORY NAME IN THE TARGETNAMES LIST THE CATEGORY INTEGER ID OF EACH SAMPLE IS STORED IN THETARGET ATTRIBUTE

```
TWENTYTRAINTARGET10
ARRAY1 1 3 3 3 3 3 2 2 2
```

IT IS POSSIBLE TO GET BACK THE CATEGORY NAMES AS FOLLOWS

```
 FOR TINTWENTYTRAINTARGET10
 PRINTTWENTYTRAINTARGETNAMEST

COMPGRAPHICS
COMPGRAPHICS
SOCRELIGIONCHRISTIAN
SOCRELIGIONCHRISTIAN
SOCRELIGIONCHRISTIAN
SOCRELIGIONCHRISTIAN
SOCRELIGIONCHRISTIAN
SCIMED
SCIMED
SCIMED
```

YOU MIGHT HAVE NOTICED THAT THE SAMPLES WERE SHUFFLED RANDOMLY WHEN WE CALLED FETCH20NEWSGROUPS SHUFFLETRUE RANDOMSTATE42 THIS IS USEFUL IF YOU WISH TO SELECT ONLY A SUBSET OF SAMPLES TO QUICKLY TRAIN A MODEL AND GET A FIRST IDEA OF THE RESULTS BEFORE RETRAINING ON THE COMPLETE DATASET LATER

233 EXTRACTING FEATURES FROM TEXT FILES

IN ORDER TO PERFORM MACHINE LEARNING ON TEXT DOCUMENTS WE FIRST NEED TO TURN THE TEXT CONTENT INTO NUMERICAL FEATURE VECTORS

BAGS OF WORDS

THE MOST INTUITIVE WAY TO DO SO IS TO USE A BAGS OF WORDS REPRESENTATION

1 ASSIGN A FIXED INTEGER ID TO EACH WORD OCCURRING IN ANY DOCUMENT OF THE TRAINING SET FOR INSTANCE BY BUILDING A DICTIONARY FROM WORDS TO INTEGER INDICES

2 FOR EACH DOCUMENT I COUNT THE NUMBER OF OCCURRENCES OF EACH WORD WAND STORE IT IN XI J AS THE VALUE OF FEATUREJWHEREJIS THE INDEX OF WORD WIN THE DICTIONARY

THE BAGS OF WORDS REPRESENTATION IMPLIES THAT NFEATURES IS THE NUMBER OF DISTINCT WORDS IN THE CORPUS THIS NUMBER IS TYPICALLY LARGER THAN 100000

IFNSAMPLES 10000 STORINGXAS A NUMPY ARRAY OF TYPE FLOAT32 WOULD REQUIRE 10000 X 100000 X 4 BYTES 4GB IN RAM WHICH IS BARELY MANAGEABLE ON TODAY'S COMPUTERS

FORTUNATELY MOST VALUES IN X WILL BE ZEROS SINCE FOR A GIVEN DOCUMENT LESS THAN A FEW THOUSAND DISTINCT WORDS WILL BE USED FOR THIS REASON WE SAY THAT BAGS OF WORDS ARE TYPICALLY HIGHDIMENSIONAL SPARSE DATASETS WE CAN SAVE A LOT OF MEMORY BY ONLY STORING THE NONZERO PARTS OF THE FEATURE VECTORS IN MEMORY

SCIPYSPARSE MATRICES ARE DATA STRUCTURES THAT DO EXACTLY THIS AND SCIKITLEARN HAS BUILTIN SUPPORT FOR THESE STRUCTURES

TOKENIZING TEXT WITH SCIKITLEARN

TEXT PREPROCESSING TOKENIZING AND FILTERING OF STOPWORDS ARE ALL INCLUDED IN COUNTVECTORIZER WHICH BUILDS A DICTIONARY OF FEATURES AND TRANSFORMS DOCUMENTS TO FEATURE VECTORS

```
 FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT COUNTVECTORIZER
COUNTVECT  COUNTVECTORIZER
XTRAINCOUNTS  COUNTVECTFITTRANSFORMTWENTYTRAINDATA
XTRAINCOUNTSSHAPE
2257 35788
```

COUNTVECTORIZER SUPPORTS COUNTS OF NGRAMS OF WORDS OR CONSECUTIVE CHARACTERS ONCE FITTED THE VECTORIZER HAS BUILT A DICTIONARY OF FEATURE INDICES

```
COUNTVECTVOCABULARYGETUALGORITHM
4690
```

THE INDEX VALUE OF A WORD IN THE VOCABULARY IS LINKED TO ITS FREQUENCY IN THE WHOLE TRAINING CORPUS

FROM OCCURRENCES TO FREQUENCIES

OCCURRENCE COUNT IS A GOOD START BUT THERE IS AN ISSUE LONGER DOCUMENTS WILL HAVE HIGHER AVERAGE COUNT VALUES THAN SHORTER DOCUMENTS EVEN THOUGH THEY MIGHT TALK ABOUT THE SAME TOPICS

TO AVOID THESE POTENTIAL DISCREPANCIES IT SUFFICES TO DIVIDE THE NUMBER OF OCCURRENCES OF EACH WORD IN A DOCUMENT BY THE TOTAL NUMBER OF WORDS IN THE DOCUMENT THESE NEW FEATURES ARE CALLED TFFOR TERM FREQUENCIES

ANOTHER REFINEMENT ON TOP OF TF IS TO DOWNSCALE WEIGHTS FOR WORDS THAT OCCUR IN MANY DOCUMENTS IN THE CORPUS AND ARE THEREFORE LESS INFORMATIVE THAN THOSE THAT OCCUR ONLY IN A SMALLER PORTION OF THE CORPUS

THIS DOWNSCALING IS CALLED TF–IDF FOR “TERM FREQUENCY TIMES INVERSE DOCUMENT FREQUENCY”

BOTH TFANDTF–IDF CAN BE COMPUTED AS FOLLOWS USING TFIDFTRANSFORMER

```
 FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFTRANSFORMER
TFTRANSFORMER  TFIDFTRANSFORMERUSEIDF FALSEFITXTRAINCOUNTS
XTRAINTF  TFTRANSFORMERTRANSFORMXTRAINCOUNTS
XTRAINTFSHAPE
2257 35788
```

IN THE ABOVE EXAMPLECODE WE FIRSTLY USE THE FIT METHOD TO FIT OUR ESTIMATOR TO THE DATA AND SECONDLY THE TRANSFORM METHOD TO TRANSFORM OUR COUNTMATRIX TO A TFIDF REPRESENTATION THESE TWO STEPS CAN BE COM BINED TO ACHIEVE THE SAME END RESULT FASTER BY SKIPPING REDUNDANT PROCESSING THIS IS DONE THROUGH USING THE FITTRANSFORM METHOD AS SHOWN BELOW AND AS MENTIONED IN THE NOTE IN THE PREVIOUS SECTION

```
TFIDFTRANSFORMER  TFIDFTRANSFORMER
XTRAINTFIDF  TFIDFTRANSFORMERFITTRANSFORMXTRAINCOUNTS
XTRAINTFIDFSHAPE
2257 35788
```

234 TRAINING A CLASSIFIER

NOW THAT WE HAVE OUR FEATURES WE CAN TRAIN A CLASSIFIER TO TRY TO PREDICT THE CATEGORY OF A POST LET'S START WITH A NAÏVE BAYES CLASSIFIER WHICH PROVIDES A NICE BASELINE FOR THIS TASK SCIKITLEARN INCLUDES SEVERAL VARIANTS OF THIS CLASSIFIER THE ONE MOST SUITABLE FOR WORD COUNTS IS THE MULTINOMIAL VARIANT

```
 FROM SKLEARNNAIVEBAYES IMPORT MULTINOMIALNB
CLF  MULTINOMIALNBFITXTRAINTFIDF TWENTYTRAINTARGET
```

TO TRY TO PREDICT THE OUTCOME ON A NEW DOCUMENT WE NEED TO EXTRACT THE FEATURES USING ALMOST THE SAME FEATURE EXTRACTING CHAIN AS BEFORE THE DIFFERENCE IS THAT WE CALL TRANSFORM INSTEAD OFFITTRANSFORM ON THE TRANSFORMERS SINCE THEY HAVE ALREADY BEEN FIT TO THE TRAINING SET

```
DOCSNEW  GOD IS LOVE OPENGL ON THE GPU IS FAST
XNEWCOUNTS  COUNTVECTTRANSFORMDOCSNEW
XNEWTFIDF  TFIDFTRANSFORMERTRANSFORMXNEWCOUNTS
PREDICTED  CLFPREDICTXNEWTFIDF
 FOR DOC CATEGORY INZIPDOCSNEW PREDICTED
 PRINTRS  DOC TWENTYTRAINTARGETNAMESCATEGORY

GOD IS LOVE  SOCRELIGIONCHRISTIAN
OPENGL ON THE GPU IS FAST  COMPGRAPHICS
```

235 BUILDING A PIPELINE

IN ORDER TO MAKE THE VECTORIZER TRANSFORMER CLASSIFIER EASIER TO WORK WITH SCIKITLEARN PROVIDES A PIPELINE CLASS THAT BEHAVES LIKE A COMPOUND CLASSIFIER

```
 FROM SKLEARNPIPELINE IMPORT PIPELINE
TEXTCLF  PIPELINE
 VECT COUNTVECTORIZER
 TFIDF TFIDFTRANSFORMER
 CLF MULTINOMIALNB
```

THE NAMES VECT TFIDF ANDCLF CLASSIFIER ARE ARBITRARY WE WILL USE THEM TO PERFORM GRID SEARCH FOR SUITABLE HYPERPARAMETERS BELOW WE CAN NOW TRAIN THE MODEL WITH A SINGLE COMMAND

```
TEXTCLFFITTWENTYTRAINDATA TWENTYTRAINTARGET
```


236 EVALUATION OF THE PERFORMANCE ON THE TEST SET

EVALUATING THE PREDICTIVE ACCURACY OF THE MODEL IS EQUALLY EASY

```
 IMPORT NUMPY AS NP
TWENTYTEST  FETCH20NEWSGROUPSSUBSETTEST
 CATEGORIESCATEGORIES SHUFFLE TRUE RANDOMSTATE42
DOCSTEST  TWENTYTESTDATA
PREDICTED  TEXTCLFPREDICTDOCSTEST
NPMEANPREDICTED  TWENTYTESTTARGET
08348
```

WE ACHIEVED 835 ACCURACY LET’S SEE IF WE CAN DO BETTER WITH A LINEAR SUPPORT VECTOR MACHINE SVM WHICH IS WIDELY REGARDED AS ONE OF THE BEST TEXT CLASSIFICATION ALGORITHMS ALTHOUGH IT’S ALSO A BIT SLOWER THAN NAÏVE BAYES WE CAN CHANGE THE LEARNER BY SIMPLY PLUGGING A DIFFERENT CLASSIFIER OBJECT INTO OUR PIPELINE

```
 FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
TEXTCLF  PIPELINE
 VECT COUNTVECTORIZER
 TFIDF TFIDFTRANSFORMER
 CLF SGDCLASSIFIERLOSSHINGE PENALTYL2
 ALPHA1E3 RANDOMSTATE42
 MAXITER5 TOL NONE

TEXTCLFFITTWENTYTRAINDATA TWENTYTRAINTARGET
PIPELINE
PREDICTED  TEXTCLFPREDICTDOCSTEST
NPMEANPREDICTED  TWENTYTESTTARGET
09101
```

WE ACHIEVED 913 ACCURACY USING THE SVM SCIKITLEARN PROVIDES FURTHER UTILITIES FOR MORE DETAILED PERFOR MANCE ANALYSIS OF THE RESULTS

```
 FROM SKLEARN IMPORT METRICS
PRINTMETRICSCLASSIFICATIONREPORTTWENTYTESTTARGET PREDICTED
 TARGETNAMESTWENTYTESTTARGETNAMES

PRECISION RECALL F1SCORE SUPPORT
ALTATHEISM 095 080 087 319
COMPGRAPHICS 087 098 092 389
SCIMED 094 089 091 396
SOCRELIGIONCHRISTIAN 090 095 093 398
ACCURACY 091 1502
MACRO AVG 091 091 091 1502
WEIGHTED AVG 091 091 091 1502
METRICSCONFUSIONMATRIXTWENTYTESTTARGET PREDICTED
ARRAY256 11 16 36
 4 380 3 2
 5 35 353 3
 5 11 4 378
```

AS EXPECTED THE CONFUSION MATRIX SHOWS THAT POSTS FROM THE NEWSGROUPS ON ATHEISM AND CHRISTIANITY ARE MORE OFTEN CONFUSED FOR ONE ANOTHER THAN WITH COMPUTER GRAPHICS

237 PARAMETER TUNING USING GRID SEARCH

WE’VE ALREADY ENCOUNTERED SOME PARAMETERS SUCH AS USEIDF IN THETFIDFTRANSFORMER CLASSIFIERS TEND TO HAVE MANY PARAMETERS AS WELL EG MULTINOMIALNB INCLUDES A SMOOTHING PARAMETER ALPHA ANDSGDCLASSIFIER HAS A PENALTY PARAMETER ALPHA AND CONFIGURABLE LOSS AND PENALTY TERMS IN THE OBJECTIVE FUNCTION SEE THE MODULE DOCUMENTATION OR USE THE PYTHON HELP FUNCTION TO GET A DESCRIPTION OF THESE

INSTEAD OF TWEAKING THE PARAMETERS OF THE VARIOUS COMPONENTS OF THE CHAIN IT IS POSSIBLE TO RUN AN EXHAUSTIVE SEARCH OF THE BEST PARAMETERS ON A GRID OF POSSIBLE VALUES WE TRY OUT ALL CLASSIFIERS ON EITHER WORDS OR BIGRAMS WITH OR WITHOUT IDF AND WITH A PENALTY PARAMETER OF EITHER 001 OR 0001 FOR THE LINEAR SVM

```
 FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
PARAMETERS
 VECTNGRAMRANGE 1 1 1 2
 TFIDFUSEIDF  TRUEFALSE
 CLFALPHA 1E2 1E3
```

OBVIOUSLY SUCH AN EXHAUSTIVE SEARCH CAN BE EXPENSIVE IF WE HAVE MULTIPLE CPU CORES AT OUR DISPOSAL WE CAN TELL THE GRID SEARCHER TO TRY THESE EIGHT PARAMETER COMBINATIONS IN PARALLEL WITH THE NJOBS PARAMETER IF WE GIVE THIS PARAMETER A VALUE OF 1 GRID SEARCH WILL DETECT HOW MANY CORES ARE INSTALLED AND USE THEM ALL

```
GSCLF  GRIDSEARCHCVTEXTCLF PARAMETERS CV5 IID FALSE NJOBS1
```

THE GRID SEARCH INSTANCE BEHAVES LIKE A NORMAL SCIKITLEARN MODEL LET'S PERFORM THE SEARCH ON A SMALLER SUBSET OF THE TRAINING DATA TO SPEED UP THE COMPUTATION

```
GSCLF  GSCLFFITTWENTYTRAINDATA400 TWENTYTRAINTARGET400
```

THE RESULT OF CALLING FIT ON AGRIDSEARCHCV OBJECT IS A CLASSIFIER THAT WE CAN USE TO PREDICT

```
TWENTYTRAINTARGETNAMESGSCLFPREDICTGOD IS LOVE0
SOCRELIGIONCHRISTIAN
```

THE OBJECT'S BESTSCORE ANDBESTPARAMS ATTRIBUTES STORE THE BEST MEAN SCORE AND THE PARAMETERS SETTING CORRESPONDING TO THAT SCORE

```
GSCLFBESTSCORE
09
 FOR PARAMNAME INSORTEDPARAMETERSKEYS
 PRINTSR  PARAMNAME GSCLFBESTPARAMSPARAMNAME

CLFALPHA 0001
TFIDFUSEIDF TRUE
VECTNGRAMRANGE 1 1
```

A MORE DETAILED SUMMARY OF THE SEARCH IS AVAILABLE AT GSCLFCVRESULTS

THECVRESULTS PARAMETER CAN BE EASILY IMPORTED INTO PANDAS AS A DATAFRAME FOR FURTHER INSPECTION

EXERCISES

TO DO THE EXERCISES COPY THE CONTENT OF THE 'SKELETONS' FOLDER AS A NEW FOLDER NAMED 'WORKSPACE'

```
 CP R SKELETONS WORKSPACE
```

YOU CAN THEN EDIT THE CONTENT OF THE WORKSPACE WITHOUT FEAR OF LOSING THE ORIGINAL EXERCISE INSTRUCTIONS

THEN FIRE AN IPYTHON SHELL AND RUN THE WORKINPROGRESS SCRIPT WITH

```
1 RUN WORKSPACEEXERCISEXXSCRIPTPY ARG1 ARG2 ARG3
```

IF AN EXCEPTION IS TRIGGERED USE DEBUG TO FIREUP A POST MORTEM IPDB SESSION

REFINE THE IMPLEMENTATION AND ITERATE UNTIL THE EXERCISE IS SOLVED

FOR EACH EXERCISE THE SKELETON FILE PROVIDES ALL THE NECESSARY IMPORT STATEMENTS BOILERPLATE CODE TO LOAD THE DATA AND SAMPLE CODE TO EVALUATE THE PREDICTIVE ACCURACY OF THE MODEL

238 EXERCISE 1 LANGUAGE IDENTIFICATION
• WRITE A TEXT CLASSIFICATION PIPELINE USING A CUSTOM PREPROCESSOR AND CHARNGRAMANALYZER USING DATA FROM WIKIPEDIA ARTICLES AS TRAINING SET
• EVALUATE THE PERFORMANCE ON SOME HELD OUT TEST SET
IPYTHON COMMAND LINE
RUN WORKSPACEEXERCISE01LANGUAGETRAINMODELPY DATALANGUAGESPARAGRAPHS
239 EXERCISE 2 SENTIMENT ANALYSIS ON MOVIE REVIEWS
• WRITE A TEXT CLASSIFICATION PIPELINE TO CLASSIFY MOVIE REVIEWS AS EITHER POSITIVE OR NEGATIVE
• FIND A GOOD SET OF PARAMETERS USING GRID SEARCH
• EVALUATE THE PERFORMANCE ON A HELD OUT TEST SET
IPYTHON COMMAND LINE
RUN WORKSPACEEXERCISE02SENTIMENTPY DATAMOVIEREVIEWSTXTSENTOKEN
2310 EXERCISE 3 CLI TEXT CLASSIFICATION UTILITY
USING THE RESULTS OF THE PREVIOUS EXERCISES AND THE CPICKLE MODULE OF THE STANDARD LIBRARY WRITE A COMMAND LINE UTILITY THAT DETECTS THE LANGUAGE OF SOME TEXT PROVIDED ON STDIN AND ESTIMATE THE POLARITY POSITIVE OR NEGATIVE IF THE TEXT IS WRITTEN IN ENGLISH
BONUS POINT IF THE UTILITY IS ABLE TO GIVE A CONFIDENCE LEVEL FOR ITS PREDICTIONS
2311 WHERE TO FROM HERE
HERE ARE A FEW SUGGESTIONS TO HELP FURTHER YOUR SCIKITLEARN INTUITION UPON THE COMPLETION OF THIS TUTORIAL
• TRY PLAYING AROUND WITH THE ANALYZER ANDTOKEN NORMALISATION UNDERCOUNTVECTORIZER
• IF YOU DON’T HAVE LABELS TRY USING CLUSTERING ON YOUR PROBLEM
• IF YOU HAVE MULTIPLE LABELS PER DOCUMENT EG CATEGORIES HAVE A LOOK AT THE MULTICLASS AND MULTILABEL SECTION
• TRY USING TRUNCATED SVD FOR LATENT SEMANTIC ANALYSIS
• HAVE A LOOK AT USING OUTOFCORE CLASSIFICATION TO LEARN FROM DATA THAT WOULD NOT FIT INTO THE COMPUTER MAIN MEMORY
• HAVE A LOOK AT THE HASHING VECTORIZER AS A MEMORY EFFICIENT ALTERNATIVE TO COUNTVECTORIZER
24 CHOOSING THE RIGHT ESTIMATOR
OFTEN THE HARDEST PART OF SOLVING A MACHINE LEARNING PROBLEM CAN BE FINDING THE RIGHT ESTIMATOR FOR THE JOB DIFFERENT ESTIMATORS ARE BETTER SUITED FOR DIFFERENT TYPES OF DATA AND DIFFERENT PROBLEMS
THE FLOWCHART BELOW IS DESIGNED TO GIVE USERS A BIT OF A ROUGH GUIDE ON HOW TO APPROACH PROBLEMS WITH REGARD TO WHICH ESTIMATORS TO TRY ON YOUR DATA

SCIKITLEARN USER GUIDE RELEASE 0213
CLICK ON ANY ESTIMATOR IN THE CHART BELOW TO SEE ITS DOCUMENTATION
25 EXTERNAL RESOURCES VIDEOS AND TALKS
FOR WRITTEN TUTORIALS SEE THE TUTORIAL SECTION OF THE DOCUMENTATION
251 NEW TO SCIENTIFIC PYTHON
FOR THOSE THAT ARE STILL NEW TO THE SCIENTIFIC PYTHON ECOSYSTEM WE HIGHLY RECOMMEND THE PYTHON SCIENTIFIC LECTURE NOTES THIS WILL HELP YOU FIND YOUR FOOTING A BIT AND WILL DEFINITELY IMPROVE YOUR SCIKITLEARN EXPERIENCE A BASIC UNDERSTANDING OF NUMPY ARRAYS IS RECOMMENDED TO MAKE THE MOST OF SCIKITLEARN
252 EXTERNAL TUTORIALS
THERE ARE SEVERAL ONLINE TUTORIALS AVAILABLE WHICH ARE GEARED TOWARD SPECIFIC SUBJECT AREAS
• MACHINE LEARNING FOR NEUROIMAGING IN PYTHON
• MACHINE LEARNING FOR ASTRONOMICAL DATA ANALYSIS
253 VIDEOS
• AN INTRODUCTION TO SCIKITLEARN PART I AND PART II AT SCIPY 2013 BY GAEL VAROQUAUX JAKE VANDERPLAS AND OLIVIER GRISEL NOTEBOOKS ON GITHUB
• INTRODUCTION TO SCIKITLEARN BY GAEL VAROQUAUX AT ICML 2010
A THREE MINUTE VIDEO FROM A VERY EARLY STAGE OF SCIKITLEARN EXPLAINING THE BASIC IDEA AND APPROACH WE ARE FOLLOWING
• INTRODUCTION TO STATISTICAL LEARNING WITH SCIKITLEARN BY GAEL VAROQUAUX AT SCIPY 2011
AN EXTENSIVE TUTORIAL CONSISTING OF FOUR SESSIONS OF ONE HOUR THE TUTORIAL COVERS THE BASICS OF MA CHINE LEARNING MANY ALGORITHMS AND HOW TO APPLY THEM USING SCIKITLEARN THE MATERIAL CORRESPOND ING IS NOW IN THE SCIKITLEARN DOCUMENTATION SECTION A TUTORIAL ON STATISTICALLEARNING FOR SCIENTIFIC DATA PROCESSING
• STATISTICAL LEARNING FOR TEXT CLASSIFICATION WITH SCIKITLEARN AND NLTK AND SLIDES BY OLIVIER GRISEL AT PYCON 2011
THIRTY MINUTE INTRODUCTION TO TEXT CLASSIFICATION EXPLAINS HOW TO USE NLTK AND SCIKITLEARN TO SOLVE REALWORLD TEXT CLASSIFICATION TASKS AND COMPARES AGAINST CLOUDBASED SOLUTIONS
• INTRODUCTION TO INTERACTIVE PREDICTIVE ANALYTICS IN PYTHON WITH SCIKITLEARN BY OLIVIER GRISEL AT PYCON 2012
3HOURS LONG INTRODUCTION TO PREDICTION TASKS USING SCIKITLEARN
• SCIKITLEARN MACHINE LEARNING IN PYTHON BY JAKE VANDERPLAS AT THE 2012 PYDATA WORKSHOP AT GOOGLE
INTERACTIVE DEMONSTRATION OF SOME SCIKITLEARN FEATURES 75 MINUTES
• SCIKITLEARN TUTORIAL BY JAKE VANDERPLAS AT PYDATA NYC 2012
PRESENTATION USING THE ONLINE TUTORIAL 45 MINUTES

NOTE DOCTEST MODE
THE CODEEXAMPLES IN THE ABOVE TUTORIALS ARE WRITTEN IN A PYTHONCONSOLE FORMAT IF YOU WISH TO EASILY EXECUTE THESE EXAMPLES IN IPYTHON USE
DOCTESTMODE
IN THE IPYTHONCONSOLE YOU CAN THEN SIMPLY COPY AND PASTE THE EXAMPLES DIRECTLY INTO IPYTHON WITHOUT HAVING TO WORRY ABOUT REMOVING THE MANUALLY

CHAPTER
THREE
USER GUIDE
31 SUPERVISED LEARNING
311 GENERALIZED LINEAR MODELS
THE FOLLOWING ARE A SET OF METHODS INTENDED FOR REGRESSION IN WHICH THE TARGET VALUE IS EXPECTED TO BE A LINEAR COMBI
NATION OF THE FEATURES IN MATHEMATICAL NOTATION IF □IS THE PREDICTED VALUE
□□ □ □0□1□1□□□□
ACROSS THE MODULE WE DESIGNATE THE VECTOR □ □1 □ □ASCOEF AND□0ASINTERCEPT
TO PERFORM CLASSIFICATION WITH GENERALIZED LINEAR MODELS SEE LOGISTIC REGRESSION
ORDINARY LEAST SQUARES
LINEARREGRESSION FITS A LINEAR MODEL WITH COEFFICIENTS □ □1 □ □TO MINIMIZE THE RESIDUAL SUM OF SQUARES
BETWEEN THE OBSERVED TARGETS IN THE DATASET AND THE TARGETS PREDICTED BY THE LINEAR APPROXIMATION MATHEMATICALLY IT
SOLVES A PROBLEM OF THE FORM
MIN
□□□−□2
2
LINEARREGRESSION WILL TAKE IN ITS FIT METHOD ARRAYS X Y AND WILL STORE THE COEFFICIENTS □OF THE LINEAR MODEL
IN ITSCOEF MEMBER
197

```
 FROM SKLEARN IMPORT LINEARMODEL
REG  LINEARMODELLINEARREGRESSION
REGFIT0 0 1 1 2 2 0 1 2

LINEARREGRESSIONCOPYXTRUE FITINTERCEPTTRUE NJOBSNONE
NORMALIZEFALSE
REGCOEF
ARRAY05 05
```
THE COEFFICIENT ESTIMATES FOR ORDINARY LEAST SQUARES RELY ON THE INDEPENDENCE OF THE FEATURES WHEN FEATURES ARE CORRELATED AND THE COLUMNS OF THE DESIGN MATRIX □HAVE AN APPROXIMATE LINEAR DEPENDENCE THE DESIGN MATRIX BECOMES CLOSE TO SINGULAR AND AS A RESULT THE LEASTSQUARES ESTIMATE BECOMES HIGHLY SENSITIVE TO RANDOM ERRORS IN THE OBSERVED TARGET PRODUCING A LARGE VARIANCE THIS SITUATION OF MULTICOLLINEARITY CAN ARISE FOR EXAMPLE WHEN DATA ARE COLLECTED WITHOUT AN EXPERIMENTAL DESIGN

EXAMPLES

•LINEAR REGRESSION EXAMPLE

ORDINARY LEAST SQUARES COMPLEXITY

THE LEAST SQUARES SOLUTION IS COMPUTED USING THE SINGULAR VALUE DECOMPOSITION OF X IF X IS A MATRIX OF SHAPE NSAMPLES NFEATURES THIS METHOD HAS A COST OF □□SAMPLES □2
FEATURES ASSUMING THAT □SAMPLES≥□FEATURES

RIDGE REGRESSION

RIDGE REGRESSION ADDRESSES SOME OF THE PROBLEMS OF ORDINARY LEAST SQUARES BY IMPOSING A PENALTY ON THE SIZE OF THE COEFFICIENTS THE RIDGE COEFFICIENTS MINIMIZE A PENALIZED RESIDUAL SUM OF SQUARES

MIN
□□□−□2
2□□2
2

THE COMPLEXITY PARAMETER □≥0CONTROLS THE AMOUNT OF SHRINKAGE THE LARGER THE VALUE OF □ THE GREATER THE AMOUNT OF SHRINKAGE AND THUS THE COEFFICIENTS BECOME MORE ROBUST TO COLLINEARITY

AS WITH OTHER LINEAR MODELS RIDGE WILL TAKE IN ITS FIT METHOD ARRAYS X Y AND WILL STORE THE COEFFICIENTS □OF THE LINEAR MODEL IN ITS COEF MEMBER

```
 FROM SKLEARN IMPORT LINEARMODEL
REG  LINEARMODELRIDGEALPHA5
REGFIT0 0 0 0 1 1 0 1 1
RIDGEALPHA05 COPYXTRUE FITINTERCEPTTRUE MAXITERNONE
NORMALIZEFALSE RANDOMSTATENONE SOLVERAUTO TOL0001
REGCOEF
ARRAY034545455 034545455
REGINTERCEPT
013636
```
EXAMPLES

•PLOT RIDGE COEFFICIENTS AS A FUNCTION OF THE REGULARIZATION

•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES

RIDGE COMPLEXITY

THIS METHOD HAS THE SAME ORDER OF COMPLEXITY AS ORDINARY LEAST SQUARES

SETTING THE REGULARIZATION PARAMETER GENERALIZED CROSSVALIDATION

RIDGECV IMPLEMENTS RIDGE REGRESSION WITH BUILTIN CROSSVALIDATION OF THE ALPHA PARAMETER THE OBJECT WORKS IN THE SAME WAY AS GRIDSEARCHCV EXCEPT THAT IT DEFAULTS TO GENERALIZED CROSSVALIDATION GCV AN EFFICIENT FORM OF LEAVEONEOUT CROSSVALIDATION

```
 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT LINEARMODEL
REG  LINEARMODELRIDGECVALPHASNPLOGSPACE6 6 13
REGFIT0 0 0 0 1 1 0 1 1
RIDGECVALPHASARRAY1E06 1E05 1E04 1E03 1E02 1E01 1E00 1E01
1E02 1E03 1E04 1E05 1E06
CVNONE FITINTERCEPTTRUE GCVMODENONE NORMALIZEFALSE
SCORINGNONE STORECVVALUESFALSE
REGALPHA
001
```

SPECIFYING THE VALUE OF THE CVATTRIBUTE WILL TRIGGER THE USE OF CROSSVALIDATION WITH GRIDSEARCHCV FOR EXAMPLE CV10 FOR 10FOLD CROSSVALIDATION RATHER THAN GENERALIZED CROSSVALIDATION

REFERENCES

• “NOTES ON REGULARIZED LEAST SQUARES” RIFKIN LIPPERT TECHNICAL REPORT COURSE SLIDES

LASSO

THELASSO IS A LINEAR MODEL THAT ESTIMATES SPARSE COEFFICIENTS IT IS USEFUL IN SOME CONTEXTS DUE TO ITS TENDENCY TO PREFER SOLUTIONS WITH FEWER NONZERO COEFFICIENTS EFFECTIVELY REDUCING THE NUMBER OF FEATURES UPON WHICH THE GIVEN SOLUTION IS DEPENDENT FOR THIS REASON LASSO AND ITS VARIANTS ARE FUNDAMENTAL TO THE FIELD OF COMPRESSED SENSING

UNDER CERTAIN CONDITIONS IT CAN RECOVER THE EXACT SET OF NONZERO COEFFICIENTS SEE COMPRESSIVE SENSING TOMOGRAPHY RECONSTRUCTION WITH L1 PRIOR LASSO
MATHEMATICALLY IT CONSISTS OF A LINEAR MODEL WITH AN ADDED REGULARIZATION TERM THE OBJECTIVE FUNCTION TO MINIMIZE IS
MIN
□1
2□SAMPLES□□−□2
2□□1
THE LASSO ESTIMATE THUS SOLVES THE MINIMIZATION OF THE LEASTSQUARES PENALTY WITH □□1ADDED WHERE □IS A CONSTANT AND□1IS THE ℓ1NORM OF THE COEFFICIENT VECTOR
THE IMPLEMENTATION IN THE CLASS LASSO USES COORDINATE DESCENT AS THE ALGORITHM TO FIT THE COEFFICIENTS SEE LEAST ANGLE REGRESSION FOR ANOTHER IMPLEMENTATION
```
 FROM SKLEARN IMPORT LINEARMODEL
REG  LINEARMODELLASSOALPHA01
REGFIT0 0 1 1 0 1
LASSOALPHA01 COPYXTRUE FITINTERCEPTTRUE MAXITER1000
NORMALIZEFALSE POSITIVEFALSE PRECOMPUTEFALSE RANDOMSTATENONE
SELECTIONCYCLIC TOL00001 WARMSTARTFALSE
REGPREDICT1 1
ARRAY08
```
THE FUNCTION LASSOPATH IS USEFUL FOR LOWERLEVEL TASKS AS IT COMPUTES THE COEFFICIENTS ALONG THE FULL PATH OF POSSIBLE VALUES
EXAMPLES
•LASSO AND ELASTIC NET FOR SPARSE SIGNALS
•COMPRESSIVE SENSING TOMOGRAPHY RECONSTRUCTION WITH L1 PRIOR LASSO
NOTE FEATURE SELECTION WITH LASSO
AS THE LASSO REGRESSION YIELDS SPARSE MODELS IT CAN THUS BE USED TO PERFORM FEATURE SELECTION AS DETAILED IN L1BASED FEATURE SELECTION
THE FOLLOWING TWO REFERENCES EXPLAIN THE ITERATIONS USED IN THE COORDINATE DESCENT SOLVER OF SCIKITLEARN AS WELL AS THE DUALITY GAP COMPUTATION USED FOR CONVERGENCE CONTROL
REFERENCES
• “REGULARIZATION PATH FOR GENERALIZED LINEAR MODELS BY COORDINATE DESCENT” FRIEDMAN HASTIE TIBSHIRANI J STAT SOFTW 2010 PAPER
• “AN INTERIORPOINT METHOD FOR LARGESCALE L1REGULARIZED LEAST SQUARES” S J KIM K KOH M LUSTIG S BOYD AND D GORINEVSKY IN IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING 2007 PAPER
SETTING REGULARIZATION PARAMETER
THEALPHA PARAMETER CONTROLS THE DEGREE OF SPARSITY OF THE ESTIMATED COEFFICIENTS

USING CROSSVALIDATION
SCIKITLEARN EXPOSES OBJECTS THAT SET THE LASSO ALPHA PARAMETER BY CROSSVALIDATION LASSOCV ANDLASSOLARSCV
LASSOLARSCV IS BASED ON THE LEAST ANGLE REGRESSION ALGORITHM EXPLAINED BELOW
FOR HIGHDIMENSIONAL DATASETS WITH MANY COLLINEAR FEATURES LASSOCV IS MOST OFTEN PREFERABLE HOWEVER
LASSOLARSCV HAS THE ADVANTAGE OF EXPLORING MORE RELEVANT VALUES OF ALPHA PARAMETER AND IF THE NUMBER OF
SAMPLES IS VERY SMALL COMPARED TO THE NUMBER OF FEATURES IT IS OFTEN FASTER THAN LASSOCV
INFORMATIONCRITERIA BASED MODEL SELECTION
ALTERNATIVELY THE ESTIMATOR LASSOLARSIC PROPOSES TO USE THE AKAIKE INFORMATION CRITERION AIC AND THE BAYES
INFORMATION CRITERION BIC IT IS A COMPUTATIONALLY CHEAPER ALTERNATIVE TO FIND THE OPTIMAL VALUE OF ALPHA AS THE REGU
LARIZATION PATH IS COMPUTED ONLY ONCE INSTEAD OF K1 TIMES WHEN USING KFOLD CROSSVALIDATION HOWEVER SUCH CRITERIA
NEEDS A PROPER ESTIMATION OF THE DEGREES OF FREEDOM OF THE SOLUTION ARE DERIVED FOR LARGE SAMPLES ASYMPTOTIC RESULTS
AND ASSUME THE MODEL IS CORRECT IE THAT THE DATA ARE ACTUALLY GENERATED BY THIS MODEL THEY ALSO TEND TO BREAK WHEN
THE PROBLEM IS BADLY CONDITIONED MORE FEATURES THAN SAMPLES
EXAMPLES
•LASSO MODEL SELECTION CROSSVALIDATION AIC BIC

COMPARISON WITH THE REGULARIZATION PARAMETER OF SVM
THE EQUIVALENCE BETWEEN ALPHA AND THE REGULARIZATION PARAMETER OF SVM CIS GIVEN BY ALPHA 1 C OR
ALPHA 1 NSAMPLES C DEPENDING ON THE ESTIMATOR AND THE EXACT OBJECTIVE FUNCTION OPTIMIZED BY
THE MODEL
MULTITASK LASSO
THEMULTITASKLASSO IS A LINEAR MODEL THAT ESTIMATES SPARSE COEFFICIENTS FOR MULTIPLE REGRESSION PROBLEMS JOINTLY
YIS A 2D ARRAY OF SHAPE NSAMPLES NTASKS THE CONSTRAINT IS THAT THE SELECTED FEATURES ARE THE SAME FOR ALL
THE REGRESSION PROBLEMS ALSO CALLED TASKS
THE FOLLOWING FIGURE COMPARES THE LOCATION OF THE NONZERO ENTRIES IN THE COEFFICIENT MATRIX W OBTAINED WITH A SIMPLE
LASSO OR A MULTITASKLASSO THE LASSO ESTIMATES YIELD SCATTERED NONZEROS WHILE THE NONZEROS OF THE MULTITASKLASSO
ARE FULL COLUMNS
FITTING A TIMESERIES MODEL IMPOSING THAT ANY ACTIVE FEATURE BE ACTIVE AT ALL TIMES
EXAMPLES
•JOINT FEATURE SELECTION WITH MULTITASK LASSO
MATHEMATICALLY IT CONSISTS OF A LINEAR MODEL TRAINED WITH A MIXED ℓ1ℓ2NORM FOR REGULARIZATION THE OBJECTIVE FUNCTION

TO MINIMIZE IS
MIN
□1
2□SAMPLES□□−□2
FRO□□21
WHERE FRO INDICATES THE FROBENIUS NORM
□FRO√∑
□□□2
□□
ANDℓ1ℓ2READS
□21∑
□√∑
□□2
□□
THE IMPLEMENTATION IN THE CLASS MULTITASKLASSO USES COORDINATE DESCENT AS THE ALGORITHM TO FIT THE COEFFICIENTS
ELASTICNET
ELASTICNET IS A LINEAR REGRESSION MODEL TRAINED WITH BOTH ℓ1ANDℓ2NORM REGULARIZATION OF THE COEFFICIENTS THIS COMBINATION ALLOWS FOR LEARNING A SPARSE MODEL WHERE FEW OF THE WEIGHTS ARE NONZERO LIKE LASSO WHILE STILL MAINTAINING THE REGULARIZATION PROPERTIES OF RIDGE WE CONTROL THE CONVEX COMBINATION OF ℓ1ANDℓ2USING THEL1RATIO PARAMETER
ELASTICNET IS USEFUL WHEN THERE ARE MULTIPLE FEATURES WHICH ARE CORRELATED WITH ONE ANOTHER LASSO IS LIKELY TO PICK ONE OF THESE AT RANDOM WHILE ELASTICNET IS LIKELY TO PICK BOTH
A PRACTICAL ADVANTAGE OF TRADINGOFF BETWEEN LASSO AND RIDGE IS THAT IT ALLOWS ELASTICNET TO INHERIT SOME OF RIDGE'S STABILITY UNDER ROTATION
THE OBJECTIVE FUNCTION TO MINIMIZE IS IN THIS CASE
MIN
□1
2□SAMPLES□□−□2
2□□□1□1−□
2□2
2
THE CLASSELASTICNETCV CAN BE USED TO SET THE PARAMETERS ALPHA □ ANDL1RATIO □ BY CROSSVALIDATION

EXAMPLES
•LASSO AND ELASTIC NET FOR SPARSE SIGNALS
•LASSO AND ELASTIC NET
THE FOLLOWING TWO REFERENCES EXPLAIN THE ITERATIONS USED IN THE COORDINATE DESCENT SOLVER OF SCIKITLEARN AS WELL AS THE DUALITY GAP COMPUTATION USED FOR CONVERGENCE CONTROL
REFERENCES
• “REGULARIZATION PATH FOR GENERALIZED LINEAR MODELS BY COORDINATE DESCENT” FRIEDMAN HASTIE TIBSHIRANI J STAT SOFTW 2010 PAPER
• “AN INTERIORPOINT METHOD FOR LARGESCALE L1REGULARIZED LEAST SQUARES” S J KIM K KOH M LUSTIG S BOYD AND D GORINEVSKY IN IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING 2007 PAPER
MULTITASK ELASTICNET
THEMULTITASKELASTICNET IS AN ELASTICNET MODEL THAT ESTIMATES SPARSE COEFFICIENTS FOR MULTIPLE REGRESSION PROB LEMS JOINTLY YIS A 2D ARRAY OF SHAPE NSAMPLES NTASKS THE CONSTRAINT IS THAT THE SELECTED FEATURES ARE THE SAME FOR ALL THE REGRESSION PROBLEMS ALSO CALLED TASKS
MATHEMATICALLY IT CONSISTS OF A LINEAR MODEL TRAINED WITH A MIXED ℓ1ℓ2NORM AND ℓ2NORM FOR REGULARIZATION THE OBJECTIVE FUNCTION TO MINIMIZE IS
MIN
□1
2□SAMPLES□□−□2
FRO□□□21□1−□
2□2
FRO
THE IMPLEMENTATION IN THE CLASS MULTITASKELASTICNET USES COORDINATE DESCENT AS THE ALGORITHM TO FIT THE COEF FICIENTS
THE CLASSMULTITASKELASTICNETCV CAN BE USED TO SET THE PARAMETERS ALPHA □ ANDL1RATIO □ BY CROSS VALIDATION
LEAST ANGLE REGRESSION
LEASTANGLE REGRESSION LARS IS A REGRESSION ALGORITHM FOR HIGHDIMENSIONAL DATA DEVELOPED BY BRADLEY EFRON TREVOR HASTIE IAIN JOHNSTONE AND ROBERT TIBSHIRANI LARS IS SIMILAR TO FORWARD STEPWISE REGRESSION AT EACH STEP IT FINDS THE FEATURE MOST CORRELATED WITH THE TARGET WHEN THERE ARE MULTIPLE FEATURES HAVING EQUAL CORRELATION INSTEAD OF CONTINUING ALONG THE SAME FEATURE IT PROCEEDS IN A DIRECTION EQUIANGULAR BETWEEN THE FEATURES
THE ADVANTAGES OF LARS ARE
• IT IS NUMERICALLY EFFICIENT IN CONTEXTS WHERE THE NUMBER OF FEATURES IS SIGNIFICANTLY GREATER THAN THE NUMBER OF SAMPLES
• IT IS COMPUTATIONALLY JUST AS FAST AS FORWARD SELECTION AND HAS THE SAME ORDER OF COMPLEXITY AS ORDINARY LEAST SQUARES
• IT PRODUCES A FULL PIECEWISE LINEAR SOLUTION PATH WHICH IS USEFUL IN CROSSVALIDATION OR SIMILAR ATTEMPTS TO TUNE THE MODEL
• IF TWO FEATURES ARE ALMOST EQUALLY CORRELATED WITH THE TARGET THEN THEIR COEFFICIENTS SHOULD INCREASE AT APPROXI MATELY THE SAME RATE THE ALGORITHM THUS BEHAVES AS INTUITION WOULD EXPECT AND ALSO IS MORE STABLE

• IT IS EASILY MODIFIED TO PRODUCE SOLUTIONS FOR OTHER ESTIMATORS LIKE THE LASSO
THE DISADVANTAGES OF THE LARS METHOD INCLUDE
• BECAUSE LARS IS BASED UPON AN ITERATIVE REFITTING OF THE RESIDUALS IT WOULD APPEAR TO BE ESPECIALLY SENSITIVE TO THE EFFECTS OF NOISE THIS PROBLEM IS DISCUSSED IN DETAIL BY WEISBERG IN THE DISCUSSION SECTION OF THE EFRON ET AL 2004 ANNALS OF STATISTICS ARTICLE
THE LARS MODEL CAN BE USED USING ESTIMATOR LARS OR ITS LOWLEVEL IMPLEMENTATION LARSPATH OR LARSPATHGRAM
LARS LASSO
LASSOLARS IS A LASSO MODEL IMPLEMENTED USING THE LARS ALGORITHM AND UNLIKE THE IMPLEMENTATION BASED ON COORDINATE DESCENT THIS YIELDS THE EXACT SOLUTION WHICH IS PIECEWISE LINEAR AS A FUNCTION OF THE NORM OF ITS COEFFICIENTS
FROM SKLEARN IMPORT LINEARMODEL
REG LINEARMODELLASSOLARSALPHA1
REGFIT0 0 1 1 0 1
LASSOLARSALPHA01 COPYXTRUE EPS FITINTERCEPTTRUE
FITPATHTRUE MAXITER500 NORMALIZETRUE POSITIVEFALSE
PRECOMPUTEAUTO VERBOSEFALSE
REGCOEF
ARRAY0717157 0
EXAMPLES
•LASSO PATH USING LARS
THE LARS ALGORITHM PROVIDES THE FULL PATH OF THE COEFFICIENTS ALONG THE REGULARIZATION PARAMETER ALMOST FOR FREE THUS A COMMON OPERATION IS TO RETRIEVE THE PATH WITH ONE OF THE FUNCTIONS LARSPATH ORLARSPATHGRAM
MATHEMATICAL FORMULATION
THE ALGORITHM IS SIMILAR TO FORWARD STEPWISE REGRESSION BUT INSTEAD OF INCLUDING FEATURES AT EACH STEP THE ESTIMATED COEFFICIENTS ARE INCREASED IN A DIRECTION EQUIANGULAR TO EACH ONE’S CORRELATIONS WITH THE RESIDUAL

INSTEAD OF GIVING A VECTOR RESULT THE LARS SOLUTION CONSISTS OF A CURVE DENOTING THE SOLUTION FOR EACH VALUE OF THE ℓ1NORM OF THE PARAMETER VECTOR THE FULL COEFFICIENTS PATH IS STORED IN THE ARRAY COEFPATH WHICH HAS SIZE NFEATURES MAXFEATURES1 THE FIRST COLUMN IS ALWAYS ZERO

REFERENCES

• ORIGINAL ALGORITHM IS DETAILED IN THE PAPER LEAST ANGLE REGRESSION BY HASTIE ET AL

ORTHOGONAL MATCHING PURSUIT OMP

ORTHOGONALMATCHINGPURSUIT ANDORTHOGONALMP IMPLEMENTS THE OMP ALGORITHM FOR APPROXIMATING THE FIT OF A LINEAR MODEL WITH CONSTRAINTS IMPOSED ON THE NUMBER OF NONZERO COEFFICIENTS IE THE ℓ0PSEUDONORM

BEING A FORWARD FEATURE SELECTION METHOD LIKE LEAST ANGLE REGRESSION ORTHOGONAL MATCHING PURSUIT CAN APPROXIMATE THE OPTIMUM SOLUTION VECTOR WITH A FIXED NUMBER OF NONZERO ELEMENTS

ARG MIN

□□−□□2

2SUBJECT TO□0≤□NONZEROCOEFS

ALTERNATIVELY ORTHOGONAL MATCHING PURSUIT CAN TARGET A SPECIFIC ERROR INSTEAD OF A SPECIFIC NUMBER OF NONZERO COEFFICIENTS THIS CAN BE EXPRESSED AS

ARG MIN

□□0SUBJECT TO□−□□2

2≤TOL

OMP IS BASED ON A GREEDY ALGORITHM THAT INCLUDES AT EACH STEP THE ATOM MOST HIGHLY CORRELATED WITH THE CURRENT RESIDUAL IT IS SIMILAR TO THE SIMPLER MATCHING PURSUIT MP METHOD BUT BETTER IN THAT AT EACH ITERATION THE RESIDUAL IS RECOMPUTED USING AN ORTHOGONAL PROJECTION ON THE SPACE OF THE PREVIOUSLY CHOSEN DICTIONARY ELEMENTS

EXAMPLES

•ORTHOGONAL MATCHING PURSUIT

REFERENCES

• HTTPSWWWCSTECHNIONACILRONRUBINPUBLICATIONSKSVDOMPV2PDF

• MATCHING PURSUITS WITH TIMEFREQUENCY DICTIONARIES S G MALLAT Z ZHANG

BAYESIAN REGRESSION

BAYESIAN REGRESSION TECHNIQUES CAN BE USED TO INCLUDE REGULARIZATION PARAMETERS IN THE ESTIMATION PROCEDURE THE REGULARIZATION PARAMETER IS NOT SET IN A HARD SENSE BUT TUNED TO THE DATA AT HAND

THIS CAN BE DONE BY INTRODUCING UNINFORMATIVE PRIORS OVER THE HYPER PARAMETERS OF THE MODEL THE ℓ2REGULARIZATION USED IN RIDGE REGRESSION IS EQUIVALENT TO FINDING A MAXIMUM A POSTERIORI ESTIMATION UNDER A GAUSSIAN PRIOR OVER THE COEFFICIENTS □WITH PRECISION □−1 INSTEAD OF SETTING LAMBDA MANUALLY IT IS POSSIBLE TO TREAT IT AS A RANDOM VARIABLE TO BE ESTIMATED FROM THE DATA

TO OBTAIN A FULLY PROBABILISTIC MODEL THE OUTPUT □IS ASSUMED TO BE GAUSSIAN DISTRIBUTED AROUND □□

□□□ □ □ □□□□ □

WHERE □IS AGAIN TREATED AS A RANDOM VARIABLE THAT IS TO BE ESTIMATED FROM THE DATA
THE ADVANTAGES OF BAYESIAN REGRESSION ARE
• IT ADAPTS TO THE DATA AT HAND
• IT CAN BE USED TO INCLUDE REGULARIZATION PARAMETERS IN THE ESTIMATION PROCEDURE
THE DISADVANTAGES OF BAYESIAN REGRESSION INCLUDE
• INFERENCE OF THE MODEL CAN BE TIME CONSUMING
REFERENCES
• A GOOD INTRODUCTION TO BAYESIAN METHODS IS GIVEN IN C BISHOP PATTERN RECOGNITION AND MACHINE LEARNING
• ORIGINAL ALGORITHM IS DETAILED IN THE BOOK BAYESIAN LEARNING FOR NEURAL NETWORKS BY RAD
FORD M NEAL
BAYESIAN RIDGE REGRESSION
BAYESIANRIDGE ESTIMATES A PROBABILISTIC MODEL OF THE REGRESSION PROBLEM AS DESCRIBED ABOVE THE PRIOR FOR THE COEFFICIENT □IS GIVEN BY A SPHERICAL GAUSSIAN
□□□ □□0 □−1I□
THE PRIORS OVER □AND□ARE CHOSEN TO BE GAMMA DISTRIBUTIONS THE CONJUGATE PRIOR FOR THE PRECISION OF THE GAUSSIAN
THE RESULTING MODEL IS CALLED BAYESIAN RIDGE REGRESSION AND IS SIMILAR TO THE CLASSICAL RIDGE
THE PARAMETERS □□AND□ARE ESTIMATED JOINTLY DURING THE FIT OF THE MODEL THE REGULARIZATION PARAMETERS □AND□ BEING ESTIMATED BY MAXIMIZING THE LOG MARGINAL LIKELIHOOD THE SCIKITLEARN IMPLEMENTATION IS BASED ON THE ALGORITHM DESCRIBED IN APPENDIX A OF TIPPING 2001 WHERE THE UPDATE OF THE PARAMETERS □AND□IS DONE AS SUGGESTED IN MACKAY 1992
THE REMAINING HYPERPARAMETERS ARE THE PARAMETERS □1□2□1AND□2OF THE GAMMA PRIORS OVER □AND□ THESE ARE USUALLY CHOSEN TO BE NONINFORMATIVE BY DEFAULT □1□2□1□2 10−6
BAYESIAN RIDGE REGRESSION IS USED FOR REGRESSION

```
 FROM SKLEARN IMPORT LINEARMODEL
X  0 0 1 1 2 2 3 3
Y  0 1 2 3
REG  LINEARMODELBAYESIANRIDGE
REGFITX Y
BAYESIANRIDGEALPHA11E06 ALPHA21E06 COMPUTESCOREFALSE COPYXTRUE
FITINTERCEPTTRUE LAMBDA11E06 LAMBDA21E06 NITER300
NORMALIZEFALSE TOL0001 VERBOSEFALSE
```
AFTER BEING FITTED THE MODEL CAN THEN BE USED TO PREDICT NEW VALUES
```
REGPREDICT1 0
ARRAY050000013
```
THE COEFFICIENTS □OF THE MODEL CAN BE ACCESSED
```
REGCOEF
ARRAY049999993 049999993
```
DUE TO THE BAYESIAN FRAMEWORK THE WEIGHTS FOUND ARE SLIGHTLY DIFFERENT TO THE ONES FOUND BY ORDINARY LEAST SQUARES
HOWEVER BAYESIAN RIDGE REGRESSION IS MORE ROBUST TO ILLPOSED PROBLEMS

EXAMPLES

•BAYESIAN RIDGE REGRESSION

REFERENCES

• SECTION 33 IN CHRISTOPHER M BISHOP PATTERN RECOGNITION AND MACHINE LEARNING 2006
• DAVID J C MACKAY BAYESIAN INTERPOLATION 1992
• MICHAEL E TIPPING SPARSE BAYESIAN LEARNING AND THE RELEVANCE VECTOR MACHINE 2001

AUTOMATIC RELEVANCE DETERMINATION ARD

ARDREGRESSION IS VERY SIMILAR TO BAYESIAN RIDGE REGRESSION BUT CAN LEAD TO SPARSER COEFFICIENTS □12
ARDREGRESSION POSES A DIFFERENT PRIOR OVER □ BY DROPPING THE ASSUMPTION OF THE GAUSSIAN BEING SPHERICAL
INSTEAD THE DISTRIBUTION OVER □IS ASSUMED TO BE AN AXISPARALLEL ELLIPTICAL GAUSSIAN DISTRIBUTION
THIS MEANS EACH COEFFICIENT □□IS DRAWN FROM A GAUSSIAN DISTRIBUTION CENTERED ON ZERO AND WITH A PRECISION □□
□□□ □□0 □−1
WITH DIAG □ □□1 □ □
IN CONTRAST TO BAYESIAN RIDGE REGRESSION EACH COORDINATE OF □□HAS ITS OWN STANDARD DEVIATION □□ THE PRIOR OVER ALL
□□IS CHOSEN TO BE THE SAME GAMMA DISTRIBUTION GIVEN BY HYPERPARAMETERS □1AND□2
ARD IS ALSO KNOWN IN THE LITERATURE AS SPARSE BAYESIAN LEARNING ANDRELEVANCE VECTOR MACHINE34

1CHRISTOPHER M BISHOP PATTERN RECOGNITION AND MACHINE LEARNING CHAPTER 721
2DAVID WIPF AND SRIKANTAN NAGARAJAN A NEW VIEW OF AUTOMATIC RELEVANCE DETERMINATION
3MICHAEL E TIPPING SPARSE BAYESIAN LEARNING AND THE RELEVANCE VECTOR MACHINE
4TRISTAN FLETCHER RELEVANCE VECTOR MACHINES EXPLAINED

EXAMPLES

•AUTOMATIC RELEVANCE DETERMINATION REGRESSION ARD

REFERENCES

LOGISTIC REGRESSION

LOGISTIC REGRESSION DESPITE ITS NAME IS A LINEAR MODEL FOR CLASSIFICATION RATHER THAN REGRESSION LOGISTIC REGRESSION IS ALSO KNOWN IN THE LITERATURE AS LOGIT REGRESSION MAXIMUMENTROPY CLASSIFICATION MAXENT OR THE LOGLINEAR CLASSIFIER IN THIS MODEL THE PROBABILITIES DESCRIBING THE POSSIBLE OUTCOMES OF A SINGLE TRIAL ARE MODELED USING A LOGISTIC FUNCTION LOGISTIC REGRESSION IS IMPLEMENTED IN LOGISTICREGRESSION THIS IMPLEMENTATION CAN FIT BINARY ONEVSREST OR MULTINOMIAL LOGISTIC REGRESSION WITH OPTIONAL ℓ1ℓ2OR ELASTICNET REGULARIZATION

NOTE REGULARIZATION IS APPLIED BY DEFAULT WHICH IS COMMON IN MACHINE LEARNING BUT NOT IN STATISTICS ANOTHER ADVANTAGE OF REGULARIZATION IS THAT IT IMPROVES NUMERICAL STABILITY NO REGULARIZATION AMOUNTS TO SETTING C TO A VERY HIGH VALUE

AS AN OPTIMIZATION PROBLEM BINARY CLASS ℓ2PENALIZED LOGISTIC REGRESSION MINIMIZES THE FOLLOWING COST FUNCTION

MIN

□□1

2□□□□□Σ

□1LOGEXP−□□□□

□□□ 1

SIMILARLY ℓ1REGULARIZED LOGISTIC REGRESSION SOLVES THE FOLLOWING OPTIMIZATION PROBLEM

MIN

□□‖□‖1□□Σ

□1LOGEXP−□□□□

□□□ 1

ELASTICNET REGULARIZATION IS A COMBINATION OF ℓ1ANDℓ2 AND MINIMIZES THE FOLLOWING COST FUNCTION

MIN

□□1−□

2□□□□‖□‖1□□Σ

□1LOGEXP−□□□□

□□□ 1

WHERE □CONTROLS THE STRENGTH OF ℓ1REGULARIZATION VS ℓ2REGULARIZATION IT CORRESPONDS TO THE L1RATIO PARAMETER
NOTE THAT IN THIS NOTATION IT'S ASSUMED THAT THE TARGET □□TAKES VALUES IN THE SET −11AT TRIAL □ WE CAN ALSO SEE THAT
ELASTICNET IS EQUIVALENT TO ℓ1WHEN □ 1AND EQUIVALENT TO ℓ2WHEN □ 0
THE SOLVERS IMPLEMENTED IN THE CLASS LOGISTICREGRESSION ARE "LIBLINEAR" "NEWTONCG" "LBFGS" "SAG" AND
"SAGA"
THE SOLVER "LIBLINEAR" USES A COORDINATE DESCENT CD ALGORITHM AND RELIES ON THE EXCELLENT C LIBLINEAR LIBRARY
WHICH IS SHIPPED WITH SCIKITLEARN HOWEVER THE CD ALGORITHM IMPLEMENTED IN LIBLINEAR CANNOT LEARN A TRUE MULTI
NOMIAL MULTICLASS MODEL INSTEAD THE OPTIMIZATION PROBLEM IS DECOMPOSED IN A "ONEVSREST" FASHION SO SEPARATE
BINARY CLASSIFIERS ARE TRAINED FOR ALL CLASSES THIS HAPPENS UNDER THE HOOD SO LOGISTICREGRESSION INSTANCES US
ING THIS SOLVER BEHAVE AS MULTICLASS CLASSIFIERS FOR ℓ1REGULARIZATION SKLEARNSVML1MINC ALLOWS TO CALCULATE
THE LOWER BOUND FOR C IN ORDER TO GET A NON "NULL" ALL FEATURE WEIGHTS TO ZERO MODEL
THE "LBFGS" "SAG" AND "NEWTONCG" SOLVERS ONLY SUPPORT ℓ2REGULARIZATION OR NO REGULARIZATION AND ARE FOUND TO
CONVERGE FASTER FOR SOME HIGHDIMENSIONAL DATA SETTING MULTICLASS TO "MULTINOMIAL" WITH THESE SOLVERS LEARNS
A TRUE MULTINOMIAL LOGISTIC REGRESSION MODEL5 WHICH MEANS THAT ITS PROBABILITY ESTIMATES SHOULD BE BETTER CALIBRATED
THAN THE DEFAULT "ONEVSREST" SETTING
THE "SAG" SOLVER USES STOCHASTIC AVERAGE GRADIENT DESCENT6 IT IS FASTER THAN OTHER SOLVERS FOR LARGE DATASETS WHEN
BOTH THE NUMBER OF SAMPLES AND THE NUMBER OF FEATURES ARE LARGE
THE "SAGA" SOLVER7IS A VARIANT OF "SAG" THAT ALSO SUPPORTS THE NONSMOOTH PENALTYL1 THIS IS THERE
FORE THE SOLVER OF CHOICE FOR SPARSE MULTINOMIAL LOGISTIC REGRESSION IT IS ALSO THE ONLY SOLVER THAT SUPPORTS
PENALTYELASTICNET
THE "LBFGS" IS AN OPTIMIZATION ALGORITHM THAT APPROXIMATES THE BROYDEN–FLETCHER–GOLDFARB–SHANNO ALGORITHM8
WHICH BELONGS TO QUASINEWTON METHODS THE "LBFGS" SOLVER IS RECOMMENDED FOR USE FOR SMALL DATASETS BUT FOR
LARGER DATASETS ITS PERFORMANCE SUFFERS9
THE FOLLOWING TABLE SUMMARIZES THE PENALTIES SUPPORTED BY EACH SOLVER

SOLVERS					
PENALTIES 'LIBLINEAR' 'LBFGS' 'NEWTONCG' 'SAG' 'SAGA'					
MULTINOMIAL L2 PENALTY	NO	YES	YES	YES	YES
OVR L2 PENALTY	YES	YES	YES	YES	YES
MULTINOMIAL L1 PENALTY	NO	NO	NO	NO	YES
OVR L1 PENALTY	YES	NO	NO	NO	YES
ELASTICNET	NO	NO	NO	NO	YES
NO PENALTY 'NONE'	NO	YES	YES	YES	YES
BEHAVIORS					
PENALIZE THE INTERCEPT BAD	YES	NO	NO	NO	NO
FASTER FOR LARGE DATASETS	NO	NO	NO	YES	YES
ROBUST TO UNSCALED DATASETS	YES	YES	YES	NO	NO

THE "LBFGS" SOLVER IS USED BY DEFAULT FOR ITS ROBUSTNESS FOR LARGE DATASETS THE "SAGA" SOLVER IS USUALLY FASTER FOR LARGE
DATASET YOU MAY ALSO CONSIDER USING SGDCLASSIFIER WITH 'LOG' LOSS WHICH MIGHT BE EVEN FASTER BUT REQUIRES MORE
TUNING
5CHRISTOPHER M BISHOP PATTERN RECOGNITION AND MACHINE LEARNING CHAPTER 434
6MARK SCHMIDT NICOLAS LE ROUX AND FRANCIS BACH MINIMIZING FINITE SUMS WITH THE STOCHASTIC AVERAGE GRADIENT
7AARON DEFAZIO FRANCIS BACH SIMON LACOSTEJULIEN SAGA A FAST INCREMENTAL GRADIENT METHOD WITH SUPPORT FOR NONSTRONGLY CON
COMPOSITE OBJECTIVES
8HTTPSENWIKIPEDIAORGWIKIBROYDENE28093FLETCHERE28093GOLDFARBE28093SHANNOALGORITHM
9"PERFORMANCE EVALUATION OF LBFGS VS OTHER SOLVERS"

EXAMPLES
•L1 PENALTY AND SPARSITY IN LOGISTIC REGRESSION
•REGULARIZATION PATH OF L1 LOGISTIC REGRESSION
•PLOT MULTINOMIAL AND ONEVSREST LOGISTIC REGRESSION
•MULTICLASS SPARSE LOGISITIC REGRESSION ON NEWGROUPS20
•MNIST CLASSFIFICATION USING MULTINOMIAL LOGISTIC L1
DIFFERENCES FROM LIBLINEAR
THERE MIGHT BE A DIFFERENCE IN THE SCORES OBTAINED BETWEEN LOGISTICREGRESSION WITHSOLVERLIBLINEAR
ORLINEARSVC AND THE EXTERNAL LIBLINEAR LIBRARY DIRECTLY WHEN FITINTERCEPTFALSE AND THE FIT COEF
OR THE DATA TO BE PREDICTED ARE ZEROES THIS IS BECAUSE FOR THE SAMPLES WITH DECISIONFUNCTION ZERO
LOGISTICREGRESSION ANDLINEARSVC PREDICT THE NEGATIVE CLASS WHILE LIBLINEAR PREDICTS THE POSITIVE CLASS
NOTE THAT A MODEL WITH FITINTERCEPTFALSE AND HAVING MANY SAMPLES WITH DECISIONFUNCTION ZERO
IS LIKELY TO BE A UNDERFIT BAD MODEL AND YOU ARE ADVISED TO SET FITINTERCEPTTRUE AND INCREASE THE INTER
CEPTSCALING
NOTE FEATURE SELECTION WITH SPARSE LOGISTIC REGRESSION
A LOGISTIC REGRESSION WITH ℓ1PENALTY YIELDS SPARSE MODELS AND CAN THUS BE USED TO PERFORM FEATURE SELECTION AS
DETAILED IN L1BASED FEATURE SELECTION
LOGISTICREGRESSIONCV IMPLEMENTS LOGISTIC REGRESSION WITH BUILTIN CROSSVALIDATION SUPPORT TO FIND THE OPTI
MALCANDL1RATIO PARAMETERS ACCORDING TO THE SCORING ATTRIBUTE THE “NEWTONCG” “SAG” “SAGA” AND “LBFGS”
SOLVERS ARE FOUND TO BE FASTER FOR HIGHDIMENSIONAL DENSE DATA DUE TO WARMSTARTING SEE GLOSSARY
REFERENCES
STOCHASTIC GRADIENT DESCENT SGD
STOCHASTIC GRADIENT DESCENT IS A SIMPLE YET VERY EFFICIENT APPROACH TO FIT LINEAR MODELS IT IS PARTICULARLY USEFUL WHEN THE
NUMBER OF SAMPLES AND THE NUMBER OF FEATURES IS VERY LARGE THE PARTIALFIT METHOD ALLOWS ONLINEOUTOFCORE
LEARNING
THE CLASSES SGDCLASSIFIER ANDSGDREGRESSOR PROVIDE FUNCTIONALITY TO FIT LINEAR MODELS FOR CLASSIFICA
TION AND REGRESSION USING DIFFERENT CONVEX LOSS FUNCTIONS AND DIFFERENT PENALTIES EG WITH LOSSLOG
SGDCLASSIFIER FITS A LOGISTIC REGRESSION MODEL WHILE WITH LOSSHINGE IT FITS A LINEAR SUPPORT VECTOR MA
CHINE SVM
REFERENCES
•STOCHASTIC GRADIENT DESCENT

PERCEPTRON

THEPERCEPTRON IS ANOTHER SIMPLE CLASSIFICATION ALGORITHM SUITABLE FOR LARGE SCALE LEARNING BY DEFAULT

- IT DOES NOT REQUIRE A LEARNING RATE
- IT IS NOT REGULARIZED PENALIZED
- IT UPDATES ITS MODEL ONLY ON MISTAKES

THE LAST CHARACTERISTIC IMPLIES THAT THE PERCEPTRON IS SLIGHTLY FASTER TO TRAIN THAN SGD WITH THE HINGE LOSS AND THAT THE RESULTING MODELS ARE SPARSER

PASSIVE AGGRESSIVE ALGORITHMS

THE PASSIVEAGGRESSIVE ALGORITHMS ARE A FAMILY OF ALGORITHMS FOR LARGESCALE LEARNING THEY ARE SIMILAR TO THE PER CEPTRON IN THAT THEY DO NOT REQUIRE A LEARNING RATE HOWEVER CONTRARY TO THE PERCEPTRON THEY INCLUDE A REGULARIZATION PARAMETERC

FOR CLASSIFICATION PASSIVEAGGRESSIVECLASSIFIER CAN BE USED WITH LOSSHINGE PAI OR LOSSSQUAREDHINGE PAII FOR REGRESSION PASSIVEAGGRESSIVEREGRESSOR CAN BE USED WITH LOSSEPSILONINSENSITIVE PAI ORLOSSSQUAREDEPSILONINSENSITIVE PAII

REFERENCES

- “ONLINE PASSIVEAGGRESSIVE ALGORITHMS” K CRAMMER O DEKEL J KESHAT S SHALEVSHWARTZ Y SINGER JMLR 7 2006

ROBUSTNESS REGRESSION OUTLIERS AND MODELING ERRORS

ROBUST REGRESSION AIMS TO FIT A REGRESSION MODEL IN THE PRESENCE OF CORRUPT DATA EITHER OUTLIERS OR ERROR IN THE MODEL

DIFFERENT SCENARIO AND USEFUL CONCEPTS

THERE ARE DIFFERENT THINGS TO KEEP IN MIND WHEN DEALING WITH DATA CORRUPTED BY OUTLIERS

•OUTLIERS IN X OR IN Y
OUTLIERS IN THE Y DIRECTION OUTLIERS IN THE X DIRECTION
•FRACTION OF OUTLIERS VERSUS AMPLITUDE OF ERROR
THE NUMBER OF OUTLYING POINTS MATTERS BUT ALSO HOW MUCH THEY ARE OUTLIERS
SMALL OUTLIERS LARGE OUTLIERS
AN IMPORTANT NOTION OF ROBUST FITTING IS THAT OF BREAKDOWN POINT THE FRACTION OF DATA THAT CAN BE OUTLYING FOR THE FIT TO START MISSING THE INLYING DATA
NOTE THAT IN GENERAL ROBUST FITTING IN HIGHDIMENSIONAL SETTING LARGE NFEATURES IS VERY HARD THE ROBUST MODELS HERE WILL PROBABLY NOT WORK IN THESE SETTINGS
TRADEOFFS WHICH ESTIMATOR
SCIKITLEARN PROVIDES 3 ROBUST REGRESSION ESTIMATORS RANSAC THEIL SEN ANDHUBERREGRESSOR
•HUBERREGRESSOR SHOULD BE FASTER THAN RANSAC ANDTHEIL SEN UNLESS THE NUMBER OF SAMPLES ARE VERY LARGE IE NSAMPLES NFEATURES THIS IS BECAUSE RANSAC ANDTHEIL SEN FIT ON SMALLER SUBSETS OF THE DATA HOWEVER BOTH THEIL SEN ANDRANSAC ARE UNLIKELY TO BE AS ROBUST AS HUBERREGRESSOR FOR THE DEFAULT PARAMETERS

•RANSAC IS FASTER THAN THEIL SEN AND SCALES MUCH BETTER WITH THE NUMBER OF SAMPLES
•RANSAC WILL DEAL BETTER WITH LARGE OUTLIERS IN THE Y DIRECTION MOST COMMON SITUATION
•THEIL SEN WILL COPE BETTER WITH MEDIUMSIZE OUTLIERS IN THE X DIRECTION BUT THIS PROPERTY WILL DISAPPEAR IN HIGHDIMENSIONAL SETTINGS
WHEN IN DOUBT USE RANSAC
RANSAC RANDOM SAMPLE CONSENSUS
RANSAC RANDOM SAMPLE CONSENSUS FITS A MODEL FROM RANDOM SUBSETS OF INLIERS FROM THE COMPLETE DATA SET
RANSAC IS A NONDETERMINISTIC ALGORITHM PRODUCING ONLY A REASONABLE RESULT WITH A CERTAIN PROBABILITY WHICH IS DEPENDENT ON THE NUMBER OF ITERATIONS SEE MAXTRIALS PARAMETER IT IS TYPICALLY USED FOR LINEAR AND NONLINEAR REGRESSION PROBLEMS AND IS ESPECIALLY POPULAR IN THE FIELD OF PHOTOGRAMMETRIC COMPUTER VISION
THE ALGORITHM SPLITS THE COMPLETE INPUT SAMPLE DATA INTO A SET OF INLIERS WHICH MAY BE SUBJECT TO NOISE AND OUTLIERS WHICH ARE EG CAUSED BY ERRONEOUS MEASUREMENTS OR INVALID HYPOTHESES ABOUT THE DATA THE RESULTING MODEL IS THEN ESTIMATED ONLY FROM THE DETERMINED INLIERS
DETAILS OF THE ALGORITHM
EACH ITERATION PERFORMS THE FOLLOWING STEPS
1 SELECTMINSAMPLES RANDOM SAMPLES FROM THE ORIGINAL DATA AND CHECK WHETHER THE SET OF DATA IS VALID SEE ISDATAVALID
2 FIT A MODEL TO THE RANDOM SUBSET BASEESTIMATORFIT AND CHECK WHETHER THE ESTIMATED MODEL IS VALID SEEISMODELVALID
3 CLASSIFY ALL DATA AS INLIERS OR OUTLIERS BY CALCULATING THE RESIDUALS TO THE ESTIMATED MODEL BASEESTIMATOR PREDICTX Y   ALL DATA SAMPLES WITH ABSOLUTE RESIDUALS SMALLER THAN THE RESIDUALTHRESHOLD ARE CONSIDERED AS INLIERS
4 SAVE FITTED MODEL AS BEST MODEL IF NUMBER OF INLIER SAMPLES IS MAXIMAL IN CASE THE CURRENT ESTIMATED MODEL HAS THE SAME NUMBER OF INLIERS IT IS ONLY CONSIDERED AS THE BEST MODEL IF IT HAS BETTER SCORE

THESE STEPS ARE PERFORMED EITHER A MAXIMUM NUMBER OF TIMES MAXTRIALS OR UNTIL ONE OF THE SPECIAL STOP CRITERIA ARE MET SEE STOPNINLIERS ANDSTOPSCORE THE FINAL MODEL IS ESTIMATED USING ALL INLIER SAMPLES CONSENSUS SET OF THE PREVIOUSLY DETERMINED BEST MODEL

THEISDATAVALID ANDISMODELVALID FUNCTIONS ALLOW TO IDENTIFY AND REJECT DEGENERATE COMBINATIONS OF RANDOM SUBSAMPLES IF THE ESTIMATED MODEL IS NOT NEEDED FOR IDENTIFYING DEGENERATE CASES ISDATAVALID SHOULD BE USED AS IT IS CALLED PRIOR TO FITTING THE MODEL AND THUS LEADING TO BETTER COMPUTATIONAL PERFORMANCE

EXAMPLES

•ROBUST LINEAR MODEL ESTIMATION USING RANSAC

•ROBUST LINEAR ESTIMATOR FITTING

REFERENCES

• HTTPSENWIKIPEDIAORGWIKIRANSAC

• “RANDOM SAMPLE CONSENSUS A PARADIGM FOR MODEL FITTING WITH APPLICATIONS TO IMAGE ANALYSIS AND AUTO MATED CARTOGRAPHY” MARTIN A FISCHLER AND ROBERT C BOLLES SRI INTERNATIONAL 1981

• “PERFORMANCE EVALUATION OF RANSAC FAMILY” SUNGLOK CHOI TAEMIN KIM AND WONPIL YU BMVC 2009

THEILSEN ESTIMATOR GENERALIZEDMEDIANBASED ESTIMATOR

THETHEILSENREGRESSOR ESTIMATOR USES A GENERALIZATION OF THE MEDIAN IN MULTIPLE DIMENSIONS IT IS THUS ROBUST TO MULTIVARIATE OUTLIERS NOTE HOWEVER THAT THE ROBUSTNESS OF THE ESTIMATOR DECREASES QUICKLY WITH THE DIMENSIONALITY OF THE PROBLEM IT LOSES ITS ROBUSTNESS PROPERTIES AND BECOMES NO BETTER THAN AN ORDINARY LEAST SQUARES IN HIGH DIMENSION

EXAMPLES

•THEILSEN REGRESSION

•ROBUST LINEAR ESTIMATOR FITTING

REFERENCES

• HTTPSENWIKIPEDIAORGWIKITHEILE28093SENESTIMATOR

THEORETICAL CONSIDERATIONS

THEILSENREGRESSOR IS COMPARABLE TO THE ORDINARY LEAST SQUARES OLS IN TERMS OF ASYMPTOTIC EFFICIENCY AND AS AN UNBIASED ESTIMATOR IN CONTRAST TO OLS THEILSEN IS A NONPARAMETRIC METHOD WHICH MEANS IT MAKES NO ASSUMPTION ABOUT THE UNDERLYING DISTRIBUTION OF THE DATA SINCE THEILSEN IS A MEDIANBASED ESTIMATOR IT IS MORE ROBUST AGAINST CORRUPTED DATA AKA OUTLIERS IN UNIVARIATE SETTING THEILSEN HAS A BREAKDOWN POINT OF ABOUT 293 IN CASE OF A SIMPLE LINEAR REGRESSION WHICH MEANS THAT IT CAN TOLERATE ARBITRARY CORRUPTED DATA OF UP TO 293

THE IMPLEMENTATION OF THEILSENREGRESSOR IN SCIKITLEARN FOLLOWS A GENERALIZATION TO A MULTIVARIATE LINEAR RE
GRESSION MODEL10USING THE SPATIAL MEDIAN WHICH IS A GENERALIZATION OF THE MEDIAN TO MULTIPLE DIMENSIONS11
IN TERMS OF TIME AND SPACE COMPLEXITY THEILSEN SCALES ACCORDING TO
□SAMPLES
□SUBSAMPLES
WHICH MAKES IT INFEASIBLE TO BE APPLIED EXHAUSTIVELY TO PROBLEMS WITH A LARGE NUMBER OF SAMPLES AND FEATURES THERE
FORE THE MAGNITUDE OF A SUBPOPULATION CAN BE CHOSEN TO LIMIT THE TIME AND SPACE COMPLEXITY BY CONSIDERING ONLY A
RANDOM SUBSET OF ALL POSSIBLE COMBINATIONS
EXAMPLES
•THEILSEN REGRESSION
REFERENCES
HUBER REGRESSION
THEHUBERREGRESSOR IS DIFFERENT TO RIDGE BECAUSE IT APPLIES A LINEAR LOSS TO SAMPLES THAT ARE CLASSIFIED AS OUTLIERS
A SAMPLE IS CLASSIFIED AS AN INLIER IF THE ABSOLUTE ERROR OF THAT SAMPLE IS LESSER THAN A CERTAIN THRESHOLD IT DIFFERS FROM
THEILSENREGRESSOR ANDRANSACREGRESSOR BECAUSE IT DOES NOT IGNORE THE EFFECT OF THE OUTLIERS BUT GIVES A
LESSER WEIGHT TO THEM
THE LOSS FUNCTION THAT HUBERREGRESSOR MINIMIZES IS GIVEN BY
MIN
□□□Σ
□1
□□□□□□−□□
□
□
□□22
10XIN DANG HANXIANG PENG XUEQIN WANG AND HEPING ZHANG THEILSEN ESTIMATORS IN A MULTIPLE LINEAR REGRESSION MODEL
11
20 KÄRKKÄINEN AND S ÄYRÄMÖ ON COMPUTATION OF SPATIAL MEDIAN FOR ROBUST DATA MINING

WHERE
□□□
□2 IF□ □
2□□−□2OTHERWISE
IT IS ADVISED TO SET THE PARAMETER EPSILON TO 135 TO ACHIEVE 95 STATISTICAL EFFICIENCY
NOTES
THEHUBERREGRESSOR DIFFERS FROM USING SGDREGRESSOR WITH LOSS SET TO HUBER IN THE FOLLOWING WAYS
•HUBERREGRESSOR IS SCALING INVARIANT ONCE EPSILON IS SET SCALING XANDYDOWN OR UP BY DIFFERENT VALUES WOULD PRODUCE THE SAME ROBUSTNESS TO OUTLIERS AS BEFORE AS COMPARED TO SGDREGRESSOR WHEREEPSILON HAS TO BE SET AGAIN WHEN XANDYARE SCALED
•HUBERREGRESSOR SHOULD BE MORE EFFICIENT TO USE ON DATA WITH SMALL NUMBER OF SAMPLES WHILE SGDREGRESSOR NEEDS A NUMBER OF PASSES ON THE TRAINING DATA TO PRODUCE THE SAME ROBUSTNESS
EXAMPLES
•HUBERREGRESSOR VS RIDGE ON DATASET WITH STRONG OUTLIERS
REFERENCES
• PETER J HUBER ELVEZIO M RONCHETTI ROBUST STATISTICS CONCOMITANT SCALE ESTIMATES PG 172
NOTE THAT THIS ESTIMATOR IS DIFFERENT FROM THE R IMPLEMENTATION OF ROBUST REGRESSION HTTPWWWATSUCLAEDUSTATR DAERREGHTM BECAUSE THE R IMPLEMENTATION DOES A WEIGHTED LEAST SQUARES IMPLEMENTATION WITH WEIGHTS GIVEN TO EACH SAMPLE ON THE BASIS OF HOW MUCH THE RESIDUAL IS GREATER THAN A CERTAIN THRESHOLD
POLYNOMIAL REGRESSION EXTENDING LINEAR MODELS WITH BASIS FUNCTIONS
ONE COMMON PATTERN WITHIN MACHINE LEARNING IS TO USE LINEAR MODELS TRAINED ON NONLINEAR FUNCTIONS OF THE DATA THIS APPROACH MAINTAINS THE GENERALLY FAST PERFORMANCE OF LINEAR METHODS WHILE ALLOWING THEM TO FIT A MUCH WIDER RANGE OF DATA

FOR EXAMPLE A SIMPLE LINEAR REGRESSION CAN BE EXTENDED BY CONSTRUCTING POLYNOMIAL FEATURES FROM THE COEFFICIENTS IN THE STANDARD LINEAR REGRESSION CASE YOU MIGHT HAVE A MODEL THAT LOOKS LIKE THIS FOR TWODIMENSIONAL DATA
□□ □ □0□1□1□2□2
IF WE WANT TO FIT A PARABOLOID TO THE DATA INSTEAD OF A PLANE WE CAN COMBINE THE FEATURES IN SECONDORDER POLYNOMIALS SO THAT THE MODEL LOOKS LIKE THIS
□□ □ □0□1□1□2□2□3□1□2□4□2
1□5□2
2
THE SOMETIMES SURPRISING OBSERVATION IS THAT THIS IS STILL A LINEAR MODEL TO SEE THIS IMAGINE CREATING A NEW SET OF FEATURES
□ □1 □2 □1□2 □2
1 □2
2
WITH THIS RELABELING OF THE DATA OUR PROBLEM CAN BE WRITTEN
□□ □ □0□1□1□2□2□3□3□4□4□5□5
WE SEE THAT THE RESULTING POLYNOMIAL REGRESSION IS IN THE SAME CLASS OF LINEAR MODELS WE CONSIDERED ABOVE IE THE MODEL IS LINEAR IN □ AND CAN BE SOLVED BY THE SAME TECHNIQUES BY CONSIDERING LINEAR FITS WITHIN A HIGHERDIMENSIONAL SPACE BUILT WITH THESE BASIS FUNCTIONS THE MODEL HAS THE FLEXIBILITY TO FIT A MUCH BROADER RANGE OF DATA
HERE IS AN EXAMPLE OF APPLYING THIS IDEA TO ONEDIMENSIONAL DATA USING POLYNOMIAL FEATURES OF VARYING DEGREES
THIS FIGURE IS CREATED USING THE POLYNOMIALFEATURES TRANSFORMER WHICH TRANSFORMS AN INPUT DATA MATRIX INTO A NEW DATA MATRIX OF A GIVEN DEGREE IT CAN BE USED AS FOLLOWS
```
 FROM SKLEARNPREPROCESSING IMPORT POLYNOMIALFEATURES
 IMPORT NUMPY AS NP
X  NPARANGE6RESHAPE3 2
X
ARRAY0 1
2 3
4 5
POLY  POLYNOMIALFEATURESDEGREE2
POLYFITTRANSFORMX
ARRAY 1 0 1 0 0 1
 1 2 3 4 6 9
 1 4 5 16 20 25
```

THE FEATURES OF XHAVE BEEN TRANSFORMED FROM □1 □2TO1 □1 □2 □2
1 □1□2 □2
2 AND CAN NOW BE USED WITHIN ANY
LINEAR MODEL
THIS SORT OF PREPROCESSING CAN BE STREAMLINED WITH THE PIPELINE TOOLS A SINGLE OBJECT REPRESENTING A SIMPLE POLYNOMIAL
REGRESSION CAN BE CREATED AND USED AS FOLLOWS
```
 FROM SKLEARNPREPROCESSING IMPORT POLYNOMIALFEATURES
 FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION
 FROM SKLEARNPIPELINE IMPORT PIPELINE
 IMPORT NUMPY AS NP
MODEL  PIPELINEPOLY POLYNOMIALFEATURESDEGREE3
 LINEAR LINEARREGRESSIONFITINTERCEPT FALSE
 FIT TO AN ORDER3 POLYNOMIAL DATA
X  NPARANGE5
Y  3  2 X  X2  X3
MODEL  MODELFITX NPNEWAXIS Y
MODELNAMEDSTEPSLINEARCOEF
ARRAY 3 2 1 1
```
THE LINEAR MODEL TRAINED ON POLYNOMIAL FEATURES IS ABLE TO EXACTLY RECOVER THE INPUT POLYNOMIAL COEFFICIENTS
IN SOME CASES IT’S NOT NECESSARY TO INCLUDE HIGHER POWERS OF ANY SINGLE FEATURE BUT ONLY THE SOCALLED INTERACTION
FEATURES THAT MULTIPLY TOGETHER AT MOST □DISTINCT FEATURES THESE CAN BE GOTTEN FROM POLYNOMIALFEATURES WITH
THE SETTINGINTERACTIONONLYTRUE
FOR EXAMPLE WHEN DEALING WITH BOOLEAN FEATURES □□
□□□FOR ALL □AND IS THEREFORE USELESS BUT □□□□REPRESENTS THE
CONJUNCTION OF TWO BOOLEANS THIS WAY WE CAN SOLVE THE XOR PROBLEM WITH A LINEAR CLASSIFIER
```
 FROM SKLEARNLINEARMODEL IMPORT PERCEPTRON
 FROM SKLEARNPREPROCESSING IMPORT POLYNOMIALFEATURES
 IMPORT NUMPY AS NP
X  NPARRAY0 0 0 1 1 0 1 1
Y  X 0  X 1
Y
ARRAY0 1 1 0
X  POLYNOMIALFEATURESINTERACTIONONLY TRUEFITTRANSFORMXASTYPEINT
X
ARRAY1 0 0 0
1 0 1 0
1 1 0 0
1 1 1 1
CLF  PERCEPTRONFITINTERCEPT FALSE MAXITER10 TOL NONE
 SHUFFLE FALSEFITX Y
```
AND THE CLASSIFIER “PREDICTIONS” ARE PERFECT
```
CLFPREDICTX
ARRAY0 1 1 0
CLFSCOREX Y
10
```
312 LINEAR AND QUADRATIC DISCRIMINANT ANALYSIS
LINEAR DISCRIMINANT ANALYSIS DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS AND
QUADRATIC DISCRIMINANT ANALYSIS DISCRIMINANTANALYSISQUADRATICDISCRIMINANTANALYSIS
ARE TWO CLASSIC CLASSIFIERS WITH AS THEIR NAMES SUGGEST A LINEAR AND A QUADRATIC DECISION SURFACE RESPECTIVELY

THESE CLASSIFIERS ARE ATTRACTIVE BECAUSE THEY HAVE CLOSEDFORM SOLUTIONS THAT CAN BE EASILY COMPUTED ARE INHERENTLY MULTICLASS HAVE PROVEN TO WORK WELL IN PRACTICE AND HAVE NO HYPERPARAMETERS TO TUNE
THE PLOT SHOWS DECISION BOUNDARIES FOR LINEAR DISCRIMINANT ANALYSIS AND QUADRATIC DISCRIMINANT ANALYSIS THE BOTTOM ROW DEMONSTRATES THAT LINEAR DISCRIMINANT ANALYSIS CAN ONLY LEARN LINEAR BOUNDARIES WHILE QUADRATIC DIS CRIMINANT ANALYSIS CAN LEARN QUADRATIC BOUNDARIES AND IS THEREFORE MORE FLEXIBLE
EXAMPLES
LINEAR AND QUADRATIC DISCRIMINANT ANALYSIS WITH COVARIANCE ELLIPSOID COMPARISON OF LDA AND QDA ON SYNTHETIC DATA
DIMENSIONALITY REDUCTION USING LINEAR DISCRIMINANT ANALYSIS
DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS CAN BE USED TO PERFORM SUPERVISED DIMEN SIONALITY REDUCTION BY PROJECTING THE INPUT DATA TO A LINEAR SUBSPACE CONSISTING OF THE DIRECTIONS WHICH MAXIMIZE THE SEPARATION BETWEEN CLASSES IN A PRECISE SENSE DISCUSSED IN THE MATHEMATICS SECTION BELOW THE DIMENSION OF THE OUTPUT IS NECESSARILY LESS THAN THE NUMBER OF CLASSES SO THIS IS IN GENERAL A RATHER STRONG DIMENSIONALITY REDUCTION AND ONLY MAKES SENSE IN A MULTICLASS SETTING

THIS IS IMPLEMENTED IN DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSISTRANSFORM THE
DESIRED DIMENSIONALITY CAN BE SET USING THE NCOMPONENTS CONSTRUCTOR PARAMETER THIS PARAMETER HAS NO INFLUENCE
ONDISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSISFIT ORDISCRIMINANTANALYSIS
LINEARDISCRIMINANTANALYSISPREDICT
EXAMPLES
COMPARISON OF LDA AND PCA 2D PROJECTION OF IRIS DATASET COMPARISON OF LDA AND PCA FOR DIMENSIONALITY
REDUCTION OF THE IRIS DATASET
MATHEMATICAL FORMULATION OF THE LDA AND QDA CLASSIFIERS
BOTH LDA AND QDA CAN BE DERIVED FROM SIMPLE PROBABILISTIC MODELS WHICH MODEL THE CLASS CONDITIONAL DISTRIBUTION
OF THE DATA □□□□FOR EACH CLASS □ PREDICTIONS CAN THEN BE OBTAINED BY USING BAYES' RULE
□□□□ □□□□□□□
□□□□□□□□□□Σ
□□□□□·□□□
AND WE SELECT THE CLASS □WHICH MAXIMIZES THIS CONDITIONAL PROBABILITY
MORE SPECIFICALLY FOR LINEAR AND QUADRATIC DISCRIMINANT ANALYSIS □□□IS MODELED AS A MULTIVARIATE GAUSSIAN DISTRI
BUTION WITH DENSITY
□□□□ 1
2□□2□□12EXP
−1
2□−□□□□−1
□□−□□
WHERE □IS THE NUMBER OF FEATURES
TO USE THIS MODEL AS A CLASSIFIER WE JUST NEED TO ESTIMATE FROM THE TRAINING DATA THE CLASS PRIORS □□□BY THE
PROPORTION OF INSTANCES OF CLASS □ THE CLASS MEANS □□BY THE EMPIRICAL SAMPLE CLASS MEANS AND THE COVARIANCE
MATRICES EITHER BY THE EMPIRICAL SAMPLE CLASS COVARIANCE MATRICES OR BY A REGULARIZED ESTIMATOR SEE THE SECTION ON
SHRINKAGE BELOW
IN THE CASE OF LDA THE GAUSSIANS FOR EACH CLASS ARE ASSUMED TO SHARE THE SAME COVARIANCE MATRIX □□ □ FOR
ALL□ THIS LEADS TO LINEAR DECISION SURFACES WHICH CAN BE SEEN BY COMPARING THE LOGPROBABILITY RATIOS LOG□□
□□□□□□□
LOG□□□□
□□□□
 LOG□□□□□□□
□□□□□□□
 0⇔
□□−□□□□−1□1
2□□
□□−1□□−□□
□□−1□□−LOG□□□
□□□
IN THE CASE OF QDA THERE ARE NO ASSUMPTIONS ON THE COVARIANCE MATRICES □□OF THE GAUSSIANS LEADING TO QUADRATIC
DECISION SURFACES SEE3FOR MORE DETAILS
NOTE RELATION WITH GAUSSIAN NAIVE BAYES
IF IN THE QDA MODEL ONE ASSUMES THAT THE COVARIANCE MATRICES ARE DIAGONAL THEN THE INPUTS ARE ASSUMED TO BE CON
DITIONALLY INDEPENDENT IN EACH CLASS AND THE RESULTING CLASSIFIER IS EQUIVALENT TO THE GAUSSIAN NAIVE BAYES CLASSIFIER
NAIVEBAYESGAUSSIANNB
3"THE ELEMENTS OF STATISTICAL LEARNING" HASTIE T TIBSHIRANI R FRIEDMAN J SECTION 43 P106119 2008

MATHEMATICAL FORMULATION OF LDA DIMENSIONALITY REDUCTION

TO UNDERSTAND THE USE OF LDA IN DIMENSIONALITY REDUCTION IT IS USEFUL TO START WITH A GEOMETRIC REFORMULATION OF THE LDA CLASSIFICATION RULE EXPLAINED ABOVE WE WRITE □FOR THE TOTAL NUMBER OF TARGET CLASSES SINCE IN LDA WE ASSUME THAT ALL CLASSES HAVE THE SAME ESTIMATED COVARIANCE □ WE CAN RESCALE THE DATA SO THAT THIS COVARIANCE IS THE IDENTITY □□−12□□□WITH□ □□□□

THEN ONE CAN SHOW THAT TO CLASSIFY A DATA POINT AFTER SCALING IS EQUIVALENT TO FINDING THE ESTIMATED CLASS MEAN □ □WHICH

IS CLOSEST TO THE DATA POINT IN THE EUCLIDEAN DISTANCE BUT THIS CAN BE DONE JUST AS WELL AFTER PROJECTING ON THE □−1 AFFINE SUBSPACE □□GENERATED BY ALL THE □

□FOR ALL CLASSES THIS SHOWS THAT IMPLICIT IN THE LDA CLASSIFIER THERE IS A

DIMENSIONALITY REDUCTION BY LINEAR PROJECTION ONTO A □−1DIMENSIONAL SPACE

WE CAN REDUCE THE DIMENSION EVEN MORE TO A CHOSEN □ BY PROJECTING ONTO THE LINEAR SUBSPACE □□WHICH MAX IMIZES THE VARIANCE OF THE □

□AFTER PROJECTION IN EFFECT WE ARE DOING A FORM OF PCA FOR THE TRANSFORMED CLASS MEANS □

□ THIS □CORRESPONDS TO THE NCOMPONENTS PARAMETER USED IN THE DISCRIMINANTANALYSIS LINEARDISCRIMINANTANALYSISTRANSFORM METHOD SEE3FOR MORE DETAILS

SHRINKAGE

SHRINKAGE IS A TOOL TO IMPROVE ESTIMATION OF COVARIANCE MATRICES IN SITUATIONS WHERE THE NUMBER OF TRAINING SAM PLES IS SMALL COMPARED TO THE NUMBER OF FEATURES IN THIS SCENARIO THE EMPIRICAL SAMPLE COVARIANCE IS A POOR ES TIMATOR SHRINKAGE LDA CAN BE USED BY SETTING THE SHRINKAGE PARAMETER OF THE DISCRIMINANTANALYSIS LINEARDISCRIMINANTANALYSIS CLASS TO ‘AUTO’ THIS AUTOMATICALLY DETERMINES THE OPTIMAL SHRINKAGE PARAMETER IN AN ANALYTIC WAY FOLLOWING THE LEMMA INTRODUCED BY LEDOIT AND WOLF4 NOTE THAT CURRENTLY SHRINKAGE ONLY WORKS WHEN SETTING THE SOLVER PARAMETER TO ‘LSQR’ OR ‘EIGEN’

THESHRINKAGE PARAMETER CAN ALSO BE MANUALLY SET BETWEEN 0 AND 1 IN PARTICULAR A VALUE OF 0 CORRESPONDS TO NO SHRINKAGE WHICH MEANS THE EMPIRICAL COVARIANCE MATRIX WILL BE USED AND A VALUE OF 1 CORRESPONDS TO COMPLETE SHRINKAGE WHICH MEANS THAT THE DIAGONAL MATRIX OF VARIANCES WILL BE USED AS AN ESTIMATE FOR THE COVARIANCE MATRIX SETTING THIS PARAMETER TO A VALUE BETWEEN THESE TWO EXTREMA WILL ESTIMATE A SHRUNK VERSION OF THE COVARIANCE MATRIX

4LEDOIT O WOLF M HONEY I SHRUNK THE SAMPLE COVARIANCE MATRIX THE JOURNAL OF PORTFOLIO MANAGEMENT 304 110119 2004

ESTIMATION ALGORITHMS
THE DEFAULT SOLVER IS ‘SVD’ IT CAN PERFORM BOTH CLASSIFICATION AND TRANSFORM AND IT DOES NOT RELY ON THE CALCULATION OF THE COVARIANCE MATRIX THIS CAN BE AN ADVANTAGE IN SITUATIONS WHERE THE NUMBER OF FEATURES IS LARGE HOWEVER THE ‘SVD’ SOLVER CANNOT BE USED WITH SHRINKAGE
THE ‘LSQR’ SOLVER IS AN EFFICIENT ALGORITHM THAT ONLY WORKS FOR CLASSIFICATION IT SUPPORTS SHRINKAGE
THE ‘EIGEN’ SOLVER IS BASED ON THE OPTIMIZATION OF THE BETWEEN CLASS SCATTER TO WITHIN CLASS SCATTER RATIO IT CAN BE USED FOR BOTH CLASSIFICATION AND TRANSFORM AND IT SUPPORTS SHRINKAGE HOWEVER THE ‘EIGEN’ SOLVER NEEDS TO COMPUTE THE COVARIANCE MATRIX SO IT MIGHT NOT BE SUITABLE FOR SITUATIONS WITH A HIGH NUMBER OF FEATURES
EXAMPLES
NORMAL AND SHRINKAGE LINEAR DISCRIMINANT ANALYSIS FOR CLASSIFICATION COMPARISON OF LDA CLASSIFIERS WITH AND WITHOUT SHRINKAGE
REFERENCES
313 KERNEL RIDGE REGRESSION
KERNEL RIDGE REGRESSION KRR M2012 COMBINES RIDGE REGRESSION LINEAR LEAST SQUARES WITH L2NORM REGULARIZATION WITH THE KERNEL TRICK IT THUS LEARNS A LINEAR FUNCTION IN THE SPACE INDUCED BY THE RESPECTIVE KERNEL AND THE DATA FOR NONLINEAR KERNELS THIS CORRESPONDS TO A NONLINEAR FUNCTION IN THE ORIGINAL SPACE
THE FORM OF THE MODEL LEARNED BY KERNELRIDGE IS IDENTICAL TO SUPPORT VECTOR REGRESSION SVR HOWEVER DIFFERENT LOSS FUNCTIONS ARE USED KRR USES SQUARED ERROR LOSS WHILE SUPPORT VECTOR REGRESSION USES □INSENSITIVE LOSS BOTH COMBINED WITH L2 REGULARIZATION IN CONTRAST TO SVR FITTINGKERNELRIDGE CAN BE DONE IN CLOSEDFORM AND IS TYPICALLY FASTER FOR MEDIUMSIZED DATASETS ON THE OTHER HAND THE LEARNED MODEL IS NONSPARSE AND THUS SLOWER THAN SVR WHICH LEARNS A SPARSE MODEL FOR □ 0 AT PREDICTIONTIME
THE FOLLOWING FIGURE COMPARES KERNELRIDGE ANDSVR ON AN ARTIFICIAL DATASET WHICH CONSISTS OF A SINUSOIDAL TARGET FUNCTION AND STRONG NOISE ADDED TO EVERY FIFTH DATAPOINT THE LEARNED MODEL OF KERNELRIDGE ANDSVR IS PLOTTED WHERE BOTH COMPLEXITYREGULARIZATION AND BANDWIDTH OF THE RBF KERNEL HAVE BEEN OPTIMIZED USING GRIDSEARCH THE LEARNED FUNCTIONS ARE VERY SIMILAR HOWEVER FITTING KERNELRIDGE IS APPROX SEVEN TIMES FASTER THAN FITTING SVR BOTH WITH GRIDSEARCH HOWEVER PREDICTION OF 100000 TARGET VALUES IS MORE THAN THREE TIMES FASTER WITH SVR SINCE IT HAS LEARNED A SPARSE MODEL USING ONLY APPROX 13 OF THE 100 TRAINING DATAPOINTS AS SUPPORT VECTORS
THE NEXT FIGURE COMPARES THE TIME FOR FITTING AND PREDICTION OF KERNELRIDGE ANDSVR FOR DIFFERENT SIZES OF THE TRAINING SET FITTING KERNELRIDGE IS FASTER THAN SVR FOR MEDIUMSIZED TRAINING SETS LESS THAN 1000 SAMPLES HOWEVER FOR LARGER TRAINING SETS SVR SCALES BETTER WITH REGARD TO PREDICTION TIME SVR IS FASTER THAN KERNELRIDGE FOR ALL SIZES OF THE TRAINING SET BECAUSE OF THE LEARNED SPARSE SOLUTION NOTE THAT THE DEGREE OF SPARSITY AND THUS THE PREDICTION TIME DEPENDS ON THE PARAMETERS □AND□OF THESVR□ 0WOULD CORRESPOND TO A DENSE MODEL
REFERENCES
314 SUPPORT VECTOR MACHINES
SUPPORT VECTOR MACHINES SVMS ARE A SET OF SUPERVISED LEARNING METHODS USED FOR CLASSIFICATION REGRESSION AND OUTLIERS DETECTION

THE ADVANTAGES OF SUPPORT VECTOR MACHINES ARE
• EFFECTIVE IN HIGH DIMENSIONAL SPACES
• STILL EFFECTIVE IN CASES WHERE NUMBER OF DIMENSIONS IS GREATER THAN THE NUMBER OF SAMPLES
• USES A SUBSET OF TRAINING POINTS IN THE DECISION FUNCTION CALLED SUPPORT VECTORS SO IT IS ALSO MEMORY EFFICIENT
• VERSATILE DIFFERENT KERNEL FUNCTIONS CAN BE SPECIFIED FOR THE DECISION FUNCTION COMMON KERNELS ARE PROVIDED BUT IT IS ALSO POSSIBLE TO SPECIFY CUSTOM KERNELS
THE DISADVANTAGES OF SUPPORT VECTOR MACHINES INCLUDE
• IF THE NUMBER OF FEATURES IS MUCH GREATER THAN THE NUMBER OF SAMPLES AVOID OVERFITTING IN CHOOSING KERNEL FUNCTIONS AND REGULARIZATION TERM IS CRUCIAL
• SVMS DO NOT DIRECTLY PROVIDE PROBABILITY ESTIMATES THESE ARE CALCULATED USING AN EXPENSIVE FIVEFOLD CROSS VALIDATION SEE SCORES AND PROBABILITIES BELOW
THE SUPPORT VECTOR MACHINES IN SCIKITLEARN SUPPORT BOTH DENSE NUMPYNDARRAY AND CONVERTIBLE TO THAT BY NUMPY ASARRAY AND SPARSE ANY SCIPYSPARSE SAMPLE VECTORS AS INPUT HOWEVER TO USE AN SVM TO MAKE PREDICTIONS FOR SPARSE DATA IT MUST HAVE BEEN FIT ON SUCH DATA FOR OPTIMAL PERFORMANCE USE CORDERED NUMPYNDARRAY DENSE ORSCIPYSPARSECSRMATRIX SPARSE WITH DTYPEFLOAT64
CLASSIFICATION
SVCNUSVC ANDLINEARSVC ARE CLASSES CAPABLE OF PERFORMING MULTICLASS CLASSIFICATION ON A DATASET

SVC ANDNUSVC ARE SIMILAR METHODS BUT ACCEPT SLIGHTLY DIFFERENT SETS OF PARAMETERS AND HAVE DIFFERENT MATHEMATICAL FORMULATIONS SEE SECTION MATHEMATICAL FORMULATION ON THE OTHER HAND LINEARSVC IS ANOTHER IMPLEMENTATION OF SUPPORT VECTOR CLASSIFICATION FOR THE CASE OF A LINEAR KERNEL NOTE THAT LINEARSVC DOES NOT ACCEPT KEYWORD KERNEL AS THIS IS ASSUMED TO BE LINEAR IT ALSO LACKS SOME OF THE MEMBERS OF SVC ANDNUSVC LIKESUPPORT AS OTHER CLASSIFIERS SVCNUSVC ANDLINEARSVC TAKE AS INPUT TWO ARRAYS AN ARRAY X OF SIZE NSAMPLES NFEATURES HOLDING THE TRAINING SAMPLES AND AN ARRAY Y OF CLASS LABELS STRINGS OR INTEGERS SIZE NSAMPLES

```
 FROM SKLEARN IMPORT SVM
X  0 0 1 1
Y  0 1
CLF  SVMSVCGAMMASCALE
CLFFITX Y
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMASCALE KERNELRBF
MAXITER1 PROBABILITYFALSE RANDOMSTATENONE SHRINKINGTRUE
TOL0001 VERBOSEFALSE
```

AFTER BEING FITTED THE MODEL CAN THEN BE USED TO PREDICT NEW VALUES

```
CLFPREDICT2 2
ARRAY1
```

SVMS DECISION FUNCTION DEPENDS ON SOME SUBSET OF THE TRAINING DATA CALLED THE SUPPORT VECTORS SOME PROPERTIES OF THESE SUPPORT VECTORS CAN BE FOUND IN MEMBERS SUPPORTVECTORS SUPPORT ANDNSUPPORT

```
 GET SUPPORT VECTORS
CLFSUPPORTVECTORS
ARRAY0 0
1 1
 GET INDICES OF SUPPORT VECTORS
CLFSUPPORT
ARRAY0 1
 GET NUMBER OF SUPPORT VECTORS FOR EACH CLASS
CLFNSUPPORT
ARRAY1 1
```

MULTICLASS CLASSIFICATION

SVC ANDNUSVC IMPLEMENT THE “ONEAGAINSTONE” APPROACH KNERR ET AL 1990 FOR MULTI CLASS CLASSIFICATION IFNCLASS IS THE NUMBER OF CLASSES THEN NCLASS NCLASS 1 2 CLASSIFIERS ARE CONSTRUCTED AND EACH ONE TRAINS DATA FROM TWO CLASSES TO PROVIDE A CONSISTENT INTERFACE WITH OTHER CLASSIFIERS THE DECISIONFUNCTIONSHAPE OPTION ALLOWS TO MONOTICALLY TRANSFORM THE RESULTS OF THE “ONEAGAINSTONE” CLASSIFIERS TO A DECISION FUNCTION OF SHAPE NSAMPLES NCLASSES

```
X  0 1 2 3
Y  0 1 2 3
CLF  SVMSVCGAMMASCALE DECISIONFUNCTIONSHAPEOVO
CLFFITX Y
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVO DEGREE3 GAMMASCALE KERNELRBF
MAXITER1 PROBABILITYFALSE RANDOMSTATENONE SHRINKINGTRUE
TOL0001 VERBOSEFALSE
DEC  CLFDECISIONFUNCTION1
DECSHAPE1  4 CLASSES 4 32  6
6
```

SCIKITLEARN USER GUIDE RELEASE 0213
CLFDECISIONFUNCTIONSHAPE OVR
DEC CLFDECISIONFUNCTION1
DECSHAPE1 4 CLASSES
4
ON THE OTHER HAND LINEARSVC IMPLEMENTS “ONEVSTHEREST” MULTICLASS STRATEGY THUS TRAINING NCLASS MODELS IF
THERE ARE ONLY TWO CLASSES ONLY ONE MODEL IS TRAINED
LINCLF SVMLINEARSVC
LINCLFFITX Y
LINEARSVCC10 CLASSWEIGHTNONE DUALTRUE FITINTERCEPTTRUE
INTERCEPTSCALING1 LOSSSQUAREDHINGE MAXITER1000
MULTICLASSOVR PENALTYL2 RANDOMSTATENONE TOL00001
VERBOSE0
DEC LINCLFDECISIONFUNCTION1
DECSHAPE1
4
SEEMATHEMATICAL FORMULATION FOR A COMPLETE DESCRIPTION OF THE DECISION FUNCTION
NOTE THAT THE LINEARSVC ALSO IMPLEMENTS AN ALTERNATIVE MULTICLASS STRATEGY THE SOCALLED MULTICLASS SVM FORMU
LATED BY CRAMMER AND SINGER BY USING THE OPTION MULTICLASSCRAMMERSINGER THIS METHOD IS CONSIS
TENT WHICH IS NOT TRUE FOR ONEVSREST CLASSIFICATION IN PRACTICE ONEVSREST CLASSIFICATION IS USUALLY PREFERRED SINCE
THE RESULTS ARE MOSTLY SIMILAR BUT THE RUNTIME IS SIGNIFICANTLY LESS
FOR “ONEVSREST” LINEARSVC THE ATTRIBUTES COEF ANDINTERCEPT HAVE THE SHAPE NCLASS
NFEATURES ANDNCLASS RESPECTIVELY EACH ROW OF THE COEFFICIENTS CORRESPONDS TO ONE OF THE NCLASS
MANY “ONEVSREST” CLASSIFIERS AND SIMILAR FOR THE INTERCEPTS IN THE ORDER OF THE “ONE” CLASS
IN THE CASE OF “ONEVSONE” SVC THE LAYOUT OF THE ATTRIBUTES IS A LITTLE MORE INVOLVED IN THE CASE OF HAVING
A LINEAR KERNEL THE ATTRIBUTES COEF ANDINTERCEPT HAVE THE SHAPE NCLASS NCLASS 1
2 NFEATURES ANDNCLASS NCLASS 1 2 RESPECTIVELY THIS IS SIMILAR TO THE LAYOUT FOR
LINEARSVC DESCRIBED ABOVE WITH EACH ROW NOW CORRESPONDING TO A BINARY CLASSIFIER THE ORDER FOR CLASSES 0 TO N IS
“0 VS 1” “0 VS 2” “0 VS N” “1 VS 2” “1 VS 3” “1 VS N” “N1 VS N”
THE SHAPE OF DUALCOEF ISNCLASS1 NSV WITH A SOMEWHAT HARD TO GRASP LAYOUT THE COLUMNS CORRE
SPOND TO THE SUPPORT VECTORS INVOLVED IN ANY OF THE NCLASS NCLASS 1 2 “ONEVSONE” CLASSIFIERS
EACH OF THE SUPPORT VECTORS IS USED IN NCLASS 1 CLASSIFIERS THE NCLASS 1 ENTRIES IN EACH ROW CORRESPOND
TO THE DUAL COEFFICIENTS FOR THESE CLASSIFIERS
THIS MIGHT BE MADE MORE CLEAR BY AN EXAMPLE
CONSIDER A THREE CLASS PROBLEM WITH CLASS 0 HAVING THREE SUPPORT VECTORS □0
0 □1
0 □2
0AND CLASS 1 AND 2 HAVING TWO
SUPPORT VECTORS □0
1 □1
1AND□0
2 □1
2RESPECTIVELY FOR EACH SUPPORT VECTOR □□
□ THERE ARE TWO DUAL COEFFICIENTS LET’S CALL
THE COEFFICIENT OF SUPPORT VECTOR □□
□IN THE CLASSIFIER BETWEEN CLASSES □AND□ □□
□□ THENDUALCOEF LOOKS LIKE THIS
□0
01□0
02COEFFICIENTS FOR SVS OF CLASS 0
□1
01□1
02
□2
01□2
02
□0
10□0
12COEFFICIENTS FOR SVS OF CLASS 1
□1
10□1
12
□0
20□0
21COEFFICIENTS FOR SVS OF CLASS 2
□1
20□1
21

SCORES AND PROBABILITIES
THEDECISIONFUNCTION METHOD OFSVC ANDNUSVC GIVES PERCLASS SCORES FOR EACH SAMPLE OR A SINGLE SCORE
PER SAMPLE IN THE BINARY CASE WHEN THE CONSTRUCTOR OPTION PROBABILITY IS SET TOTRUE CLASS MEMBERSHIP
PROBABILITY ESTIMATES FROM THE METHODS PREDICTPROBA ANDPREDICTLOGPROBA ARE ENABLED IN THE BINARY
CASE THE PROBABILITIES ARE CALIBRATED USING PLATT SCALING LOGISTIC REGRESSION ON THE SVM'S SCORES FIT BY AN ADDITIONAL
CROSSVALIDATION ON THE TRAINING DATA IN THE MULTICLASS CASE THIS IS EXTENDED AS PER WU ET AL 2004
NEEDLESS TO SAY THE CROSSVALIDATION INVOLVED IN PLATT SCALING IS AN EXPENSIVE OPERATION FOR LARGE DATASETS IN ADDITION
THE PROBABILITY ESTIMATES MAY BE INCONSISTENT WITH THE SCORES IN THE SENSE THAT THE "ARGMAX" OF THE SCORES MAY NOT BE
THE ARGMAX OF THE PROBABILITIES EG IN BINARY CLASSIFICATION A SAMPLE MAY BE LABELED BY PREDICT AS BELONGING
TO A CLASS THAT HAS PROBABILITY ½ ACCORDING TO PREDICTPROBA PLATT'S METHOD IS ALSO KNOWN TO HAVE THEORET
ICAL ISSUES IF CONFIDENCE SCORES ARE REQUIRED BUT THESE DO NOT HAVE TO BE PROBABILITIES THEN IT IS ADVISABLE TO SET
PROBABILITYFALSE AND USEDECISIONFUNCTION INSTEAD OFPREDICTPROBA
REFERENCES
• WU LIN AND WENG "PROBABILITY ESTIMATES FOR MULTICLASS CLASSIFICATION BY PAIRWISE COUPLING" JMLR 5975
1005 2004
• PLATT "PROBABILISTIC OUTPUTS FOR SVMS AND COMPARISONS TO REGULARIZED LIKELIHOOD METHODS"
UNBALANCED PROBLEMS
IN PROBLEMS WHERE IT IS DESIRED TO GIVE MORE IMPORTANCE TO CERTAIN CLASSES OR CERTAIN INDIVIDUAL SAMPLES KEYWORDS
CLASSWEIGHT ANDSAMPLEWEIGHT CAN BE USED
SVC BUT NOTNUSVC IMPLEMENT A KEYWORD CLASSWEIGHT IN THEFIT METHOD IT'S A DICTIONARY OF THE FORM
CLASSLABEL VALUE WHERE VALUE IS A FLOATING POINT NUMBER 0 THAT SETS THE PARAMETER COF CLASS
CLASSLABEL TOCVALUE

SVCNUSVC SVRNUSVR ANDONECLASSSVM IMPLEMENT ALSO WEIGHTS FOR INDIVIDUAL SAMPLES IN METHOD FIT THROUGH KEYWORD SAMPLEWEIGHT SIMILAR TO CLASSWEIGHT THESE SET THE PARAMETER CFOR THE ITH EXAMPLE TO CSAMPLEWEIGHTI

EXAMPLES

•PLOT DIFFERENT SVM CLASSIFIERS IN THE IRIS DATASET
•SVM MAXIMUM MARGIN SEPARATING HYPERPLANE
•SVM SEPARATING HYPERPLANE FOR UNBALANCED CLASSES
•SVMANOVA SVM WITH UNIVARIATE FEATURE SELECTION
•NONLINEAR SVM
•SVM WEIGHTED SAMPLES

REGRESSION

THE METHOD OF SUPPORT VECTOR CLASSIFICATION CAN BE EXTENDED TO SOLVE REGRESSION PROBLEMS THIS METHOD IS CALLED SUPPORT VECTOR REGRESSION

THE MODEL PRODUCED BY SUPPORT VECTOR CLASSIFICATION AS DESCRIBED ABOVE DEPENDS ONLY ON A SUBSET OF THE TRAINING DATA BECAUSE THE COST FUNCTION FOR BUILDING THE MODEL DOES NOT CARE ABOUT TRAINING POINTS THAT LIE BEYOND THE MARGIN ANALOGOUSLY THE MODEL PRODUCED BY SUPPORT VECTOR REGRESSION DEPENDS ONLY ON A SUBSET OF THE TRAINING DATA BECAUSE THE COST FUNCTION FOR BUILDING THE MODEL IGNORES ANY TRAINING DATA CLOSE TO THE MODEL PREDICTION

THERE ARE THREE DIFFERENT IMPLEMENTATIONS OF SUPPORT VECTOR REGRESSION SVRNUSVR ANDLINEARSVR LINEARSVR PROVIDES A FASTER IMPLEMENTATION THAN SVR BUT ONLY CONSIDERS LINEAR KERNELS WHILE NUSVR IMPLEMENTS A SLIGHTLY DIFFERENT FORMULATION THAN SVR ANDLINEARSVR SEE IMPLEMENTATION DETAILS FOR FURTHER DETAILS

AS WITH CLASSIFICATION CLASSES THE FIT METHOD WILL TAKE AS ARGUMENT VECTORS X Y ONLY THAT IN THIS CASE Y IS EXPECTED TO HAVE FLOATING POINT VALUES INSTEAD OF INTEGER VALUES

```
 FROM SKLEARN IMPORT SVM
X  0 0 2 2
```

Y 05 25
CLF SVMSVR
CLFFITX Y
SVRC10 CACHESIZE200 COEF000 DEGREE3 EPSILON01
GAMMAAUTODEPRECATED KERNELRBF MAXITER1 SHRINKINGTRUE
TOL0001 VERBOSEFALSE
CLFPREDICT1 1
ARRAY15
EXAMPLES
•SUPPORT VECTOR REGRESSION SVR USING LINEAR AND NONLINEAR KERNELS
DENSITY ESTIMATION NOVELTY DETECTION
THE CLASSONECLASSSVM IMPLEMENTS A ONECLASS SVM WHICH IS USED IN OUTLIER DETECTION
SEENOVELTY AND OUTLIER DETECTION FOR THE DESCRIPTION AND USAGE OF ONECLASSSVM
COMPLEXITY
SUPPORT VECTOR MACHINES ARE POWERFUL TOOLS BUT THEIR COMPUTE AND STORAGE REQUIREMENTS INCREASE RAPIDLY WITH THE NUMBER OF TRAINING VECTORS THE CORE OF AN SVM IS A QUADRATIC PROGRAMMING PROBLEM QP SEPARATING SUPPORT VECTORS FROM THE REST OF THE TRAINING DATA THE QP SOLVER USED BY THIS LIBSVMBASED IMPLEMENTATION SCALES BETWEEN □□□□□□□□□□×□2
□□□□□□□□ AND□□□□□□□□□□×□3
□□□□□□□□ DEPENDING ON HOW EFFICIENTLY THE LIBSVM CACHE IS USED IN
PRACTICE DATASET DEPENDENT IF THE DATA IS VERY SPARSE □□□□□□□□□□ SHOULD BE REPLACED BY THE AVERAGE NUMBER OF NON ZERO FEATURES IN A SAMPLE VECTOR
ALSO NOTE THAT FOR THE LINEAR CASE THE ALGORITHM USED IN LINEARSVC BY THE LIBLINEAR IMPLEMENTATION IS MUCH MORE EFFICIENT THAN ITS LIBSVMBASED SVC COUNTERPART AND CAN SCALE ALMOST LINEARLY TO MILLIONS OF SAMPLES ANDOR FEATURES
TIPS ON PRACTICAL USE
•AVOIDING DATA COPY FORSVCSVRNUSVC ANDNUSVR IF THE DATA PASSED TO CERTAIN METHODS IS NOT CORDERED CONTIGUOUS AND DOUBLE PRECISION IT WILL BE COPIED BEFORE CALLING THE UNDERLYING C IMPLEMENTATION YOU CAN CHECK WHETHER A GIVEN NUMPY ARRAY IS CCONTIGUOUS BY INSPECTING ITS FLAGS ATTRIBUTE
FORLINEARSVC ANDLOGISTICREGRESSION ANY INPUT PASSED AS A NUMPY ARRAY WILL BE COPIED AND CON
VERTED TO THE LIBLINEAR INTERNAL SPARSE DATA REPRESENTATION DOUBLE PRECISION FLOATS AND INT32 INDICES OF NONZERO COMPONENTS IF YOU WANT TO FIT A LARGESCALE LINEAR CLASSIFIER WITHOUT COPYING A DENSE NUMPY CCONTIGUOUS DOUBLE PRECISION ARRAY AS INPUT WE SUGGEST TO USE THE SGDCLASSIFIER CLASS INSTEAD THE OBJECTIVE FUNCTION CAN BE CONFIGURED TO BE ALMOST THE SAME AS THE LINEARSVC MODEL
•KERNEL CACHE SIZE FORSVCSVRNUSVC ANDNUSVR THE SIZE OF THE KERNEL CACHE HAS A STRONG IMPACT ON RUN TIMES FOR LARGER PROBLEMS IF YOU HAVE ENOUGH RAM AVAILABLE IT IS RECOMMENDED TO SET CACHESIZE TO A HIGHER VALUE THAN THE DEFAULT OF 200MB SUCH AS 500MB OR 1000MB
•SETTING C CIS1BY DEFAULT AND IT'S A REASONABLE DEFAULT CHOICE IF YOU HAVE A LOT OF NOISY OBSERVATIONS YOU SHOULD DECREASE IT IT CORRESPONDS TO REGULARIZE MORE THE ESTIMATION
LINEARSVC ANDLINEARSVR ARE LESS SENSITIVE TO CWHEN IT BECOMES LARGE AND PREDICTION RESULTS STOP IM PROVING AFTER A CERTAIN THRESHOLD MEANWHILE LARGER CVALUES WILL TAKE MORE TIME TO TRAIN SOMETIMES UP TO 10 TIMES LONGER AS SHOWN BY FAN ET AL 2008

• SUPPORT VECTOR MACHINE ALGORITHMS ARE NOT SCALE INVARIANT SO IT IS HIGHLY RECOMMENDED TO SCALE YOUR DATA FOR EXAMPLE SCALE EACH ATTRIBUTE ON THE INPUT VECTOR X TO 01 OR 11 OR STANDARDIZE IT TO HAVE MEAN 0 AND VARIANCE 1 NOTE THAT THE SAME SCALING MUST BE APPLIED TO THE TEST VECTOR TO OBTAIN MEANINGFUL RESULTS SEE SECTION PREPROCESSING DATA FOR MORE DETAILS ON SCALING AND NORMALIZATION
• PARAMETER NUINNUSVC ONECLASSSVM NUSVR APPROXIMATES THE FRACTION OF TRAINING ERRORS AND SUPPORT VEC TORS
• INSVC IF DATA FOR CLASSIFICATION ARE UNBALANCED EG MANY POSITIVE AND FEW NEGATIVE SET CLASSWEIGHTBALANCED ANDOR TRY DIFFERENT PENALTY PARAMETERS C
•RANDOMNESS OF THE UNDERLYING IMPLEMENTATIONS THE UNDERLYING IMPLEMENTATIONS OF SVC ANDNUSVC USE A RANDOM NUMBER GENERATOR ONLY TO SHUFFLE THE DATA FOR PROBABILITY ESTIMATION WHEN PROBABILITY IS SET TO TRUE THIS RANDOMNESS CAN BE CONTROLLED WITH THE RANDOMSTATE PARAMETER IF PROBABILITY IS SET TOFALSE THESE ESTIMATORS ARE NOT RANDOM AND RANDOMSTATE HAS NO EFFECT ON THE RESULTS THE UNDERLYING ONECLASSSVM IMPLEMENTATION IS SIMILAR TO THE ONES OF SVC ANDNUSVC AS NO PROBABILITY ESTIMATION IS PROVIDED FOR ONECLASSSVM IT IS NOT RANDOM
THE UNDERLYING LINEARSVC IMPLEMENTATION USES A RANDOM NUMBER GENERATOR TO SELECT FEATURES WHEN FITTING THE MODEL WITH A DUAL COORDINATE DESCENT IE WHEN DUAL IS SET TOTRUE IT IS THUS NOT UNCOMMON TO HAVE SLIGHTLY DIFFERENT RESULTS FOR THE SAME INPUT DATA IF THAT HAPPENS TRY WITH A SMALLER TOL PARAMETER THIS RANDOMNESS CAN ALSO BE CONTROLLED WITH THE RANDOMSTATE PARAMETER WHEN DUAL IS SET TOFALSE THE UNDERLYING IMPLEMENTATION OF LINEARSVC IS NOT RANDOM AND RANDOMSTATE HAS NO EFFECT ON THE RESULTS
• USING L1 PENALIZATION AS PROVIDED BY LINEARSVCLOSSL2 PENALTYL1 DUALFALSE YIELDS A SPARSE SOLUTION IE ONLY A SUBSET OF FEATURE WEIGHTS IS DIFFERENT FROM ZERO AND CONTRIBUTE TO THE DE CISION FUNCTION INCREASING CYIELDS A MORE COMPLEX MODEL MORE FEATURE ARE SELECTED THE CVALUE THAT YIELDS A “NULL” MODEL ALL WEIGHTS EQUAL TO ZERO CAN BE CALCULATED USING L1MINC
REFERENCES
• FAN RONGEN ET AL “LIBLINEAR A LIBRARY FOR LARGE LINEAR CLASSIFICATION” JOURNAL OF MACHINE LEARNING RESEARCH 9AUG 2008 18711874
KERNEL FUNCTIONS
THEKERNEL FUNCTION CAN BE ANY OF THE FOLLOWING
• LINEAR⟨□ □′⟩
• POLYNOMIAL □⟨□ □′⟩□□□IS SPECIFIED BY KEYWORD DEGREE □BYCOEF0
• RBF EXP−□‖□−□′‖2□IS SPECIFIED BY KEYWORD GAMMA MUST BE GREATER THAN 0
• SIGMOID TANH □⟨□ □′⟩□ WHERE □IS SPECIFIED BY COEF0
DIFFERENT KERNELS ARE SPECIFIED BY KEYWORD KERNEL AT INITIALIZATION
LINEARSVC SVMSVCKERNELLINEAR
LINEARSVCKERNEL
LINEAR
RBFSVC SVMSVCKERNELRBF
RBFSVCKERNEL
RBF

CUSTOM KERNELS

YOU CAN DEFINE YOUR OWN KERNELS BY EITHER GIVING THE KERNEL AS A PYTHON FUNCTION OR BY PRECOMPUTING THE GRAM MATRIX

CLASSIFIERS WITH CUSTOM KERNELS BEHAVE THE SAME WAY AS ANY OTHER CLASSIFIERS EXCEPT THAT

• FIELDSUPPORTVECTORS IS NOW EMPTY ONLY INDICES OF SUPPORT VECTORS ARE STORED IN SUPPORT

• A REFERENCE AND NOT A COPY OF THE FIRST ARGUMENT IN THE FIT METHOD IS STORED FOR FUTURE REFERENCE IF THAT ARRAY CHANGES BETWEEN THE USE OF FIT ANDPREDICT YOU WILL HAVE UNEXPECTED RESULTS

USING PYTHON FUNCTIONS AS KERNELS

YOU CAN ALSO USE YOUR OWN DEFINED KERNELS BY PASSING A FUNCTION TO THE KEYWORD KERNEL IN THE CONSTRUCTOR

YOUR KERNEL MUST TAKE AS ARGUMENTS TWO MATRICES OF SHAPE NSAMPLES1 NFEATURES NSAMPLES2 NFEATURES AND RETURN A KERNEL MATRIX OF SHAPE NSAMPLES1 NSAMPLES2

THE FOLLOWING CODE DEFINES A LINEAR KERNEL AND CREATES A CLASSIFIER INSTANCE THAT WILL USE THAT KERNEL

```
 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT SVM
 DEF MYKERNELX Y
 RETURN NPDOTX YT

CLF  SVMSVCKERNELMYKERNEL
```

EXAMPLES

•SVM WITH CUSTOM KERNEL

USING THE GRAM MATRIX

SETKERNELPRECOMPUTED AND PASS THE GRAM MATRIX INSTEAD OF X IN THE FIT METHOD AT THE MOMENT THE KERNEL VALUES BETWEEN ALLTRAINING VECTORS AND THE TEST VECTORS MUST BE PROVIDED

```
 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT SVM
X  NPARRAY0 0 1 1
Y  0 1
CLF  SVMSVCKERNELPRECOMPUTED
 LINEAR KERNEL COMPUTATION
GRAM  NPDOTX XT
CLFFITGRAM Y
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMAAUTODEPRECATED
KERNELPRECOMPUTED MAXITER1 PROBABILITYFALSE
RANDOMSTATENONE SHRINKINGTRUE TOL0001 VERBOSEFALSE
 PREDICT ON TRAINING EXAMPLES
CLFPREDICTGRAM
ARRAY0 1
```

PARAMETERS OF THE RBF KERNEL
WHEN TRAINING AN SVM WITH THE RADIAL BASIS FUNCTION RBF KERNEL TWO PARAMETERS MUST BE CONSIDERED CAND GAMMA THE PARAMETER C COMMON TO ALL SVM KERNELS TRADES OFF MISCLASSIFICATION OF TRAINING EXAMPLES AGAINST SIMPLICITY OF THE DECISION SURFACE A LOW CMAKES THE DECISION SURFACE SMOOTH WHILE A HIGH CAIMS AT CLASSIFYING ALL TRAINING EXAMPLES CORRECTLY GAMMA DEFINES HOW MUCH INFLUENCE A SINGLE TRAINING EXAMPLE HAS THE LARGER GAMMA IS THE CLOSER OTHER EXAMPLES MUST BE TO BE AFFECTED
PROPER CHOICE OF CANDGAMMA IS CRITICAL TO THE SVM'S PERFORMANCE ONE IS ADVISED TO USE SKLEARN MODELSELECTIONGRIDSEARCHCV WITHCANDGAMMA SPACED EXPONENTIALLY FAR APART TO CHOOSE GOOD VALUES
EXAMPLES
•RBF SVM PARAMETERS
MATHEMATICAL FORMULATION
A SUPPORT VECTOR MACHINE CONSTRUCTS A HYPERPLANE OR SET OF HYPERPLANES IN A HIGH OR INFINITE DIMENSIONAL SPACE WHICH CAN BE USED FOR CLASSIFICATION REGRESSION OR OTHER TASKS INTUITIVELY A GOOD SEPARATION IS ACHIEVED BY THE HYPERPLANE THAT HAS THE LARGEST DISTANCE TO THE NEAREST TRAINING DATA POINTS OF ANY CLASS SOCALLED FUNCTIONAL MARGIN SINCE IN GENERAL THE LARGER THE MARGIN THE LOWER THE GENERALIZATION ERROR OF THE CLASSIFIER

SVC
GIVEN TRAINING VECTORS □□∈R□ I1 N IN TWO CLASSES AND A VECTOR □∈1−1□ SVC SOLVES THE FOLLOWING PRIMAL PROBLEM
MIN
□□□1
2□□□□□∑
□1□□
SUBJECT TO □□□□□□□□ □≥1−□□
□□≥0 □ 1 □
ITS DUAL IS
MIN
□1
2□□□□−□□□
SUBJECT TO □□□ 0
0≤□□≤□ □ 1 □
WHERE □IS THE VECTOR OF ALL ONES □ 0IS THE UPPER BOUND □IS AN □BY□POSITIVE SEMIDEFINITE MATRIX □□□≡ □□□□□□□ □□ WHERE □□□ □□ □□□□□□□IS THE KERNEL HERE TRAINING VECTORS ARE IMPLICITLY MAPPED INTO A HIGHER MAYBE INFINITE DIMENSIONAL SPACE BY THE FUNCTION □
THE DECISION FUNCTION IS
SGN□∑
□1□□□□□□□ □ □
NOTE WHILE SVM MODELS DERIVED FROM LIBSVM AND LIBLINEAR USE CAS REGULARIZATION PARAMETER MOST OTHER ESTIMATORS USEALPHA THE EXACT EQUIVALENCE BETWEEN THE AMOUNT OF REGULARIZATION OF TWO MODELS DEPENDS ON THE EXACT OBJECTIVE FUNCTION OPTIMIZED BY THE MODEL FOR EXAMPLE WHEN THE ESTIMATOR USED IS SKLEARNLINEARMODELRIDGE REGRESSION THE RELATION BETWEEN THEM IS GIVEN AS □1
□□□*h*□
THIS PARAMETERS CAN BE ACCESSED THROUGH THE MEMBERS DUALCOEF WHICH HOLDS THE PRODUCT □□□□
SUPPORTVECTORS WHICH HOLDS THE SUPPORT VECTORS AND INTERCEPT WHICH HOLDS THE INDEPENDENT TERM □

REFERENCES
• “AUTOMATIC CAPACITY TUNING OF VERY LARGE VCDIMENSION CLASSIFIERS” I GUYON B BOSER V VAPNIK ADVANCES IN NEURAL INFORMATION PROCESSING 1993
• “SUPPORTVECTOR NETWORKS” C CORTES V VAPNIK MACHINE LEARNING 20 273297 1995
NUSVC
WE INTRODUCE A NEW PARAMETER □WHICH CONTROLS THE NUMBER OF SUPPORT VECTORS AND TRAINING ERRORS THE PARAMETER □∈01IS AN UPPER BOUND ON THE FRACTION OF TRAINING ERRORS AND A LOWER BOUND OF THE FRACTION OF SUPPORT VECTORS IT CAN BE SHOWN THAT THE □SVC FORMULATION IS A REPARAMETERIZATION OF THE □SVC AND THEREFORE MATHEMATICALLY EQUIVALENT

SVR
GIVEN TRAINING VECTORS □□∈R□ I1 N AND A VECTOR □∈R□□SVR SOLVES THE FOLLOWING PRIMAL PROBLEM
MIN
□□□□1
2□□□□□∑
□1□□□
□
SUBJECT TO □□−□□□□□−□≤□□□
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□
□□ □
□≥0 □ 1 □
ITS DUAL IS
MIN
□□1
2□−□□□□−□ □□□□□−□□□−□
SUBJECT TO □□□−□ 0
0≤□□ □
□≤□ □ 1 □
WHERE □IS THE VECTOR OF ALL ONES □ 0IS THE UPPER BOUND □IS AN □BY□POSITIVE SEMIDEFINITE MATRIX □□□≡
□□□ □□ □□□□□□□□IS THE KERNEL HERE TRAINING VECTORS ARE IMPLICITLY MAPPED INTO A HIGHER MAYBE INFINITE
DIMENSIONAL SPACE BY THE FUNCTION □
THE DECISION FUNCTION IS
□∑
□1□□−□
□□□□ □ □
THESE PARAMETERS CAN BE ACCESSED THROUGH THE MEMBERS DUALCOEF WHICH HOLDS THE DIFFERENCE □□−□
□
SUPPORTVECTORS WHICH HOLDS THE SUPPORT VECTORS AND INTERCEPT WHICH HOLDS THE INDEPENDENT TERM □
REFERENCES
• “A TUTORIAL ON SUPPORT VECTOR REGRESSION” ALEX J SMOLA BERNHARD SCHÖLKOPF STATISTICS AND COMPUTING
ARCHIVE V OLUME 14 ISSUE 3 AUGUST 2004 P 199222
IMPLEMENTATION DETAILS
INTERNALLY WE USE LIBSVM AND LIBLINEAR TO HANDLE ALL COMPUTATIONS THESE LIBRARIES ARE WRAPPED USING C AND CYTHON
REFERENCES
FOR A DESCRIPTION OF THE IMPLEMENTATION AND DETAILS OF THE ALGORITHMS USED PLEASE REFER TO
• LIBSVM A LIBRARY FOR SUPPORT VECTOR MACHINES
• LIBLINEAR – A LIBRARY FOR LARGE LINEAR CLASSIFICATION
315 STOCHASTIC GRADIENT DESCENT
STOCHASTIC GRADIENT DESCENT SGD IS A SIMPLE YET VERY EFFICIENT APPROACH TO DISCRIMINATIVE LEARNING OF LINEAR CLAS
SIFIERS UNDER CONVEX LOSS FUNCTIONS SUCH AS LINEAR SUPPORT VECTOR MACHINES AND LOGISTIC REGRESSION EVEN THOUGH

SGD HAS BEEN AROUND IN THE MACHINE LEARNING COMMUNITY FOR A LONG TIME IT HAS RECEIVED A CONSIDERABLE AMOUNT OF ATTENTION JUST RECENTLY IN THE CONTEXT OF LARGESCALE LEARNING
SGD HAS BEEN SUCCESSFULLY APPLIED TO LARGESCALE AND SPARSE MACHINE LEARNING PROBLEMS OFTEN ENCOUNTERED IN TEXT CLASSIFICATION AND NATURAL LANGUAGE PROCESSING GIVEN THAT THE DATA IS SPARSE THE CLASSIFIERS IN THIS MODULE EASILY SCALE TO PROBLEMS WITH MORE THAN 105 TRAINING EXAMPLES AND MORE THAN 105 FEATURES
THE ADVANTAGES OF STOCHASTIC GRADIENT DESCENT ARE
• EFFICIENCY
• EASE OF IMPLEMENTATION LOTS OF OPPORTUNITIES FOR CODE TUNING
THE DISADVANTAGES OF STOCHASTIC GRADIENT DESCENT INCLUDE
• SGD REQUIRES A NUMBER OF HYPERPARAMETERS SUCH AS THE REGULARIZATION PARAMETER AND THE NUMBER OF ITERATIONS
• SGD IS SENSITIVE TO FEATURE SCALING
CLASSIFICATION
WARNING MAKE SURE YOU PERMUTE SHUFFLE YOUR TRAINING DATA BEFORE FITTING THE MODEL OR USE SHUFFLETRUE TO SHUFFLE AFTER EACH ITERATION
THE CLASSSGDCLASSIFIER IMPLEMENTS A PLAIN STOCHASTIC GRADIENT DESCENT LEARNING ROUTINE WHICH SUPPORTS DIFFERENT LOSS FUNCTIONS AND PENALTIES FOR CLASSIFICATION
AS OTHER CLASSIFIERS SGD HAS TO BE FITTED WITH TWO ARRAYS AN ARRAY X OF SIZE NSAMPLES NFEATURES HOLDING THE TRAINING SAMPLES AND AN ARRAY Y OF SIZE NSAMPLES HOLDING THE TARGET VALUES CLASS LABELS FOR THE TRAINING SAMPLES
```
 FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
X  0 0 1 1
```

Y 0 1
CLF SGDCLASSIFIERLOSSHINGE PENALTYL2 MAXITER5
CLFFITX Y
SGDCLASSIFIERALPHA00001 AVERAGEFALSE CLASSWEIGHTNONE
EARLYSTOPPINGFALSE EPSILON01 ETA000 FITINTERCEPTTRUE
L1RATIO015 LEARNINGRATEOPTIMAL LOSSHINGE MAXITER5
NITERNOCHANGE5 NJOBSNONE PENALTYL2 POWERT05
RANDOMSTATENONE SHUFFLETRUE TOL0001
VALIDATIONFRACTION01 VERBOSE0 WARMSTARTFALSE
AFTER BEING FITTED THE MODEL CAN THEN BE USED TO PREDICT NEW VALUES
CLFPREDICT2 2
ARRAY1
SGD FITS A LINEAR MODEL TO THE TRAINING DATA THE MEMBER COEF HOLDS THE MODEL PARAMETERS
CLFCOEF
ARRAY99 99
MEMBERINTERCEPT HOLDS THE INTERCEPT AKA OFFSET OR BIAS
CLFINTERCEPT
ARRAY99
WHETHER OR NOT THE MODEL SHOULD USE AN INTERCEPT IE A BIASED HYPERPLANE IS CONTROLLED BY THE PARAMETER
FITINTERCEPT
TO GET THE SIGNED DISTANCE TO THE HYPERPLANE USE SGDCLASSIFIERDECISIONFUNCTION
CLFDECISIONFUNCTION2 2
ARRAY296
THE CONCRETE LOSS FUNCTION CAN BE SET VIA THE LOSS PARAMETER SGDCLASSIFIER SUPPORTS THE FOLLOWING LOSS FUNC
TIONS
•LOSSHINGE SOFTMARGIN LINEAR SUPPORT VECTOR MACHINE
•LOSSMODIFIEDHUBER SMOOTHED HINGE LOSS
•LOSSLOG LOGISTIC REGRESSION
• AND ALL REGRESSION LOSSES BELOW
THE FIRST TWO LOSS FUNCTIONS ARE LAZY THEY ONLY UPDATE THE MODEL PARAMETERS IF AN EXAMPLE VIOLATES THE MARGIN CON
STRAINT WHICH MAKES TRAINING VERY EFFICIENT AND MAY RESULT IN SPARSER MODELS EVEN WHEN L2 PENALTY IS USED
USINGLOSSLOG ORLOSSMODIFIEDHUBER ENABLES THE PREDICTPROBA METHOD WHICH GIVES A VECTOR
OF PROBABILITY ESTIMATES □□□PER SAMPLE □
CLF SGDCLASSIFIERLOSSLOG MAXITER5FITX Y
CLFPREDICTPROBA1 1
ARRAY000 099
THE CONCRETE PENALTY CAN BE SET VIA THE PENALTY PARAMETER SGD SUPPORTS THE FOLLOWING PENALTIES
•PENALTYL2 L2 NORM PENALTY ON COEF
•PENALTYL1 L1 NORM PENALTY ON COEF

•PENALTYELASTICNET CONVEX COMBINATION OF L2 AND L1 1 L1RATIO L2
L1RATIO L1
THE DEFAULT SETTING IS PENALTYL2 THE L1 PENALTY LEADS TO SPARSE SOLUTIONS DRIVING MOST COEFFICIENTS TO ZERO
THE ELASTIC NET SOLVES SOME DEFICIENCIES OF THE L1 PENALTY IN THE PRESENCE OF HIGHLY CORRELATED ATTRIBUTES THE PARAM
ETERL1RATIO CONTROLS THE CONVEX COMBINATION OF L1 AND L2 PENALTY
SGDCLASSIFIER SUPPORTS MULTICLASS CLASSIFICATION BY COMBINING MULTIPLE BINARY CLASSIFIERS IN A “ONE VERSUS ALL”
OV A SCHEME FOR EACH OF THE CLASSES A BINARY CLASSIFIER IS LEARNED THAT DISCRIMINATES BETWEEN THAT AND ALL OTHER
−1CLASSES AT TESTING TIME WE COMPUTE THE CONFIDENCE SCORE IE THE SIGNED DISTANCES TO THE HYPERPLANE FOR EACH
CLASSIFIER AND CHOOSE THE CLASS WITH THE HIGHEST CONFIDENCE THE FIGURE BELOW ILLUSTRATES THE OV A APPROACH ON THE IRIS
DATASET THE DASHED LINES REPRESENT THE THREE OV A CLASSIFIERS THE BACKGROUND COLORS SHOW THE DECISION SURFACE INDUCED
BY THE THREE CLASSIFIERS
IN THE CASE OF MULTICLASS CLASSIFICATION COEF IS A TWODIMENSIONAL ARRAY OF SHAPENCLASSES
NFEATURES ANDINTERCEPT IS A ONEDIMENSIONAL ARRAY OF SHAPENCLASSES THE ITH ROW OF COEF
HOLDS THE WEIGHT VECTOR OF THE OV A CLASSIFIER FOR THE ITH CLASS CLASSES ARE INDEXED IN ASCENDING ORDER SEE AT
TRIBUTECLASSES NOTE THAT IN PRINCIPLE SINCE THEY ALLOW TO CREATE A PROBABILITY MODEL LOSSLOG AND
LOSSMODIFIEDHUBER ARE MORE SUITABLE FOR ONEVSALL CLASSIFICATION
SGDCLASSIFIER SUPPORTS BOTH WEIGHTED CLASSES AND WEIGHTED INSTANCES VIA THE FIT PARAMETERS CLASSWEIGHT
ANDSAMPLEWEIGHT SEE THE EXAMPLES BELOW AND THE DOCSTRING OF SGDCLASSIFIERFIT FOR FURTHER INFORMA
TION
EXAMPLES
•SGD MAXIMUM MARGIN SEPARATING HYPERPLANE
•PLOT MULTICLASS SGD ON THE IRIS DATASET
•SGD WEIGHTED SAMPLES
•COMPARING VARIOUS ONLINE SOLVERS

•SVM SEPARATING HYPERPLANE FOR UNBALANCED CLASSES SEE THENOTE
SGDCLASSIFIER SUPPORTS AVERAGED SGD ASGD AVERAGING CAN BE ENABLED BY SETTING AVERAGETRUE
ASGD WORKS BY AVERAGING THE COEFFICIENTS OF THE PLAIN SGD OVER EACH ITERATION OVER A SAMPLE WHEN USING ASGD
THE LEARNING RATE CAN BE LARGER AND EVEN CONSTANT LEADING ON SOME DATASETS TO A SPEED UP IN TRAINING TIME
FOR CLASSIFICATION WITH A LOGISTIC LOSS ANOTHER VARIANT OF SGD WITH AN AVERAGING STRATEGY IS AVAILABLE WITH STOCHASTIC AVERAGE GRADIENT SAG ALGORITHM AVAILABLE AS A SOLVER IN LOGISTICREGRESSION
REGRESSION
THE CLASSSGDREGRESSOR IMPLEMENTS A PLAIN STOCHASTIC GRADIENT DESCENT LEARNING ROUTINE WHICH SUPPORTS DIFFERENT LOSS FUNCTIONS AND PENALTIES TO FIT LINEAR REGRESSION MODELS SGDREGRESSOR IS WELL SUITED FOR REGRESSION PROB LEMS WITH A LARGE NUMBER OF TRAINING SAMPLES 10000 FOR OTHER PROBLEMS WE RECOMMEND RIDGE LASSO OR ELASTICNET
THE CONCRETE LOSS FUNCTION CAN BE SET VIA THE LOSS PARAMETERSGDREGRESSOR SUPPORTS THE FOLLOWING LOSS FUNCTIONS
•LOSSSQUAREDLOSS ORDINARY LEAST SQUARES
•LOSSHUBER HUBER LOSS FOR ROBUST REGRESSION
•LOSSEPSILONINSENSITIVE LINEAR SUPPORT VECTOR REGRESSION
THE HUBER AND EPSILONINSENSITIVE LOSS FUNCTIONS CAN BE USED FOR ROBUST REGRESSION THE WIDTH OF THE INSENSITIVE REGION HAS TO BE SPECIFIED VIA THE PARAMETER EPSILON THIS PARAMETER DEPENDS ON THE SCALE OF THE TARGET VARIABLES
SGDREGRESSOR SUPPORTS AVERAGED SGD AS SGDCLASSIFIER AVERAGING CAN BE ENABLED BY SETTING AVERAGETRUE
FOR REGRESSION WITH A SQUARED LOSS AND A L2 PENALTY ANOTHER VARIANT OF SGD WITH AN AVERAGING STRATEGY IS AVAILABLE WITH STOCHASTIC AVERAGE GRADIENT SAG ALGORITHM AVAILABLE AS A SOLVER IN RIDGE
STOCHASTIC GRADIENT DESCENT FOR SPARSE DATA
NOTE THE SPARSE IMPLEMENTATION PRODUCES SLIGHTLY DIFFERENT RESULTS THAN THE DENSE IMPLEMENTATION DUE TO A SHRUNK LEARNING RATE FOR THE INTERCEPT
THERE IS BUILTIN SUPPORT FOR SPARSE DATA GIVEN IN ANY MATRIX IN A FORMAT SUPPORTED BY SCIPYSPARSE FOR MAXIMUM EFFICIENCY HOWEVER USE THE CSR MATRIX FORMAT AS DEFINED IN SCIPYSPARSECSRMATRIX
EXAMPLES
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
COMPLEXITY
THE MAJOR ADVANTAGE OF SGD IS ITS EFFICIENCY WHICH IS BASICALLY LINEAR IN THE NUMBER OF TRAINING EXAMPLES IF X IS A MATRIX OF SIZE N P TRAINING HAS A COST OF □□□□□ WHERE K IS THE NUMBER OF ITERATIONS EPOCHS AND □□IS THE AVERAGE NUMBER OF NONZERO ATTRIBUTES PER SAMPLE
RECENT THEORETICAL RESULTS HOWEVER SHOW THAT THE RUNTIME TO GET SOME DESIRED OPTIMIZATION ACCURACY DOES NOT INCREASE AS THE TRAINING SET SIZE INCREASES

STOPPING CRITERION

THE CLASSES SGDCLASSIFIER ANDSGDREGRESSOR PROVIDE TWO CRITERIA TO STOP THE ALGORITHM WHEN A GIVEN LEVEL OF CONVERGENCE IS REACHED

• WITHEARLYSTOPPINGTRUE THE INPUT DATA IS SPLIT INTO A TRAINING SET AND A VALIDATION SET THE MODEL IS THEN FITTED ON THE TRAINING SET AND THE STOPPING CRITERION IS BASED ON THE PREDICTION SCORE COMPUTED ON THE VALIDATION SET THE SIZE OF THE VALIDATION SET CAN BE CHANGED WITH THE PARAMETER VALIDATIONFRACTION

• WITHEARLYSTOPPINGFALSE THE MODEL IS FITTED ON THE ENTIRE INPUT DATA AND THE STOPPING CRITERION IS BASED ON THE OBJECTIVE FUNCTION COMPUTED ON THE INPUT DATA

IN BOTH CASES THE CRITERION IS EVALUATED ONCE BY EPOCH AND THE ALGORITHM STOPS WHEN THE CRITERION DOES NOT IMPROVE NITERNOCHANGE TIMES IN A ROW THE IMPROVEMENT IS EVALUATED WITH A TOLERANCE TOL AND THE ALGORITHM STOPS IN ANY CASE AFTER A MAXIMUM NUMBER OF ITERATION MAXITER

TIPS ON PRACTICAL USE

• STOCHASTIC GRADIENT DESCENT IS SENSITIVE TO FEATURE SCALING SO IT IS HIGHLY RECOMMENDED TO SCALE YOUR DATA FOR EXAMPLE SCALE EACH ATTRIBUTE ON THE INPUT VECTOR X TO 01 OR 11 OR STANDARDIZE IT TO HAVE MEAN 0 AND VARIANCE 1 NOTE THAT THE SAME SCALING MUST BE APPLIED TO THE TEST VECTOR TO OBTAIN MEANINGFUL RESULTS THIS CAN BE EASILY DONE USING STANDARDSCALER

```
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
SCALER  STANDARDSCALER
SCALERFITXTRAIN  DONT CHEAT  FIT ONLY ON TRAINING DATA
XTRAIN  SCALERTRANSFORMXTRAIN
XTEST  SCALERTRANSFORMXTEST  APPLY SAME TRANSFORMATION TO TEST DATA
```

IF YOUR ATTRIBUTES HAVE AN INTRINSIC SCALE EG WORD FREQUENCIES OR INDICATOR FEATURES SCALING IS NOT NEEDED

• FINDING A REASONABLE REGULARIZATION TERM □IS BEST DONE USING GRIDSEARCHCV USUALLY IN THE RANGE 10 0NPARANGE17

• EMPIRICALLY WE FOUND THAT SGD CONVERGES AFTER OBSERVING APPROX 106 TRAINING SAMPLES THUS A REASONABLE FIRST GUESS FOR THE NUMBER OF ITERATIONS IS MAXITER NPCEIL10 6 N WHERENIS THE SIZE OF THE TRAINING SET

• IF YOU APPLY SGD TO FEATURES EXTRACTED USING PCA WE FOUND THAT IT IS OFTEN WISE TO SCALE THE FEATURE VALUES BY SOME CONSTANT CSUCH THAT THE AVERAGE L2 NORM OF THE TRAINING DATA EQUALS ONE

• WE FOUND THAT AVERAGED SGD WORKS BEST WITH A LARGER NUMBER OF FEATURES AND A HIGHER ETA0

REFERENCES

• “EFFICIENT BACKPROP” Y LECUN L BOTTOU G ORR K MÜLLER IN NEURAL NETWORKS TRICKS OF THE TRADE 1998

MATHEMATICAL FORMULATION

GIVEN A SET OF TRAINING EXAMPLES □1 □1 □□ □□WHERE □□∈R□AND□□∈− 11 OUR GOAL IS TO LEARN A LINEAR SCORING FUNCTION □□ □□□□WITH MODEL PARAMETERS □∈R□AND INTERCEPT □∈R IN ORDER TO MAKE PREDICTIONS WE SIMPLY LOOK AT THE SIGN OF □□ A COMMON CHOICE TO FIND THE MODEL PARAMETERS IS BY MINIMIZING THE REGULARIZED TRAINING ERROR GIVEN BY

□□ □ 1
□□Σ
□1□□□ □□□ □□□

WHERE □IS A LOSS FUNCTION THAT MEASURES MODEL MISFIT AND □IS A REGULARIZATION TERM AKA PENALTY THAT PENALIZES MODEL COMPLEXITY □ 0IS A NONNEGATIVE HYPERPARAMETER
DIFFERENT CHOICES FOR □ENTAIL DIFFERENT CLASSIFIERS SUCH AS
• HINGE SOFTMARGIN SUPPORT VECTOR MACHINES
• LOG LOGISTIC REGRESSION
• LEASTSQUARES RIDGE REGRESSION
• EPSILONINSENSITIVE SOFTMARGIN SUPPORT VECTOR REGRESSION
ALL OF THE ABOVE LOSS FUNCTIONS CAN BE REGARDED AS AN UPPER BOUND ON THE MISCLASSIFICATION ERROR ZEROONE LOSS AS SHOWN IN THE FIGURE BELOW
POPULAR CHOICES FOR THE REGULARIZATION TERM □INCLUDE
• L2 NORM □□ 1
2∑□
□1□2
□
• L1 NORM □□ ∑□
□1□□ WHICH LEADS TO SPARSE SOLUTIONS
• ELASTIC NET □□ □
2∑□
□1□2
□ 1−□∑□
□1□□ A CONVEX COMBINATION OF L2 AND L1 WHERE □IS GIVEN
BY1 L1RATIO
THE FIGURE BELOW SHOWS THE CONTOURS OF THE DIFFERENT REGULARIZATION TERMS IN THE PARAMETER SPACE WHEN □□ 1
SGD
STOCHASTIC GRADIENT DESCENT IS AN OPTIMIZATION METHOD FOR UNCONSTRAINED OPTIMIZATION PROBLEMS IN CONTRAST TO BATCH GRADIENT DESCENT SGD APPROXIMATES THE TRUE GRADIENT OF □□ □BY CONSIDERING A SINGLE TRAINING EXAMPLE AT A TIME
THE CLASSSGDCLASSIFIER IMPLEMENTS A FIRSTORDER SGD LEARNING ROUTINE THE ALGORITHM ITERATES OVER THE TRAINING

EXAMPLES AND FOR EACH EXAMPLE UPDATES THE MODEL PARAMETERS ACCORDING TO THE UPDATE RULE GIVEN BY
□←□−□□□□□
□□□□□□□□□□ □□
□□
WHERE □IS THE LEARNING RATE WHICH CONTROLS THE STEPSIZE IN THE PARAMETER SPACE THE INTERCEPT □IS UPDATED SIMILARLY BUT WITHOUT REGULARIZATION
THE LEARNING RATE □CAN BE EITHER CONSTANT OR GRADUALLY DECAYING FOR CLASSIFICATION THE DEFAULT LEARNING RATE SCHEDULE LEARNINGRATEOPTIMAL IS GIVEN BY
□□1
□□0□
WHERE □IS THE TIME STEP THERE ARE A TOTAL OF NSAMPLES NITER TIME STEPS □0IS DETERMINED BASED ON A HEURISTIC PROPOSED BY LÉON BOTTOU SUCH THAT THE EXPECTED INITIAL UPDATES ARE COMPARABLE WITH THE EXPECTED SIZE OF THE WEIGHTS THIS ASSUMING THAT THE NORM OF THE TRAINING SAMPLES IS APPROX 1 THE EXACT DEFINITION CAN BE FOUND IN INITT IN BASESGD
FOR REGRESSION THE DEFAULT LEARNING RATE SCHEDULE IS INVERSE SCALING LEARNINGRATEINVSCALING GIVEN BY
□□□□□0
□□□□□□ □
WHERE □□□0AND□□□□□ □ARE HYPERPARAMETERS CHOSEN BY THE USER VIA ETA0 ANDPOWERT RESP
FOR A CONSTANT LEARNING RATE USE LEARNINGRATECONSTANT AND USEETA0 TO SPECIFY THE LEARNING RATE
FOR AN ADAPTIVELY DECREASING LEARNING RATE USE LEARNINGRATEADAPTIVE AND USEETA0 TO SPECIFY THE START
ING LEARNING RATE WHEN THE STOPPING CRITERION IS REACHED THE LEARNING RATE IS DIVIDED BY 5 AND THE ALGORITHM DOES NOT STOP THE ALGORITHM STOPS WHEN THE LEARNING RATE GOES BELOW 1E6
THE MODEL PARAMETERS CAN BE ACCESSED THROUGH THE MEMBERS COEF ANDINTERCEPT
• MEMBERCOEF HOLDS THE WEIGHTS □
• MEMBERINTERCEPT HOLDS □
REFERENCES
• “SOLVING LARGE SCALE LINEAR PREDICTION PROBLEMS USING STOCHASTIC GRADIENT DESCENT ALGORITHMS” T ZHANG IN PROCEEDINGS OF ICML ‘04
• “REGULARIZATION AND VARIABLE SELECTION VIA THE ELASTIC NET” H ZOU T HASTIE JOURNAL OF THE ROYAL STATISTICAL SOCIETY SERIES B 67 2 301320
• “TOWARDS OPTIMAL ONE PASS LARGE SCALE LEARNING WITH AVERAGED STOCHASTIC GRADIENT DESCENT” XU WEI
IMPLEMENTATION DETAILS
THE IMPLEMENTATION OF SGD IS INFLUENCED BY THE STOCHASTIC GRADIENT SVM OF LÉON BOTTOU SIMILAR TO SVMSGD
THE WEIGHT VECTOR IS REPRESENTED AS THE PRODUCT OF A SCALAR AND A VECTOR WHICH ALLOWS AN EFFICIENT WEIGHT UPDATE IN THE CASE OF L2 REGULARIZATION IN THE CASE OF SPARSE FEATURE VECTORS THE INTERCEPT IS UPDATED WITH A SMALLER LEARNING RATE MULTIPLIED BY 001 TO ACCOUNT FOR THE FACT THAT IT IS UPDATED MORE FREQUENTLY TRAINING EXAMPLES ARE PICKED UP SEQUENTIALLY AND THE LEARNING RATE IS LOWERED AFTER EACH OBSERVED EXAMPLE WE ADOPTED THE LEARNING RATE SCHEDULE FROM SHALEVSHWARTZ ET AL 2007 FOR MULTICLASS CLASSIFICATION A “ONE VERSUS ALL” APPROACH IS USED WE USE THE TRUNCATED GRADIENT ALGORITHM PROPOSED BY TSURUOKA ET AL 2009 FOR L1 REGULARIZATION AND THE ELASTIC NET THE CODE IS WRITTEN IN CYTHON

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• “PEGASOS PRIMAL ESTIMATED SUBGRADIENT SOLVER FOR SVM” S SHALEVSHWARTZ Y SINGER N SREBRO IN PRO
CEEDINGS OF ICML ‘07
• “STOCHASTIC GRADIENT DESCENT TRAINING FOR L1REGULARIZED LOGLINEAR MODELS WITH CUMULATIVE PENALTY” Y TSU
RUOKA J TSUJII S ANANIADOU IN PROCEEDINGS OF THE AFNLPACL ‘09
316 NEAREST NEIGHBORS
SKLEARNNEIGHBORS PROVIDES FUNCTIONALITY FOR UNSUPERVISED AND SUPERVISED NEIGHBORSBASED LEARNING METHODS UNSUPERVISED NEAREST NEIGHBORS IS THE FOUNDATION OF MANY OTHER LEARNING METHODS NOTABLY MANIFOLD LEARNING AND SPECTRAL CLUSTERING SUPERVISED NEIGHBORSBASED LEARNING COMES IN TWO FLAVORS CLASSIFICATION FOR DATA WITH DISCRETE LABELS AND REGRESSION FOR DATA WITH CONTINUOUS LABELS
THE PRINCIPLE BEHIND NEAREST NEIGHBOR METHODS IS TO FIND A PREDEFINED NUMBER OF TRAINING SAMPLES CLOSEST IN DISTANCE TO THE NEW POINT AND PREDICT THE LABEL FROM THESE THE NUMBER OF SAMPLES CAN BE A USERDEFINED CONSTANT KNEAREST NEIGHBOR LEARNING OR VARY BASED ON THE LOCAL DENSITY OF POINTS RADIUSBASED NEIGHBOR LEARNING THE DISTANCE CAN IN GENERAL BE ANY METRIC MEASURE STANDARD EUCLIDEAN DISTANCE IS THE MOST COMMON CHOICE NEIGHBORSBASED METH ODS ARE KNOWN AS NONGENERALIZING MACHINE LEARNING METHODS SINCE THEY SIMPLY “REMEMBER” ALL OF ITS TRAINING DATA POSSIBLY TRANSFORMED INTO A FAST INDEXING STRUCTURE SUCH AS A BALL TREE ORKD TREE
DESPITE ITS SIMPLICITY NEAREST NEIGHBORS HAS BEEN SUCCESSFUL IN A LARGE NUMBER OF CLASSIFICATION AND REGRESSION PROB LEMS INCLUDING HANDWRITTEN DIGITS AND SATELLITE IMAGE SCENES BEING A NONPARAMETRIC METHOD IT IS OFTEN SUCCESSFUL IN CLASSIFICATION SITUATIONS WHERE THE DECISION BOUNDARY IS VERY IRREGULAR
THE CLASSES IN SKLEARNNEIGHBORS CAN HANDLE EITHER NUMPY ARRAYS OR SCIPYSPARSE MATRICES AS INPUT FOR DENSE MATRICES A LARGE NUMBER OF POSSIBLE DISTANCE METRICS ARE SUPPORTED FOR SPARSE MATRICES ARBITRARY MINKOWSKI METRICS ARE SUPPORTED FOR SEARCHES
THERE ARE MANY LEARNING ROUTINES WHICH RELY ON NEAREST NEIGHBORS AT THEIR CORE ONE EXAMPLE IS KERNEL DENSITY ESTIMA TION DISCUSSED IN THE DENSITY ESTIMATION SECTION
UNSUPERVISED NEAREST NEIGHBORS
NEARESTNEIGHBORS IMPLEMENTS UNSUPERVISED NEAREST NEIGHBORS LEARNING IT ACTS AS A UNIFORM INTERFACE TO THREE DIFFERENT NEAREST NEIGHBORS ALGORITHMS BALLTREE KDTREE AND A BRUTEFORCE ALGORITHM BASED ON ROUTINES IN SKLEARNMETRICSPAIRWISE THE CHOICE OF NEIGHBORS SEARCH ALGORITHM IS CONTROLLED THROUGH THE KEYWORD ALGORITHM WHICH MUST BE ONE OF AUTO BALLTREE KDTREE BRUTE WHEN THE DE
FAULT VALUE AUTO IS PASSED THE ALGORITHM ATTEMPTS TO DETERMINE THE BEST APPROACH FROM THE TRAINING DATA FOR A DISCUSSION OF THE STRENGTHS AND WEAKNESSES OF EACH OPTION SEE NEAREST NEIGHBOR ALGORITHMS
WARNING REGARDING THE NEAREST NEIGHBORS ALGORITHMS IF TWO NEIGHBORS □ 1AND□HAVE IDENTICAL DISTANCES BUT DIFFERENT LABELS THE RESULT WILL DEPEND ON THE ORDERING OF THE TRAINING DATA

FINDING THE NEAREST NEIGHBORS
FOR THE SIMPLE TASK OF FINDING THE NEAREST NEIGHBORS BETWEEN TWO SETS OF DATA THE UNSUPERVISED ALGORITHMS WITHIN SKLEARNNEIGHBORS CAN BE USED
```
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
NBRS  NEARESTNEIGHBORSNNEIGHBORS2 ALGORITHMBALLTREEFITX
DISTANCES INDICES  NBRSKNEIGHBORSX
INDICES
ARRAY0 1
1 0
2 1
3 4
4 3
5 4
DISTANCES
ARRAY0  1
0  1
0  141421356
0  1
0  1
0  141421356
```
BECAUSE THE QUERY SET MATCHES THE TRAINING SET THE NEAREST NEIGHBOR OF EACH POINT IS THE POINT ITSELF AT A DISTANCE OF ZERO
IT IS ALSO POSSIBLE TO EFFICIENTLY PRODUCE A SPARSE GRAPH SHOWING THE CONNECTIONS BETWEEN NEIGHBORING POINTS
```
NBRSKNEIGHBORSGRAPHXTOARRAY
ARRAY1 1 0 0 0 0
1 1 0 0 0 0
0 1 1 0 0 0
0 0 0 1 1 0
0 0 0 1 1 0
0 0 0 0 1 1
```
THE DATASET IS STRUCTURED SUCH THAT POINTS NEARBY IN INDEX ORDER ARE NEARBY IN PARAMETER SPACE LEADING TO AN AP PROXIMATELY BLOCKDIAGONAL MATRIX OF KNEAREST NEIGHBORS SUCH A SPARSE GRAPH IS USEFUL IN A VARIETY OF CIR CUMSTANCES WHICH MAKE USE OF SPATIAL RELATIONSHIPS BETWEEN POINTS FOR UNSUPERVISED LEARNING IN PARTICULAR SEESKLEARNMANIFOLDISOMAP SKLEARNMANIFOLDLOCALLYLINEAREMBEDDING ANDSKLEARN CLUSTERSPECTRALCLUSTERING
KDTREE AND BALLTREE CLASSES
ALTERNATIVELY ONE CAN USE THE KDTREE ORBALLTREE CLASSES DIRECTLY TO FIND NEAREST NEIGHBORS THIS IS THE FUNCTION ALITY WRAPPED BY THE NEARESTNEIGHBORS CLASS USED ABOVE THE BALL TREE AND KD TREE HAVE THE SAME INTERFACE WE’LL SHOW AN EXAMPLE OF USING THE KD TREE HERE
```
 FROM SKLEARNNEIGHBORS IMPORT KDTREE
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
KDT  KDTREEX LEAFSIZE30 METRICEUCLIDEAN
KDTQUERYX K2 RETURNDISTANCE FALSE
ARRAY0 1
```

1 0
2 1
3 4
4 3
5 4
REFER TO THE KDTREE ANDBALLTREE CLASS DOCUMENTATION FOR MORE INFORMATION ON THE OPTIONS AVAILABLE FOR NEAREST NEIGHBORS SEARCHES INCLUDING SPECIFICATION OF QUERY STRATEGIES DISTANCE METRICS ETC FOR A LIST OF AVAILABLE METRICS SEE THE DOCUMENTATION OF THE DISTANCEMETRIC CLASS

NEAREST NEIGHBORS CLASSIFICATION

NEIGHBORSBASED CLASSIFICATION IS A TYPE OF INSTANCEBASED LEARNING ORNONGENERALIZING LEARNING IT DOES NOT ATTEMPT TO CONSTRUCT A GENERAL INTERNAL MODEL BUT SIMPLY STORES INSTANCES OF THE TRAINING DATA CLASSIFICATION IS COMPUTED FROM A SIMPLE MAJORITY VOTE OF THE NEAREST NEIGHBORS OF EACH POINT A QUERY POINT IS ASSIGNED THE DATA CLASS WHICH HAS THE MOST REPRESENTATIVES WITHIN THE NEAREST NEIGHBORS OF THE POINT

SCIKITLEARN IMPLEMENTS TWO DIFFERENT NEAREST NEIGHBORS CLASSIFIERS KNEIGHBORSCLASSIFIER IMPLEMENTS LEARNING BASED ON THE □NEAREST NEIGHBORS OF EACH QUERY POINT WHERE □IS AN INTEGER VALUE SPECIFIED BY THE USER RADIUSNEIGHBORSCLASSIFIER IMPLEMENTS LEARNING BASED ON THE NUMBER OF NEIGHBORS WITHIN A FIXED RADIUS □OF EACH TRAINING POINT WHERE □IS A FLOATINGPOINT VALUE SPECIFIED BY THE USER

THE□NEIGHBORS CLASSIFICATION IN KNEIGHBORSCLASSIFIER IS THE MOST COMMONLY USED TECHNIQUE THE OPTIMAL CHOICE OF THE VALUE □IS HIGHLY DATADEPENDENT IN GENERAL A LARGER □SUPPRESSES THE EFFECTS OF NOISE BUT MAKES THE CLASSIFICATION BOUNDARIES LESS DISTINCT

IN CASES WHERE THE DATA IS NOT UNIFORMLY SAMPLED RADIUSBASED NEIGHBORS CLASSIFICATION IN RADIUSNEIGHBORSCLASSIFIER CAN BE A BETTER CHOICE THE USER SPECIFIES A FIXED RADIUS □ SUCH THAT POINTS IN SPARSER NEIGHBORHOODS USE FEWER NEAREST NEIGHBORS FOR THE CLASSIFICATION FOR HIGHDIMENSIONAL PARAMETER SPACES THIS METHOD BECOMES LESS EFFECTIVE DUE TO THE SOCALLED “CURSE OF DIMENSIONALITY”

THE BASIC NEAREST NEIGHBORS CLASSIFICATION USES UNIFORM WEIGHTS THAT IS THE VALUE ASSIGNED TO A QUERY POINT IS COMPUTED FROM A SIMPLE MAJORITY VOTE OF THE NEAREST NEIGHBORS UNDER SOME CIRCUMSTANCES IT IS BETTER TO WEIGHT THE NEIGHBORS SUCH THAT NEARER NEIGHBORS CONTRIBUTE MORE TO THE FIT THIS CAN BE ACCOMPLISHED THROUGH THE WEIGHTS KEYWORD THE DEFAULT VALUE WEIGHTS UNIFORM ASSIGNS UNIFORM WEIGHTS TO EACH NEIGHBOR WEIGHTS DISTANCE ASSIGNS WEIGHTS PROPORTIONAL TO THE INVERSE OF THE DISTANCE FROM THE QUERY POINT ALTERNATIVELY A USERDEFINED FUNCTION OF THE DISTANCE CAN BE SUPPLIED TO COMPUTE THE WEIGHTS

EXAMPLES
•NEAREST NEIGHBORS CLASSIFICATION AN EXAMPLE OF CLASSIFICATION USING NEAREST NEIGHBORS
NEAREST NEIGHBORS REGRESSION
NEIGHBORSBASED REGRESSION CAN BE USED IN CASES WHERE THE DATA LABELS ARE CONTINUOUS RATHER THAN DISCRETE VARIABLES THE LABEL ASSIGNED TO A QUERY POINT IS COMPUTED BASED ON THE MEAN OF THE LABELS OF ITS NEAREST NEIGHBORS
SCIKITLEARN IMPLEMENTS TWO DIFFERENT NEIGHBORS REGRESSORS KNEIGHBORSREGRESSOR IMPLEMENTS LEARNING BASED ON THE □NEAREST NEIGHBORS OF EACH QUERY POINT WHERE □IS AN INTEGER VALUE SPECIFIED BY THE USER
RADIUSNEIGHBORSREGRESSOR IMPLEMENTS LEARNING BASED ON THE NEIGHBORS WITHIN A FIXED RADIUS □OF THE QUERY POINT WHERE □IS A FLOATINGPOINT VALUE SPECIFIED BY THE USER
THE BASIC NEAREST NEIGHBORS REGRESSION USES UNIFORM WEIGHTS THAT IS EACH POINT IN THE LOCAL NEIGHBORHOOD CONTRIBUTES UNIFORMLY TO THE CLASSIFICATION OF A QUERY POINT UNDER SOME CIRCUMSTANCES IT CAN BE ADVANTAGEOUS TO WEIGHT POINTS SUCH THAT NEARBY POINTS CONTRIBUTE MORE TO THE REGRESSION THAN FARAWAY POINTS THIS CAN BE ACCOMPLISHED THROUGH THE WEIGHTS KEYWORD THE DEFAULT VALUE WEIGHTS UNIFORM ASSIGNS EQUAL WEIGHTS TO ALL POINTS WEIGHTS
 DISTANCE ASSIGNS WEIGHTS PROPORTIONAL TO THE INVERSE OF THE DISTANCE FROM THE QUERY POINT ALTERNATIVELY A USERDEFINED FUNCTION OF THE DISTANCE CAN BE SUPPLIED WHICH WILL BE USED TO COMPUTE THE WEIGHTS
THE USE OF MULTIOUTPUT NEAREST NEIGHBORS FOR REGRESSION IS DEMONSTRATED IN FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS IN THIS EXAMPLE THE INPUTS X ARE THE PIXELS OF THE UPPER HALF OF FACES AND THE OUTPUTS Y ARE THE PIXELS OF THE LOWER HALF OF THOSE FACES
EXAMPLES
•NEAREST NEIGHBORS REGRESSION AN EXAMPLE OF REGRESSION USING NEAREST NEIGHBORS

•FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS AN EXAMPLE OF MULTIOUTPUT REGRESSION USING NEAREST NEIGH
BORS
NEAREST NEIGHBOR ALGORITHMS
BRUTE FORCE
FAST COMPUTATION OF NEAREST NEIGHBORS IS AN ACTIVE AREA OF RESEARCH IN MACHINE LEARNING THE MOST NAIVE NEIGHBOR SEARCH IMPLEMENTATION INVOLVES THE BRUTEFORCE COMPUTATION OF DISTANCES BETWEEN ALL PAIRS OF POINTS IN THE DATASET FOR □SAMPLES IN □DIMENSIONS THIS APPROACH SCALES AS □□□2 EFFICIENT BRUTEFORCE NEIGHBORS SEARCHES CAN BE VERY COMPETITIVE FOR SMALL DATA SAMPLES HOWEVER AS THE NUMBER OF SAMPLES □GROWS THE BRUTEFORCE APPROACH QUICKLY BECOMES INFEASIBLE IN THE CLASSES WITHIN SKLEARNNEIGHBORS BRUTEFORCE NEIGHBORS SEARCHES ARE SPECIFIED USING THE KEYWORD ALGORITHM BRUTE AND ARE COMPUTED USING THE ROUTINES AVAILABLE IN SKLEARNMETRICS
PAIRWISE
KD TREE
TO ADDRESS THE COMPUTATIONAL INEFFICIENCIES OF THE BRUTEFORCE APPROACH A VARIETY OF TREEBASED DATA STRUCTURES HAVE BEEN INVENTED IN GENERAL THESE STRUCTURES ATTEMPT TO REDUCE THE REQUIRED NUMBER OF DISTANCE CALCULATIONS BY EFFICIENTLY ENCODING AGGREGATE DISTANCE INFORMATION FOR THE SAMPLE THE BASIC IDEA IS THAT IF POINT □IS VERY DISTANT FROM POINT □ AND POINT □IS VERY CLOSE TO POINT □ THEN WE KNOW THAT POINTS □AND□ARE VERY DISTANT WITHOUT HAVING TO EXPLICITLY CALCULATE THEIR DISTANCE IN THIS WAY THE COMPUTATIONAL COST OF A NEAREST NEIGHBORS SEARCH CAN BE REDUCED TO □□□LOG□OR BETTER THIS IS A SIGNIFICANT IMPROVEMENT OVER BRUTEFORCE FOR LARGE □
AN EARLY APPROACH TO TAKING ADVANTAGE OF THIS AGGREGATE INFORMATION WAS THE KD TREE DATA STRUCTURE SHORT FOR K DIMENSIONAL TREE WHICH GENERALIZES TWODIMENSIONAL QUADTREES AND 3DIMENSIONAL OCTTREES TO AN ARBITRARY NUMBER OF DIMENSIONS THE KD TREE IS A BINARY TREE STRUCTURE WHICH RECURSIVELY PARTITIONS THE PARAMETER SPACE ALONG THE DATA AXES DIVIDING IT INTO NESTED ORTHOTROPIC REGIONS INTO WHICH DATA POINTS ARE FILED THE CONSTRUCTION OF A KD TREE IS VERY FAST BECAUSE PARTITIONING IS PERFORMED ONLY ALONG THE DATA AXES NO □DIMENSIONAL DISTANCES NEED TO BE COMPUTED ONCE CONSTRUCTED THE NEAREST NEIGHBOR OF A QUERY POINT CAN BE DETERMINED WITH ONLY □LOG□DISTANCE COMPUTATIONS THOUGH THE KD TREE APPROACH IS VERY FAST FOR LOWDIMENSIONAL □ 20 NEIGHBORS SEARCHES IT BECOMES INEFFICIENT AS□GROWS VERY LARGE THIS IS ONE MANIFESTATION OF THE SOCALLED “CURSE OF DIMENSIONALITY” IN SCIKITLEARN KD TREE NEIGHBORS SEARCHES ARE SPECIFIED USING THE KEYWORD ALGORITHM KDTREE AND ARE COMPUTED USING THE CLASS KDTREE
REFERENCES
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BALL TREE
TO ADDRESS THE INEFFICIENCIES OF KD TREES IN HIGHER DIMENSIONS THE BALL TREE DATA STRUCTURE WAS DEVELOPED WHERE KD TREES PARTITION DATA ALONG CARTESIAN AXES BALL TREES PARTITION DATA IN A SERIES OF NESTING HYPERSPHERES THIS MAKES TREE CONSTRUCTION MORE COSTLY THAN THAT OF THE KD TREE BUT RESULTS IN A DATA STRUCTURE WHICH CAN BE VERY EFFICIENT ON HIGHLY STRUCTURED DATA EVEN IN VERY HIGH DIMENSIONS
A BALL TREE RECURSIVELY DIVIDES THE DATA INTO NODES DEFINED BY A CENTROID □AND RADIUS □ SUCH THAT EACH POINT IN THE NODE LIES WITHIN THE HYPERSPHERE DEFINED BY □AND□ THE NUMBER OF CANDIDATE POINTS FOR A NEIGHBOR SEARCH IS REDUCED

THROUGH USE OF THE TRIANGLE INEQUALITY
□□≤□□
WITH THIS SETUP A SINGLE DISTANCE CALCULATION BETWEEN A TEST POINT AND THE CENTROID IS SUFFICIENT TO DETERMINE A LOWER AND UPPER BOUND ON THE DISTANCE TO ALL POINTS WITHIN THE NODE BECAUSE OF THE SPHERICAL GEOMETRY OF THE BALL TREE NODES IT CAN OUTPERFORM A KDTREE IN HIGH DIMENSIONS THOUGH THE ACTUAL PERFORMANCE IS HIGHLY DEPENDENT ON THE STRUCTURE OF THE TRAINING DATA IN SCIKITLEARN BALLTREEBASED NEIGHBORS SEARCHES ARE SPECIFIED USING THE KEYWORD ALGORITHM = 'BALLTREE' AND ARE COMPUTED USING THE CLASS SKLEARNNEIGHBORSBALLTREE ALTERNATIVELY THE USER CAN WORK WITH THE BALLTREE CLASS DIRECTLY

REFERENCES

• "FIVE BALLTREE CONSTRUCTION ALGORITHMS" OMOHUNDRO SM INTERNATIONAL COMPUTER SCIENCE INSTITUTE TECHNICAL REPORT 1989

CHOICE OF NEAREST NEIGHBORS ALGORITHM

THE OPTIMAL ALGORITHM FOR A GIVEN DATASET IS A COMPLICATED CHOICE AND DEPENDS ON A NUMBER OF FACTORS

• NUMBER OF SAMPLES □(N_SAMPLES) AND DIMENSIONALITY □(N_FEATURES)
–BRUTE FORCE QUERY TIME GROWS AS □(□□)
–BALL TREE QUERY TIME GROWS AS APPROXIMATELY □(□LOG□)
–KD TREE QUERY TIME CHANGES WITH □IN A WAY THAT IS DIFFICULT TO PRECISELY CHARACTERISE FOR SMALL □(LESS THAN 20 OR SO) THE COST IS APPROXIMATELY □(□LOG□) AND THE KD TREE QUERY CAN BE VERY EFFICIENT FOR LARGER □ THE COST INCREASES TO NEARLY □(□□) AND THE OVERHEAD DUE TO THE TREE STRUCTURE CAN LEAD TO QUERIES WHICH ARE SLOWER THAN BRUTE FORCE
FOR SMALL DATA SETS (□LESS THAN 30 OR SO) LOG□IS COMPARABLE TO □ AND BRUTE FORCE ALGORITHMS CAN BE MORE EFFICIENT THAN A TREEBASED APPROACH BOTH KDTREE ANDBALLTREE ADDRESS THIS THROUGH PROVIDING A LEAF SIZE PARAMETER THIS CONTROLS THE NUMBER OF SAMPLES AT WHICH A QUERY SWITCHES TO BRUTEFORCE THIS ALLOWS BOTH ALGORITHMS TO APPROACH THE EFFICIENCY OF A BRUTEFORCE COMPUTATION FOR SMALL □
• DATA STRUCTURE INTRINSIC DIMENSIONALITY OF THE DATA ANDOR SPARSITY OF THE DATA INTRINSIC DIMENSIONALITY REFERS TO THE DIMENSION □≤□OF A MANIFOLD ON WHICH THE DATA LIES WHICH CAN BE LINEARLY OR NONLINEARLY EMBEDDED IN THE PARAMETER SPACE SPARSITY REFERS TO THE DEGREE TO WHICH THE DATA FILLS THE PARAMETER SPACE THIS IS TO BE DISTINGUISHED FROM THE CONCEPT AS USED IN "SPARSE" MATRICES THE DATA MATRIX MAY HAVE NO ZERO ENTRIES BUT THE STRUCTURE CAN STILL BE "SPARSE" IN THIS SENSE
–BRUTE FORCE QUERY TIME IS UNCHANGED BY DATA STRUCTURE
–BALL TREE ANDKD TREE QUERY TIMES CAN BE GREATLY INFLUENCED BY DATA STRUCTURE IN GENERAL SPARSER DATA WITH A SMALLER INTRINSIC DIMENSIONALITY LEADS TO FASTER QUERY TIMES BECAUSE THE KD TREE INTERNAL REPRESENTATION IS ALIGNED WITH THE PARAMETER AXES IT WILL NOT GENERALLY SHOW AS MUCH IMPROVEMENT AS BALL TREE FOR ARBITRARILY STRUCTURED DATA

DATASETS USED IN MACHINE LEARNING TEND TO BE VERY STRUCTURED AND ARE VERY WELLSUITED FOR TREEBASED QUERIES

• NUMBER OF NEIGHBORS □REQUESTED FOR A QUERY POINT
–BRUTE FORCE QUERY TIME IS LARGELY UNAFFECTED BY THE VALUE OF □
–BALL TREE ANDKD TREE QUERY TIME WILL BECOME SLOWER AS □INCREASES THIS IS DUE TO TWO EFFECTS FIRST A LARGER □LEADS TO THE NECESSITY TO SEARCH A LARGER PORTION OF THE PARAMETER SPACE SECOND USING □ 1 REQUIRES INTERNAL QUEUEING OF RESULTS AS THE TREE IS TRAVERSED

AS□BECOMES LARGE COMPARED TO □ THE ABILITY TO PRUNE BRANCHES IN A TREEBASED QUERY IS REDUCED IN THIS SITUATION BRUTE FORCE QUERIES CAN BE MORE EFFICIENT

• NUMBER OF QUERY POINTS BOTH THE BALL TREE AND THE KD TREE REQUIRE A CONSTRUCTION PHASE THE COST OF THIS CONSTRUCTION BECOMES NEGLIGIBLE WHEN AMORTIZED OVER MANY QUERIES IF ONLY A SMALL NUMBER OF QUERIES WILL BE PERFORMED HOWEVER THE CONSTRUCTION CAN MAKE UP A SIGNIFICANT FRACTION OF THE TOTAL COST IF VERY FEW QUERY POINTS WILL BE REQUIRED BRUTE FORCE IS BETTER THAN A TREEBASED METHOD

CURRENTLY ALGORITHM AUTO SELECTSBRUTE IF□ □2 THE INPUT DATA IS SPARSE OR EFFECTIVEMETRIC ISN'T IN THE VALIDMETRICS LIST FOR EITHER KDTREE ORBALLTREE OTHERWISE IT SELECTS THE FIRST OUT OF KDTREE ANDBALLTREE THAT HASEFFECTIVEMETRIC IN ITSVALIDMETRICS LIST THIS CHOICE IS BASED ON THE ASSUMPTION THAT THE NUMBER OF QUERY POINTS IS AT LEAST THE SAME ORDER AS THE NUMBER OF TRAINING POINTS AND THAT LEAFSIZE IS CLOSE TO ITS DEFAULT VALUE OF 30

EFFECT OFLEAFSIZE

AS NOTED ABOVE FOR SMALL SAMPLE SIZES A BRUTE FORCE SEARCH CAN BE MORE EFFICIENT THAN A TREEBASED QUERY THIS FACT IS ACCOUNTED FOR IN THE BALL TREE AND KD TREE BY INTERNALLY SWITCHING TO BRUTE FORCE SEARCHES WITHIN LEAF NODES THE LEVEL OF THIS SWITCH CAN BE SPECIFIED WITH THE PARAMETER LEAFSIZE THIS PARAMETER CHOICE HAS MANY EFFECTS

CONSTRUCTION TIME A LARGERLEAFSIZE LEADS TO A FASTER TREE CONSTRUCTION TIME BECAUSE FEWER NODES NEED TO BE CREATED

QUERY TIME BOTH A LARGE OR SMALL LEAFSIZE CAN LEAD TO SUBOPTIMAL QUERY COST FOR LEAFSIZE APPROACHING 1 THE OVERHEAD INVOLVED IN TRAVERSING NODES CAN SIGNIFICANTLY SLOW QUERY TIMES FOR LEAFSIZE APPROACH ING THE SIZE OF THE TRAINING SET QUERIES BECOME ESSENTIALLY BRUTE FORCE A GOOD COMPROMISE BETWEEN THESE IS LEAFSIZE 30 THE DEFAULT VALUE OF THE PARAMETER

MEMORY ASLEAFSIZE INCREASES THE MEMORY REQUIRED TO STORE A TREE STRUCTURE DECREASES THIS IS ESPECIALLY IMPORTANT IN THE CASE OF BALL TREE WHICH STORES A □DIMENSIONAL CENTROID FOR EACH NODE THE REQUIRED STORAGE SPACE FORBALLTREE IS APPROXIMATELY 1 LEAFSIZE TIMES THE SIZE OF THE TRAINING SET

LEAFSIZE IS NOT REFERENCED FOR BRUTE FORCE QUERIES

NEAREST CENTROID CLASSIFIER

THENEARESTCENTROID CLASSIFIER IS A SIMPLE ALGORITHM THAT REPRESENTS EACH CLASS BY THE CENTROID OF ITS MEMBERS IN EFFECT THIS MAKES IT SIMILAR TO THE LABEL UPDATING PHASE OF THE SKLEARNKMEANS ALGORITHM IT ALSO HAS NO PARAM ETERS TO CHOOSE MAKING IT A GOOD BASELINE CLASSIFIER IT DOES HOWEVER SUFFER ON NONCONVEX CLASSES AS WELL AS WHEN CLASSES HAVE DRASTICALLY DIFFERENT VARIANCES AS EQUAL VARIANCE IN ALL DIMENSIONS IS ASSUMED SEE LINEAR DISCRIM INANT ANALYSIS SKLEARNDISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS AND QUADRATIC DISCRIMINANT ANALYSIS SKLEARNDISCRIMINANTANALYSISQUADRATICDISCRIMINANTANALYSIS FOR MORE COMPLEX METHODS THAT DO NOT MAKE THIS ASSUMPTION USAGE OF THE DEFAULT NEARESTCENTROID IS SIMPLE

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 FROM SKLEARNNEIGHBORSNEARESTCENTROID IMPORT NEARESTCENTROID
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
Y  NPARRAY1 1 1 2 2 2
CLF  NEARESTCENTROID
CLFFITX Y
NEARESTCENTROIDMETRICEUCLIDEAN SHRINKTHRESHOLDNONE
PRINTCLFPREDICT08 1
1
```

NEAREST SHRUNKEN CENTROID

THENEARESTCENTROID CLASSIFIER HAS A SHRINKTHRESHOLD PARAMETER WHICH IMPLEMENTS THE NEAREST SHRUNKEN CENTROID CLASSIFIER IN EFFECT THE VALUE OF EACH FEATURE FOR EACH CENTROID IS DIVIDED BY THE WITHINCLASS VARIANCE OF THAT FEATURE THE FEATURE VALUES ARE THEN REDUCED BY SHRINKTHRESHOLD MOST NOTABLY IF A PARTICULAR FEATURE VALUE CROSSES ZERO IT IS SET TO ZERO IN EFFECT THIS REMOVES THE FEATURE FROM AFFECTING THE CLASSIFICATION THIS IS USEFUL FOR EXAMPLE FOR REMOVING NOISY FEATURES

IN THE EXAMPLE BELOW USING A SMALL SHRINK THRESHOLD INCREASES THE ACCURACY OF THE MODEL FROM 081 TO 082

EXAMPLES

•NEAREST CENTROID CLASSIFICATION AN EXAMPLE OF CLASSIFICATION USING NEAREST CENTROID WITH DIFFERENT SHRINK THRESHOLDS

NEIGHBORHOOD COMPONENTS ANALYSIS

NEIGHBORHOOD COMPONENTS ANALYSIS NCA NEIGHBORHOODCOMPONENTSANALYSIS IS A DISTANCE METRIC LEARN ING ALGORITHM WHICH AIMS TO IMPROVE THE ACCURACY OF NEAREST NEIGHBORS CLASSIFICATION COMPARED TO THE STANDARD EU CLIDEAN DISTANCE THE ALGORITHM DIRECTLY MAXIMIZES A STOCHASTIC VARIANT OF THE LEAVEONEOUT KNEAREST NEIGHBORS KNN SCORE ON THE TRAINING SET IT CAN ALSO LEARN A LOWDIMENSIONAL LINEAR PROJECTION OF DATA THAT CAN BE USED FOR DATA VISUALIZATION AND FAST CLASSIFICATION

IN THE ABOVE ILLUSTRATING FIGURE WE CONSIDER SOME POINTS FROM A RANDOMLY GENERATED DATASET WE FOCUS ON THE STOCHASTIC KNN CLASSIFICATION OF POINT NO 3 THE THICKNESS OF A LINK BETWEEN SAMPLE 3 AND ANOTHER POINT IS PROPORTIONAL TO THEIR DISTANCE AND CAN BE SEEN AS THE RELATIVE WEIGHT OR PROBABILITY THAT A STOCHASTIC NEAREST NEIGHBOR PREDICTION RULE WOULD ASSIGN TO THIS POINT IN THE ORIGINAL SPACE SAMPLE 3 HAS MANY STOCHASTIC NEIGHBORS FROM VARIOUS CLASSES SO THE RIGHT CLASS IS NOT VERY LIKELY HOWEVER IN THE PROJECTED SPACE LEARNED BY NCA THE ONLY STOCHASTIC NEIGHBORS WITH NON NEGLIGIBLE WEIGHT ARE FROM THE SAME CLASS AS SAMPLE 3 GUARANTEEING THAT THE LATTER WILL BE WELL CLASSIFIED SEE THE MATHEMATICAL FORMULATION FOR MORE DETAILS

CLASSIFICATION

COMBINED WITH A NEAREST NEIGHBORS CLASSIFIER KNEIGHBORSCLASSIFIER NCA IS ATTRACTIVE FOR CLASSIFICATION BE CAUSE IT CAN NATURALLY HANDLE MULTICLASS PROBLEMS WITHOUT ANY INCREASE IN THE MODEL SIZE AND DOES NOT INTRODUCE ADDITIONAL PARAMETERS THAT REQUIRE FINETUNING BY THE USER

NCA CLASSIFICATION HAS BEEN SHOWN TO WORK WELL IN PRACTICE FOR DATA SETS OF VARYING SIZE AND DIFFICULTY IN CONTRAST TO RELATED METHODS SUCH AS LINEAR DISCRIMINANT ANALYSIS NCA DOES NOT MAKE ANY ASSUMPTIONS ABOUT THE CLASS DISTRIBU TIONS THE NEAREST NEIGHBOR CLASSIFICATION CAN NATURALLY PRODUCE HIGHLY IRREGULAR DECISION BOUNDARIES

TO USE THIS MODEL FOR CLASSIFICATION ONE NEEDS TO COMBINE A NEIGHBORHOODCOMPONENTSANALYSIS INSTANCE THAT LEARNS THE OPTIMAL TRANSFORMATION WITH A KNEIGHBORSCLASSIFIER INSTANCE THAT PERFORMS THE CLASSIFICATION IN THE PROJECTED SPACE HERE IS AN EXAMPLE USING THE TWO CLASSES

```
 FROM SKLEARNNEIGHBORS IMPORT NEIGHBORHOODCOMPONENTSANALYSIS
KNEIGHBORSCLASSIFIER
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
 FROM SKLEARNPIPELINE IMPORT PIPELINE
X Y  LOADIRISRETURNXY TRUE
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLITX Y
STRATIFYY TESTSIZE07 RANDOMSTATE42
NCA  NEIGHBORHOODCOMPONENTSANALYSISRANDOMSTATE42
KNN  KNEIGHBORSCLASSIFIERNNEIGHBORS3
NCAPIPE  PIPELINENCA NCA KNN KNN
NCAPIPEFITXTRAIN YTRAIN
PIPELINE
PRINTNCAPIPESCOREXTEST YTEST
096190476
```

THE PLOT SHOWS DECISION BOUNDARIES FOR NEAREST NEIGHBOR CLASSIFICATION AND NEIGHBORHOOD COMPONENTS ANALYSIS CLASSIFICATION ON THE IRIS DATASET WHEN TRAINING AND SCORING ON ONLY TWO FEATURES FOR VISUALISATION PURPOSES

DIMENSIONALITY REDUCTION
NCA CAN BE USED TO PERFORM SUPERVISED DIMENSIONALITY REDUCTION THE INPUT DATA ARE PROJECTED ONTO A LINEAR SUB SPACE CONSISTING OF THE DIRECTIONS WHICH MINIMIZE THE NCA OBJECTIVE THE DESIRED DIMENSIONALITY CAN BE SET US ING THE PARAMETER NCOMPONENTS FOR INSTANCE THE FOLLOWING FIGURE SHOWS A COMPARISON OF DIMENSIONALITY RE DUCTION WITH PRINCIPAL COMPONENT ANALYSIS SKLEARNDECOMPOSITIONPCA LINEAR DISCRIMINANT ANALYSIS SKLEARNDISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS AND NEIGHBORHOOD COMPONENT ANALYSIS NEIGHBORHOODCOMPONENTSANALYSIS ON THE DIGITS DATASET A DATASET WITH SIZE □□□□□□□□ 1797 AND□□□□□□□□□ 64 THE DATA SET IS SPLIT INTO A TRAINING AND A TEST SET OF EQUAL SIZE THEN STANDARDIZED FOR EVALUA TION THE 3NEAREST NEIGHBOR CLASSIFICATION ACCURACY IS COMPUTED ON THE 2DIMENSIONAL PROJECTED POINTS FOUND BY EACH METHOD EACH DATA SAMPLE BELONGS TO ONE OF 10 CLASSES

EXAMPLES

•COMPARING NEAREST NEIGHBORS WITH AND WITHOUT NEIGHBORHOOD COMPONENTS ANALYSIS
•DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP

MATHEMATICAL FORMULATION

THE GOAL OF NCA IS TO LEARN AN OPTIMAL LINEAR TRANSFORMATION MATRIX OF SIZE NCOMPONENTS NFEATURES WHICH MAXIMISES THE SUM OVER ALL SAMPLES □OF THE PROBABILITY □□THAT□IS CORRECTLY CLASSIFIED IE

ARG MAX
□□−1∑
□0□□

WITH□NSAMPLES AND□□THE PROBABILITY OF SAMPLE □BEING CORRECTLY CLASSIFIED ACCORDING TO A STOCHASTIC NEAREST NEIGHBORS RULE IN THE LEARNED EMBEDDED SPACE

□□∑
□∈□□□□□

WHERE □□IS THE SET OF POINTS IN THE SAME CLASS AS SAMPLE □ AND □□□IS THE SOFTMAX OVER EUCLIDEAN DISTANCES IN THE EMBEDDED SPACE

□□□EXP−□□□−□□□2∑
⁄□□EXP−□□□−□□□2 □ □□ 0

MAHALANOBIS DISTANCE
NCA CAN BE SEEN AS LEARNING A SQUARED MAHALANOBIS DISTANCE METRIC
□□□−□□2 □□−□□□□□□−□□
WHERE □□□□IS A SYMMETRIC POSITIVE SEMIDEFINITE MATRIX OF SIZE NFEATURES NFEATURES
IMPLEMENTATION
THIS IMPLEMENTATION FOLLOWS WHAT IS EXPLAINED IN THE ORIGINAL PAPER1 FOR THE OPTIMISATION METHOD IT CURRENTLY USES SCIPY'S LBFGSB WITH A FULL GRADIENT COMPUTATION AT EACH ITERATION TO AVOID TO TUNE THE LEARNING RATE AND PROVIDE STABLE LEARNING
SEE THE EXAMPLES BELOW AND THE DOCSTRING OF NEIGHBORHOODCOMPONENTSANALYSISFIT FOR FURTHER INFORMA TION
COMPLEXITY
TRAINING
NCA STORES A MATRIX OF PAIRWISE DISTANCES TAKING NSAMPLES 2MEMORY TIME COMPLEXITY DEPENDS ON THE NUMBER OF ITERATIONS DONE BY THE OPTIMISATION ALGORITHM HOWEVER ONE CAN SET THE MAXIMUM NUMBER OF ITERA TIONS WITH THE ARGUMENT MAXITER FOR EACH ITERATION TIME COMPLEXITY IS ONCOMPONENTS X NSAMPLES X MINNSAMPLES NFEATURES
TRANSFORM
HERE THE TRANSFORM OPERATION RETURNS □□□ THEREFORE ITS TIME COMPLEXITY EQUALS NCOMPONENTS NFEATURES NSAMPLESTEST THERE IS NO ADDED SPACE COMPLEXITY IN THE OPERATION
REFERENCES
317 GAUSSIAN PROCESSES
GAUSSIAN PROCESSES GP ARE A GENERIC SUPERVISED LEARNING METHOD DESIGNED TO SOLVE REGRESSION ANDPROBABILISTIC CLASSIFICATION PROBLEMS
THE ADVANTAGES OF GAUSSIAN PROCESSES ARE
• THE PREDICTION INTERPOLATES THE OBSERVATIONS AT LEAST FOR REGULAR KERNELS
• THE PREDICTION IS PROBABILISTIC GAUSSIAN SO THAT ONE CAN COMPUTE EMPIRICAL CONFIDENCE INTERVALS AND DECIDE BASED ON THOSE IF ONE SHOULD REFIT ONLINE FITTING ADAPTIVE FITTING THE PREDICTION IN SOME REGION OF INTEREST
• VERSATILE DIFFERENT KERNELS CAN BE SPECIFIED COMMON KERNELS ARE PROVIDED BUT IT IS ALSO POSSIBLE TO SPECIFY CUSTOM KERNELS
1"NEIGHBOURHOOD COMPONENTS ANALYSIS" ADVANCES IN NEURAL INFORMATION" J GOLDBERGER G HINTON S ROWEIS R SALAKHUTDINOV ADV IN NEURAL INFORMATION PROCESSING SYSTEMS V OL 17 MAY 2005 PP 513520

THE DISADVANTAGES OF GAUSSIAN PROCESSES INCLUDE
• THEY ARE NOT SPARSE IE THEY USE THE WHOLE SAMPLESFEATURES INFORMATION TO PERFORM THE PREDICTION
• THEY LOSE EFFICIENCY IN HIGH DIMENSIONAL SPACES – NAMELY WHEN THE NUMBER OF FEATURES EXCEEDS A FEW DOZENS
GAUSSIAN PROCESS REGRESSION GPR
THEGAUSSIANPROCESSREGRESSOR IMPLEMENTS GAUSSIAN PROCESSES GP FOR REGRESSION PURPOSES FOR THIS THE PRIOR OF THE GP NEEDS TO BE SPECIFIED THE PRIOR MEAN IS ASSUMED TO BE CONSTANT AND ZERO FOR NORMALIZEYFALSE OR THE TRAINING DATA'S MEAN FOR NORMALIZEYTRUE THE PRIOR'S COVARIANCE IS SPECIFIED BY PASSING A KERNEL OBJECT THE HYPERPARAMETERS OF THE KERNEL ARE OPTIMIZED DURING FITTING OF GAUSSIANPROCESSREGRESSOR BY MAXIMIZING THE LOG MARGINALLIKELIHOOD LML BASED ON THE PASSED OPTIMIZER AS THE LML MAY HAVE MULTIPLE LOCAL OPTIMA THE OPTIMIZER CAN BE STARTED REPEATEDLY BY SPECIFYING NRESTARTSOPTIMIZER THE FIRST RUN IS ALWAYS CONDUCTED STARTING FROM THE INITIAL HYPERPARAMETER VALUES OF THE KERNEL SUBSEQUENT RUNS ARE CONDUCTED FROM HYPERPARAMETER VALUES THAT HAVE BEEN CHOSEN RANDOMLY FROM THE RANGE OF ALLOWED VALUES IF THE INITIAL HYPERPARAMETERS SHOULD BE KEPT FIXEDNONE CAN BE PASSED AS OPTIMIZER
THE NOISE LEVEL IN THE TARGETS CAN BE SPECIFIED BY PASSING IT VIA THE PARAMETER ALPHA EITHER GLOBALLY AS A SCALAR OR PER DATAPOINT NOTE THAT A MODERATE NOISE LEVEL CAN ALSO BE HELPFUL FOR DEALING WITH NUMERIC ISSUES DURING FITTING AS IT IS EFFECTIVELY IMPLEMENTED AS TIKHONOV REGULARIZATION IE BY ADDING IT TO THE DIAGONAL OF THE KERNEL MATRIX AN ALTERNATIVE TO SPECIFYING THE NOISE LEVEL EXPLICITLY IS TO INCLUDE A WHITEKERNEL COMPONENT INTO THE KERNEL WHICH CAN ESTIMATE THE GLOBAL NOISE LEVEL FROM THE DATA SEE EXAMPLE BELOW
THE IMPLEMENTATION IS BASED ON ALGORITHM 21 OF RW2006 IN ADDITION TO THE API OF STANDARD SCIKITLEARN ESTIMATORS GAUSSIANPROCESSREGRESSOR
• ALLOWS PREDICTION WITHOUT PRIOR FITTING BASED ON THE GP PRIOR
• PROVIDES AN ADDITIONAL METHOD SAMPLEYX WHICH EVALUATES SAMPLES DRAWN FROM THE GPR PRIOR OR POSTE RIOR AT GIVEN INPUTS
• EXPOSES A METHOD LOGMARGINALLIKELIHOODTHETA WHICH CAN BE USED EXTERNALLY FOR OTHER WAYS OF SELECTING HYPERPARAMETERS EG VIA MARKOV CHAIN MONTE CARLO
GPR EXAMPLES
GPR WITH NOISELEVEL ESTIMATION
THIS EXAMPLE ILLUSTRATES THAT GPR WITH A SUMKERNEL INCLUDING A WHITEKERNEL CAN ESTIMATE THE NOISE LEVEL OF DATA AN ILLUSTRATION OF THE LOGMARGINALLIKELIHOOD LML LANDSCAPE SHOWS THAT THERE EXIST TWO LOCAL MAXIMA OF LML THE FIRST CORRESPONDS TO A MODEL WITH A HIGH NOISE LEVEL AND A LARGE LENGTH SCALE WHICH EXPLAINS ALL VARIATIONS IN THE DATA BY NOISE
THE SECOND ONE HAS A SMALLER NOISE LEVEL AND SHORTER LENGTH SCALE WHICH EXPLAINS MOST OF THE VARIATION BY THE NOISE FREE FUNCTIONAL RELATIONSHIP THE SECOND MODEL HAS A HIGHER LIKELIHOOD HOWEVER DEPENDING ON THE INITIAL VALUE FOR THE HYPERPARAMETERS THE GRADIENTBASED OPTIMIZATION MIGHT ALSO CONVERGE TO THE HIGHNOISE SOLUTION IT IS THUS IMPORTANT TO REPEAT THE OPTIMIZATION SEVERAL TIMES FOR DIFFERENT INITIALIZATIONS
COMPARISON OF GPR AND KERNEL RIDGE REGRESSION
BOTH KERNEL RIDGE REGRESSION KRR AND GPR LEARN A TARGET FUNCTION BY EMPLOYING INTERNALLY THE "KERNEL TRICK" KRR LEARNS A LINEAR FUNCTION IN THE SPACE INDUCED BY THE RESPECTIVE KERNEL WHICH CORRESPONDS TO A NONLINEAR FUNCTION IN THE ORIGINAL SPACE THE LINEAR FUNCTION IN THE KERNEL SPACE IS CHOSEN BASED ON THE MEANSQUARED ERROR LOSS WITH RIDGE REGULARIZATION GPR USES THE KERNEL TO DEFINE THE COVARIANCE OF A PRIOR DISTRIBUTION OVER THE TARGET FUNCTIONS AND USES

THE OBSERVED TRAINING DATA TO DEFINE A LIKELIHOOD FUNCTION BASED ON BAYES THEOREM A GAUSSIAN POSTERIOR DISTRIBUTION OVER TARGET FUNCTIONS IS DEFINED WHOSE MEAN IS USED FOR PREDICTION
A MAJOR DIFFERENCE IS THAT GPR CAN CHOOSE THE KERNEL'S HYPERPARAMETERS BASED ON GRADIENTASCENT ON THE MARGINAL LIKELIHOOD FUNCTION WHILE KRR NEEDS TO PERFORM A GRID SEARCH ON A CROSSVALIDATED LOSS FUNCTION MEANSQUARED ERROR LOSS A FURTHER DIFFERENCE IS THAT GPR LEARNS A GENERATIVE PROBABILISTIC MODEL OF THE TARGET FUNCTION AND CAN THUS PROVIDE MEANINGFUL CONFIDENCE INTERVALS AND POSTERIOR SAMPLES ALONG WITH THE PREDICTIONS WHILE KRR ONLY PROVIDES PREDICTIONS
THE FOLLOWING FIGURE ILLUSTRATES BOTH METHODS ON AN ARTIFICIAL DATASET WHICH CONSISTS OF A SINUSOIDAL TARGET FUNCTION AND STRONG NOISE THE FIGURE COMPARES THE LEARNED MODEL OF KRR AND GPR BASED ON A EXPSINESQUARED KERNEL WHICH IS SUITED FOR LEARNING PERIODIC FUNCTIONS THE KERNEL'S HYPERPARAMETERS CONTROL THE SMOOTHNESS LENGTHSCALE AND PERIODICITY OF THE KERNEL PERIODICITY MOREOVER THE NOISE LEVEL OF THE DATA IS LEARNED EXPLICITLY BY GPR BY AN ADDITIONAL WHITEKERNEL COMPONENT IN THE KERNEL AND BY THE REGULARIZATION PARAMETER ALPHA OF KRR
THE FIGURE SHOWS THAT BOTH METHODS LEARN REASONABLE MODELS OF THE TARGET FUNCTION GPR CORRECTLY IDENTIFIES THE PERI ODICITY OF THE FUNCTION TO BE ROUGHLY 2□628 WHILE KRR CHOOSES THE DOUBLED PERIODICITY 4□ BESIDES THAT GPR PROVIDES REASONABLE CONFIDENCE BOUNDS ON THE PREDICTION WHICH ARE NOT AVAILABLE FOR KRR A MAJOR DIFFERENCE BETWEEN THE TWO METHODS IS THE TIME REQUIRED FOR FITTING AND PREDICTING WHILE FITTING KRR IS FAST IN PRINCIPLE THE GRIDSEARCH FOR HYPERPARAMETER OPTIMIZATION SCALES EXPONENTIALLY WITH THE NUMBER OF HYPERPARAMETERS "CURSE OF DIMENSIONAL ITY" THE GRADIENTBASED OPTIMIZATION OF THE PARAMETERS IN GPR DOES NOT SUFFER FROM THIS EXPONENTIAL SCALING AND IS THUS CONSIDERABLE FASTER ON THIS EXAMPLE WITH 3DIMENSIONAL HYPERPARAMETER SPACE THE TIME FOR PREDICTING IS SIMILAR HOWEVER GENERATING THE VARIANCE OF THE PREDICTIVE DISTRIBUTION OF GPR TAKES CONSIDERABLE LONGER THAN JUST PREDICTING THE MEAN
GPR ON MAUNA LOA CO2 DATA
THIS EXAMPLE IS BASED ON SECTION 543 OF RW2006 IT ILLUSTRATES AN EXAMPLE OF COMPLEX KERNEL ENGINEERING AND HYPERPARAMETER OPTIMIZATION USING GRADIENT ASCENT ON THE LOGMARGINALLIKELIHOOD THE DATA CONSISTS OF THE MONTHLY AVERAGE ATMOSPHERIC CO2 CONCENTRATIONS IN PARTS PER MILLION BY VOLUME PPMV COLLECTED AT THE MAUNA LOA OBSER VATORY IN HAWAII BETWEEN 1958 AND 1997 THE OBJECTIVE IS TO MODEL THE CO2 CONCENTRATION AS A FUNCTION OF THE TIME T
THE KERNEL IS COMPOSED OF SEVERAL TERMS THAT ARE RESPONSIBLE FOR EXPLAINING DIFFERENT PROPERTIES OF THE SIGNAL

• A LONG TERM SMOOTH RISING TREND IS TO BE EXPLAINED BY AN RBF KERNEL THE RBF KERNEL WITH A LARGE LENGTHSCALE ENFORCES THIS COMPONENT TO BE SMOOTH IT IS NOT ENFORCED THAT THE TREND IS RISING WHICH LEAVES THIS CHOICE TO THE GP THE SPECIFIC LENGTHSCALE AND THE AMPLITUDE ARE FREE HYPERPARAMETERS
• A SEASONAL COMPONENT WHICH IS TO BE EXPLAINED BY THE PERIODIC EXPSINESQUARED KERNEL WITH A FIXED PERIODICITY OF 1 YEAR THE LENGTHSCALE OF THIS PERIODIC COMPONENT CONTROLLING ITS SMOOTHNESS IS A FREE PARAMETER IN ORDER TO ALLOW DECAYING AWAY FROM EXACT PERIODICITY THE PRODUCT WITH AN RBF KERNEL IS TAKEN THE LENGTHSCALE OF THIS RBF COMPONENT CONTROLS THE DECAY TIME AND IS A FURTHER FREE PARAMETER
• SMALLER MEDIUM TERM IRREGULARITIES ARE TO BE EXPLAINED BY A RATIONALQUADRATIC KERNEL COMPONENT WHOSE LENGTH SCALE AND ALPHA PARAMETER WHICH DETERMINES THE DIFFUSENESS OF THE LENGTHSCALES ARE TO BE DETERMINED AC CORDING TO RW2006 THESE IRREGULARITIES CAN BETTER BE EXPLAINED BY A RATIONALQUADRATIC THAN AN RBF KERNEL COMPONENT PROBABLY BECAUSE IT CAN ACCOMMODATE SEVERAL LENGTHSCALES
• A “NOISE” TERM CONSISTING OF AN RBF KERNEL CONTRIBUTION WHICH SHALL EXPLAIN THE CORRELATED NOISE COMPONENTS SUCH AS LOCAL WEATHER PHENOMENA AND A WHITEKERNEL CONTRIBUTION FOR THE WHITE NOISE THE RELATIVE AMPLITUDES AND THE RBF’S LENGTH SCALE ARE FURTHER FREE PARAMETERS
MAXIMIZING THE LOGMARGINALLIKELIHOOD AFTER SUBTRACTING THE TARGET’S MEAN YIELDS THE FOLLOWING KERNEL WITH AN LML OF 83214
3442RBFLENGTHSCALE418
3272RBFLENGTHSCALE180 EXPSINESQUAREDLENGTHSCALE144
PERIODICITY1
04462RATIONALQUADRATICALPHA177 LENGTHSCALE0957
01972RBFLENGTHSCALE0138 WHITEKERNELNOISELEVEL00336
THUS MOST OF THE TARGET SIGNAL 344PPM IS EXPLAINED BY A LONGTERM RISING TREND LENGTHSCALE 418 YEARS THE PERIODIC COMPONENT HAS AN AMPLITUDE OF 327PPM A DECAY TIME OF 180 YEARS AND A LENGTHSCALE OF 144 THE LONG DECAY TIME INDICATES THAT WE HAVE A LOCALLY VERY CLOSE TO PERIODIC SEASONAL COMPONENT THE CORRELATED NOISE HAS AN AMPLITUDE OF 0197PPM WITH A LENGTH SCALE OF 0138 YEARS AND A WHITENOISE CONTRIBUTION OF 0197PPM THUS THE OVERALL NOISE LEVEL IS VERY SMALL INDICATING THAT THE DATA CAN BE VERY WELL EXPLAINED BY THE MODEL THE FIGURE SHOWS ALSO THAT THE MODEL MAKES VERY CONFIDENT PREDICTIONS UNTIL AROUND 2015
GAUSSIAN PROCESS CLASSIFICATION GPC
THEGAUSSIANPROCESSCLASSIFIER IMPLEMENTS GAUSSIAN PROCESSES GP FOR CLASSIFICATION PURPOSES MORE SPECIFICALLY FOR PROBABILISTIC CLASSIFICATION WHERE TEST PREDICTIONS TAKE THE FORM OF CLASS PROBABILITIES GAUSSIANPRO CESSCLASSIFIER PLACES A GP PRIOR ON A LATENT FUNCTION WHICH IS THEN SQUASHED THROUGH A LINK FUNCTION TO OBTAIN THE PROBABILISTIC CLASSIFICATION THE LATENT FUNCTION IS A SOCALLED NUISANCE FUNCTION WHOSE VALUES ARE NOT OBSERVED AND ARE NOT RELEVANT BY THEMSELVES ITS PURPOSE IS TO ALLOW A CONVENIENT FORMULATION OF THE MODEL AND IS REMOVED INTE GRATED OUT DURING PREDICTION GAUSSIANPROCESSCLASSIFIER IMPLEMENTS THE LOGISTIC LINK FUNCTION FOR WHICH THE INTEGRAL CANNOT BE COMPUTED ANALYTICALLY BUT IS EASILY APPROXIMATED IN THE BINARY CASE
IN CONTRAST TO THE REGRESSION SETTING THE POSTERIOR OF THE LATENT FUNCTION IS NOT GAUSSIAN EVEN FOR A GP PRIOR SINCE A GAUSSIAN LIKELIHOOD IS INAPPROPRIATE FOR DISCRETE CLASS LABELS RATHER A NONGAUSSIAN LIKELIHOOD CORRESPONDING TO THE LOGISTIC LINK FUNCTION LOGIT IS USED GAUSSIANPROCESSCLASSIFIER APPROXIMATES THE NONGAUSSIAN POSTERIOR WITH A GAUSSIAN BASED ON THE LAPLACE APPROXIMATION MORE DETAILS CAN BE FOUND IN CHAPTER 3 OF RW2006
THE GP PRIOR MEAN IS ASSUMED TO BE ZERO THE PRIOR’S COVARIANCE IS SPECIFIED BY PASSING A KERNEL OBJECT THE HYPER PARAMETERS OF THE KERNEL ARE OPTIMIZED DURING FITTING OF GAUSSIANPROCESSREGRESSOR BY MAXIMIZING THE LOGMARGINAL LIKELIHOOD LML BASED ON THE PASSED OPTIMIZER AS THE LML MAY HAVE MULTIPLE LOCAL OPTIMA THE OPTIMIZER CAN BE STARTED REPEATEDLY BY SPECIFYING NRESTARTSOPTIMIZER THE FIRST RUN IS ALWAYS CONDUCTED STARTING FROM THE INITIAL HYPERPARAMETER VALUES OF THE KERNEL SUBSEQUENT RUNS ARE CONDUCTED FROM HYPERPARAMETER VALUES THAT HAVE BEEN CHOSEN RANDOMLY FROM THE RANGE OF ALLOWED VALUES IF THE INITIAL HYPERPARAMETERS SHOULD BE KEPT FIXED NONE CAN BE PASSED AS OPTIMIZER

GAUSSIANPROCESSCLASSIFIER SUPPORTS MULTICLASS CLASSIFICATION BY PERFORMING EITHER ONEVERSUSREST OR ONE VERSUSONE BASED TRAINING AND PREDICTION IN ONEVERSUSREST ONE BINARY GAUSSIAN PROCESS CLASSIFIER IS FITTED FOR EACH CLASS WHICH IS TRAINED TO SEPARATE THIS CLASS FROM THE REST IN “ONEVSONE” ONE BINARY GAUSSIAN PROCESS CLASSIFIER IS FITTED FOR EACH PAIR OF CLASSES WHICH IS TRAINED TO SEPARATE THESE TWO CLASSES THE PREDICTIONS OF THESE BINARY PREDICTORS ARE COMBINED INTO MULTICLASS PREDICTIONS SEE THE SECTION ON MULTICLASS CLASSIFICATION FOR MORE DETAILS

IN THE CASE OF GAUSSIAN PROCESS CLASSIFICATION “ONEVSONE” MIGHT BE COMPUTATIONALLY CHEAPER SINCE IT HAS TO SOLVE MANY PROBLEMS INVOLVING ONLY A SUBSET OF THE WHOLE TRAINING SET RATHER THAN FEWER PROBLEMS ON THE WHOLE DATASET SINCE GAUSSIAN PROCESS CLASSIFICATION SCALES CUBICALLY WITH THE SIZE OF THE DATASET THIS MIGHT BE CONSIDERABLY FASTER HOW EVER NOTE THAT “ONEVSONE” DOES NOT SUPPORT PREDICTING PROBABILITY ESTIMATES BUT ONLY PLAIN PREDICTIONS MOREOVER NOTE THATGAUSSIANPROCESSCLASSIFIER DOES NOT YET IMPLEMENT A TRUE MULTICLASS LAPLACE APPROXIMATION IN TERNALLY BUT AS DISCUSSED ABOVE IS BASED ON SOLVING SEVERAL BINARY CLASSIFICATION TASKS INTERNALLY WHICH ARE COMBINED USING ONEVERSUSREST OR ONEVERSUSONE

GPC EXAMPLES

PROBABILISTIC PREDICTIONS WITH GPC

THIS EXAMPLE ILLUSTRATES THE PREDICTED PROBABILITY OF GPC FOR AN RBF KERNEL WITH DIFFERENT CHOICES OF THE HYPERPARAM ETERS THE FIRST FIGURE SHOWS THE PREDICTED PROBABILITY OF GPC WITH ARBITRARILY CHOSEN HYPERPARAMETERS AND WITH THE HYPERPARAMETERS CORRESPONDING TO THE MAXIMUM LOGMARGINALLIKELIHOOD LML

WHILE THE HYPERPARAMETERS CHOSEN BY OPTIMIZING LML HAVE A CONSIDERABLE LARGER LML THEY PERFORM SLIGHTLY WORSE ACCORDING TO THE LOGLOSS ON TEST DATA THE FIGURE SHOWS THAT THIS IS BECAUSE THEY EXHIBIT A STEEP CHANGE OF THE CLASS PROBABILITIES AT THE CLASS BOUNDARIES WHICH IS GOOD BUT HAVE PREDICTED PROBABILITIES CLOSE TO 05 FAR AWAY FROM THE CLASS BOUNDARIES WHICH IS BAD THIS UNDESIRABLE EFFECT IS CAUSED BY THE LAPLACE APPROXIMATION USED INTERNALLY BY GPC

THE SECOND FIGURE SHOWS THE LOGMARGINALLIKELIHOOD FOR DIFFERENT CHOICES OF THE KERNEL’S HYPERPARAMETERS HIGHLIGHTING THE TWO CHOICES OF THE HYPERPARAMETERS USED IN THE FIRST FIGURE BY BLACK DOTS

ILLUSTRATION OF GPC ON THE XOR DATASET

THIS EXAMPLE ILLUSTRATES GPC ON XOR DATA COMPARED ARE A STATIONARY ISOTROPIC KERNEL RBF AND A NONSTATIONARY KERNEL DOTPRODUCT ON THIS PARTICULAR DATASET THE DOTPRODUCT KERNEL OBTAINS CONSIDERABLY BETTER RESULTS BE CAUSE THE CLASSBOUNDARIES ARE LINEAR AND COINCIDE WITH THE COORDINATE AXES IN PRACTICE HOWEVER STATIONARY KERNELS SUCH ASRBF OFTEN OBTAIN BETTER RESULTS

GAUSSIAN PROCESS CLASSIFICATION GPC ON IRIS DATASET

THIS EXAMPLE ILLUSTRATES THE PREDICTED PROBABILITY OF GPC FOR AN ISOTROPIC AND ANISOTROPIC RBF KERNEL ON A TWO DIMENSIONAL VERSION FOR THE IRISDATASET THIS ILLUSTRATES THE APPLICABILITY OF GPC TO NONBINARY CLASSIFICATION THE ANISOTROPIC RBF KERNEL OBTAINS SLIGHTLY HIGHER LOGMARGINALLIKELIHOOD BY ASSIGNING DIFFERENT LENGTHSCALES TO THE TWO FEATURE DIMENSIONS

KERNELS FOR GAUSSIAN PROCESSES

KERNELS ALSO CALLED “COVARIANCE FUNCTIONS” IN THE CONTEXT OF GPS ARE A CRUCIAL INGREDIENT OF GPS WHICH DETERMINE THE SHAPE OF PRIOR AND POSTERIOR OF THE GP THEY ENCODE THE ASSUMPTIONS ON THE FUNCTION BEING LEARNED BY DEFINING THE “SIMILARITY” OF TWO DATAPOINTS COMBINED WITH THE ASSUMPTION THAT SIMILAR DATAPOINTS SHOULD HAVE SIMILAR TARGET VALUES TWO CATEGORIES OF KERNELS CAN BE DISTINGUISHED STATIONARY KERNELS DEPEND ONLY ON THE DISTANCE OF TWO DATAPOINTS AND NOT ON THEIR ABSOLUTE VALUES □□□ □□ □□□□ □□AND ARE THUS INVARIANT TO TRANSLATIONS IN THE INPUT SPACE

WHILE NONSTATIONARY KERNELS DEPEND ALSO ON THE SPECIFIC VALUES OF THE DATAPOINTS STATIONARY KERNELS CAN FURTHER BE SUBDIVIDED INTO ISOTROPIC AND ANISOTROPIC KERNELS WHERE ISOTROPIC KERNELS ARE ALSO INVARIANT TO ROTATIONS IN THE INPUT SPACE FOR MORE DETAILS WE REFER TO CHAPTER 4 OF RW2006

GAUSSIAN PROCESS KERNEL API

THE MAIN USAGE OF A KERNEL IS TO COMPUTE THE GP'S COVARIANCE BETWEEN DATAPOINTS FOR THIS THE METHOD CALL OF THE KERNEL CAN BE CALLED THIS METHOD CAN EITHER BE USED TO COMPUTE THE "AUTOCOVARIANCE" OF ALL PAIRS OF DATAPOINTS IN A 2D ARRAY X OR THE "CROSSCOVARIANCE" OF ALL COMBINATIONS OF DATAPOINTS OF A 2D ARRAY X WITH DATAPOINTS IN A 2D ARRAY Y THE FOLLOWING IDENTITY HOLDS TRUE FOR ALL KERNELS K EXCEPT FOR THE WHITEKERNEL KX KX YX

IF ONLY THE DIAGONAL OF THE AUTOCOVARIANCE IS BEING USED THE METHOD DIAG OF A KERNEL CAN BE CALLED WHICH IS MORE COMPUTATIONALLY EFFICIENT THAN THE EQUIVALENT CALL TO CALL NPDIAGKX X KDIAGX

KERNELS ARE PARAMETERIZED BY A VECTOR □OF HYPERPARAMETERS THESE HYPERPARAMETERS CAN FOR INSTANCE CONTROL LENGTH SCALES OR PERIODICITY OF A KERNEL SEE BELOW ALL KERNELS SUPPORT COMPUTING ANALYTIC GRADIENTS OF THE KERNEL'S AUTO COVARIANCE WITH RESPECT TO □VIA SETTINGEVALGRADIENTTRUE IN THECALL METHOD THIS GRADIENT IS USED BY THE GAUSSIAN PROCESS BOTH REGRESSOR AND CLASSIFIER IN COMPUTING THE GRADIENT OF THE LOGMARGINALLIKELIHOOD WHICH IN TURN IS USED TO DETERMINE THE VALUE OF □ WHICH MAXIMIZES THE LOGMARGINALLIKELIHOOD VIA GRADIENT ASCENT FOR EACH HYPERPARAMETER THE INITIAL VALUE AND THE BOUNDS NEED TO BE SPECIFIED WHEN CREATING AN INSTANCE OF THE KERNEL THE CURRENT VALUE OF □CAN BE GET AND SET VIA THE PROPERTY THETA OF THE KERNEL OBJECT MOREOVER THE BOUNDS OF THE HYPERPARAMETERS CAN BE ACCESSED BY THE PROPERTY BOUNDS OF THE KERNEL NOTE THAT BOTH PROPERTIES THETA AND BOUNDS RETURN LOGTRANSFORMED VALUES OF THE INTERNALLY USED VALUES SINCE THOSE ARE TYPICALLY MORE AMENABLE TO GRADIENTBASED OPTIMIZATION THE SPECIFICATION OF EACH HYPERPARAMETER IS STORED IN THE FORM OF AN INSTANCE OF HYPERPARAMETER IN THE RESPECTIVE KERNEL NOTE THAT A KERNEL USING A HYPERPARAMETER WITH NAME "X" MUST HAVE THE ATTRIBUTES SELFX AND SELFXBOUNDS

THE ABSTRACT BASE CLASS FOR ALL KERNELS IS KERNEL KERNEL IMPLEMENTS A SIMILAR INTERFACE AS ESTIMATOR PROVIDING THE METHODS GETPARAMS SETPARAMS ANDCLONE THIS ALLOWS SETTING KERNEL VALUES ALSO VIA META ESTIMATORS SUCH AS PIPELINE ORGRIDSEARCH NOTE THAT DUE TO THE NESTED STRUCTURE OF KERNELS BY APPLYING KERNEL OPERATORS SEE BELOW THE NAMES OF KERNEL PARAMETERS MIGHT BECOME RELATIVELY COMPLICATED IN GENERAL FOR A BINARY KERNEL OPERATOR PARAMETERS OF THE LEFT OPERAND ARE PREFIXED WITH K1 AND PARAMETERS OF THE RIGHT OPERAND WITH K2 AN ADDITIONAL CONVENIENCE METHOD IS CLONEWITHTHETATHETA WHICH RETURNS A CLONED VERSION OF THE KERNEL

BUT WITH THE HYPERPARAMETERS SET TO THETA AN ILLUSTRATIVE EXAMPLE
 FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT CONSTANTKERNEL RBF
KERNEL CONSTANTKERNELCONSTANTVALUE10 CONSTANTVALUEBOUNDS00 100
‘→RBFLENGTHSCALE05 LENGTHSCALEBOUNDS00 100 RBFLENGTHSCALE20
‘→LENGTHSCALEBOUNDS00 100
 FOR HYPERPARAMETER INKERNELHYPERPARAMETERS PRINTHYPERPARAMETER
HYPERPARAMETERNAMEK1K1CONSTANTVALUE VALUETYPENUMERIC BOUNDSARRAY 0
‘→ 10 NELEMENTS1 FIXEDFALSE
HYPERPARAMETERNAMEK1K2LENGTHSCALE VALUETYPENUMERIC BOUNDSARRAY 0
‘→10 NELEMENTS1 FIXEDFALSE
HYPERPARAMETERNAMEK2LENGTHSCALE VALUETYPENUMERIC BOUNDSARRAY 0 10
‘→ NELEMENTS1 FIXEDFALSE
PARAMS KERNELGETPARAMS
 FOR KEYINSORTEDPARAMS PRINT SS KEY PARAMSKEY
K1 12RBFLENGTHSCALE05
K1K1 1 2
K1K1CONSTANTVALUE 10
K1K1CONSTANTVALUEBOUNDS 00 100
K1K2 RBFLENGTHSCALE05
K1K2LENGTHSCALE 05
K1K2LENGTHSCALEBOUNDS 00 100
K2 RBFLENGTHSCALE2
K2LENGTHSCALE 20
K2LENGTHSCALEBOUNDS 00 100
PRINTKERNELTHETA NOTE LOGTRANSFORMED
 0 069314718 069314718
PRINTKERNELBOUNDS NOTE LOGTRANSFORMED
 INF 230258509
 INF 230258509
 INF 230258509
ALL GAUSSIAN PROCESS KERNELS ARE INTEROPERABLE WITH SKLEARNMETRICSPAIRWISE AND VICE VERSA INSTANCES
OF SUBCLASSES OF KERNEL CAN BE PASSED AS METRIC TOPAIRWISEKERNELS FROMSKLEARNMETRICS
PAIRWISE MOREOVER KERNEL FUNCTIONS FROM PAIRWISE CAN BE USED AS GP KERNELS BY USING THE WRAPPER CLASS
PAIRWISEKERNEL THE ONLY CAVEAT IS THAT THE GRADIENT OF THE HYPERPARAMETERS IS NOT ANALYTIC BUT NUMERIC AND
ALL THOSE KERNELS SUPPORT ONLY ISOTROPIC DISTANCES THE PARAMETER GAMMA IS CONSIDERED TO BE A HYPERPARAMETER AND
MAY BE OPTIMIZED THE OTHER KERNEL PARAMETERS ARE SET DIRECTLY AT INITIALIZATION AND ARE KEPT FIXED
BASIC KERNELS
THECONSTANTKERNEL KERNEL CAN BE USED AS PART OF A PRODUCT KERNEL WHERE IT SCALES THE MAGNITUDE OF THE OTHER
FACTOR KERNEL OR AS PART OF A SUM KERNEL WHERE IT MODIFIES THE MEAN OF THE GAUSSIAN PROCESS IT DEPENDS ON A
PARAMETER □□□□□□□□□ □□□□□□ IT IS DEFINED AS
□□□ □□ □□□□□□□□□ □□□□□□∀□1 □2
THE MAIN USECASE OF THE WHITEKERNEL KERNEL IS AS PART OF A SUMKERNEL WHERE IT EXPLAINS THE NOISECOMPONENT OF
THE SIGNAL TUNING ITS PARAMETER □□□□□□ □□□□□□ CORRESPONDS TO ESTIMATING THE NOISELEVEL IT IS DEFINED AS
□□□ □□ □□□□□□ □□□□□□ IF□□□□ELSE0
KERNEL OPERATORS
KERNEL OPERATORS TAKE ONE OR TWO BASE KERNELS AND COMBINE THEM INTO A NEW KERNEL THE SUM KERNEL TAKES TWO KERNELS
□1AND□2AND COMBINES THEM VIA □□□□□□ □ □1□ □ □2□ □ THEPRODUCT KERNEL TAKES TWO KERNELS □1

AND□2AND COMBINES THEM VIA □□□□□□□□ □ □ □1□ □ □2□ □ THEEXPONENTIATION KERNEL TAKES ONE BASE KERNEL AND A SCALAR PARAMETER □□□□□□□□ AND COMBINES THEM VIA □□□□□ □ □□ □ EXPONENT

RADIALBASIS FUNCTION RBF KERNEL

THERBF KERNEL IS A STATIONARY KERNEL IT IS ALSO KNOWN AS THE “SQUARED EXPONENTIAL” KERNEL IT IS PARAMETERIZED BY A LENGTHSCALE PARAMETER □ 0 WHICH CAN EITHER BE A SCALAR ISOTROPIC VARIANT OF THE KERNEL OR A VECTOR WITH THE SAME NUMBER OF DIMENSIONS AS THE INPUTS □ANISOTROPIC VARIANT OF THE KERNEL THE KERNEL IS GIVEN BY

□□□ □□ EXP

−1

2□□□□ □ □□2

THIS KERNEL IS INFINITELY DIFFERENTIABLE WHICH IMPLIES THAT GPS WITH THIS KERNEL AS COVARIANCE FUNCTION HAVE MEAN SQUARE DERIVATIVES OF ALL ORDERS AND ARE THUS VERY SMOOTH THE PRIOR AND POSTERIOR OF A GP RESULTING FROM AN RBF KERNEL ARE SHOWN IN THE FOLLOWING FIGURE

MATÉRN KERNEL

THEMATERN KERNEL IS A STATIONARY KERNEL AND A GENERALIZATION OF THE RBF KERNEL IT HAS AN ADDITIONAL PARAMETER □ WHICH CONTROLS THE SMOOTHNESS OF THE RESULTING FUNCTION IT IS PARAMETERIZED BY A LENGTHSCALE PARAMETER □ 0 WHICH CAN EITHER BE A SCALAR ISOTROPIC VARIANT OF THE KERNEL OR A VECTOR WITH THE SAME NUMBER OF DIMENSIONS AS THE INPUTS □ ANISOTROPIC VARIANT OF THE KERNEL THE KERNEL IS GIVEN BY

□□□ □□ □2 1

□□2□−1

□√

2□□□□□ □ □□□

□□

□√

2□□□□□ □ □□

AS□→∞ THE MATÉRN KERNEL CONVERGES TO THE RBF KERNEL WHEN □ 12 THE MATÉRN KERNEL BECOMES IDENTICAL TO THE ABSOLUTE EXPONENTIAL KERNEL IE

□□□ □□ □2EXP

−□□□□□ □ □□

□1

2

IN PARTICULAR □ 32

□□□ □□ □2

1 □√

3□□□□ □ □□

EXP

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3□□□□ □ □□

□3

2

AND□ 52

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1 □√

5□□□□ □ □□ 5

3□2□□□□ □ □□2

EXP

−□√

5□□□□ □ □□

□5

2

ARE POPULAR CHOICES FOR LEARNING FUNCTIONS THAT ARE NOT INFINITELY DIFFERENTIABLE AS ASSUMED BY THE RBF KERNEL BUT AT LEAST ONCE □ 32 OR TWICE DIFFERENTIABLE □ 52

THE FLEXIBILITY OF CONTROLLING THE SMOOTHNESS OF THE LEARNED FUNCTION VIA □ALLOWS ADAPTING TO THE PROPERTIES OF THE TRUE UNDERLYING FUNCTIONAL RELATION THE PRIOR AND POSTERIOR OF A GP RESULTING FROM A MATÉRN KERNEL ARE SHOWN IN THE FOLLOWING FIGURE

SEERW2006 PP84 FOR FURTHER DETAILS REGARDING THE DIFFERENT VARIANTS OF THE MATÉRN KERNEL

RATIONAL QUADRATIC KERNEL

THERATIONALQUADRATIC KERNEL CAN BE SEEN AS A SCALE MIXTURE AN INFINITE SUM OF RBF KERNELS WITH DIFFERENT CHARACTERISTIC LENGTHSCALES IT IS PARAMETERIZED BY A LENGTHSCALE PARAMETER □ 0AND A SCALE MIXTURE PARAMETER □ 0 ONLY THE ISOTROPIC VARIANT WHERE □IS A SCALAR IS SUPPORTED AT THE MOMENT THE KERNEL IS GIVEN BY

□□□ □□
1 □□□ □□2
2□□2−□

THE PRIOR AND POSTERIOR OF A GP RESULTING FROM A RATIONALQUADRATIC KERNEL ARE SHOWN IN THE FOLLOWING FIGURE

EXPSINESQUARED KERNEL
THEEXPSINESQUARED KERNEL ALLOWS MODELING PERIODIC FUNCTIONS IT IS PARAMETERIZED BY A LENGTHSCALE PARAMETER
□ 0AND A PERIODICITY PARAMETER □ 0 ONLY THE ISOTROPIC VARIANT WHERE □IS A SCALAR IS SUPPORTED AT THE MOMENT
THE KERNEL IS GIVEN BY
□□□ □□ EXP
−2 SIN□□□□□ □□□2
THE PRIOR AND POSTERIOR OF A GP RESULTING FROM AN EXPSINESQUARED KERNEL ARE SHOWN IN THE FOLLOWING FIGURE

DOTPRODUCT KERNEL
THEDOTPRODUCT KERNEL IS NONSTATIONARY AND CAN BE OBTAINED FROM LINEAR REGRESSION BY PUTTING □01PRIORS ON THE COEFFICIENTS OF □□□ 1 □ AND A PRIOR OF □0 □2
0ON THE BIAS THE DOTPRODUCT KERNEL IS INVARIANT TO A
ROTATION OF THE COORDINATES ABOUT THE ORIGIN BUT NOT TRANSLATIONS IT IS PARAMETERIZED BY A PARAMETER □2
0 FOR □2
0 0
THE KERNEL IS CALLED THE HOMOGENEOUS LINEAR KERNEL OTHERWISE IT IS INHOMOGENEOUS THE KERNEL IS GIVEN BY
□□□ □□ □2
0□□·□□
THEDOTPRODUCT KERNEL IS COMMONLY COMBINED WITH EXPONENTIATION AN EXAMPLE WITH EXPONENT 2 IS SHOWN IN THE FOLLOWING FIGURE

SCIKITLEARN USER GUIDE RELEASE 0213
REFERENCES
318 CROSS DECOMPOSITION
THE CROSS DECOMPOSITION MODULE CONTAINS TWO MAIN FAMILIES OF ALGORITHMS THE PARTIAL LEAST SQUARES PLS AND THE CANONICAL CORRELATION ANALYSIS CCA
THESE FAMILIES OF ALGORITHMS ARE USEFUL TO FIND LINEAR RELATIONS BETWEEN TWO MULTIVARIATE DATASETS THE XANDYARGUMENTS OF THE FIT METHOD ARE 2D ARRAYS
CROSS DECOMPOSITION ALGORITHMS FIND THE FUNDAMENTAL RELATIONS BETWEEN TWO MATRICES X AND Y THEY ARE LATENT VARIABLE APPROACHES TO MODELING THE COVARIANCE STRUCTURES IN THESE TWO SPACES THEY WILL TRY TO FIND THE MULTIDIMENSIONAL DIRECTION IN THE X SPACE THAT EXPLAINS THE MAXIMUM MULTIDIMENSIONAL VARIANCE DIRECTION IN THE Y SPACE PLSREGRESSION IS PARTICULARLY SUITED WHEN THE MATRIX OF PREDICTORS HAS MORE VARIABLES THAN OBSERVATIONS AND WHEN THERE IS MULTICOLLINEARITY AMONG X VALUES BY CONTRAST STANDARD REGRESSION WILL FAIL IN THESE CASES
CLASSES INCLUDED IN THIS MODULE ARE PLSREGRESSIONPLSCANONICAL CCA ANDPLSSVD
REFERENCE
• JA WEGELIN A SURVEY OF PARTIAL LEAST SQUARES PLS METHODS WITH EMPHASIS ON THE TWOBLOCK CASE
EXAMPLES
31 SUPERVISED LEARNING 275

•COMPARE CROSS DECOMPOSITION METHODS
319 NAIVE BAYES
NAIVE BAYES METHODS ARE A SET OF SUPERVISED LEARNING ALGORITHMS BASED ON APPLYING BAYES' THEOREM WITH THE "NAIVE" ASSUMPTION OF CONDITIONAL INDEPENDENCE BETWEEN EVERY PAIR OF FEATURES GIVEN THE VALUE OF THE CLASS VARIABLE BAYES' THEOREM STATES THE FOLLOWING RELATIONSHIP GIVEN CLASS VARIABLE □AND DEPENDENT FEATURE VECTOR □1THROUGH □□
□□□1 □ □ □□□□1 □ □□
□□1 □ □
USING THE NAIVE CONDITIONAL INDEPENDENCE ASSUMPTION THAT
□□□□ □1 □ □−1 □□1 □ □ □□□□
FOR ALL □ THIS RELATIONSHIP IS SIMPLIFIED TO
□□□1 □ □ □□Π□
□1□□□□
□□1 □ □
SINCE □□1 □ □IS CONSTANT GIVEN THE INPUT WE CAN USE THE FOLLOWING CLASSIFICATION RULE
□□□1 □ □∝□□□Π
□1□□□□
⇓
□ ARG MAX
□□□□Π
□1□□□□
AND WE CAN USE MAXIMUM A POSTERIORI MAP ESTIMATION TO ESTIMATE □□AND□□□□ THE FORMER IS THEN THE RELATIVE FREQUENCY OF CLASS □IN THE TRAINING SET
THE DIFFERENT NAIVE BAYES CLASSIFIERS DIFFER MAINLY BY THE ASSUMPTIONS THEY MAKE REGARDING THE DISTRIBUTION OF □□□ □
IN SPITE OF THEIR APPARENTLY OVERSIMPLIFIED ASSUMPTIONS NAIVE BAYES CLASSIFIERS HAVE WORKED QUITE WELL IN MANY REAL WORLD SITUATIONS FAMOUSLY DOCUMENT CLASSIFICATION AND SPAM FILTERING THEY REQUIRE A SMALL AMOUNT OF TRAINING DATA TO ESTIMATE THE NECESSARY PARAMETERS FOR THEORETICAL REASONS WHY NAIVE BAYES WORKS WELL AND ON WHICH TYPES OF DATA IT DOES SEE THE REFERENCES BELOW
NAIVE BAYES LEARNERS AND CLASSIFIERS CAN BE EXTREMELY FAST COMPARED TO MORE SOPHISTICATED METHODS THE DECOUPLING OF THE CLASS CONDITIONAL FEATURE DISTRIBUTIONS MEANS THAT EACH DISTRIBUTION CAN BE INDEPENDENTLY ESTIMATED AS A ONE DIMENSIONAL DISTRIBUTION THIS IN TURN HELPS TO ALLEVIATE PROBLEMS STEMMING FROM THE CURSE OF DIMENSIONALITY
ON THE FLIP SIDE ALTHOUGH NAIVE BAYES IS KNOWN AS A DECENT CLASSIFIER IT IS KNOWN TO BE A BAD ESTIMATOR SO THE PROBABILITY OUTPUTS FROM PREDICTPROBA ARE NOT TO BE TAKEN TOO SERIOUSLY
REFERENCES
• H ZHANG 2004 THE OPTIMALITY OF NAIVE BAYES PROC FLAIRS

GAUSSIAN NAIVE BAYES

GAUSSIANNB IMPLEMENTS THE GAUSSIAN NAIVE BAYES ALGORITHM FOR CLASSIFICATION THE LIKELIHOOD OF THE FEATURES IS ASSUMED TO BE GAUSSIAN

□□□□ 1√
2□□2□EXP
−□□−□□2
2□2□

THE PARAMETERS □□AND□□ARE ESTIMATED USING MAXIMUM LIKELIHOOD

```
 FROM SKLEARN IMPORT DATASETS
IRIS  DATASETSLOADIRIS
 FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
GNB  GAUSSIANNB
YPRED  GNBFITIRISDATA IRISTARGETPREDICTIRISDATA
PRINTNUMBER OF MISLABELED POINTS OUT OF A TOTAL DPOINTS  D
  IRISDATASHAPE0IRISTARGET  YPREDSUM
NUMBER OF MISLABELED POINTS OUT OF A TOTAL 150 POINTS  6
```

MULTINOMIAL NAIVE BAYES

MULTINOMIALNB IMPLEMENTS THE NAIVE BAYES ALGORITHM FOR MULTINOMIALLY DISTRIBUTED DATA AND IS ONE OF THE TWO CLASSIC NAIVE BAYES VARIANTS USED IN TEXT CLASSIFICATION WHERE THE DATA ARE TYPICALLY REPRESENTED AS WORD VECTOR COUNTS ALTHOUGH TFIDF VECTORS ARE ALSO KNOWN TO WORK WELL IN PRACTICE THE DISTRIBUTION IS PARAMETRIZED BY VECTORS □□ □□1 □ □□FOR EACH CLASS □ WHERE □IS THE NUMBER OF FEATURES IN TEXT CLASSIFICATION THE SIZE OF THE VOCABULARY AND□□□IS THE PROBABILITY □□□□OF FEATURE □APPEARING IN A SAMPLE BELONGING TO CLASS □

THE PARAMETERS □□IS ESTIMATED BY A SMOOTHED VERSION OF MAXIMUM LIKELIHOOD IE RELATIVE FREQUENCY COUNTING

□□□□□□□□
□□□□

WHERE □□□∑
□∈□□□IS THE NUMBER OF TIMES FEATURE □APPEARS IN A SAMPLE OF CLASS □IN THE TRAINING SET □ AND
□□∑□
□1□□□IS THE TOTAL COUNT OF ALL FEATURES FOR CLASS □

THE SMOOTHING PRIORS □≥0ACCOUNTS FOR FEATURES NOT PRESENT IN THE LEARNING SAMPLES AND PREVENTS ZERO PROBABILITIES IN FURTHER COMPUTATIONS SETTING □ 1IS CALLED LAPLACE SMOOTHING WHILE □ 1IS CALLED LIDSTONE SMOOTHING

COMPLEMENT NAIVE BAYES

COMPLEMENTNB IMPLEMENTS THE COMPLEMENT NAIVE BAYES CNB ALGORITHM CNB IS AN ADAPTATION OF THE STANDARD MULTINOMIAL NAIVE BAYES MNB ALGORITHM THAT IS PARTICULARLY SUITED FOR IMBALANCED DATA SETS SPECIFICALLY CNB USES STATISTICS FROM THE COMPLEMENT OF EACH CLASS TO COMPUTE THE MODEL'S WEIGHTS THE INVENTORS OF CNB SHOW EMPIRICALLY THAT THE PARAMETER ESTIMATES FOR CNB ARE MORE STABLE THAN THOSE FOR MNB FURTHER CNB REGULARLY OUTPERFORMS MNB OFTEN BY A CONSIDERABLE MARGIN ON TEXT CLASSIFICATION TASKS THE PROCEDURE FOR CALCULATING THE WEIGHTS IS AS FOLLOWS

□□□□□∑
□□∕□□□□
□∑
□□∕□□∑
□□□□
□□□ LOG □□□
□□□□□□∑
□□□□

WHERE THE SUMMATIONS ARE OVER ALL DOCUMENTS □NOT IN CLASS □□□□IS EITHER THE COUNT OR TFIDF VALUE OF TERM □IN DOCUMENT □□□IS A SMOOTHING HYPERPARAMETER LIKE THAT FOUND IN MNB AND □∑
□□□ THE SECOND NORMALIZATION

ADDRESSES THE TENDENCY FOR LONGER DOCUMENTS TO DOMINATE PARAMETER ESTIMATES IN MNB THE CLASSIFICATION RULE IS
□ ARG MIN
□Σ
□□□□□□
IE A DOCUMENT IS ASSIGNED TO THE CLASS THAT IS THE POOREST COMPLEMENT MATCH
REFERENCES
• RENNIE J D SHIH L TEEVAN J KARGER D R 2003 TACKLING THE POOR ASSUMPTIONS OF NAIVE BAYES TEXT
CLASSIFIERS IN ICML V OL 3 PP 616623
BERNOULLI NAIVE BAYES
BERNOULLINB IMPLEMENTS THE NAIVE BAYES TRAINING AND CLASSIFICATION ALGORITHMS FOR DATA THAT IS DISTRIBUTED AC
CORDING TO MULTIVARIATE BERNOULLI DISTRIBUTIONS IE THERE MAY BE MULTIPLE FEATURES BUT EACH ONE IS ASSUMED TO BE A
BINARYVALUED BERNOULLI BOOLEAN VARIABLE THEREFORE THIS CLASS REQUIRES SAMPLES TO BE REPRESENTED AS BINARYVALUED
FEATURE VECTORS IF HANDED ANY OTHER KIND OF DATA A BERNOULLINB INSTANCE MAY BINARIZE ITS INPUT DEPENDING ON THE
BINARIZE PARAMETER
THE DECISION RULE FOR BERNOULLI NAIVE BAYES IS BASED ON
□□□□ □□□□□ 1−□□□1−□□
WHICH DIFFERS FROM MULTINOMIAL NB’S RULE IN THAT IT EXPLICITLY PENALIZES THE NONOCCURRENCE OF A FEATURE □THAT IS AN
INDICATOR FOR CLASS □ WHERE THE MULTINOMIAL VARIANT WOULD SIMPLY IGNORE A NONOCCURRING FEATURE
IN THE CASE OF TEXT CLASSIFICATION WORD OCCURRENCE VECTORS RATHER THAN WORD COUNT VECTORS MAY BE USED TO TRAIN AND
USE THIS CLASSIFIER BERNOULLINB MIGHT PERFORM BETTER ON SOME DATASETS ESPECIALLY THOSE WITH SHORTER DOCUMENTS
IT IS ADVISABLE TO EVALUATE BOTH MODELS IF TIME PERMITS
REFERENCES
• CD MANNING P RAGHAVAN AND H SCHÜTZE 2008 INTRODUCTION TO INFORMATION RETRIEVAL CAMBRIDGE UNI
VERSITY PRESS PP 234265
• A MCCALLUM AND K NIGAM 1998 A COMPARISON OF EVENT MODELS FOR NAIVE BAYES TEXT CLASSIFICATION PROC
AAAIICML98 WORKSHOP ON LEARNING FOR TEXT CATEGORIZATION PP 4148
• V METSIS I ANDROUTSOPOULOS AND G PALIOURAS 2006 SPAM FILTERING WITH NAIVE BAYES – WHICH NAIVE
BAYES 3RD CONF ON EMAIL AND ANTISPAM CEAS
OUTOFCORE NAIVE BAYES MODEL FITTING
NAIVE BAYES MODELS CAN BE USED TO TACKLE LARGE SCALE CLASSIFICATION PROBLEMS FOR WHICH THE FULL TRAINING SET MIGHT NOT FIT
IN MEMORY TO HANDLE THIS CASE MULTINOMIALNB BERNOULLINB ANDGAUSSIANNB EXPOSE APARTIALFIT
METHOD THAT CAN BE USED INCREMENTALLY AS DONE WITH OTHER CLASSIFIERS AS DEMONSTRATED IN OUTOFCORE CLASSIFICATION OF
TEXT DOCUMENTS ALL NAIVE BAYES CLASSIFIERS SUPPORT SAMPLE WEIGHTING
CONTRARY TO THE FIT METHOD THE FIRST CALL TO PARTIALFIT NEEDS TO BE PASSED THE LIST OF ALL THE EXPECTED CLASS LABELS
FOR AN OVERVIEW OF AVAILABLE STRATEGIES IN SCIKITLEARN SEE ALSO THE OUTOFCORE LEARNING DOCUMENTATION

NOTE THEPARTIALFIT METHOD CALL OF NAIVE BAYES MODELS INTRODUCES SOME COMPUTATIONAL OVERHEAD IT IS RECOMMENDED TO USE DATA CHUNK SIZES THAT ARE AS LARGE AS POSSIBLE THAT IS AS THE AVAILABLE RAM ALLOWS

3110 DECISION TREES

DECISION TREES DTS ARE A NONPARAMETRIC SUPERVISED LEARNING METHOD USED FOR CLASSIFICATION ANDREGRESSION THE GOAL IS TO CREATE A MODEL THAT PREDICTS THE VALUE OF A TARGET VARIABLE BY LEARNING SIMPLE DECISION RULES INFERRED FROM THE DATA FEATURES

FOR INSTANCE IN THE EXAMPLE BELOW DECISION TREES LEARN FROM DATA TO APPROXIMATE A SINE CURVE WITH A SET OF IFTHENELSE DECISION RULES THE DEEPER THE TREE THE MORE COMPLEX THE DECISION RULES AND THE FITTER THE MODEL

SOME ADVANTAGES OF DECISION TREES ARE

• SIMPLE TO UNDERSTAND AND TO INTERPRET TREES CAN BE VISUALISED

• REQUIRES LITTLE DATA PREPARATION OTHER TECHNIQUES OFTEN REQUIRE DATA NORMALISATION DUMMY VARIABLES NEED TO BE CREATED AND BLANK VALUES TO BE REMOVED NOTE HOWEVER THAT THIS MODULE DOES NOT SUPPORT MISSING VALUES

• THE COST OF USING THE TREE IE PREDICTING DATA IS LOGARITHMIC IN THE NUMBER OF DATA POINTS USED TO TRAIN THE TREE

• ABLE TO HANDLE BOTH NUMERICAL AND CATEGORICAL DATA OTHER TECHNIQUES ARE USUALLY SPECIALISED IN ANALYSING DATASETS THAT HAVE ONLY ONE TYPE OF VARIABLE SEE ALGORITHMS FOR MORE INFORMATION

• ABLE TO HANDLE MULTIOUTPUT PROBLEMS

• USES A WHITE BOX MODEL IF A GIVEN SITUATION IS OBSERVABLE IN A MODEL THE EXPLANATION FOR THE CONDITION IS EASILY EXPLAINED BY BOOLEAN LOGIC BY CONTRAST IN A BLACK BOX MODEL EG IN AN ARTIFICIAL NEURAL NETWORK RESULTS MAY BE MORE DIFFICULT TO INTERPRET

• POSSIBLE TO VALIDATE A MODEL USING STATISTICAL TESTS THAT MAKES IT POSSIBLE TO ACCOUNT FOR THE RELIABILITY OF THE MODEL

• PERFORMS WELL EVEN IF ITS ASSUMPTIONS ARE SOMEWHAT VIOLATED BY THE TRUE MODEL FROM WHICH THE DATA WERE GENERATED

THE DISADVANTAGES OF DECISION TREES INCLUDE

• DECISIONTREE LEARNERS CAN CREATE OVERCOMPLEX TREES THAT DO NOT GENERALISE THE DATA WELL THIS IS CALLED OVERFITTING MECHANISMS SUCH AS PRUNING NOT CURRENTLY SUPPORTED SETTING THE MINIMUM NUMBER OF SAMPLES REQUIRED AT A LEAF NODE OR SETTING THE MAXIMUM DEPTH OF THE TREE ARE NECESSARY TO AVOID THIS PROBLEM

• DECISION TREES CAN BE UNSTABLE BECAUSE SMALL VARIATIONS IN THE DATA MIGHT RESULT IN A COMPLETELY DIFFERENT TREE BEING GENERATED THIS PROBLEM IS MITIGATED BY USING DECISION TREES WITHIN AN ENSEMBLE

• THE PROBLEM OF LEARNING AN OPTIMAL DECISION TREE IS KNOWN TO BE NPCOMPLETE UNDER SEVERAL ASPECTS OF OPTIMALITY AND EVEN FOR SIMPLE CONCEPTS CONSEQUENTLY PRACTICAL DECISIONTREE LEARNING ALGORITHMS ARE BASED ON HEURISTIC ALGORITHMS SUCH AS THE GREEDY ALGORITHM WHERE LOCALLY OPTIMAL DECISIONS ARE MADE AT EACH NODE SUCH ALGORITHMS CANNOT GUARANTEE TO RETURN THE GLOBALLY OPTIMAL DECISION TREE THIS CAN BE MITIGATED BY TRAINING MULTIPLE TREES IN AN ENSEMBLE LEARNER WHERE THE FEATURES AND SAMPLES ARE RANDOMLY SAMPLED WITH REPLACEMENT

• THERE ARE CONCEPTS THAT ARE HARD TO LEARN BECAUSE DECISION TREES DO NOT EXPRESS THEM EASILY SUCH AS XOR PARITY OR MULTIPLEXER PROBLEMS

• DECISION TREE LEARNERS CREATE BIASED TREES IF SOME CLASSES DOMINATE IT IS THEREFORE RECOMMENDED TO BALANCE THE DATASET PRIOR TO FITTING WITH THE DECISION TREE

CLASSIFICATION

DECISIONTREECLASSIFIER IS A CLASS CAPABLE OF PERFORMING MULTICLASS CLASSIFICATION ON A DATASET

AS WITH OTHER CLASSIFIERS DECISIONTREECLASSIFIER TAKES AS INPUT TWO ARRAYS AN ARRAY X SPARSE OR DENSE OF SIZENSAMPLES NFEATURES HOLDING THE TRAINING SAMPLES AND AN ARRAY Y OF INTEGER VALUES SIZE NSAMPLES HOLDING THE CLASS LABELS FOR THE TRAINING SAMPLES

```
 FROM SKLEARN IMPORT TREE
X  0 0 1 1
Y  0 1
CLF  TREEDECISIONTREECLASSIFIER
CLF  CLFFITX Y
```

AFTER BEING FITTED THE MODEL CAN THEN BE USED TO PREDICT THE CLASS OF SAMPLES

```
CLFPREDICT2 2
ARRAY1
```

ALTERNATIVELY THE PROBABILITY OF EACH CLASS CAN BE PREDICTED WHICH IS THE FRACTION OF TRAINING SAMPLES OF THE SAME CLASS IN A LEAF

```
CLFPREDICTPROBA2 2
ARRAY0 1
```

DECISIONTREECLASSIFIER IS CAPABLE OF BOTH BINARY WHERE THE LABELS ARE 1 1 CLASSIFICATION AND MULTICLASS WHERE THE LABELS ARE 0   K1 CLASSIFICATION

USING THE IRIS DATASET WE CAN CONSTRUCT A TREE AS FOLLOWS

```
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARN IMPORT TREE
IRIS  LOADIRIS
CLF  TREEDECISIONTREECLASSIFIER
CLF  CLFFITIRISDATA IRISTARGET
```

ONCE TRAINED YOU CAN PLOT THE TREE WITH THE PLOTTREE FUNCTION
TREEPLOTTREECLFFITIRISDATA IRISTARGET
WE CAN ALSO EXPORT THE TREE IN GRAPHVIZ FORMAT USING THE EXPORTGRAPHVIZ EXPORTER IF YOU USE THE CONDA PACKAGE MANAGER THE GRAPHVIZ BINARIES
AND THE PYTHON PACKAGE CAN BE INSTALLED WITH
CONDA INSTALL PYTHONGRAPHVIZ
ALTERNATIVELY BINARIES FOR GRAPHVIZ CAN BE DOWNLOADED FROM THE GRAPHVIZ PROJECT HOMEPAGE AND THE PYTHON WRAPPER INSTALLED FROM PYPI WITH PIP INSTALL GRAPHVIZ
BELOW IS AN EXAMPLE GRAPHVIZ EXPORT OF THE ABOVE TREE TRAINED ON THE ENTIRE IRIS DATASET THE RESULTS ARE SAVED IN AN OUTPUT FILEIRISPDF
```
 IMPORT GRAPHVIZ
DOTDATA  TREEEXPORTGRAPHVIZCLF OUTFILE NONE
GRAPH  GRAPHVIZSOURCEDOTDATA
GRAPHRENDERIRIS
```
THEEXPORTGRAPHVIZ EXPORTER ALSO SUPPORTS A VARIETY OF AESTHETIC OPTIONS INCLUDING COLORING NODES BY THEIR CLASS OR VALUE FOR REGRESSION AND USING EXPLICIT VARIABLE AND CLASS NAMES IF DESIRED JUPYTER NOTEBOOKS ALSO RENDER THESE PLOTS INLINE AUTOMATICALLY
```
DOTDATA  TREEEXPORTGRAPHVIZCLF OUTFILE NONE
 FEATURENAMESIRISFEATURENAMES
 CLASSNAMESIRISTARGETNAMES
 FILLEDTRUE ROUNDED TRUE
 SPECIALCHARACTERS TRUE
GRAPH  GRAPHVIZSOURCEDOTDATA
GRAPH
```

ALTERNATIVELY THE TREE CAN ALSO BE EXPORTED IN TEXTUAL FORMAT WITH THE FUNCTION EXPORTTEXT THIS METHOD DOESN’T REQUIRE THE INSTALLATION OF EXTERNAL LIBRARIES AND IS MORE COMPACT

```
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
 FROM SKLEARNTREEEXPORT IMPORT EXPORTTEXT
IRIS  LOADIRIS
X  IRISDATA
Y  IRISTARGET
DECISIONTREE  DECISIONTREECLASSIFIERRANDOMSTATE0 MAXDEPTH2
DECISIONTREE  DECISIONTREEFITX Y
R  EXPORTTEXTDECISIONTREE FEATURENAMESIRISFEATURENAMES
PRINTR
 PETAL WIDTH CM  080
  CLASS 0
 PETAL WIDTH CM  080
  PETAL WIDTH CM  175
   CLASS 1
  PETAL WIDTH CM  175
   CLASS 2
```

EXAMPLES

•PLOT THE DECISION SURFACE OF A DECISION TREE ON THE IRIS DATASET

•UNDERSTANDING THE DECISION TREE STRUCTURE

REGRESSION

DECISION TREES CAN ALSO BE APPLIED TO REGRESSION PROBLEMS USING THE DECISIONTREEREGRESSOR CLASS

AS IN THE CLASSIFICATION SETTING THE FIT METHOD WILL TAKE AS ARGUMENT ARRAYS X AND Y ONLY THAT IN THIS CASE Y IS EXPECTED TO HAVE FLOATING POINT VALUES INSTEAD OF INTEGER VALUES

```
 FROM SKLEARN IMPORT TREE
X  0 0 2 2
Y  05 25
CLF  TREEDECISIONTREEREGRESSOR
CLF  CLFFITX Y
CLFPREDICT1 1
ARRAY05
```

EXAMPLES

•DECISION TREE REGRESSION

MULTIOUTPUT PROBLEMS

A MULTIOUTPUT PROBLEM IS A SUPERVISED LEARNING PROBLEM WITH SEVERAL OUTPUTS TO PREDICT THAT IS WHEN Y IS A 2D ARRAY OF SIZENSAMPLES NOUTPUTS

WHEN THERE IS NO CORRELATION BETWEEN THE OUTPUTS A VERY SIMPLE WAY TO SOLVE THIS KIND OF PROBLEM IS TO BUILD N INDEPENDENT MODELS IE ONE FOR EACH OUTPUT AND THEN TO USE THOSE MODELS TO INDEPENDENTLY PREDICT EACH ONE OF THE N OUTPUTS HOWEVER BECAUSE IT IS LIKELY THAT THE OUTPUT VALUES RELATED TO THE SAME INPUT ARE THEMSELVES CORRELATED AN OFTEN BETTER WAY IS TO BUILD A SINGLE MODEL CAPABLE OF PREDICTING SIMULTANEOUSLY ALL N OUTPUTS FIRST IT REQUIRES LOWER TRAINING TIME SINCE ONLY A SINGLE ESTIMATOR IS BUILT SECOND THE GENERALIZATION ACCURACY OF THE RESULTING ESTIMATOR MAY OFTEN BE INCREASED

WITH REGARD TO DECISION TREES THIS STRATEGY CAN READILY BE USED TO SUPPORT MULTIOUTPUT PROBLEMS THIS REQUIRES THE FOLLOWING CHANGES

• STORE N OUTPUT VALUES IN LEAVES INSTEAD OF 1

• USE SPLITTING CRITERIA THAT COMPUTE THE AVERAGE REDUCTION ACROSS ALL N OUTPUTS

THIS MODULE OFFERS SUPPORT FOR MULTIOUTPUT PROBLEMS BY IMPLEMENTING THIS STRATEGY IN BOTH DECISIONTREECLASSIFIER ANDDECISIONTREEREGRESSOR IF A DECISION TREE IS FIT ON AN OUTPUT ARRAY Y OF SIZE NSAMPLES NOUTPUTS THEN THE RESULTING ESTIMATOR WILL

• OUTPUT NOUTPUT VALUES UPON PREDICT

• OUTPUT A LIST OF NOUTPUT ARRAYS OF CLASS PROBABILITIES UPON PREDICTPROBA

THE USE OF MULTIOUTPUT TREES FOR REGRESSION IS DEMONSTRATED IN MULTIOUTPUT DECISION TREE REGRESSION IN THIS EXAMPLE THE INPUT X IS A SINGLE REAL VALUE AND THE OUTPUTS Y ARE THE SINE AND COSINE OF X

THE USE OF MULTIOUTPUT TREES FOR CLASSIFICATION IS DEMONSTRATED IN FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS IN THIS EXAMPLE THE INPUTS X ARE THE PIXELS OF THE UPPER HALF OF FACES AND THE OUTPUTS Y ARE THE PIXELS OF THE LOWER HALF OF THOSE FACES

EXAMPLES

•MULTIOUTPUT DECISION TREE REGRESSION

•FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS

REFERENCES

• M DUMONT ET AL FAST MULTICLASS IMAGE ANNOTATION WITH RANDOM SUBWINDOWS AND MULTIPLE OUTPUT RANDOMIZED TREES INTERNATIONAL CONFERENCE ON COMPUTER VISION THEORY AND APPLICATIONS 2009

COMPLEXITY

IN GENERAL THE RUN TIME COST TO CONSTRUCT A BALANCED BINARY TREE IS □□□□□□□□□ □□□□□□□□□ LOG□□□□□□□□□ AND QUERY TIME□LOG□□□□□□□□□ ALTHOUGH THE TREE CONSTRUCTION ALGORITHM ATTEMPTS TO GENERATE BALANCED TREES THEY WILL NOT ALWAYS BE BALANCED ASSUMING THAT THE SUBTREES REMAIN APPROXIMATELY BALANCED THE COST AT EACH NODE CONSISTS OF SEARCHING THROUGH □□□□□□□□□□ TO FIND THE FEATURE THAT OFFERS THE LARGEST REDUCTION IN ENTROPY THIS HAS A COST OF □□□□□□□□□□ □□□□□□□□□ LOG□□□□□□□□□ AT EACH NODE LEADING TO A TOTAL COST OVER THE ENTIRE TREES BY SUMMING THE COST AT EACH NODE OF □□□□□□□□□□ □2
□□□□□□□ LOG□□□□□□□□□

SCIKITLEARN OFFERS A MORE EFFICIENT IMPLEMENTATION FOR THE CONSTRUCTION OF DECISION TREES A NAIVE IMPLEMENTATION AS ABOVE WOULD RECOMPUTE THE CLASS LABEL HISTOGRAMS FOR CLASSIFICATION OR THE MEANS FOR REGRESSION AT FOR EACH NEW SPLIT POINT ALONG A GIVEN FEATURE PRESORTING THE FEATURE OVER ALL RELEVANT SAMPLES AND RETAINING A RUNNING LA BEL COUNT WILL REDUCE THE COMPLEXITY AT EACH NODE TO □□□□□□□□□□ LOG□□□□□□□□□ WHICH RESULTS IN A TOTAL COST OF □□□□□□□□□□ □□□□□□□□□ LOG□□□□□□□□□ THIS IS AN OPTION FOR ALL TREE BASED ALGORITHMS BY DEFAULT IT IS TURNED ON FOR GRADIENT BOOSTING WHERE IN GENERAL IT MAKES TRAINING FASTER BUT TURNED OFF FOR ALL OTHER ALGORITHMS AS IT TENDS TO SLOW DOWN TRAINING WHEN TRAINING DEEP TREES

TIPS ON PRACTICAL USE

• DECISION TREES TEND TO OVERFIT ON DATA WITH A LARGE NUMBER OF FEATURES GETTING THE RIGHT RATIO OF SAMPLES TO NUMBER OF FEATURES IS IMPORTANT SINCE A TREE WITH FEW SAMPLES IN HIGH DIMENSIONAL SPACE IS VERY LIKELY TO OVERFIT

• CONSIDER PERFORMING DIMENSIONALITY REDUCTION PCA ICA ORFEATURE SELECTION BEFOREHAND TO GIVE YOUR TREE A BETTER CHANCE OF FINDING FEATURES THAT ARE DISCRIMINATIVE
•UNDERSTANDING THE DECISION TREE STRUCTURE WILL HELP IN GAINING MORE INSIGHTS ABOUT HOW THE DECISION TREE MAKES PREDICTIONS WHICH IS IMPORTANT FOR UNDERSTANDING THE IMPORTANT FEATURES IN THE DATA
• VISUALISE YOUR TREE AS YOU ARE TRAINING BY USING THE EXPORT FUNCTION USE MAXDEPTH3 AS AN INITIAL TREE DEPTH TO GET A FEEL FOR HOW THE TREE IS FITTING TO YOUR DATA AND THEN INCREASE THE DEPTH
• REMEMBER THAT THE NUMBER OF SAMPLES REQUIRED TO POPULATE THE TREE DOUBLES FOR EACH ADDITIONAL LEVEL THE TREE GROWS TO USE MAXDEPTH TO CONTROL THE SIZE OF THE TREE TO PREVENT OVERFITTING
• USEMINSAMPLESSPLIT ORMINSAMPLESLEAF TO ENSURE THAT MULTIPLE SAMPLES INFORM EVERY DECISION IN THE TREE BY CONTROLLING WHICH SPLITS WILL BE CONSIDERED A VERY SMALL NUMBER WILL USUALLY MEAN THE TREE WILL OVERFIT WHEREAS A LARGE NUMBER WILL PREVENT THE TREE FROM LEARNING THE DATA TRY MINSAMPLESLEAF5 AS AN INITIAL VALUE IF THE SAMPLE SIZE VARIES GREATLY A FLOAT NUMBER CAN BE USED AS PERCENTAGE IN THESE TWO PARAMETERS WHILEMINSAMPLESSPLIT CAN CREATE ARBITRARILY SMALL LEAVES MINSAMPLESLEAF GUARANTEES THAT EACH LEAF HAS A MINIMUM SIZE AVOIDING LOWVARIANCE OVERFIT LEAF NODES IN REGRESSION PROBLEMS FOR CLASSIFICATION WITH FEW CLASSES MINSAMPLESLEAF1 IS OFTEN THE BEST CHOICE
• BALANCE YOUR DATASET BEFORE TRAINING TO PREVENT THE TREE FROM BEING BIASED TOWARD THE CLASSES THAT ARE DOMINANT CLASS BALANCING CAN BE DONE BY SAMPLING AN EQUAL NUMBER OF SAMPLES FROM EACH CLASS OR PREFERABLY BY NOR MALIZING THE SUM OF THE SAMPLE WEIGHTS SAMPLEWEIGHT FOR EACH CLASS TO THE SAME VALUE ALSO NOTE THAT WEIGHTBASED PREPRUNING CRITERIA SUCH AS MINWEIGHTFRACTIONLEAF WILL THEN BE LESS BIASED TOWARD DOMINANT CLASSES THAN CRITERIA THAT ARE NOT AWARE OF THE SAMPLE WEIGHTS LIKE MINSAMPLESLEAF
• IF THE SAMPLES ARE WEIGHTED IT WILL BE EASIER TO OPTIMIZE THE TREE STRUCTURE USING WEIGHTBASED PREPRUNING CRITERION SUCH AS MINWEIGHTFRACTIONLEAF WHICH ENSURE THAT LEAF NODES CONTAIN AT LEAST A FRACTION OF THE OVERALL SUM OF THE SAMPLE WEIGHTS
• ALL DECISION TREES USE NPFLOAT32 ARRAYS INTERNALLY IF TRAINING DATA IS NOT IN THIS FORMAT A COPY OF THE DATASET WILL BE MADE
• IF THE INPUT MATRIX X IS VERY SPARSE IT IS RECOMMENDED TO CONVERT TO SPARSE CSCMATRIX BEFORE CALLING FIT AND SPARSECSRMATRIX BEFORE CALLING PREDICT TRAINING TIME CAN BE ORDERS OF MAGNITUDE FASTER FOR A SPARSE MATRIX INPUT COMPARED TO A DENSE MATRIX WHEN FEATURES HAVE ZERO VALUES IN MOST OF THE SAMPLES
TREE ALGORITHMS ID3 C45 C50 AND CART
WHAT ARE ALL THE VARIOUS DECISION TREE ALGORITHMS AND HOW DO THEY DIFFER FROM EACH OTHER WHICH ONE IS IMPLEMENTED IN SCIKITLEARN
ID3 ITERATIVE DICHOTOMISER 3 WAS DEVELOPED IN 1986 BY ROSS QUINLAN THE ALGORITHM CREATES A MULTIWAY TREE FINDING FOR EACH NODE IE IN A GREEDY MANNER THE CATEGORICAL FEATURE THAT WILL YIELD THE LARGEST INFORMATION GAIN FOR CATEGORICAL TARGETS TREES ARE GROWN TO THEIR MAXIMUM SIZE AND THEN A PRUNING STEP IS USUALLY APPLIED TO IMPROVE THE ABILITY OF THE TREE TO GENERALISE TO UNSEEN DATA
C45 IS THE SUCCESSOR TO ID3 AND REMOVED THE RESTRICTION THAT FEATURES MUST BE CATEGORICAL BY DYNAMICALLY DEFINING A DISCRETE ATTRIBUTE BASED ON NUMERICAL VARIABLES THAT PARTITIONS THE CONTINUOUS ATTRIBUTE VALUE INTO A DISCRETE SET OF INTERVALS C45 CONVERTS THE TRAINED TREES IE THE OUTPUT OF THE ID3 ALGORITHM INTO SETS OF IFTHEN RULES THESE ACCURACY OF EACH RULE IS THEN EVALUATED TO DETERMINE THE ORDER IN WHICH THEY SHOULD BE APPLIED PRUNING IS DONE BY REMOVING A RULE’S PRECONDITION IF THE ACCURACY OF THE RULE IMPROVES WITHOUT IT
C50 IS QUINLAN’S LATEST VERSION RELEASE UNDER A PROPRIETARY LICENSE IT USES LESS MEMORY AND BUILDS SMALLER RULESETS THAN C45 WHILE BEING MORE ACCURATE
CART CLASSIFICATION AND REGRESSION TREES IS VERY SIMILAR TO C45 BUT IT DIFFERS IN THAT IT SUPPORTS NUMERICAL TARGET VARIABLES REGRESSION AND DOES NOT COMPUTE RULE SETS CART CONSTRUCTS BINARY TREES USING THE FEATURE AND THRESHOLD THAT YIELD THE LARGEST INFORMATION GAIN AT EACH NODE

SCIKITLEARN USES AN OPTIMISED VERSION OF THE CART ALGORITHM HOWEVER SCIKITLEARN IMPLEMENTATION DOES NOT SUPPORT CATEGORICAL VARIABLES FOR NOW

MATHEMATICAL FORMULATION

GIVEN TRAINING VECTORS □□∈□□ I1 L AND A LABEL VECTOR □∈□□ A DECISION TREE RECURSIVELY PARTITIONS THE SPACE SUCH THAT THE SAMPLES WITH THE SAME LABELS ARE GROUPED TOGETHER

LET THE DATA AT NODE □BE REPRESENTED BY □ FOR EACH CANDIDATE SPLIT □ □ □□CONSISTING OF A FEATURE □AND THRESHOLD □□ PARTITION THE DATA INTO □□□□□□ANDD□□□□*h*□□SUBSETS

□□□□□□□ □ □□□□□□

□□□□*h*□□ □\□□□□□□□

THE IMPURITY AT □IS COMPUTED USING AN IMPURITY FUNCTION □ THE CHOICE OF WHICH DEPENDS ON THE TASK BEING SOLVED CLASSIFICATION OR REGRESSION

□□ □ □□□□□□

□□□□□□□□□□ □□□□*h*□

□□□□□□□□*h*□□

SELECT THE PARAMETERS THAT MINIMISES THE IMPURITY

□ ARGMIN□□□ □

RECURSE FOR SUBSETS □□□□□□ANDD□□□□*h*□□UNTIL THE MAXIMUM ALLOWABLE DEPTH IS REACHED □□MIN□□□□□□□ OR □□ 1

CLASSIFICATION CRITERIA

IF A TARGET IS A CLASSIFICATION OUTCOME TAKING ON VALUES 01 K1 FOR NODE □ REPRESENTING A REGION □□WITH□□ OBSERVATIONS LET

□□□ 1□□Σ

□□∈□□□□□□

BE THE PROPORTION OF CLASS K OBSERVATIONS IN NODE □

COMMON MEASURES OF IMPURITY ARE GINI

□□□ Σ

□□□□1−□□□

ENTROPY

□□□ −Σ

□□□□LOG□□□

AND MISCLASSIFICATION

□□□ 1−MAX □□□

WHERE □□IS THE TRAINING DATA IN NODE □

REGRESSION CRITERIA
IF THE TARGET IS A CONTINUOUS VALUE THEN FOR NODE □ REPRESENTING A REGION □□WITH□□OBSERVATIONS COMMON CRITERIA TO MINIMISE AS FOR DETERMINING LOCATIONS FOR FUTURE SPLITS ARE MEAN SQUARED ERROR WHICH MINIMIZES THE L2 ERROR USING MEAN VALUES AT TERMINAL NODES AND MEAN ABSOLUTE ERROR WHICH MINIMIZES THE L1 ERROR USING MEDIAN VALUES AT TERMINAL NODES
MEAN SQUARED ERROR
□□□1
□□∑
□∈□□□□
□□□ 1
□□∑
□∈□□□□−□□□2
MEAN ABSOLUTE ERROR
□□□1
□□∑
□∈□□□□
□□□ 1
□□∑
□∈□□□□−□□□
WHERE □□IS THE TRAINING DATA IN NODE □
REFERENCES
• HTTPSENWIKIPEDIAORGWIKIDECISIONTREELEARNING
• HTTPSENWIKIPEDIAORGWIKIPREDICTIVEANALYTICS
• L BREIMAN J FRIEDMAN R OLSHEN AND C STONE CLASSIFICATION AND REGRESSION TREES WADSWORTH BELMONT CA 1984
• JR QUINLAN C4 5 PROGRAMS FOR MACHINE LEARNING MORGAN KAUFMANN 1993
• T HASTIE R TIBSHIRANI AND J FRIEDMAN ELEMENTS OF STATISTICAL LEARNING SPRINGER 2009
3111 ENSEMBLE METHODS
THE GOAL OF ENSEMBLE METHODS IS TO COMBINE THE PREDICTIONS OF SEVERAL BASE ESTIMATORS BUILT WITH A GIVEN LEARNING ALGORITHM IN ORDER TO IMPROVE GENERALIZABILITY ROBUSTNESS OVER A SINGLE ESTIMATOR
TWO FAMILIES OF ENSEMBLE METHODS ARE USUALLY DISTINGUISHED
• IN AVERAGING METHODS THE DRIVING PRINCIPLE IS TO BUILD SEVERAL ESTIMATORS INDEPENDENTLY AND THEN TO AVERAGE THEIR PREDICTIONS ON AVERAGE THE COMBINED ESTIMATOR IS USUALLY BETTER THAN ANY OF THE SINGLE BASE ESTIMATOR BECAUSE ITS VARIANCE IS REDUCED
EXAMPLES BAGGING METHODS FORESTS OF RANDOMIZED TREES
• BY CONTRAST IN BOOSTING METHODS BASE ESTIMATORS ARE BUILT SEQUENTIALLY AND ONE TRIES TO REDUCE THE BIAS OF THE COMBINED ESTIMATOR THE MOTIVATION IS TO COMBINE SEVERAL WEAK MODELS TO PRODUCE A POWERFUL ENSEMBLE
EXAMPLES ADABOOST GRADIENT TREE BOOSTING

BAGGING METAESTIMATOR

IN ENSEMBLE ALGORITHMS BAGGING METHODS FORM A CLASS OF ALGORITHMS WHICH BUILD SEVERAL INSTANCES OF A BLACKBOX ESTIMATOR ON RANDOM SUBSETS OF THE ORIGINAL TRAINING SET AND THEN AGGREGATE THEIR INDIVIDUAL PREDICTIONS TO FORM A FINAL PREDICTION THESE METHODS ARE USED AS A WAY TO REDUCE THE VARIANCE OF A BASE ESTIMATOR EG A DECISION TREE BY INTRODUCING RANDOMIZATION INTO ITS CONSTRUCTION PROCEDURE AND THEN MAKING AN ENSEMBLE OUT OF IT IN MANY CASES BAGGING METHODS CONSTITUTE A VERY SIMPLE WAY TO IMPROVE WITH RESPECT TO A SINGLE MODEL WITHOUT MAKING IT NECESSARY TO ADAPT THE UNDERLYING BASE ALGORITHM AS THEY PROVIDE A WAY TO REDUCE OVERFITTING BAGGING METHODS WORK BEST WITH STRONG AND COMPLEX MODELS EG FULLY DEVELOPED DECISION TREES IN CONTRAST WITH BOOSTING METHODS WHICH USUALLY WORK BEST WITH WEAK MODELS EG SHALLOW DECISION TREES

BAGGING METHODS COME IN MANY FLAVOURS BUT MOSTLY DIFFER FROM EACH OTHER BY THE WAY THEY DRAW RANDOM SUBSETS OF THE TRAINING SET

• WHEN RANDOM SUBSETS OF THE DATASET ARE DRAWN AS RANDOM SUBSETS OF THE SAMPLES THEN THIS ALGORITHM IS KNOWN AS PASTING B1999

• WHEN SAMPLES ARE DRAWN WITH REPLACEMENT THEN THE METHOD IS KNOWN AS BAGGING B1996

• WHEN RANDOM SUBSETS OF THE DATASET ARE DRAWN AS RANDOM SUBSETS OF THE FEATURES THEN THE METHOD IS KNOWN AS RANDOM SUBSPACES H1998

• FINALLY WHEN BASE ESTIMATORS ARE BUILT ON SUBSETS OF BOTH SAMPLES AND FEATURES THEN THE METHOD IS KNOWN AS RANDOM PATCHES LG2012

IN SCIKITLEARN BAGGING METHODS ARE OFFERED AS A UNIFIED BAGGINGCLASSIFIER METAESTIMATOR RESP BAGGINGREGRESSOR TAKING AS INPUT A USERSPECIFIED BASE ESTIMATOR ALONG WITH PARAMETERS SPECIFYING THE STRATEGY TO DRAW RANDOM SUBSETS IN PARTICULAR MAXSAMPLES ANDMAXFEATURES CONTROL THE SIZE OF THE SUBSETS IN TERMS OF SAMPLES AND FEATURES WHILE BOOTSTRAP ANDBOOTSTRAPFEATURES CONTROL WHETHER SAMPLES AND FEATURES ARE DRAWN WITH OR WITHOUT REPLACEMENT WHEN USING A SUBSET OF THE AVAILABLE SAMPLES THE GENERALIZATION ACCURACY CAN BE ESTIMATED WITH THE OUTOFBAG SAMPLES BY SETTING OOBSCORETRUE AS AN EXAMPLE THE SNIPPET BELOW ILLUSTRATES HOW TO INSTANTIATE A BAGGING ENSEMBLE OF KNEIGHBORSCLASSIFIER BASE ESTIMATORS EACH BUILT ON RANDOM SUBSETS OF 50 OF THE SAMPLES AND 50 OF THE FEATURES

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 FROM SKLEARNENSEMBLE IMPORT BAGGINGCLASSIFIER
 FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSCLASSIFIER
BAGGING  BAGGINGCLASSIFIERKNEIGHBORSCLASSIFIER
 MAXSAMPLES05 MAXFEATURES05
```

EXAMPLES

•SINGLE ESTIMATOR VERSUS BAGGING BIASVARIANCE DECOMPOSITION

REFERENCES

FORESTS OF RANDOMIZED TREES

THESKLEARNENSEMBLE MODULE INCLUDES TWO AVERAGING ALGORITHMS BASED ON RANDOMIZED DECISION TREES THE RANDOMFOREST ALGORITHM AND THE EXTRATREES METHOD BOTH ALGORITHMS ARE PERTURBANDCOMBINE TECHNIQUES B1998 SPECIFICALLY DESIGNED FOR TREES THIS MEANS A DIVERSE SET OF CLASSIFIERS IS CREATED BY INTRODUCING RANDOMNESS IN THE CLASSIFIER CONSTRUCTION THE PREDICTION OF THE ENSEMBLE IS GIVEN AS THE AVERAGED PREDICTION OF THE INDIVIDUAL CLASSIFIERS

AS OTHER CLASSIFIERS FOREST CLASSIFIERS HAVE TO BE FITTED WITH TWO ARRAYS A SPARSE OR DENSE ARRAY X OF SIZE NSAMPLES NFEATURES HOLDING THE TRAINING SAMPLES AND AN ARRAY Y OF SIZE NSAMPLES HOLDING THE TARGET VALUES CLASS LABELS FOR THE TRAINING SAMPLES

```
 FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
X  0 0 1 1
Y  0 1
CLF  RANDOMFORESTCLASSIFIERNESTIMATORS10
CLF  CLFFITX Y
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LIKE DECISION TREES FORESTS OF TREES ALSO EXTEND TO MULTIOUTPUT PROBLEMS IF Y IS AN ARRAY OF SIZE NSAMPLES NOUTPUTS

RANDOM FORESTS

IN RANDOM FORESTS SEE RANDOMFORESTCLASSIFIER ANDRANDOMFORESTREGRESSOR CLASSES EACH TREE IN THE ENSEMBLE IS BUILT FROM A SAMPLE DRAWN WITH REPLACEMENT IE A BOOTSTRAP SAMPLE FROM THE TRAINING SET FURTHERMORE WHEN SPLITTING EACH NODE DURING THE CONSTRUCTION OF A TREE THE BEST SPLIT IS FOUND EITHER FROM ALL INPUT FEATURES OR A RANDOM SUBSET OF SIZE MAXFEATURES SEE THE PARAMETER TUNING GUIDELINES FOR MORE DETAILS

THE PURPOSE OF THESE TWO SOURCES OF RANDOMNESS IS TO DECREASE THE VARIANCE OF THE FOREST ESTIMATOR INDEED INDIVIDUAL DECISION TREES TYPICALLY EXHIBIT HIGH VARIANCE AND TEND TO OVERFIT THE INJECTED RANDOMNESS IN FORESTS YIELD DECISION TREES WITH SOMEWHAT DECOUPLED PREDICTION ERRORS BY TAKING AN AVERAGE OF THOSE PREDICTIONS SOME ERRORS CAN CANCEL OUT RANDOM FORESTS ACHIEVE A REDUCED VARIANCE BY COMBINING DIVERSE TREES SOMETIMES AT THE COST OF A SLIGHT INCREASE IN BIAS IN PRACTICE THE VARIANCE REDUCTION IS OFTEN SIGNIFICANT HENCE YIELDING AN OVERALL BETTER MODEL

IN CONTRAST TO THE ORIGINAL PUBLICATION B2001 THE SCIKITLEARN IMPLEMENTATION COMBINES CLASSIFIERS BY AVERAGING THEIR PROBABILISTIC PREDICTION INSTEAD OF LETTING EACH CLASSIFIER VOTE FOR A SINGLE CLASS

EXTREMELY RANDOMIZED TREES

IN EXTREMELY RANDOMIZED TREES SEE EXTRATREESCLASSIFIER ANDEXTRATREESREGRESSOR CLASSES RANDOM NESS GOES ONE STEP FURTHER IN THE WAY SPLITS ARE COMPUTED AS IN RANDOM FORESTS A RANDOM SUBSET OF CANDIDATE FEATURES IS USED BUT INSTEAD OF LOOKING FOR THE MOST DISCRIMINATIVE THRESHOLDS THRESHOLDS ARE DRAWN AT RANDOM FOR EACH CANDI DATE FEATURE AND THE BEST OF THESE RANDOMLYGENERATED THRESHOLDS IS PICKED AS THE SPLITTING RULE THIS USUALLY ALLOWS TO REDUCE THE VARIANCE OF THE MODEL A BIT MORE AT THE EXPENSE OF A SLIGHTLY GREATER INCREASE IN BIAS

```
 FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
 FROM SKLEARNDATASETS IMPORT MAKEBLOBS
 FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
 FROM SKLEARNENSEMBLE IMPORT EXTRATREESCLASSIFIER
 FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
X Y  MAKEBLOBSNSAMPLES10000 NFEATURES10 CENTERS100
 RANDOMSTATE0
CLF  DECISIONTREECLASSIFIERMAXDEPTH NONE MINSAMPLESSPLIT2
 RANDOMSTATE0
SCORES  CROSSVALSCORECLF X Y CV5
SCORESMEAN
098
CLF  RANDOMFORESTCLASSIFIERNESTIMATORS10 MAXDEPTH NONE
 MINSAMPLESSPLIT2 RANDOMSTATE0
SCORES  CROSSVALSCORECLF X Y CV5
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SCIKITLEARN USER GUIDE RELEASE 0213
SCORESMEAN
0999
CLF EXTRATREESCLASSIFIERNESTIMATORS10 MAXDEPTH NONE
 MINSAMPLESSPLIT2 RANDOMSTATE0
SCORES CROSSVALSCORECLF X Y CV5
SCORESMEAN 0999
TRUE
PARAMETERS
THE MAIN PARAMETERS TO ADJUST WHEN USING THESE METHODS IS NESTIMATORS ANDMAXFEATURES THE FORMER
IS THE NUMBER OF TREES IN THE FOREST THE LARGER THE BETTER BUT ALSO THE LONGER IT WILL TAKE TO COMPUTE IN ADDITION
NOTE THAT RESULTS WILL STOP GETTING SIGNIFICANTLY BETTER BEYOND A CRITICAL NUMBER OF TREES THE LATTER IS THE SIZE OF THE
RANDOM SUBSETS OF FEATURES TO CONSIDER WHEN SPLITTING A NODE THE LOWER THE GREATER THE REDUCTION OF VARIANCE BUT ALSO
THE GREATER THE INCREASE IN BIAS EMPIRICAL GOOD DEFAULT VALUES ARE MAXFEATURESNONE ALWAYS CONSIDERING ALL
FEATURES INSTEAD OF A RANDOM SUBSET FOR REGRESSION PROBLEMS AND MAXFEATURESSQRT USING A RANDOM SUBSET
OF SIZESQRTNFEATURES FOR CLASSIFICATION TASKS WHERE NFEATURES IS THE NUMBER OF FEATURES IN THE DATA
GOOD RESULTS ARE OFTEN ACHIEVED WHEN SETTING MAXDEPTHNONE IN COMBINATION WITH MINSAMPLESSPLIT2
IE WHEN FULLY DEVELOPING THE TREES BEAR IN MIND THOUGH THAT THESE VALUES ARE USUALLY NOT OPTIMAL AND MIGHT RESULT
IN MODELS THAT CONSUME A LOT OF RAM THE BEST PARAMETER VALUES SHOULD ALWAYS BE CROSSVALIDATED IN ADDITION NOTE
THAT IN RANDOM FORESTS BOOTSTRAP SAMPLES ARE USED BY DEFAULT BOOTSTRAPTRUE WHILE THE DEFAULT STRATEGY FOR
EXTRATREES IS TO USE THE WHOLE DATASET BOOTSTRAPFALSE WHEN USING BOOTSTRAP SAMPLING THE GENERALIZATION
ACCURACY CAN BE ESTIMATED ON THE LEFT OUT OR OUTOFBAG SAMPLES THIS CAN BE ENABLED BY SETTING OOBSCORETRUE
NOTE THE SIZE OF THE MODEL WITH THE DEFAULT PARAMETERS IS □□□□□□□ WHERE □IS THE NUMBER OF
TREES AND □IS THE NUMBER OF SAMPLES IN ORDER TO REDUCE THE SIZE OF THE MODEL YOU CAN CHANGE THESE PARAMETERS
MINSAMPLESSPLIT MAXLEAFNODES MAXDEPTH ANDMINSAMPLESLEAF

PARALLELIZATION
FINALLY THIS MODULE ALSO FEATURES THE PARALLEL CONSTRUCTION OF THE TREES AND THE PARALLEL COMPUTATION OF THE PREDICTIONS THROUGH THE NJOBS PARAMETER IF NJOBSK THEN COMPUTATIONS ARE PARTITIONED INTO KJOBS AND RUN ON KCORES OF THE MACHINE IF NJOBS1 THEN ALL CORES AVAILABLE ON THE MACHINE ARE USED NOTE THAT BECAUSE OF INTERPROCESS COMMUNICATION OVERHEAD THE SPEEDUP MIGHT NOT BE LINEAR IE USING KJOBS WILL UNFORTUNATELY NOT BE KTIMES AS FAST SIGNIFICANT SPEEDUP CAN STILL BE ACHIEVED THOUGH WHEN BUILDING A LARGE NUMBER OF TREES OR WHEN BUILDING A SINGLE TREE REQUIRES A FAIR AMOUNT OF TIME EG ON LARGE DATASETS
EXAMPLES
•PLOT THE DECISION SURFACES OF ENSEMBLES OF TREES ON THE IRIS DATASET
•PIXEL IMPORTANCES WITH A PARALLEL FOREST OF TREES
•FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS
REFERENCES
• P GEURTS D ERNST AND L WEHENKEL “EXTREMELY RANDOMIZED TREES” MACHINE LEARNING 631 342 2006
FEATURE IMPORTANCE EVALUATION
THE RELATIVE RANK IE DEPTH OF A FEATURE USED AS A DECISION NODE IN A TREE CAN BE USED TO ASSESS THE RELATIVE IMPORTANCE OF THAT FEATURE WITH RESPECT TO THE PREDICTABILITY OF THE TARGET VARIABLE FEATURES USED AT THE TOP OF THE TREE CONTRIBUTE TO THE FINAL PREDICTION DECISION OF A LARGER FRACTION OF THE INPUT SAMPLES THE EXPECTED FRACTION OF THE SAMPLES THEY CONTRIBUTE TO CAN THUS BE USED AS AN ESTIMATE OF THE RELATIVE IMPORTANCE OF THE FEATURES IN SCIKITLEARN THE FRACTION OF SAMPLES A FEATURE CONTRIBUTES TO IS COMBINED WITH THE DECREASE IN IMPURITY FROM SPLITTING THEM TO CREATE A NORMALIZED ESTIMATE OF THE PREDICTIVE POWER OF THAT FEATURE
BYAVERAGING THE ESTIMATES OF PREDICTIVE ABILITY OVER SEVERAL RANDOMIZED TREES ONE CAN REDUCE THE VARIANCE OF SUCH AN ESTIMATE AND USE IT FOR FEATURE SELECTION THIS IS KNOWN AS THE MEAN DECREASE IN IMPURITY OR MDI REFER TO L2014 FOR MORE INFORMATION ON MDI AND FEATURE IMPORTANCE EVALUATION WITH RANDOM FORESTS
THE FOLLOWING EXAMPLE SHOWS A COLORCODED REPRESENTATION OF THE RELATIVE IMPORTANCES OF EACH INDIVIDUAL PIXEL FOR A FACE RECOGNITION TASK USING A EXTRATREESCLASSIFIER MODEL
IN PRACTICE THOSE ESTIMATES ARE STORED AS AN ATTRIBUTE NAMED FEATUREIMPORTANCES ON THE FITTED MODEL THIS IS AN ARRAY WITH SHAPE NFEATURES WHOSE VALUES ARE POSITIVE AND SUM TO 10 THE HIGHER THE VALUE THE MORE IMPORTANT IS THE CONTRIBUTION OF THE MATCHING FEATURE TO THE PREDICTION FUNCTION
EXAMPLES
•PIXEL IMPORTANCES WITH A PARALLEL FOREST OF TREES
•FEATURE IMPORTANCES WITH FORESTS OF TREES
REFERENCES

TOTALLY RANDOM TREES EMBEDDING
RANDOMTREESEMBEDDING IMPLEMENTS AN UNSUPERVISED TRANSFORMATION OF THE DATA USING A FOREST OF COMPLETELY RANDOM TREES RANDOMTREESEMBEDDING ENCODES THE DATA BY THE INDICES OF THE LEAVES A DATA POINT ENDS UP IN THIS INDEX IS THEN ENCODED IN A ONEOFK MANNER LEADING TO A HIGH DIMENSIONAL SPARSE BINARY CODING THIS CODING CAN BE COMPUTED VERY EFFICIENTLY AND CAN THEN BE USED AS A BASIS FOR OTHER LEARNING TASKS THE SIZE AND SPARSITY OF THE CODE CAN BE INFLUENCED BY CHOOSING THE NUMBER OF TREES AND THE MAXIMUM DEPTH PER TREE FOR EACH TREE IN THE ENSEMBLE THE CODING CONTAINS ONE ENTRY OF ONE THE SIZE OF THE CODING IS AT MOST NESTIMATORS 2MAXDEPTH THE MAXIMUM NUMBER OF LEAVES IN THE FOREST
AS NEIGHBORING DATA POINTS ARE MORE LIKELY TO LIE WITHIN THE SAME LEAF OF A TREE THE TRANSFORMATION PERFORMS AN IMPLICIT NONPARAMETRIC DENSITY ESTIMATION
EXAMPLES
•HASHING FEATURE TRANSFORMATION USING TOTALLY RANDOM TREES
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP COMPARES NONLINEAR DIMEN SIONALITY REDUCTION TECHNIQUES ON HANDWRITTEN DIGITS
•FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES COMPARES SUPERVISED AND UNSUPERVISED TREE BASED FEATURE TRANSFORMATIONS
SEE ALSO
MANIFOLD LEARNING TECHNIQUES CAN ALSO BE USEFUL TO DERIVE NONLINEAR REPRESENTATIONS OF FEATURE SPACE ALSO THESE AP PROACHES FOCUS ALSO ON DIMENSIONALITY REDUCTION

ADABOOST

THE MODULE SKLEARNENSEMBLE INCLUDES THE POPULAR BOOSTING ALGORITHM ADABOOST INTRODUCED IN 1995 BY FREUND AND SCHAPIRE FS1995

THE CORE PRINCIPLE OF ADABOOST IS TO FIT A SEQUENCE OF WEAK LEARNERS IE MODELS THAT ARE ONLY SLIGHTLY BETTER THAN RANDOM GUESSING SUCH AS SMALL DECISION TREES ON REPEATEDLY MODIFIED VERSIONS OF THE DATA THE PREDICTIONS FROM ALL OF THEM ARE THEN COMBINED THROUGH A WEIGHTED MAJORITY VOTE OR SUM TO PRODUCE THE FINAL PREDICTION THE DATA MODIFICATIONS AT EACH SOCALLED BOOSTING ITERATION CONSIST OF APPLYING WEIGHTS □1□2 □□TO EACH OF THE TRAINING SAMPLES INITIALLY THOSE WEIGHTS ARE ALL SET TO □□ 1□ SO THAT THE FIRST STEP SIMPLY TRAINS A WEAK LEARNER ON THE ORIGINAL DATA FOR EACH SUCCESSIVE ITERATION THE SAMPLE WEIGHTS ARE INDIVIDUALLY MODIFIED AND THE LEARNING ALGORITHM IS REAPPLIED TO THE REWEIGHTED DATA AT A GIVEN STEP THOSE TRAINING EXAMPLES THAT WERE INCORRECTLY PREDICTED BY THE BOOSTED MODEL INDUCED AT THE PREVIOUS STEP HAVE THEIR WEIGHTS INCREASED WHEREAS THE WEIGHTS ARE DECREASED FOR THOSE THAT WERE PREDICTED CORRECTLY AS ITERATIONS PROCEED EXAMPLES THAT ARE DIFFICULT TO PREDICT RECEIVE EVERINCREASING INFLUENCE EACH SUBSEQUENT WEAK LEARNER IS THEREBY FORCED TO CONCENTRATE ON THE EXAMPLES THAT ARE MISSED BY THE PREVIOUS ONES IN THE SEQUENCE HTF

ADABOOST CAN BE USED BOTH FOR CLASSIFICATION AND REGRESSION PROBLEMS

- FOR MULTICLASS CLASSIFICATION ADABOOSTCLASSIFIER IMPLEMENTS ADABOOSTSAMME AND ADABOOST SAMMER ZZRH2009
- FOR REGRESSION ADABOOSTREGRESSOR IMPLEMENTS ADABOOSTR2 D1997

USAGE

THE FOLLOWING EXAMPLE SHOWS HOW TO FIT AN ADABOOST CLASSIFIER WITH 100 WEAK LEARNERS

```
 FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNENSEMBLE IMPORT ADABOOSTCLASSIFIER
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```
IRIS  LOADIRIS
CLF  ADABOOSTCLASSIFIERNESTIMATORS100
SCORES  CROSSVALSCORECLF IRISDATA IRISTARGET CV5
SCORESMEAN
09
```
THE NUMBER OF WEAK LEARNERS IS CONTROLLED BY THE PARAMETER NESTIMATORS THELEARNINGRATE PARAMETER CONTROLS THE CONTRIBUTION OF THE WEAK LEARNERS IN THE FINAL COMBINATION BY DEFAULT WEAK LEARNERS ARE DECISION STUMPS DIFFERENT WEAK LEARNERS CAN BE SPECIFIED THROUGH THE BASEESTIMATOR PARAMETER THE MAIN PARAMETERS TO TUNE TO OBTAIN GOOD RESULTS ARE NESTIMATORS AND THE COMPLEXITY OF THE BASE ESTIMATORS EG ITS DEPTH MAXDEPTH OR MINIMUM REQUIRED NUMBER OF SAMPLES TO CONSIDER A SPLIT MINSAMPLESSPLIT

EXAMPLES

•DISCRETE VERSUS REAL ADABOOST COMPARES THE CLASSIFICATION ERROR OF A DECISION STUMP DECISION TREE AND A BOOSTED DECISION STUMP USING ADABOOSTSAMME AND ADABOOSTSAMMER

•MULTICLASS ADABOOSTED DECISION TREES SHOWS THE PERFORMANCE OF ADABOOSTSAMME AND ADABOOST SAMMER ON A MULTICLASS PROBLEM

•TWOCLASS ADABOOST SHOWS THE DECISION BOUNDARY AND DECISION FUNCTION VALUES FOR A NONLINEARLY SEPARABLE TWOCLASS PROBLEM USING ADABOOSTSAMME

•DECISION TREE REGRESSION WITH ADABOOST DEMONSTRATES REGRESSION WITH THE ADABOOSTR2 ALGORITHM

REFERENCES

GRADIENT TREE BOOSTING

GRADIENT TREE BOOSTING OR GRADIENT BOOSTED REGRESSION TREES GBRT IS A GENERALIZATION OF BOOSTING TO ARBITRARY DIFFERENTIABLE LOSS FUNCTIONS GBRT IS AN ACCURATE AND EFFECTIVE OFFTHESHELF PROCEDURE THAT CAN BE USED FOR BOTH REGRESSION AND CLASSIFICATION PROBLEMS GRADIENT TREE BOOSTING MODELS ARE USED IN A VARIETY OF AREAS INCLUDING WEB SEARCH RANKING AND ECOLOGY

THE ADVANTAGES OF GBRT ARE

• NATURAL HANDLING OF DATA OF MIXED TYPE HETEROGENEOUS FEATURES

• PREDICTIVE POWER

• ROBUSTNESS TO OUTLIERS IN OUTPUT SPACE VIA ROBUST LOSS FUNCTIONS

THE DISADVANTAGES OF GBRT ARE

• SCALABILITY DUE TO THE SEQUENTIAL NATURE OF BOOSTING IT CAN HARDLY BE PARALLELIZED

THE MODULE SKLEARNENSEMBLE PROVIDES METHODS FOR BOTH CLASSIFICATION AND REGRESSION VIA GRADIENT BOOSTED REGRESSION TREES

NOTE SCIKITLEARN 021 INTRODUCES TWO NEW EXPERIMENTAL IMPLEMENTATION OF GRADIENT BOOSTING TREES NAMELY HISTGRADIENTBOOSTINGCLASSIFIER ANDHISTGRADIENTBOOSTINGREGRESSOR INSPIRED BY LIGHT GBM THESE FAST ESTIMATORS FIRST BIN THE INPUT SAMPLES XINTO INTEGERVALUED BINS TYPICALLY 256 BINS WHICH TREMEN DOUSLY REDUCES THE NUMBER OF SPLITTING POINTS TO CONSIDER AND ALLOW THE ALGORITHM TO LEVERAGE INTEGERBASED DATA STRUCTURES HISTOGRAMS INSTEAD OF RELYING ON SORTED CONTINUOUS VALUES

THE NEW HISTOGRAMBASED ESTIMATORS CAN BE ORDERS OF MAGNITUDE FASTER THAN THEIR CONTINUOUS COUNTERPARTS WHEN THE NUMBER OF SAMPLES IS LARGER THAN TENS OF THOUSANDS OF SAMPLES THE API OF THESE NEW ESTIMATORS IS SLIGHTLY DIFFERENT AND SOME OF THE FEATURES FROM GRADIENTBOOSTINGCLASSIFIER ANDGRADIENTBOOSTINGREGRESSOR ARE NOT YET SUPPORTED

THESE NEW ESTIMATORS ARE STILL EXPERIMENTAL FOR NOW THEIR PREDICTIONS AND THEIR API MIGHT CHANGE WITHOUT ANY DEPRECATION CYCLE TO USE THEM YOU NEED TO EXPLICITLY IMPORT ENABLEHISTGRADIENTBOOSTING

```
 EXPLICITLY REQUIRE THIS EXPERIMENTAL FEATURE
 FROM SKLEARNEXPERIMENTAL IMPORT ENABLEHISTGRADIENTBOOSTING  NOQA
 NOW YOU CAN IMPORT NORMALLY FROM ENSEMBLE
 FROM SKLEARNENSEMBLE IMPORT HISTGRADIENTBOOSTINGCLASSIFIER
```

THE FOLLOWING GUIDE FOCUSES ON GRADIENTBOOSTINGCLASSIFIER ANDGRADIENTBOOSTINGREGRESSOR ONLY WHICH MIGHT BE PREFERRED FOR SMALL SAMPLE SIZES SINCE BINNING MAY LEAD TO SPLIT POINTS THAT ARE TOO APPROXI MATE IN THIS SETTING

CLASSIFICATION

GRADIENTBOOSTINGCLASSIFIER SUPPORTS BOTH BINARY AND MULTICLASS CLASSIFICATION THE FOLLOWING EXAMPLE SHOWS HOW TO FIT A GRADIENT BOOSTING CLASSIFIER WITH 100 DECISION STUMPS AS WEAK LEARNERS

```
 FROM SKLEARNDATASETS IMPORT MAKEHASTIE102
 FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGCLASSIFIER
X Y  MAKEHASTIE102RANDOMSTATE0
XTRAIN XTEST  X2000 X2000
YTRAIN YTEST  Y2000 Y2000
CLF  GRADIENTBOOSTINGCLASSIFIERNESTIMATORS100 LEARNINGRATE10
 MAXDEPTH1 RANDOMSTATE0FITXTRAIN YTRAIN
CLFSCOREXTEST YTEST
0913
```

THE NUMBER OF WEAK LEARNERS IE REGRESSION TREES IS CONTROLLED BY THE PARAMETER NESTIMATORS THE SIZE OF EACH TREECAN BE CONTROLLED EITHER BY SETTING THE TREE DEPTH VIA MAXDEPTH OR BY SETTING THE NUMBER OF LEAF NODES VIA MAXLEAFNODES THELEARNINGRATE IS A HYPERPARAMETER IN THE RANGE 00 10 THAT CONTROLS OVERFITTING VIA SHRINKAGE

NOTE CLASSIFICATION WITH MORE THAN 2 CLASSES REQUIRES THE INDUCTION OF NCLASSES REGRESSION TREES AT EACH ITERATION THUS THE TOTAL NUMBER OF INDUCED TREES EQUALS NCLASSES NESTIMATORS FOR DATASETS WITH A LARGE NUMBER OF CLASSES WE STRONGLY RECOMMEND TO USE RANDOMFORESTCLASSIFIER AS AN ALTERNATIVE TO GRADIENTBOOSTINGCLASSIFIER

REGRESSION

GRADIENTBOOSTINGREGRESSOR SUPPORTS A NUMBER OF DIFFERENT LOSS FUNCTIONS FOR REGRESSION WHICH CAN BE SPECI FIED VIA THE ARGUMENT LOSS THE DEFAULT LOSS FUNCTION FOR REGRESSION IS LEAST SQUARES LS

```
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT MEANSQUAREDERROR
 FROM SKLEARNDATASETS IMPORT MAKEFRIEDMAN1
```

```
 FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGREGRESSOR
X Y  MAKEFRIEDMAN1NSAMPLES1200 RANDOMSTATE0 NOISE10
XTRAIN XTEST  X200 X200
YTRAIN YTEST  Y200 Y200
EST  GRADIENTBOOSTINGREGRESSORNESTIMATORS100 LEARNINGRATE01
 MAXDEPTH1 RANDOMSTATE0 LOSSLSFITXTRAIN YTRAIN
MEANSQUAREDERRORYTEST ESTPREDICTXTEST
500
```
THE FIGURE BELOW SHOWS THE RESULTS OF APPLYING GRADIENTBOOSTINGREGRESSOR WITH LEAST SQUARES LOSS AND 500 BASE LEARNERS TO THE BOSTON HOUSE PRICE DATASET SKLEARNDATASETSLOADBOSTON THE PLOT ON THE LEFT SHOWS THE TRAIN AND TEST ERROR AT EACH ITERATION THE TRAIN ERROR AT EACH ITERATION IS STORED IN THE TRAINSCORE ATTRIBUTE OF THE GRADIENT BOOSTING MODEL THE TEST ERROR AT EACH ITERATIONS CAN BE OBTAINED VIA THE STAGEDPREDICT METHOD WHICH RETURNS A GENERATOR THAT YIELDS THE PREDICTIONS AT EACH STAGE PLOTS LIKE THESE CAN BE USED TO DETERMINE THE OPTIMAL NUMBER OF TREES IE NESTIMATORS BY EARLY STOPPING THE PLOT ON THE RIGHT SHOWS THE FEATURE IMPORTANCES WHICH CAN BE OBTAINED VIA THE FEATUREIMPORTANCES PROPERTY

EXAMPLES

- GRADIENT BOOSTING REGRESSION
- GRADIENT BOOSTING OUTOFBAG ESTIMATES

FITTING ADDITIONAL WEAKLEARNERS

BOTHGRADIENTBOOSTINGREGRESSOR ANDGRADIENTBOOSTINGCLASSIFIER SUPPORT WARMSTARTTRUE WHICH ALLOWS YOU TO ADD MORE ESTIMATORS TO AN ALREADY FITTED MODEL

```
  ESTSETPARAMSNESTIMATORS200 WARMSTART TRUE SET WARMSTART AND NEW
‘→NR OF TREES
  ESTFITXTRAIN YTRAIN  FIT ADDITIONAL 100 TREES TO EST
MEANSQUAREDERRORYTEST ESTPREDICTXTEST
```


CONTROLLING THE TREE SIZE

THE SIZE OF THE REGRESSION TREE BASE LEARNERS DEFINES THE LEVEL OF VARIABLE INTERACTIONS THAT CAN BE CAPTURED BY THE GRADIENT BOOSTING MODEL IN GENERAL A TREE OF DEPTH HCAN CAPTURE INTERACTIONS OF ORDER H THERE ARE TWO WAYS IN WHICH THE SIZE OF THE INDIVIDUAL REGRESSION TREES CAN BE CONTROLLED

IF YOU SPECIFY MAXDEPTHH THEN COMPLETE BINARY TREES OF DEPTH HWILL BE GROWN SUCH TREES WILL HAVE AT MOST 2HLEAF NODES AND 2H 1 SPLIT NODES

ALTERNATIVELY YOU CAN CONTROL THE TREE SIZE BY SPECIFYING THE NUMBER OF LEAF NODES VIA THE PARAMETER MAXLEAFNODES IN THIS CASE TREES WILL BE GROWN USING BESTFIRST SEARCH WHERE NODES WITH THE HIGHEST IMPROVE MENT IN IMPURITY WILL BE EXPANDED FIRST A TREE WITH MAXLEAFNODESK HASK 1 SPLIT NODES AND THUS CAN MODEL INTERACTIONS OF UP TO ORDER MAXLEAFNODES 1

WE FOUND THAT MAXLEAFNODESK GIVES COMPARABLE RESULTS TO MAXDEPTHK1 BUT IS SIGNIFICANTLY FASTER TO TRAIN AT THE EXPENSE OF A SLIGHTLY HIGHER TRAINING ERROR THE PARAMETER MAXLEAFNODES CORRESPONDS TO THE VARIABLE JIN THE CHAPTER ON GRADIENT BOOSTING IN F2001 AND IS RELATED TO THE PARAMETER INTERACTIONDEPTH IN R’S GBM PACKAGE WHERE MAXLEAFNODES INTERACTIONDEPTH 1

MATHEMATICAL FORMULATION

GBRT CONSIDERS ADDITIVE MODELS OF THE FOLLOWING FORM

□□ □∑
□1□□*h*□□

WHERE *h*□□ARE THE BASIS FUNCTIONS WHICH ARE USUALLY CALLED WEAK LEARNERS IN THE CONTEXT OF BOOSTING GRADIENT TREE BOOSTING USES DECISION TREES OF FIXED SIZE AS WEAK LEARNERS DECISION TREES HAVE A NUMBER OF ABILITIES THAT MAKE THEM VALUABLE FOR BOOSTING NAMELY THE ABILITY TO HANDLE DATA OF MIXED TYPE AND THE ABILITY TO MODEL COMPLEX FUNCTIONS SIMILAR TO OTHER BOOSTING ALGORITHMS GBRT BUILDS THE ADDITIVE MODEL IN A GREEDY FASHION

□□□ □□−1□ □□*h*□□

WHERE THE NEWLY ADDED TREE *h*□TRIES TO MINIMIZE THE LOSS □ GIVEN THE PREVIOUS ENSEMBLE □□−1

h□ ARG MIN
h□∑
□1□□□ □□−1□□ *h*□□

THE INITIAL MODEL □0IS PROBLEM SPECIFIC FOR LEASTSQUARES REGRESSION ONE USUALLY CHOOSES THE MEAN OF THE TARGET VALUES

NOTE THE INITIAL MODEL CAN ALSO BE SPECIFIED VIA THE INIT ARGUMENT THE PASSED OBJECT HAS TO IMPLEMENT FIT AND PREDICT
GRADIENT BOOSTING ATTEMPTS TO SOLVE THIS MINIMIZATION PROBLEM NUMERICALLY VIA STEEPEST DESCENT THE STEEPEST DESCENT DIRECTION IS THE NEGATIVE GRADIENT OF THE LOSS FUNCTION EVALUATED AT THE CURRENT MODEL □□−1WHICH CAN BE CALCULATED FOR ANY DIFFERENTIABLE LOSS FUNCTION
□□□ □□−1□−□□□∑
□1∇□□□□ □□−1□□
WHERE THE STEP LENGTH □□IS CHOSEN USING LINE SEARCH
□□ ARG MIN
□□∑
□1□□□ □□−1□□−□□□□□ □□−1□□
□□□−1□□
THE ALGORITHMS FOR REGRESSION AND CLASSIFICATION ONLY DIFFER IN THE CONCRETE LOSS FUNCTION USED
LOSS FUNCTIONS
THE FOLLOWING LOSS FUNCTIONS ARE SUPPORTED AND CAN BE SPECIFIED USING THE PARAMETER LOSS
• REGRESSION
–LEAST SQUARES LS THE NATURAL CHOICE FOR REGRESSION DUE TO ITS SUPERIOR COMPUTATIONAL PROPERTIES THE INITIAL MODEL IS GIVEN BY THE MEAN OF THE TARGET VALUES
–LEAST ABSOLUTE DEVIATION LAD A ROBUST LOSS FUNCTION FOR REGRESSION THE INITIAL MODEL IS GIVEN BY THE MEDIAN OF THE TARGET VALUES
–HUBER HUBER ANOTHER ROBUST LOSS FUNCTION THAT COMBINES LEAST SQUARES AND LEAST ABSOLUTE DEVIATION USEALPHA TO CONTROL THE SENSITIVITY WITH REGARDS TO OUTLIERS SEE F2001 FOR MORE DETAILS
–QUANTILE QUANTILE A LOSS FUNCTION FOR QUANTILE REGRESSION USE 0 ALPHA 1 TO SPECIFY THE QUANTILE THIS LOSS FUNCTION CAN BE USED TO CREATE PREDICTION INTERVALS SEE PREDICTION INTERVALS FOR GRADIENT BOOSTING REGRESSION
• CLASSIFICATION
–BINOMIAL DEVIANCE DEVIANCE THE NEGATIVE BINOMIAL LOGLIKELIHOOD LOSS FUNCTION FOR BINARY CLASSI FICATION PROVIDES PROBABILITY ESTIMATES THE INITIAL MODEL IS GIVEN BY THE LOG ODDSRATIO
–MULTINOMIAL DEVIANCE DEVIANCE THE NEGATIVE MULTINOMIAL LOGLIKELIHOOD LOSS FUNCTION FOR MULTI CLASS CLASSIFICATION WITH NCLASSES MUTUALLY EXCLUSIVE CLASSES IT PROVIDES PROBABILITY ESTIMATES THE INITIAL MODEL IS GIVEN BY THE PRIOR PROBABILITY OF EACH CLASS AT EACH ITERATION NCLASSES REGRESSION TREES HAVE TO BE CONSTRUCTED WHICH MAKES GBRT RATHER INEFFICIENT FOR DATA SETS WITH A LARGE NUMBER OF CLASSES
–EXPONENTIAL LOSS EXPONENTIAL THE SAME LOSS FUNCTION AS ADABOOSTCLASSIFIER LESS ROBUST TO MISLABELED EXAMPLES THAN DEVIANCE CAN ONLY BE USED FOR BINARY CLASSIFICATION

REGULARIZATION
SHRINKAGE
F2001 PROPOSED A SIMPLE REGULARIZATION STRATEGY THAT SCALES THE CONTRIBUTION OF EACH WEAK LEARNER BY A FACTOR □ □□□ □□−1□ □□□ℎ□□
THE PARAMETER □IS ALSO CALLED THE LEARNING RATE BECAUSE IT SCALES THE STEP LENGTH THE GRADIENT DESCENT PROCEDURE IT CAN BE SET VIA THE LEARNINGRATE PARAMETER
THE PARAMETER LEARNINGRATE STRONGLY INTERACTS WITH THE PARAMETER NESTIMATORS THE NUMBER OF WEAK LEARN
ERS TO FIT SMALLER VALUES OF LEARNINGRATE REQUIRE LARGER NUMBERS OF WEAK LEARNERS TO MAINTAIN A CONSTANT TRAINING ERROR EMPIRICAL EVIDENCE SUGGESTS THAT SMALL VALUES OF LEARNINGRATE FAVOR BETTER TEST ERROR HTF2009 RECOM
MEND TO SET THE LEARNING RATE TO A SMALL CONSTANT EG LEARNINGRATE 01 AND CHOOSE NESTIMATORS BY EARLY STOPPING FOR A MORE DETAILED DISCUSSION OF THE INTERACTION BETWEEN LEARNINGRATE ANDNESTIMATORS SEE R2007
SUBSAMPLING
F1999 PROPOSED STOCHASTIC GRADIENT BOOSTING WHICH COMBINES GRADIENT BOOSTING WITH BOOTSTRAP AVERAGING BAGGING AT EACH ITERATION THE BASE CLASSIFIER IS TRAINED ON A FRACTION SUBSAMPLE OF THE AVAILABLE TRAINING DATA THE SUBSAMPLE IS DRAWN WITHOUT REPLACEMENT A TYPICAL VALUE OF SUBSAMPLE IS 05
THE FIGURE BELOW ILLUSTRATES THE EFFECT OF SHRINKAGE AND SUBSAMPLING ON THE GOODNESSOFFIT OF THE MODEL WE CAN CLEARLY SEE THAT SHRINKAGE OUTPERFORMS NOSHRINKAGE SUBSAMPLING WITH SHRINKAGE CAN FURTHER INCREASE THE ACCURACY OF THE MODEL SUBSAMPLING WITHOUT SHRINKAGE ON THE OTHER HAND DOES POORLY
ANOTHER STRATEGY TO REDUCE THE VARIANCE IS BY SUBSAMPLING THE FEATURES ANALOGOUS TO THE RANDOM SPLITS IN RANDOMFORESTCLASSIFIER THE NUMBER OF SUBSAMPLED FEATURES CAN BE CONTROLLED VIA THE MAXFEATURES PARAMETER

NOTE USING A SMALL MAXFEATURES VALUE CAN SIGNIFICANTLY DECREASE THE RUNTIME
STOCHASTIC GRADIENT BOOSTING ALLOWS TO COMPUTE OUTOFBAG ESTIMATES OF THE TEST DEVIANCE BY COMPUTING THE IMPROVE MENT IN DEVIANCE ON THE EXAMPLES THAT ARE NOT INCLUDED IN THE BOOTSTRAP SAMPLE IE THE OUTOFBAG EXAMPLES THE IMPROVEMENTS ARE STORED IN THE ATTRIBUTE OOBIMPROVEMENT OOBIMPROVEMENTI HOLDS THE IMPROVEMENT
IN TERMS OF THE LOSS ON THE OOB SAMPLES IF YOU ADD THE ITH STAGE TO THE CURRENT PREDICTIONS OUTOFBAG ESTIMATES CAN BE USED FOR MODEL SELECTION FOR EXAMPLE TO DETERMINE THE OPTIMAL NUMBER OF ITERATIONS OOB ESTIMATES ARE USUALLY VERY PESSIMISTIC THUS WE RECOMMEND TO USE CROSSVALIDATION INSTEAD AND ONLY USE OOB IF CROSSVALIDATION IS TOO TIME CONSUMING
EXAMPLES
•GRADIENT BOOSTING REGULARIZATION
•GRADIENT BOOSTING OUTOFBAG ESTIMATES
•OOB ERRORS FOR RANDOM FORESTS
INTERPRETATION
INDIVIDUAL DECISION TREES CAN BE INTERPRETED EASILY BY SIMPLY VISUALIZING THE TREE STRUCTURE GRADIENT BOOSTING MODELS HOWEVER COMPRISE HUNDREDS OF REGRESSION TREES THUS THEY CANNOT BE EASILY INTERPRETED BY VISUAL INSPECTION OF THE INDIVIDUAL TREES FORTUNATELY A NUMBER OF TECHNIQUES HAVE BEEN PROPOSED TO SUMMARIZE AND INTERPRET GRADIENT BOOSTING MODELS
FEATURE IMPORTANCE
OFTEN FEATURES DO NOT CONTRIBUTE EQUALLY TO PREDICT THE TARGET RESPONSE IN MANY SITUATIONS THE MAJORITY OF THE FEATURES ARE IN FACT IRRELEVANT WHEN INTERPRETING A MODEL THE FIRST QUESTION USUALLY IS WHAT ARE THOSE IMPORTANT FEATURES AND HOW DO THEY CONTRIBUTING IN PREDICTING THE TARGET RESPONSE
INDIVIDUAL DECISION TREES INTRINSICALLY PERFORM FEATURE SELECTION BY SELECTING APPROPRIATE SPLIT POINTS THIS INFORMATION CAN BE USED TO MEASURE THE IMPORTANCE OF EACH FEATURE THE BASIC IDEA IS THE MORE OFTEN A FEATURE IS USED IN THE SPLIT POINTS OF A TREE THE MORE IMPORTANT THAT FEATURE IS THIS NOTION OF IMPORTANCE CAN BE EXTENDED TO DECISION TREE ENSEMBLES BY SIMPLY AVERAGING THE FEATURE IMPORTANCE OF EACH TREE SEE FEATURE IMPORTANCE EVALUATION FOR MORE DETAILS
THE FEATURE IMPORTANCE SCORES OF A FIT GRADIENT BOOSTING MODEL CAN BE ACCESSED VIA THE FEATUREIMPORTANCES PROPERTY

```
 FROM SKLEARNDATASETS IMPORT MAKEHASTIE102
 FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGCLASSIFIER
X Y  MAKEHASTIE102RANDOMSTATE0
CLF  GRADIENTBOOSTINGCLASSIFIERNESTIMATORS100 LEARNINGRATE10
 MAXDEPTH1 RANDOMSTATE0FITX Y
CLFFEATUREIMPORTANCES
ARRAY010 010 011
```

EXAMPLES

•GRADIENT BOOSTING REGRESSION
VOTING CLASSIFIER
THE IDEA BEHIND THE VOTINGCLASSIFIER IS TO COMBINE CONCEPTUALLY DIFFERENT MACHINE LEARNING CLASSIFIERS AND USE A MAJORITY VOTE OR THE AVERAGE PREDICTED PROBABILITIES SOFT VOTE TO PREDICT THE CLASS LABELS SUCH A CLASSIFIER CAN BE USEFUL FOR A SET OF EQUALLY WELL PERFORMING MODEL IN ORDER TO BALANCE OUT THEIR INDIVIDUAL WEAKNESSES
MAJORITY CLASS LABELS MAJORITYHARD VOTING
IN MAJORITY VOTING THE PREDICTED CLASS LABEL FOR A PARTICULAR SAMPLE IS THE CLASS LABEL THAT REPRESENTS THE MAJORITY MODE OF THE CLASS LABELS PREDICTED BY EACH INDIVIDUAL CLASSIFIER
EG IF THE PREDICTION FOR A GIVEN SAMPLE IS
• CLASSIFIER 1 CLASS 1
• CLASSIFIER 2 CLASS 1
• CLASSIFIER 3 CLASS 2
THE V OTINGCLASSIFIER WITH VOTINGHARD WOULD CLASSIFY THE SAMPLE AS “CLASS 1” BASED ON THE MAJORITY CLASS LABEL
IN THE CASES OF A TIE THE VOTINGCLASSIFIER WILL SELECT THE CLASS BASED ON THE ASCENDING SORT ORDER EG IN THE FOLLOWING SCENARIO
• CLASSIFIER 1 CLASS 2
• CLASSIFIER 2 CLASS 1
THE CLASS LABEL 1 WILL BE ASSIGNED TO THE SAMPLE
USAGE
THE FOLLOWING EXAMPLE SHOWS HOW TO FIT THE MAJORITY RULE CLASSIFIER
```
 FROM SKLEARN IMPORT DATASETS
 FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
 FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
 FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
 FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
 FROM SKLEARNENSEMBLE IMPORT VOTINGCLASSIFIER
IRIS  DATASETSLOADIRIS
X Y  IRISDATA 13 IRISTARGET
CLF1  LOGISTICREGRESSIONSOLVERLBFGS MULTICLASSMULTINOMIAL
 RANDOMSTATE1
CLF2  RANDOMFORESTCLASSIFIERNESTIMATORS50 RANDOMSTATE1
CLF3  GAUSSIANNB
ECLF  VOTINGCLASSIFIERESTIMATORSLR CLF1 RF CLF2 GNB CLF3
‘→VOTINGHARD
 FOR CLF LABEL INZIPCLF1 CLF2 CLF3 ECLF LOGISTIC REGRESSION RANDOM
‘→FOREST NAIVE BAYES ENSEMBLE
```

```
 SCORES  CROSSVALSCORECLF X Y CV5 SCORINGACCURACY
 PRINTACCURACY 02F02F S  SCORESMEAN SCORESSTD
‘→LABEL
ACCURACY 095  004 LOGISTIC REGRESSION
ACCURACY 094  004 RANDOM FOREST
ACCURACY 091  004 NAIVE BAYES
ACCURACY 095  004 ENSEMBLE
```
WEIGHTED AVERAGE PROBABILITIES SOFT VOTING

IN CONTRAST TO MAJORITY VOTING HARD VOTING SOFT VOTING RETURNS THE CLASS LABEL AS ARGMAX OF THE SUM OF PREDICTED PROBABILITIES

SPECIFIC WEIGHTS CAN BE ASSIGNED TO EACH CLASSIFIER VIA THE WEIGHTS PARAMETER WHEN WEIGHTS ARE PROVIDED THE PREDICTED CLASS PROBABILITIES FOR EACH CLASSIFIER ARE COLLECTED MULTIPLIED BY THE CLASSIFIER WEIGHT AND AVERAGED THE FINAL CLASS LABEL IS THEN DERIVED FROM THE CLASS LABEL WITH THE HIGHEST AVERAGE PROBABILITY

TO ILLUSTRATE THIS WITH A SIMPLE EXAMPLE LET’S ASSUME WE HAVE 3 CLASSIFIERS AND A 3CLASS CLASSIFICATION PROBLEMS WHERE WE ASSIGN EQUAL WEIGHTS TO ALL CLASSIFIERS W11 W21 W31

THE WEIGHTED AVERAGE PROBABILITIES FOR A SAMPLE WOULD THEN BE CALCULATED AS FOLLOWS

CLASSIFIER CLASS 1 CLASS 2 CLASS 3
CLASSIFIER 1 W1 02 W1 05 W1 03
CLASSIFIER 2 W2 06 W2 03 W2 01
CLASSIFIER 3 W3 03 W3 04 W3 03
WEIGHTED AVERAGE 037 04 023

HERE THE PREDICTED CLASS LABEL IS 2 SINCE IT HAS THE HIGHEST AVERAGE PROBABILITY

THE FOLLOWING EXAMPLE ILLUSTRATES HOW THE DECISION REGIONS MAY CHANGE WHEN A SOFT VOTINGCLASSIFIER IS USED BASED ON AN LINEAR SUPPORT VECTOR MACHINE A DECISION TREE AND A KNEAREST NEIGHBOR CLASSIFIER

```
 FROM SKLEARN IMPORT DATASETS
 FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
 FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSCLASSIFIER
 FROM SKLEARNSVM IMPORT SVC
 FROM ITERTOOLS IMPORT PRODUCT
 FROM SKLEARNENSEMBLE IMPORT VOTINGCLASSIFIER
 LOADING SOME EXAMPLE DATA
IRIS  DATASETSLOADIRIS
X  IRISDATA 0 2
Y  IRISTARGET
 TRAINING CLASSIFIERS
CLF1  DECISIONTREECLASSIFIERMAXDEPTH4
CLF2  KNEIGHBORSCLASSIFIERNNEIGHBORS7
CLF3  SVCGAMMASCALE KERNELRBF PROBABILITY TRUE
ECLF  VOTINGCLASSIFIERESTIMATORSDT CLF1 KNN CLF2 SVC CLF3
 VOTINGSOFT WEIGHTS2 1 2
CLF1  CLF1FITX Y
CLF2  CLF2FITX Y
CLF3  CLF3FITX Y
ECLF  ECLFFITX Y
```

USING THE VOTINGCLASSIFIER WITHGRIDSEARCHCV
THEVOTINGCLASSIFIER CAN ALSO BE USED TOGETHER WITH GRIDSEARCHCV IN ORDER TO TUNE THE HYPERPARAMETERS OF THE INDIVIDUAL ESTIMATORS

```
 FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
CLF1  LOGISTICREGRESSIONSOLVERLBFGS MULTICLASSMULTINOMIAL
 RANDOMSTATE1
CLF2  RANDOMFORESTCLASSIFIERRANDOMSTATE1
CLF3  GAUSSIANNB
ECLF  VOTINGCLASSIFIERESTIMATORSLR CLF1 RF CLF2 GNB CLF3
‘→VOTINGSOFT
PARAMS  LRC 10 1000 RFNESTIMATORS 20 200
GRID  GRIDSEARCHCVESTIMATORECLF PARAMGRIDPARAMS CV5
GRID  GRIDFITIRISDATA IRISTARGET
```

USAGE
IN ORDER TO PREDICT THE CLASS LABELS BASED ON THE PREDICTED CLASSPROBABILITIES SCIKITLEARN ESTIMATORS IN THE V OTINGCLAS SIFIER MUST SUPPORT PREDICTPROBA METHOD

```
ECLF  VOTINGCLASSIFIERESTIMATORSLR CLF1 RF CLF2 GNB CLF3
‘→VOTINGSOFT
```

OPTIONALLY WEIGHTS CAN BE PROVIDED FOR THE INDIVIDUAL CLASSIFIERS

```
ECLF  VOTINGCLASSIFIERESTIMATORSLR CLF1 RF CLF2 GNB CLF3
 VOTINGSOFT WEIGHTS2 5 1
```

VOTING REGRESSOR
THE IDEA BEHIND THE VOTINGREGRESSOR IS TO COMBINE CONCEPTUALLY DIFFERENT MACHINE LEARNING REGRESSORS AND RETURN THE AVERAGE PREDICTED VALUES SUCH A REGRESSOR CAN BE USEFUL FOR A SET OF EQUALLY WELL PERFORMING MODELS IN ORDER TO BALANCE OUT THEIR INDIVIDUAL WEAKNESSES
THE FOLLOWING EXAMPLE SHOWS HOW TO FIT THE V OTINGREGRESSOR

```
 FROM SKLEARN IMPORT DATASETS
 FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGREGRESSOR
 FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTREGRESSOR
 FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION
 FROM SKLEARNENSEMBLE IMPORT VOTINGREGRESSOR
 LOADING SOME EXAMPLE DATA
BOSTON  DATASETSLOADBOSTON
X  BOSTONDATA
Y  BOSTONTARGET
 TRAINING CLASSIFIERS
REG1  GRADIENTBOOSTINGREGRESSORRANDOMSTATE1 NESTIMATORS10
REG2  RANDOMFORESTREGRESSORRANDOMSTATE1 NESTIMATORS10
REG3  LINEARREGRESSION
```

EREG VOTINGREGRESSORESTIMATORSGB REG1 RF REG2 LR REG3
EREG EREGFITX Y
EXAMPLES
•PLOT INDIVIDUAL AND VOTING REGRESSION PREDICTIONS
3112 MULTICLASS AND MULTILABEL ALGORITHMS
WARNING ALL CLASSIFIERS IN SCIKITLEARN DO MULTICLASS CLASSIFICATION OUTOFTHEBOX YOU DON'T NEED TO USE THE SKLEARNMULTICLASS MODULE UNLESS YOU WANT TO EXPERIMENT WITH DIFFERENT MULTICLASS STRATEGIES THESKLEARNMULTICLASS MODULE IMPLEMENTS METAESTIMATORS TO SOLVEMULTICLASS ANDMULTILABEL CLAS SIFICATION PROBLEMS BY DECOMPOSING SUCH PROBLEMS INTO BINARY CLASSIFICATION PROBLEMS MULTITARGET REGRESSION IS ALSO SUPPORTED
•MULTICLASS CLASSIFICATION MEANS A CLASSIFICATION TASK WITH MORE THAN TWO CLASSES EG CLASSIFY A SET OF IMAGES OF FRUITS WHICH MAY BE ORANGES APPLES OR PEARS MULTICLASS CLASSIFICATION MAKES THE ASSUMPTION THAT EACH SAMPLE IS ASSIGNED TO ONE AND ONLY ONE LABEL A FRUIT CAN BE EITHER AN APPLE OR A PEAR BUT NOT BOTH AT THE SAME TIME
•MULTILABEL CLASSIFICATION ASSIGNS TO EACH SAMPLE A SET OF TARGET LABELS THIS CAN BE THOUGHT AS PREDICTING PROPER TIES OF A DATAPOINT THAT ARE NOT MUTUALLY EXCLUSIVE SUCH AS TOPICS THAT ARE RELEVANT FOR A DOCUMENT A TEXT MIGHT BE ABOUT ANY OF RELIGION POLITICS FINANCE OR EDUCATION AT THE SAME TIME OR NONE OF THESE
•MULTIOUTPUT REGRESSION ASSIGNS EACH SAMPLE A SET OF TARGET VALUES THIS CAN BE THOUGHT OF AS PREDICTING SEVERAL PROPERTIES FOR EACH DATAPOINT SUCH AS WIND DIRECTION AND MAGNITUDE AT A CERTAIN LOCATION

•MULTIOUTPUTMULTICLASS CLASSIFICATION ANDMULTITASK CLASSIFICATION MEANS THAT A SINGLE ESTIMATOR HAS TO HANDLE SEVERAL JOINT CLASSIFICATION TASKS THIS IS BOTH A GENERALIZATION OF THE MULTILABEL CLASSIFICATION TASK WHICH ONLY CONSIDERS BINARY CLASSIFICATION AS WELL AS A GENERALIZATION OF THE MULTICLASS CLASSIFICATION TASK THE OUTPUT FORMAT IS A 2D NUMPY ARRAY OR SPARSE MATRIX
THE SET OF LABELS CAN BE DIFFERENT FOR EACH OUTPUT VARIABLE FOR INSTANCE A SAMPLE COULD BE ASSIGNED “PEAR” FOR AN OUTPUT VARIABLE THAT TAKES POSSIBLE VALUES IN A FINITE SET OF SPECIES SUCH AS “PEAR” “APPLE” AND “BLUE” OR “GREEN” FOR A SECOND OUTPUT VARIABLE THAT TAKES POSSIBLE VALUES IN A FINITE SET OF COLORS SUCH AS “GREEN” “RED” “BLUE” “YELLOW”
THIS MEANS THAT ANY CLASSIFIERS HANDLING MULTIOUTPUT MULTICLASS OR MULTITASK CLASSIFICATION TASKS SUPPORT THE MULTILABEL CLASSIFICATION TASK AS A SPECIAL CASE MULTITASK CLASSIFICATION IS SIMILAR TO THE MULTIOUTPUT CLASSIFICA TION TASK WITH DIFFERENT MODEL FORMULATIONS FOR MORE INFORMATION SEE THE RELEVANT ESTIMATOR DOCUMENTATION
ALL SCIKITLEARN CLASSIFIERS ARE CAPABLE OF MULTICLASS CLASSIFICATION BUT THE METAESTIMATORS OFFERED BY SKLEARN MULTICLASS PERMIT CHANGING THE WAY THEY HANDLE MORE THAN TWO CLASSES BECAUSE THIS MAY HAVE AN EFFECT ON CLASSIFIER PERFORMANCE EITHER IN TERMS OF GENERALIZATION ERROR OR REQUIRED COMPUTATIONAL RESOURCES
BELOW IS A SUMMARY OF THE CLASSIFIERS SUPPORTED BY SCIKITLEARN GROUPED BY STRATEGY YOU DON’T NEED THE METAESTIMATORS IN THIS CLASS IF YOU’RE USING ONE OF THESE UNLESS YOU WANT CUSTOM MULTICLASS BEHAVIOR
•INHERENTLY MULTICLASS
–SKLEARNNAIVEBAYESBERNOULLINB
–SKLEARNTREEDECISIONTREECLASSIFIER
–SKLEARNTREEEXTRATREECLASSIFIER
–SKLEARNENSEMBLEEXTRATREESCLASSIFIER
–SKLEARNNAIVEBAYESGAUSSIANNB
–SKLEARNNEIGHBORSKNEIGHBORSCLASSIFIER
–SKLEARNSEMISUPERVISEDLABELPROPAGATION
–SKLEARNSEMISUPERVISEDLABELSPREADING
–SKLEARNDISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS
–SKLEARNSVMLINEARSVC SETTING MULTICLASS”CRAMMERSINGER”
–SKLEARNLINEARMODELLOGISTICREGRESSION SETTING MULTICLASS”MULTINOMIAL”
–SKLEARNLINEARMODELLOGISTICREGRESSIONCV SETTING MULTICLASS”MULTINOMIAL”
–SKLEARNNEURALNETWORKMLPCLASSIFIER
–SKLEARNNEIGHBORSNEARESTCENTROID
–SKLEARNDISCRIMINANTANALYSISQUADRATICDISCRIMINANTANALYSIS
–SKLEARNNEIGHBORSRADIUSNEIGHBORSCLASSIFIER
–SKLEARNENSEMBLERANDOMFORESTCLASSIFIER
–SKLEARNLINEARMODELRIDGECLASSIFIER
–SKLEARNLINEARMODELRIDGECLASSIFIERCV
•MULTICLASS AS ONEVSONE
–SKLEARNSVMNUSVC
–SKLEARNSVMSVC

–SKLEARNGAUSSIANPROCESSGAUSSIANPROCESSCLASSIFIER SETTING MULTICLASS
“ONEVSONE”
•MULTICLASS AS ONEVSALL
–SKLEARNENSEMBLEGRADIENTBOOSTINGCLASSIFIER
–SKLEARNGAUSSIANPROCESSGAUSSIANPROCESSCLASSIFIER SETTING MULTICLASS
“ONEVSREST”
–SKLEARNSVMLINEARSVC SETTING MULTICLASS”OVR”
–SKLEARNLINEARMODELLOGISTICREGRESSION SETTING MULTICLASS”OVR”
–SKLEARNLINEARMODELLOGISTICREGRESSIONCV SETTING MULTICLASS”OVR”
–SKLEARNLINEARMODELSGDCLASSIFIER
–SKLEARNLINEARMODELPERCEPTRON
–SKLEARNLINEARMODELPASSIVEAGGRESSIVECLASSIFIER
•SUPPORT MULTILABEL
–SKLEARNTREEDECISIONTREECLASSIFIER
–SKLEARNTREEEXTRATREECLASSIFIER
–SKLEARNENSEMBLEEXTRATREESCLASSIFIER
–SKLEARNNEIGHBORSKNEIGHBORSCLASSIFIER
–SKLEARNNEURALNETWORKMLPCLASSIFIER
–SKLEARNNEIGHBORSRADIUSNEIGHBORSCLASSIFIER
–SKLEARNENSEMBLERANDOMFORESTCLASSIFIER
–SKLEARNLINEARMODELRIDGECLASSIFIERCV
•SUPPORT MULTICLASSMULTIOUTPUT
–SKLEARNTREEDECISIONTREECLASSIFIER
–SKLEARNTREEEXTRATREECLASSIFIER
–SKLEARNENSEMBLEEXTRATREESCLASSIFIER
–SKLEARNNEIGHBORSKNEIGHBORSCLASSIFIER
–SKLEARNNEIGHBORSRADIUSNEIGHBORSCLASSIFIER
–SKLEARNENSEMBLERANDOMFORESTCLASSIFIER
WARNING AT PRESENT NO METRIC IN SKLEARNMETRICS SUPPORTS THE MULTIOUTPUTMULTICLASS CLASSIFICATION TASK
MULTILABEL CLASSIFICATION FORMAT
IN MULTILABEL LEARNING THE JOINT SET OF BINARY CLASSIFICATION TASKS IS EXPRESSED WITH LABEL BINARY INDICATOR ARRAY EACH
SAMPLE IS ONE ROW OF A 2D ARRAY OF SHAPE NSAMPLES NCLASSES WITH BINARY VALUES THE ONE IE THE NON ZERO ELEMENTS
CORRESPONDS TO THE SUBSET OF LABELS AN ARRAY SUCH AS NPARRAY1 0 0 0 1 1 0 0 0
REPRESENTS LABEL 0 IN THE FIRST SAMPLE LABELS 1 AND 2 IN THE SECOND SAMPLE AND NO LABELS IN THE THIRD SAMPLE
PRODUCING MULTILABEL DATA AS A LIST OF SETS OF LABELS MAY BE MORE INTUITIVE THE MULTILABELBINARIZER TRANSFORMER
CAN BE USED TO CONVERT BETWEEN A COLLECTION OF COLLECTIONS OF LABELS AND THE INDICATOR FORMAT

```
 FROM SKLEARNPREPROCESSING IMPORT MULTILABELBINARIZER
Y  2 3 4 2 0 1 3 0 1 2 3 4 0 1 2
MULTILABELBINARIZERFITTRANSFORMY
ARRAY0 0 1 1 1
0 0 1 0 0
1 1 0 1 0
1 1 1 1 1
1 1 1 0 0
```

ONEVSTHEREST

THIS STRATEGY ALSO KNOWN AS ONEVSALL IS IMPLEMENTED IN ONEVSRESTCLASSIFIER THE STRATEGY CONSISTS IN FITTING ONE CLASSIFIER PER CLASS FOR EACH CLASSIFIER THE CLASS IS FITTED AGAINST ALL THE OTHER CLASSES IN ADDITION TO ITS COMPUTA TIONAL EFFICIENCY ONLY NCLASSES CLASSIFIERS ARE NEEDED ONE ADVANTAGE OF THIS APPROACH IS ITS INTERPRETABILITY SINCE EACH CLASS IS REPRESENTED BY ONE AND ONLY ONE CLASSIFIER IT IS POSSIBLE TO GAIN KNOWLEDGE ABOUT THE CLASS BY INSPECTING ITS CORRESPONDING CLASSIFIER THIS IS THE MOST COMMONLY USED STRATEGY AND IS A FAIR DEFAULT CHOICE

MULTICLASS LEARNING

BELOW IS AN EXAMPLE OF MULTICLASS LEARNING USING OVR

```
 FROM SKLEARN IMPORT DATASETS
 FROM SKLEARNMULTICLASS IMPORT ONEVSRESTCLASSIFIER
 FROM SKLEARNSVM IMPORT LINEARSVC
IRIS  DATASETSLOADIRIS
X Y  IRISDATA IRISTARGET
ONEVSRESTCLASSIFIERLINEARSVCRANDOMSTATE0FITX YPREDICTX
ARRAY0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2
2 2 2 2 2 2 2 2 2 2 2 2
```

MULTILABEL LEARNING

ONEVSRESTCLASSIFIER ALSO SUPPORTS MULTILABEL CLASSIFICATION TO USE THIS FEATURE FEED THE CLASSIFIER AN INDICATOR MATRIX IN WHICH CELL I J INDICATES THE PRESENCE OF LABEL J IN SAMPLE I

EXAMPLES

- MULTILABEL CLASSIFICATION

ONEVSONE

ONEVSONECLASSIFIER CONSTRUCTS ONE CLASSIFIER PER PAIR OF CLASSES AT PREDICTION TIME THE CLASS WHICH RECEIVED THE MOST VOTES IS SELECTED IN THE EVENT OF A TIE AMONG TWO CLASSES WITH AN EQUAL NUMBER OF VOTES IT SELECTS THE CLASS WITH THE HIGHEST AGGREGATE CLASSIFICATION CONFIDENCE BY SUMMING OVER THE PAIRWISE CLASSIFICATION CONFIDENCE LEVELS COMPUTED BY THE UNDERLYING BINARY CLASSIFIERS

SINCE IT REQUIRES TO FIT NCLASSES NCLASSES 1 2 CLASSIFIERS THIS METHOD IS USUALLY SLOWER THAN
ONEVSTHEREST DUE TO ITS ONCLASSES2 COMPLEXITY HOWEVER THIS METHOD MAY BE ADVANTAGEOUS FOR ALGORITHMS
SUCH AS KERNEL ALGORITHMS WHICH DON'T SCALE WELL WITH NSAMPLES THIS IS BECAUSE EACH INDIVIDUAL LEARNING PROBLEM
ONLY INVOLVES A SMALL SUBSET OF THE DATA WHEREAS WITH ONEVSTHEREST THE COMPLETE DATASET IS USED NCLASSES TIMES
THE DECISION FUNCTION IS THE RESULT OF A MONOTONIC TRANSFORMATION OF THE ONEVERSUSONE CLASSIFICATION
MULTICLASS LEARNING
BELOW IS AN EXAMPLE OF MULTICLASS LEARNING USING OVO

```
 FROM SKLEARN IMPORT DATASETS
 FROM SKLEARNMULTICLASS IMPORT ONEVSONECLASSIFIER
 FROM SKLEARNSVM IMPORT LINEARSVC
IRIS  DATASETSLOADIRIS
X Y  IRISDATA IRISTARGET
ONEVSONECLASSIFIERLINEARSVCRANDOMSTATE0FITX YPREDICTX
ARRAY0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 2 1 2 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
2 2 2 2 2 2 2 2 2 2 2 2
```

REFERENCES
• “PATTERN RECOGNITION AND MACHINE LEARNING SPRINGER” CHRISTOPHER M BISHOP PAGE 183 FIRST EDITION
ERRORCORRECTING OUTPUTCODES
OUTPUTCODE BASED STRATEGIES ARE FAIRLY DIFFERENT FROM ONEVSTHEREST AND ONEVSONE WITH THESE STRATEGIES EACH CLASS IS REPRESENTED IN A EUCLIDEAN SPACE WHERE EACH DIMENSION CAN ONLY BE 0 OR 1 ANOTHER WAY TO PUT IT IS THAT EACH CLASS IS REPRESENTED BY A BINARY CODE AN ARRAY OF 0 AND 1 THE MATRIX WHICH KEEPS TRACK OF THE LOCATIONCODE OF EACH CLASS IS CALLED THE CODE BOOK THE CODE SIZE IS THE DIMENSIONALITY OF THE AFOREMENTIONED SPACE INTUITIVELY EACH CLASS SHOULD BE REPRESENTED BY A CODE AS UNIQUE AS POSSIBLE AND A GOOD CODE BOOK SHOULD BE DESIGNED TO OPTIMIZE CLASSIFICATION ACCURACY IN THIS IMPLEMENTATION WE SIMPLY USE A RANDOMLYGENERATED CODE BOOK AS ADVOCATED IN3ALTHOUGH MORE ELABORATE METHODS MAY BE ADDED IN THE FUTURE
AT FITTING TIME ONE BINARY CLASSIFIER PER BIT IN THE CODE BOOK IS FITTED AT PREDICTION TIME THE CLASSIFIERS ARE USED TO PROJECT NEW POINTS IN THE CLASS SPACE AND THE CLASS CLOSEST TO THE POINTS IS CHOSEN
INOUTPUTCODECLASSIFIER THECODESIZE ATTRIBUTE ALLOWS THE USER TO CONTROL THE NUMBER OF CLASSIFIERS WHICH WILL BE USED IT IS A PERCENTAGE OF THE TOTAL NUMBER OF CLASSES
A NUMBER BETWEEN 0 AND 1 WILL REQUIRE FEWER CLASSIFIERS THAN ONEVSTHEREST IN THEORY LOG2NCLASSES NCLASSES IS SUFFICIENT TO REPRESENT EACH CLASS UNAMBIGUOUSLY HOWEVER IN PRACTICE IT MAY NOT LEAD TO GOOD ACCURACY SINCE LOG2NCLASSES IS MUCH SMALLER THAN NCLASSES
A NUMBER GREATER THAN 1 WILL REQUIRE MORE CLASSIFIERS THAN ONEVSTHEREST IN THIS CASE SOME CLASSIFIERS WILL IN THEORY CORRECT FOR THE MISTAKES MADE BY OTHER CLASSIFIERS HENCE THE NAME “ERRORCORRECTING” IN PRACTICE HOWEVER THIS MAY NOT HAPPEN AS CLASSIFIER MISTAKES WILL TYPICALLY BE CORRELATED THE ERRORCORRECTING OUTPUT CODES HAVE A SIMILAR EFFECT TO BAGGING
MULTICLASS LEARNING
BELOW IS AN EXAMPLE OF MULTICLASS LEARNING USING OUTPUTCODES
```
 FROM SKLEARN IMPORT DATASETS
 FROM SKLEARNMULTICLASS IMPORT OUTPUTCODECLASSIFIER
 FROM SKLEARNSVM IMPORT LINEARSVC
IRIS  DATASETSLOADIRIS
X Y  IRISDATA IRISTARGET
CLF  OUTPUTCODECLASSIFIERLINEARSVCRANDOMSTATE0
 CODESIZE2 RANDOMSTATE0
CLFFITX YPREDICTX
ARRAY0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 2 1 1
1 2 1 1 1 1 1 1 2 1 1 1 1 1 2 2 2 1 1 1 1 1 1
1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 1 1 2 2 2
2 2 2 2 2 2 2 2 2 2 2 2
```
REFERENCES
3“THE ERROR CODING METHOD AND PICTS” JAMES G HASTIE T JOURNAL OF COMPUTATIONAL AND GRAPHICAL STATISTICS 7 1998

• “SOLVING MULTICLASS LEARNING PROBLEMS VIA ERRORCORRECTING OUTPUT CODES” DIETTERICH T BAKIRI G JOURNAL OF ARTIFICIAL INTELLIGENCE RESEARCH 2 1995
• “THE ELEMENTS OF STATISTICAL LEARNING” HASTIE T TIBSHIRANI R FRIEDMAN J PAGE 606 SECONDEDITION 2008
MULTIOUTPUT REGRESSION
MULTIOUTPUT REGRESSION SUPPORT CAN BE ADDED TO ANY REGRESSOR WITH MULTIOUTPUTREGRESSOR THIS STRATEGY CONSISTS OF FITTING ONE REGRESSOR PER TARGET SINCE EACH TARGET IS REPRESENTED BY EXACTLY ONE REGRESSOR IT IS POSSIBLE TO GAIN KNOWLEDGE ABOUT THE TARGET BY INSPECTING ITS CORRESPONDING REGRESSOR AS MULTIOUTPUTREGRESSOR FITS ONE REGRESSOR PER TARGET IT CAN NOT TAKE ADVANTAGE OF CORRELATIONS BETWEEN TARGETS
BELOW IS AN EXAMPLE OF MULTIOUTPUT REGRESSION
```
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
 FROM SKLEARNMULTIOUTPUT IMPORT MULTIOUTPUTREGRESSOR
 FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGREGRESSOR
X Y  MAKEREGRESSIONNSAMPLES10 NTARGETS3 RANDOMSTATE1
MULTIOUTPUTREGRESSORGRADIENTBOOSTINGREGRESSORRANDOMSTATE0FITX Y
‹→PREDICTX
ARRAY15475474165 14703498585 5003812219
 712165031 512914884 8146081961
1878948621  10044373091 1388978285
14162745778 9502891072 19148204257
 9703260883 16534867495 13952003279
 12392529176 2125719016 784253
12225193977 8516443186 10712274212
 30170388  9480956739 1216979946
 14072667194 17650941682 1750447799
 14937967282 8115699552 572850319
```
MULTIOUTPUT CLASSIFICATION
MULTIOUTPUT CLASSIFICATION SUPPORT CAN BE ADDED TO ANY CLASSIFIER WITH MULTIOUTPUTCLASSIFIER THIS STRATEGY CONSISTS OF FITTING ONE CLASSIFIER PER TARGET THIS ALLOWS MULTIPLE TARGET VARIABLE CLASSIFICATIONS THE PURPOSE OF THIS CLASS IS TO EXTEND ESTIMATORS TO BE ABLE TO ESTIMATE A SERIES OF TARGET FUNCTIONS F1F2F3 FN THAT ARE TRAINED ON A SINGLE X PREDICTOR MATRIX TO PREDICT A SERIES OF RESPONSES Y1Y2Y3 YN
BELOW IS AN EXAMPLE OF MULTIOUTPUT CLASSIFICATION
```
 FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
 FROM SKLEARNMULTIOUTPUT IMPORT MULTIOUTPUTCLASSIFIER
 FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
 FROM SKLEARNUTILS IMPORT SHUFFLE
 IMPORT NUMPY AS NP
X Y1  MAKECLASSIFICATIONNSAMPLES10 NFEATURES100 NINFORMATIVE30 N
‹→CLASSES3 RANDOMSTATE1
Y2  SHUFFLEY1 RANDOMSTATE1
Y3  SHUFFLEY1 RANDOMSTATE2
Y  NPVSTACKY1 Y2 Y3T
NSAMPLES NFEATURES  XSHAPE  10100
NOUTPUTS  YSHAPE1  3
NCLASSES  3
FOREST  RANDOMFORESTCLASSIFIERNESTIMATORS100 RANDOMSTATE1
MULTITARGETFOREST  MULTIOUTPUTCLASSIFIERFOREST NJOBS1
```

MULTITARGETFORESTFITX YPREDICTX
ARRAY2 2 0
1 2 1
2 1 0
0 0 2
0 2 1
0 0 2
1 1 0
1 1 1
0 0 2
2 0 0
CLASSIFIER CHAIN
CLASSIFIER CHAINS SEE CLASSIFIERCHAIN ARE A WAY OF COMBINING A NUMBER OF BINARY CLASSIFIERS INTO A SINGLE MULTILABEL MODEL THAT IS CAPABLE OF EXPLOITING CORRELATIONS AMONG TARGETS
FOR A MULTILABEL CLASSIFICATION PROBLEM WITH N CLASSES N BINARY CLASSIFIERS ARE ASSIGNED AN INTEGER BETWEEN 0 AND N1 THESE INTEGERS DEFINE THE ORDER OF MODELS IN THE CHAIN EACH CLASSIFIER IS THEN FIT ON THE AVAILABLE TRAINING DATA PLUS THE TRUE LABELS OF THE CLASSES WHOSE MODELS WERE ASSIGNED A LOWER NUMBER
WHEN PREDICTING THE TRUE LABELS WILL NOT BE AVAILABLE INSTEAD THE PREDICTIONS OF EACH MODEL ARE PASSED ON TO THE SUBSEQUENT MODELS IN THE CHAIN TO BE USED AS FEATURES
CLEARLY THE ORDER OF THE CHAIN IS IMPORTANT THE FIRST MODEL IN THE CHAIN HAS NO INFORMATION ABOUT THE OTHER LABELS WHILE THE LAST MODEL IN THE CHAIN HAS FEATURES INDICATING THE PRESENCE OF ALL OF THE OTHER LABELS IN GENERAL ONE DOES NOT KNOW THE OPTIMAL ORDERING OF THE MODELS IN THE CHAIN SO TYPICALLY MANY RANDOMLY ORDERED CHAINS ARE FIT AND THEIR PREDICTIONS ARE AVERAGED TOGETHER
REFERENCES
JESSE READ BERNHARD PFAHRINGER GEOFF HOLMES EIBE FRANK “CLASSIFIER CHAINS FOR MULTILABEL CLASSIFICA
TION” 2009
REGRESSOR CHAIN
REGRESSOR CHAINS SEE REGRESSORCHAIN IS ANALOGOUS TO CLASSIFIERCHAIN AS A WAY OF COMBINING A NUMBER OF RE
GRESSIONS INTO A SINGLE MULTITARGET MODEL THAT IS CAPABLE OF EXPLOITING CORRELATIONS AMONG TARGETS
3113 FEATURE SELECTION
THE CLASSES IN THE SKLEARNFEATURESELECTION MODULE CAN BE USED FOR FEATURE SELECTIONDIMENSIONALITY RE
DUCTION ON SAMPLE SETS EITHER TO IMPROVE ESTIMATORS’ ACCURACY SCORES OR TO BOOST THEIR PERFORMANCE ON VERY HIGH DIMENSIONAL DATASETS
REMOVING FEATURES WITH LOW VARIANCE
VARIANCETHRESHOLD IS A SIMPLE BASELINE APPROACH TO FEATURE SELECTION IT REMOVES ALL FEATURES WHOSE VARIANCE DOESN’T MEET SOME THRESHOLD BY DEFAULT IT REMOVES ALL ZEROVARIANCE FEATURES IE FEATURES THAT HAVE THE SAME VALUE IN ALL SAMPLES

AS AN EXAMPLE SUPPOSE THAT WE HAVE A DATASET WITH BOOLEAN FEATURES AND WE WANT TO REMOVE ALL FEATURES THAT ARE EITHER ONE OR ZERO ON OR OFF IN MORE THAN 80 OF THE SAMPLES BOOLEAN FEATURES ARE BERNOULLI RANDOM VARIABLES AND THE VARIANCE OF SUCH VARIABLES IS GIVEN BY

VAR□ □1−□

SO WE CAN SELECT USING THE THRESHOLD 81 8

```
 FROM SKLEARNFEATURESELECTION IMPORT VARIANCETHRESHOLD
X  0 0 1 0 1 0 1 0 0 0 1 1 0 1 0 0 1 1
SEL  VARIANCETHRESHOLDTHRESHOLD8 1  8
SELFITTRANSFORMX
ARRAY0 1
1 0
0 0
1 1
1 0
1 1
```

AS EXPECTED VARIANCETHRESHOLD HAS REMOVED THE FIRST COLUMN WHICH HAS A PROBABILITY □ 56 8OF CONTAINING A ZERO

UNIVARIATE FEATURE SELECTION

UNIVARIATE FEATURE SELECTION WORKS BY SELECTING THE BEST FEATURES BASED ON UNIVARIATE STATISTICAL TESTS IT CAN BE SEEN AS A PREPROCESSING STEP TO AN ESTIMATOR SCIKITLEARN EXPOSES FEATURE SELECTION ROUTINES AS OBJECTS THAT IMPLEMENT THE TRANSFORM METHOD

•SELECTKBEST REMOVES ALL BUT THE □HIGHEST SCORING FEATURES

•SELECTPERCENTILE REMOVES ALL BUT A USERSPECIFIED HIGHEST SCORING PERCENTAGE OF FEATURES

• USING COMMON UNIVARIATE STATISTICAL TESTS FOR EACH FEATURE FALSE POSITIVE RATE SELECTFPR FALSE DISCOVERY RATE SELECTFDR OR FAMILY WISE ERROR SELECTFWE

•GENERICUNIVARIATESELECT ALLOWS TO PERFORM UNIVARIATE FEATURE SELECTION WITH A CONFIGURABLE STRATEGY THIS ALLOWS TO SELECT THE BEST UNIVARIATE SELECTION STRATEGY WITH HYPERPARAMETER SEARCH ESTIMATOR

FOR INSTANCE WE CAN PERFORM A □2TEST TO THE SAMPLES TO RETRIEVE ONLY THE TWO BEST FEATURES AS FOLLOWS

```
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNFEATURESELECTION IMPORT SELECTKBEST
 FROM SKLEARNFEATURESELECTION IMPORT CHI2
IRIS  LOADIRIS
X Y  IRISDATA IRISTARGET
XSHAPE
150 4
XNEW  SELECTKBESTCHI2 K2FITTRANSFORMX Y
XNEWSHAPE
150 2
```

THESE OBJECTS TAKE AS INPUT A SCORING FUNCTION THAT RETURNS UNIVARIATE SCORES AND PVALUES OR ONLY SCORES FOR SELECTKBEST ANDSELECTPERCENTILE

• FOR REGRESSION FREGRESSION MUTUALINFOREGRESSION

• FOR CLASSIFICATION CHI2 FCLASSIF MUTUALINFOCLASSIF

THE METHODS BASED ON FTEST ESTIMATE THE DEGREE OF LINEAR DEPENDENCY BETWEEN TWO RANDOM VARIABLES ON THE OTHER HAND MUTUAL INFORMATION METHODS CAN CAPTURE ANY KIND OF STATISTICAL DEPENDENCY BUT BEING NONPARAMETRIC THEY REQUIRE MORE SAMPLES FOR ACCURATE ESTIMATION

FEATURE SELECTION WITH SPARSE DATA

IF YOU USE SPARSE DATA IE DATA REPRESENTED AS SPARSE MATRICES CHI2 MUTUALINFOREGRESSION MUTUALINFOCLASSIF WILL DEAL WITH THE DATA WITHOUT MAKING IT DENSE

WARNING BEWARE NOT TO USE A REGRESSION SCORING FUNCTION WITH A CLASSIFICATION PROBLEM YOU WILL GET USELESS RESULTS

EXAMPLES

•UNIVARIATE FEATURE SELECTION

•COMPARISON OF FTEST AND MUTUAL INFORMATION

RECURSIVE FEATURE ELIMINATION

GIVEN AN EXTERNAL ESTIMATOR THAT ASSIGNS WEIGHTS TO FEATURES EG THE COEFFICIENTS OF A LINEAR MODEL RECURSIVE FEATURE ELIMINATION RFE IS TO SELECT FEATURES BY RECURSIVELY CONSIDERING SMALLER AND SMALLER SETS OF FEATURES FIRST THE ESTIMATOR IS TRAINED ON THE INITIAL SET OF FEATURES AND THE IMPORTANCE OF EACH FEATURE IS OBTAINED EITHER THROUGH A COEF ATTRIBUTE OR THROUGH A FEATUREIMPORTANCES ATTRIBUTE THEN THE LEAST IMPORTANT FEATURES ARE PRUNED FROM CURRENT SET OF FEATURESTHAT PROCEDURE IS RECURSIVELY REPEATED ON THE PRUNED SET UNTIL THE DESIRED NUMBER OF FEATURES TO SELECT IS EVENTUALLY REACHED

RFECV PERFORMS RFE IN A CROSSVALIDATION LOOP TO FIND THE OPTIMAL NUMBER OF FEATURES

EXAMPLES

•RECURSIVE FEATURE ELIMINATION A RECURSIVE FEATURE ELIMINATION EXAMPLE SHOWING THE RELEVANCE OF PIXELS IN A DIGIT CLASSIFICATION TASK

•RECURSIVE FEATURE ELIMINATION WITH CROSSVALIDATION A RECURSIVE FEATURE ELIMINATION EXAMPLE WITH AUTOMATIC TUNING OF THE NUMBER OF FEATURES SELECTED WITH CROSSVALIDATION

FEATURE SELECTION USING SELECTFROMMODEL

SELECTFROMMODEL IS A METATRANSFORMER THAT CAN BE USED ALONG WITH ANY ESTIMATOR THAT HAS A COEF OR FEATUREIMPORTANCES ATTRIBUTE AFTER FITTING THE FEATURES ARE CONSIDERED UNIMPORTANT AND REMOVED IF THE CORRESPONDING COEF ORFEATUREIMPORTANCES VALUES ARE BELOW THE PROVIDED THRESHOLD PARAMETER APART FROM SPECIFYING THE THRESHOLD NUMERICALLY THERE ARE BUILTIN HEURISTICS FOR FINDING A THRESHOLD USING A STRING ARGUMENT AVAILABLE HEURISTICS ARE “MEAN” “MEDIAN” AND FLOAT MULTIPLES OF THESE LIKE “01MEAN”

FOR EXAMPLES ON HOW IT IS TO BE USED REFER TO THE SECTIONS BELOW

EXAMPLES
•FEATURE SELECTION USING SELECTFROMMODEL AND LASSOCV SELECTING THE TWO MOST IMPORTANT FEATURES FROM THE BOSTON DATASET WITHOUT KNOWING THE THRESHOLD BEFOREHAND
L1BASED FEATURE SELECTION
LINEAR MODELS PENALIZED WITH THE L1 NORM HAVE SPARSE SOLUTIONS MANY OF THEIR ESTIMATED COEFFICIENTS ARE ZERO WHEN THE GOAL IS TO REDUCE THE DIMENSIONALITY OF THE DATA TO USE WITH ANOTHER CLASSIFIER THEY CAN BE USED ALONG WITHFEATURESELECTIONSELECTFROMMODEL TO SELECT THE NONZERO COEFFICIENTS IN PARTICULAR SPARSE ESTIMATORS USEFUL FOR THIS PURPOSE ARE THE LINEARMODELLASSO FOR REGRESSION AND OF LINEARMODEL LOGISTICREGRESSION ANDSVMLINEARSVC FOR CLASSIFICATION

```
 FROM SKLEARNSVM IMPORT LINEARSVC
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNFEATURESELECTION IMPORT SELECTFROMMODEL
IRIS  LOADIRIS
X Y  IRISDATA IRISTARGET
XSHAPE
150 4
LSVC  LINEARSVCC001 PENALTYL1 DUAL FALSEFITX Y
MODEL  SELECTFROMMODELLSVC PREFIT TRUE
XNEW  MODELTRANSFORMX
XNEWSHAPE
150 3
```

WITH SVMS AND LOGISTICREGRESSION THE PARAMETER C CONTROLS THE SPARSITY THE SMALLER C THE FEWER FEATURES SELECTED WITH LASSO THE HIGHER THE ALPHA PARAMETER THE FEWER FEATURES SELECTED
EXAMPLES
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES COMPARISON OF DIFFERENT ALGORITHMS FOR DOCUMENT CLASSIFICATION INCLUDING L1BASED FEATURE SELECTION
L1RECOVERY AND COMPRESSIVE SENSING
FOR A GOOD CHOICE OF ALPHA THE LASSO CAN FULLY RECOVER THE EXACT SET OF NONZERO VARIABLES USING ONLY FEW OBSERVATIONS PROVIDED CERTAIN SPECIFIC CONDITIONS ARE MET IN PARTICULAR THE NUMBER OF SAMPLES SHOULD BE “SUFFICIENTLY LARGE” OR L1 MODELS WILL PERFORM AT RANDOM WHERE “SUFFICIENTLY LARGE” DEPENDS ON THE NUMBER OF NONZERO COEFFICIENTS THE LOGARITHM OF THE NUMBER OF FEATURES THE AMOUNT OF NOISE THE SMALLEST ABSOLUTE VALUE OF NONZERO COEFFICIENTS AND THE STRUCTURE OF THE DESIGN MATRIX X IN ADDITION THE DESIGN MATRIX MUST DISPLAY CERTAIN SPECIFIC PROPERTIES SUCH AS NOT BEING TOO CORRELATED
THERE IS NO GENERAL RULE TO SELECT AN ALPHA PARAMETER FOR RECOVERY OF NONZERO COEFFICIENTS IT CAN BY SET BY CROSS VALIDATION LASSOCV ORLASSOLARSCV THOUGH THIS MAY LEAD TO UNDERPENALIZED MODELS INCLUDING A SMALL NUMBER OF NONRELEVANT VARIABLES IS NOT DETRIMENTAL TO PREDICTION SCORE BIC LASSOLARSIC TENDS ON THE OPPOSITE TO SET HIGH VALUES OF ALPHA
REFERENCE RICHARD G BARANIUK “COMPRESSIVE SENSING” IEEE SIGNAL PROCESSING MAGAZINE 120 JULY 2007 HTTP USERSISRISTUTLPTAGUIARCSNOTESPDF

TREEBASED FEATURE SELECTION
TREEBASED ESTIMATORS SEE THE SKLEARNTREE MODULE AND FOREST OF TREES IN THE SKLEARNENSEMBLE MODULE
CAN BE USED TO COMPUTE FEATURE IMPORTANCES WHICH IN TURN CAN BE USED TO DISCARD IRRELEVANT FEATURES WHEN COUPLED
WITH THESKLEARNFEATURESELECTIONSELECTFROMMODEL METATRANSFORMER
```
 FROM SKLEARNENSEMBLE IMPORT EXTRATREESCLASSIFIER
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNFEATURESELECTION IMPORT SELECTFROMMODEL
IRIS  LOADIRIS
X Y  IRISDATA IRISTARGET
XSHAPE
150 4
CLF  EXTRATREESCLASSIFIERNESTIMATORS50
CLF  CLFFITX Y
CLFFEATUREIMPORTANCES
ARRAY 004 005 04 04
MODEL  SELECTFROMMODELCLF PREFIT TRUE
XNEW  MODELTRANSFORMX
XNEWSHAPE
150 2
```
EXAMPLES
•FEATURE IMPORTANCES WITH FORESTS OF TREES EXAMPLE ON SYNTHETIC DATA SHOWING THE RECOVERY OF THE ACTUALLY
MEANINGFUL FEATURES
•PIXEL IMPORTANCES WITH A PARALLEL FOREST OF TREES EXAMPLE ON FACE RECOGNITION DATA
FEATURE SELECTION AS PART OF A PIPELINE
FEATURE SELECTION IS USUALLY USED AS A PREPROCESSING STEP BEFORE DOING THE ACTUAL LEARNING THE RECOMMENDED WAY TO
DO THIS IN SCIKITLEARN IS TO USE A SKLEARNPIPELINEPIPELINE
```
CLF  PIPELINE
FEATURESELECTION SELECTFROMMODELLINEARSVCPENALTYL1
CLASSIFICATION RANDOMFORESTCLASSIFIER

CLFFITX Y
```
IN THIS SNIPPET WE MAKE USE OF A SKLEARNSVMLINEARSVC COUPLED WITH SKLEARNFEATURESELECTION
SELECTFROMMODEL TO EVALUATE FEATURE IMPORTANCES AND SELECT THE MOST RELEVANT FEATURES THEN A SKLEARN
ENSEMBLERANDOMFORESTCLASSIFIER IS TRAINED ON THE TRANSFORMED OUTPUT IE USING ONLY RELEVANT FEATURES
YOU CAN PERFORM SIMILAR OPERATIONS WITH THE OTHER FEATURE SELECTION METHODS AND ALSO CLASSIFIERS THAT PROVIDE A WAY TO
EVALUATE FEATURE IMPORTANCES OF COURSE SEE THE SKLEARNPIPELINEPIPELINE EXAMPLES FOR MORE DETAILS
3114 SEMISUPERVISED
SEMISUPERVISED LEARNING IS A SITUATION IN WHICH IN YOUR TRAINING DATA SOME OF THE SAMPLES ARE NOT LABELED THE SEMI
SUPERVISED ESTIMATORS IN SKLEARNSEMISUPERVISED ARE ABLE TO MAKE USE OF THIS ADDITIONAL UNLABELED DATA TO
BETTER CAPTURE THE SHAPE OF THE UNDERLYING DATA DISTRIBUTION AND GENERALIZE BETTER TO NEW SAMPLES THESE ALGORITHMS
CAN PERFORM WELL WHEN WE HAVE A VERY SMALL AMOUNT OF LABELED POINTS AND A LARGE AMOUNT OF UNLABELED POINTS

UNLABELED ENTRIES IN Y
IT IS IMPORTANT TO ASSIGN AN IDENTIFIER TO UNLABELED POINTS ALONG WITH THE LABELED DATA WHEN TRAINING THE MODEL WITH THEFIT METHOD THE IDENTIFIER THAT THIS IMPLEMENTATION USES IS THE INTEGER VALUE −1
LABEL PROPAGATION
LABEL PROPAGATION DENOTES A FEW VARIATIONS OF SEMISUPERVISED GRAPH INFERENCE ALGORITHMS
A FEW FEATURES AVAILABLE IN THIS MODEL
• CAN BE USED FOR CLASSIFICATION AND REGRESSION TASKS
• KERNEL METHODS TO PROJECT DATA INTO ALTERNATE DIMENSIONAL SPACES
SCIKITLEARN PROVIDES TWO LABEL PROPAGATION MODELS LABELPROPAGATION ANDLABELSPREADING BOTH WORK BY CONSTRUCTING A SIMILARITY GRAPH OVER ALL ITEMS IN THE INPUT DATASET
FIG 31 AN ILLUSTRATION OF LABELPROPAGATION THE STRUCTURE OF UNLABELED OBSERVATIONS IS CONSISTENT WITH THE CLASS STRUCTURE AND THUS THE CLASS LABEL CAN BE PROPAGATED TO THE UNLABELED OBSERVATIONS OF THE TRAINING SET
LABELPROPAGATION ANDLABELSPREADING DIFFER IN MODIFICATIONS TO THE SIMILARITY MATRIX THAT GRAPH AND THE CLAMPING EFFECT ON THE LABEL DISTRIBUTIONS CLAMPING ALLOWS THE ALGORITHM TO CHANGE THE WEIGHT OF THE TRUE GROUND LABELED DATA TO SOME DEGREE THE LABELPROPAGATION ALGORITHM PERFORMS HARD CLAMPING OF INPUT LABELS WHICH MEANS □ 0 THIS CLAMPING FACTOR CAN BE RELAXED TO SAY □ 02 WHICH MEANS THAT WE WILL ALWAYS RETAIN 80 PERCENT OF OUR ORIGINAL LABEL DISTRIBUTION BUT THE ALGORITHM GETS TO CHANGE ITS CONFIDENCE OF THE DISTRIBUTION WITHIN 20 PERCENT
LABELPROPAGATION USES THE RAW SIMILARITY MATRIX CONSTRUCTED FROM THE DATA WITH NO MODIFICATIONS IN CONTRAST LABELSPREADING MINIMIZES A LOSS FUNCTION THAT HAS REGULARIZATION PROPERTIES AS SUCH IT IS OFTEN MORE ROBUST TO NOISE THE ALGORITHM ITERATES ON A MODIFIED VERSION OF THE ORIGINAL GRAPH AND NORMALIZES THE EDGE WEIGHTS BY COMPUTING THE NORMALIZED GRAPH LAPLACIAN MATRIX THIS PROCEDURE IS ALSO USED IN SPECTRAL CLUSTERING
LABEL PROPAGATION MODELS HAVE TWO BUILTIN KERNEL METHODS CHOICE OF KERNEL EFFECTS BOTH SCALABILITY AND PERFORMANCE OF THE ALGORITHMS THE FOLLOWING ARE AVAILABLE
• RBF EXP−□□−□2 □ 0□IS SPECIFIED BY KEYWORD GAMMA
• KNN 1□′∈□□□ □□IS SPECIFIED BY KEYWORD NNEIGHBORS

THE RBF KERNEL WILL PRODUCE A FULLY CONNECTED GRAPH WHICH IS REPRESENTED IN MEMORY BY A DENSE MATRIX THIS MATRIX MAY BE VERY LARGE AND COMBINED WITH THE COST OF PERFORMING A FULL MATRIX MULTIPLICATION CALCULATION FOR EACH ITERATION OF THE ALGORITHM CAN LEAD TO PROHIBITIVELY LONG RUNNING TIMES ON THE OTHER HAND THE KNN KERNEL WILL PRODUCE A MUCH MORE MEMORYFRIENDLY SPARSE MATRIX WHICH CAN DRASTICALLY REDUCE RUNNING TIMES

EXAMPLES

•DECISION BOUNDARY OF LABEL PROPAGATION VERSUS SVM ON THE IRIS DATASET
•LABEL PROPAGATION LEARNING A COMPLEX STRUCTURE
•LABEL PROPAGATION DIGITS DEMONSTRATING PERFORMANCE
•LABEL PROPAGATION DIGITS ACTIVE LEARNING

REFERENCES

1 YOSHUA BENGIO OLIVIER DELALLEAU NICOLAS LE ROUX IN SEMISUPERVISED LEARNING 2006 PP 193216
2 OLIVIER DELALLEAU YOSHUA BENGIO NICOLAS LE ROUX EFFICIENT NONPARAMETRIC FUNCTION INDUCTION IN SEMI SUPERVISED LEARNING AISTAT 2005 HTTPSRESEARCHMICROSOFTCOMENUSPEOPLENICOLASLEFFICIENTSSLPDF

3115 ISOTONIC REGRESSION

THE CLASSISOTONICREGRESSION FITS A NONDECREASING FUNCTION TO DATA IT SOLVES THE FOLLOWING PROBLEM

MINIMIZE∑
□□□□□−□□2
SUBJECT TO □□□□ □1≤□2≤□□ □□□□

WHERE EACH □□IS STRICTLY POSITIVE AND EACH □□IS AN ARBITRARY REAL NUMBER IT YIELDS THE VECTOR WHICH IS COMPOSED OF NONDECREASING ELEMENTS THE CLOSEST IN TERMS OF MEAN SQUARED ERROR IN PRACTICE THIS LIST OF ELEMENTS FORMS A FUNCTION THAT IS PIECEWISE LINEAR

3116 PROBABILITY CALIBRATION

WHEN PERFORMING CLASSIFICATION YOU OFTEN WANT NOT ONLY TO PREDICT THE CLASS LABEL BUT ALSO OBTAIN A PROBABILITY OF THE RESPECTIVE LABEL THIS PROBABILITY GIVES YOU SOME KIND OF CONFIDENCE ON THE PREDICTION SOME MODELS CAN GIVE YOU POOR ESTIMATES OF THE CLASS PROBABILITIES AND SOME EVEN DO NOT SUPPORT PROBABILITY PREDICTION THE CALIBRATION MODULE ALLOWS YOU TO BETTER CALIBRATE THE PROBABILITIES OF A GIVEN MODEL OR TO ADD SUPPORT FOR PROBABILITY PREDICTION

WELL CALIBRATED CLASSIFIERS ARE PROBABILISTIC CLASSIFIERS FOR WHICH THE OUTPUT OF THE PREDICTPROBA METHOD CAN BE DIRECTLY INTERPRETED AS A CONFIDENCE LEVEL FOR INSTANCE A WELL CALIBRATED BINARY CLASSIFIER SHOULD CLASSIFY THE SAMPLES SUCH THAT AMONG THE SAMPLES TO WHICH IT GAVE A PREDICTPROBA VALUE CLOSE TO 08 APPROXIMATELY 80 ACTUALLY BELONG TO THE POSITIVE CLASS THE FOLLOWING PLOT COMPARES HOW WELL THE PROBABILISTIC PREDICTIONS OF DIFFERENT CLASSIFIERS ARE CALIBRATED LOGISTICREGRESSION RETURNS WELL CALIBRATED PREDICTIONS BY DEFAULT AS IT DIRECTLY OPTIMIZES LOGLOSS IN CONTRAST THE OTHER METHODS RETURN BIASED PROBABILITIES WITH DIFFERENT BIASES PER METHOD

•GAUSSIANNB TENDS TO PUSH PROBABILITIES TO 0 OR 1 NOTE THE COUNTS IN THE HISTOGRAMS THIS IS MAINLY BECAUSE IT MAKES THE ASSUMPTION THAT FEATURES ARE CONDITIONALLY INDEPENDENT GIVEN THE CLASS WHICH IS NOT THE CASE IN THIS DATASET WHICH CONTAINS 2 REDUNDANT FEATURES

•RANDOMFORESTCLASSIFIER SHOWS THE OPPOSITE BEHAVIOR THE HISTOGRAMS SHOW PEAKS AT APPROXIMATELY 02 AND 09 PROBABILITY WHILE PROBABILITIES CLOSE TO 0 OR 1 ARE VERY RARE AN EXPLANATION FOR THIS IS GIVEN BY NICULESCUMIZIL AND CARUANA4 “METHODS SUCH AS BAGGING AND RANDOM FORESTS THAT AVERAGE PREDICTIONS FROM A BASE SET OF MODELS CAN HAVE DIFFICULTY MAKING PREDICTIONS NEAR 0 AND 1 BECAUSE VARIANCE IN THE UNDERLYING BASE MODELS WILL BIAS PREDICTIONS THAT SHOULD BE NEAR ZERO OR ONE AWAY FROM THESE VALUES BECAUSE PREDICTIONS ARE RESTRICTED TO THE INTERVAL 01 ERRORS CAUSED BY VARIANCE TEND TO BE ONESIDED NEAR ZERO AND ONE FOR EXAMPLE IF A MODEL SHOULD PREDICT P 0 FOR A CASE THE ONLY WAY BAGGING CAN ACHIEVE THIS IS IF ALL BAGGED TREES PREDICT ZERO IF WE ADD NOISE TO THE TREES THAT BAGGING IS AVERAGING OVER THIS NOISE WILL CAUSE SOME TREES TO PREDICT VALUES LARGER THAN 0 FOR THIS CASE THUS MOVING THE AVERAGE PREDICTION OF THE BAGGED ENSEMBLE AWAY FROM 0 WE OBSERVE THIS EFFECT MOST STRONGLY WITH RANDOM FORESTS BECAUSE THE BASELEVEL TREES TRAINED WITH RANDOM FORESTS HAVE RELATIVELY HIGH VARIANCE DUE TO FEATURE SUBSETTING” AS A RESULT THE CALIBRATION CURVE ALSO REFERRED TO AS THE RELIABILITY DIAGRAM WILKS 19955 SHOWS A CHARACTERISTIC SIGMOID SHAPE INDICATING THAT THE CLASSIFIER COULD TRUST ITS “INTUITION” MORE AND RETURN PROBABILITIES CLOSER TO 0 OR 1 TYPICALLY

• LINEAR SUPPORT VECTOR CLASSIFICATION LINEARSVC SHOWS AN EVEN MORE SIGMOID CURVE AS THE RANDOMFOREST CLASSIFIER WHICH IS TYPICAL FOR MAXIMUMMARGIN METHODS COMPARE NICULESCUMIZIL AND CARUANA4 WHICH FOCUS ON HARD SAMPLES THAT ARE CLOSE TO THE DECISION BOUNDARY THE SUPPORT VECTORS

TWO APPROACHES FOR PERFORMING CALIBRATION OF PROBABILISTIC PREDICTIONS ARE PROVIDED A PARAMETRIC APPROACH BASED ON PLATT’S SIGMOID MODEL AND A NONPARAMETRIC APPROACH BASED ON ISOTONIC REGRESSION SKLEARNISOTONIC PROBABILITY CALIBRATION SHOULD BE DONE ON NEW DATA NOT USED FOR MODEL FITTING THE CLASS CALIBRATEDCLASSIFIERCV USES A CROSSVALIDATION GENERATOR AND ESTIMATES FOR EACH SPLIT THE MODEL PARAMETER ON THE TRAIN SAMPLES AND THE CALIBRATION OF THE TEST SAMPLES THE PROBABILITIES PREDICTED FOR THE FOLDS ARE THEN AVERAGED ALREADY FITTED CLASSIFIERS CAN BE CALIBRATED BY CALIBRATEDCLASSIFIERCV VIA THE PARAMETER CV”PREFIT” IN THIS CASE THE USER HAS TO TAKE CARE MANUALLY THAT DATA FOR MODEL FITTING AND CALIBRATION ARE DISJOINT

THE FOLLOWING IMAGES DEMONSTRATE THE BENEFIT OF PROBABILITY CALIBRATION THE FIRST IMAGE PRESENT A DATASET WITH 2 CLASSES AND 3 BLOBS OF DATA THE BLOB IN THE MIDDLE CONTAINS RANDOM SAMPLES OF EACH CLASS THE PROBABILITY FOR THE SAMPLES IN THIS BLOB SHOULD BE 05

THE FOLLOWING IMAGE SHOWS ON THE DATA ABOVE THE ESTIMATED PROBABILITY USING A GAUSSIAN NAIVE BAYES CLASSIFIER WITHOUT CALIBRATION WITH A SIGMOID CALIBRATION AND WITH A NONPARAMETRIC ISOTONIC CALIBRATION ONE CAN OBSERVE THAT THE NON PARAMETRIC MODEL PROVIDES THE MOST ACCURATE PROBABILITY ESTIMATES FOR SAMPLES IN THE MIDDLE IE 05

THE FOLLOWING EXPERIMENT IS PERFORMED ON AN ARTIFICIAL DATASET FOR BINARY CLASSIFICATION WITH 100000 SAMPLES 1000 OF THEM ARE USED FOR MODEL FITTING WITH 20 FEATURES OF THE 20 FEATURES ONLY 2 ARE INFORMATIVE AND 10 ARE REDUNDANT THE FIGURE SHOWS THE ESTIMATED PROBABILITIES OBTAINED WITH LOGISTIC REGRESSION A LINEAR SUPPORTVECTOR CLASSIFIER SVC AND LINEAR SVC WITH BOTH ISOTONIC CALIBRATION AND SIGMOID CALIBRATION THE BRIER SCORE IS A METRIC WHICH IS A COMBINATION OF CALIBRATION LOSS AND REFINEMENT LOSS BRIERSCORELOSS REPORTED IN THE LEGEND THE SMALLER THE BETTER CALIBRATION LOSS IS DEFINED AS THE MEAN SQUARED DEVIATION FROM EMPIRICAL PROBABILITIES DERIVED FROM THE SLOPE OF ROC SEGMENTS REFINEMENT LOSS CAN BE DEFINED AS THE EXPECTED OPTIMAL LOSS AS MEASURED BY THE AREA UNDER THE OPTIMAL COST CURVE

ONE CAN OBSERVE HERE THAT LOGISTIC REGRESSION IS WELL CALIBRATED AS ITS CURVE IS NEARLY DIAGONAL LINEAR SVC’S CALIBRATION CURVE OR RELIABILITY DIAGRAM HAS A SIGMOID CURVE WHICH IS TYPICAL FOR AN UNDERCONFIDENT CLASSIFIER IN THE CASE OF LINEARSVC THIS IS CAUSED BY THE MARGIN PROPERTY OF THE HINGE LOSS WHICH LETS THE MODEL FOCUS ON HARD SAMPLES THAT ARE CLOSE TO THE DECISION BOUNDARY THE SUPPORT VECTORS BOTH KINDS OF CALIBRATION CAN FIX THIS ISSUE AND YIELD NEARLY IDENTICAL RESULTS THE NEXT FIGURE SHOWS THE CALIBRATION CURVE OF GAUSSIAN NAIVE BAYES ON THE SAME DATA WITH BOTH KINDS OF CALIBRATION AND ALSO WITHOUT CALIBRATION

ONE CAN SEE THAT GAUSSIAN NAIVE BAYES PERFORMS VERY BADLY BUT DOES SO IN AN OTHER WAY THAN LINEAR SVC WHILE LINEAR SVC EXHIBITED A SIGMOID CALIBRATION CURVE GAUSSIAN NAIVE BAYES’ CALIBRATION CURVE HAS A TRANSPOSEDSIGMOID SHAPE THIS IS TYPICAL FOR AN OVERCONFIDENT CLASSIFIER IN THIS CASE THE CLASSIFIER’S OVERCONFIDENCE IS CAUSED BY THE REDUNDANT FEATURES WHICH VIOLATE THE NAIVE BAYES ASSUMPTION OF FEATUREINDEPENDENCE

4PREDICTING GOOD PROBABILITIES WITH SUPERVISED LEARNING A NICULESCUMIZIL R CARUANA ICML 2005

5ON THE COMBINATION OF FORECAST PROBABILITIES FOR CONSECUTIVE PRECIPITATION PERIODS WEA FORECASTING 5 640–650 WILKS D S 1990A

CALIBRATION OF THE PROBABILITIES OF GAUSSIAN NAIVE BAYES WITH ISOTONIC REGRESSION CAN FIX THIS ISSUE AS CAN BE SEEN FROM THE NEARLY DIAGONAL CALIBRATION CURVE SIGMOID CALIBRATION ALSO IMPROVES THE BRIER SCORE SLIGHTLY ALBEIT NOT AS STRONGLY AS THE NONPARAMETRIC ISOTONIC CALIBRATION THIS IS AN INTRINSIC LIMITATION OF SIGMOID CALIBRATION WHOSE PARAMETRIC FORM ASSUMES A SIGMOID RATHER THAN A TRANSPOSEDSIGMOID CURVE THE NONPARAMETRIC ISOTONIC CALIBRATION MODEL HOWEVER MAKES NO SUCH STRONG ASSUMPTIONS AND CAN DEAL WITH EITHER SHAPE PROVIDED THAT THERE IS SUFFICIENT CALIBRATION DATA IN GENERAL SIGMOID CALIBRATION IS PREFERABLE IN CASES WHERE THE CALIBRATION CURVE IS SIGMOID AND WHERE THERE IS LIMITED CALIBRATION DATA WHILE ISOTONIC CALIBRATION IS PREFERABLE FOR NONSIGMOID CALIBRATION CURVES AND IN SITUATIONS WHERE LARGE AMOUNTS OF DATA ARE AVAILABLE FOR CALIBRATION

CALIBRATEDCLASSIFIERCV CAN ALSO DEAL WITH CLASSIFICATION TASKS THAT INVOLVE MORE THAN TWO CLASSES IF THE BASE ESTIMATOR CAN DO SO IN THIS CASE THE CLASSIFIER IS CALIBRATED FIRST FOR EACH CLASS SEPARATELY IN AN ONEVSREST FASHION WHEN PREDICTING PROBABILITIES FOR UNSEEN DATA THE CALIBRATED PROBABILITIES FOR EACH CLASS ARE PREDICTED SEPARATELY AS THOSE PROBABILITIES DO NOT NECESSARILY SUM TO ONE A POSTPROCESSING IS PERFORMED TO NORMALIZE THEM

THE NEXT IMAGE ILLUSTRATES HOW SIGMOID CALIBRATION CHANGES PREDICTED PROBABILITIES FOR A 3CLASS CLASSIFICATION PROBLEM ILLUSTRATED IS THE STANDARD 2SIMPLEX WHERE THE THREE CORNERS CORRESPOND TO THE THREE CLASSES ARROWS POINT FROM THE PROBABILITY VECTORS PREDICTED BY AN UNCALIBRATED CLASSIFIER TO THE PROBABILITY VECTORS PREDICTED BY THE SAME CLASSIFIER AFTER SIGMOID CALIBRATION ON A HOLDOUT VALIDATION SET COLORS INDICATE THE TRUE CLASS OF AN INSTANCE RED CLASS 1 GREEN CLASS 2 BLUE CLASS 3

THE BASE CLASSIFIER IS A RANDOM FOREST CLASSIFIER WITH 25 BASE ESTIMATORS TREES IF THIS CLASSIFIER IS TRAINED ON ALL 800 TRAINING DATAPOINTS IT IS OVERLY CONFIDENT IN ITS PREDICTIONS AND THUS INCURS A LARGE LOGLOSS CALIBRATING AN IDENTICAL CLASSIFIER WHICH WAS TRAINED ON 600 DATAPOINTS WITH METHOD’SIGMOID’ ON THE REMAINING 200 DATAPOINTS REDUCES THE CONFIDENCE OF THE PREDICTIONS IE MOVES THE PROBABILITY VECTORS FROM THE EDGES OF THE SIMPLEX TOWARDS THE CENTER

THIS CALIBRATION RESULTS IN A LOWER LOGLOSS NOTE THAT AN ALTERNATIVE WOULD HAVE BEEN TO INCREASE THE NUMBER OF BASE ESTIMATORS WHICH WOULD HAVE RESULTED IN A SIMILAR DECREASE IN LOGLOSS

REFERENCES

• OBTAINING CALIBRATED PROBABILITY ESTIMATES FROM DECISION TREES AND NAIVE BAYESIAN CLASSIFIERS B ZADROZNY C ELKAN ICML 2001
• TRANSFORMING CLASSIFIER SCORES INTO ACCURATE MULTICLASS PROBABILITY ESTIMATES B ZADROZNY C ELKAN KDD 2002
• PROBABILISTIC OUTPUTS FOR SUPPORT VECTOR MACHINES AND COMPARISONS TO REGULARIZED LIKELIHOOD METHODS J PLATT 1999

3117 NEURAL NETWORK MODELS SUPERVISED

WARNING THIS IMPLEMENTATION IS NOT INTENDED FOR LARGESCALE APPLICATIONS IN PARTICULAR SCIKITLEARN OFFERS NO GPU SUPPORT FOR MUCH FASTER GPUBASED IMPLEMENTATIONS AS WELL AS FRAMEWORKS OFFERING MUCH MORE FLEXIBILITY TO BUILD DEEP LEARNING ARCHITECTURES SEE RELATED PROJECTS

MULTILAYER PERCEPTRON

MULTILAYER PERCEPTRON MLP IS A SUPERVISED LEARNING ALGORITHM THAT LEARNS A FUNCTION □· □□→□□BY TRAINING ON A DATASET WHERE □IS THE NUMBER OF DIMENSIONS FOR INPUT AND □IS THE NUMBER OF DIMENSIONS FOR OUTPUT GIVEN A SET OF FEATURES □□1 □2 □ □AND A TARGET □ IT CAN LEARN A NONLINEAR FUNCTION APPROXIMATOR FOR EITHER CLASSIFICATION OR REGRESSION IT IS DIFFERENT FROM LOGISTIC REGRESSION IN THAT BETWEEN THE INPUT AND THE OUTPUT LAYER THERE CAN BE ONE OR MORE NONLINEAR LAYERS CALLED HIDDEN LAYERS FIGURE 1 SHOWS A ONE HIDDEN LAYER MLP WITH SCALAR OUTPUT

FIG 32 FIGURE 1 ONE HIDDEN LAYER MLP

THE LEFTMOST LAYER KNOWN AS THE INPUT LAYER CONSISTS OF A SET OF NEURONS □□□1 □2 □ □REPRESENTING THE INPUT FEATURES EACH NEURON IN THE HIDDEN LAYER TRANSFORMS THE VALUES FROM THE PREVIOUS LAYER WITH A WEIGHTED LINEAR SUM MATION □1□1□2□2□□□□ FOLLOWED BY A NONLINEAR ACTIVATION FUNCTION □· □→□ LIKE THE HYPERBOLIC TAN FUNCTION THE OUTPUT LAYER RECEIVES THE VALUES FROM THE LAST HIDDEN LAYER AND TRANSFORMS THEM INTO OUTPUT VALUES

THE MODULE CONTAINS THE PUBLIC ATTRIBUTES COEFS ANDINTERCEPTS COEFS IS A LIST OF WEIGHT MATRICES WHERE WEIGHT MATRIX AT INDEX REPRESENTS THE WEIGHTS BETWEEN LAYER AND LAYER 1INTERCEPTS IS A LIST OF BIAS VECTORS WHERE THE VECTOR AT INDEX REPRESENTS THE BIAS VALUES ADDED TO LAYER 1

THE ADVANTAGES OF MULTILAYER PERCEPTRON ARE

• CAPABILITY TO LEARN NONLINEAR MODELS

• CAPABILITY TO LEARN MODELS IN REALTIME ONLINE LEARNING USING PARTIALFIT

THE DISADVANTAGES OF MULTILAYER PERCEPTRON MLP INCLUDE

• MLP WITH HIDDEN LAYERS HAVE A NONCONVEX LOSS FUNCTION WHERE THERE EXISTS MORE THAN ONE LOCAL MINIMUM THEREFORE DIFFERENT RANDOM WEIGHT INITIALIZATIONS CAN LEAD TO DIFFERENT VALIDATION ACCURACY

• MLP REQUIRES TUNING A NUMBER OF HYPERPARAMETERS SUCH AS THE NUMBER OF HIDDEN NEURONS LAYERS AND ITERATIONS

• MLP IS SENSITIVE TO FEATURE SCALING

PLEASE SEE TIPS ON PRACTICAL USE SECTION THAT ADDRESSES SOME OF THESE DISADVANTAGES

CLASSIFICATION

CLASSMLPCLASSIFIER IMPLEMENTS A MULTILAYER PERCEPTRON MLP ALGORITHM THAT TRAINS USING BACKPROPAGATION

MLP TRAINS ON TWO ARRAYS ARRAY X OF SIZE NSAMPLES NFEATURES WHICH HOLDS THE TRAINING SAMPLES REPRESENTED AS FLOATING POINT FEATURE VECTORS AND ARRAY Y OF SIZE NSAMPLES WHICH HOLDS THE TARGET VALUES CLASS LABELS FOR THE TRAINING SAMPLES

```
 FROM SKLEARNNEURALNETWORK IMPORT MLPCLASSIFIER
X  0 0 1 1
Y  0 1
CLF  MLPCLASSIFIERSOLVERLBFGS ALPHA1E5
 HIDDENLAYERSIZES5 2 RANDOMSTATE1

CLFFITX Y
MLPCLASSIFIERACTIVATIONRELU ALPHA1E05 BATCHSIZEAUTO
BETA109 BETA20999 EARLYSTOPPINGFALSE
EPSILON1E08 HIDDENLAYERSIZES5 2
LEARNINGRATECONSTANT LEARNINGRATEINIT0001
MAXITER200 MOMENTUM09 NITERNOCHANGE10
NESTEROVSMOMENTUMTRUE POWERT05 RANDOMSTATE1
SHUFFLETRUE SOLVERLBFGS TOL00001
VALIDATIONFRACTION01 VERBOSEFALSE WARMSTARTFALSE
```

AFTER FITTING TRAINING THE MODEL CAN PREDICT LABELS FOR NEW SAMPLES

```
CLFPREDICT2 2 1 2
ARRAY1 0
```

MLP CAN FIT A NONLINEAR MODEL TO THE TRAINING DATA CLFCOEFS CONTAINS THE WEIGHT MATRICES THAT CONSTITUTE THE MODEL PARAMETERS

```
COEFSHAPE FORCOEFINCLFCOEFS
2 5 5 2 2 1
```

CURRENTLYMLPCLASSIFIER SUPPORTS ONLY THE CROSSENTROPY LOSS FUNCTION WHICH ALLOWS PROBABILITY ESTIMATES BY RUNNING THE PREDICTPROBA METHOD

MLP TRAINS USING BACKPROPAGATION MORE PRECISELY IT TRAINS USING SOME FORM OF GRADIENT DESCENT AND THE GRADIENTS ARE CALCULATED USING BACKPROPAGATION FOR CLASSIFICATION IT MINIMIZES THE CROSSENTROPY LOSS FUNCTION GIVING A VECTOR OF PROBABILITY ESTIMATES □□□PER SAMPLE □

```
CLFPREDICTPROBA2 2 1 2
ARRAY1967E04 999801
1967E04 999801
```

MLPCLASSIFIER SUPPORTS MULTICLASS CLASSIFICATION BY APPLYING SOFTMAX AS THE OUTPUT FUNCTION

FURTHER THE MODEL SUPPORTS MULTILABEL CLASSIFICATION IN WHICH A SAMPLE CAN BELONG TO MORE THAN ONE CLASS FOR EACH CLASS THE RAW OUTPUT PASSES THROUGH THE LOGISTIC FUNCTION VALUES LARGER OR EQUAL TO 05 ARE ROUNDED TO 1 OTHERWISE TO 0 FOR A PREDICTED OUTPUT OF A SAMPLE THE INDICES WHERE THE VALUE IS 1REPRESENTS THE ASSIGNED CLASSES OF THAT SAMPLE

```
X  0 0 1 1
Y  0 1 1 1
CLF  MLPCLASSIFIERSOLVERLBFGS ALPHA1E5
 HIDDENLAYERSIZES15 RANDOMSTATE1

CLFFITX Y
MLPCLASSIFIERACTIVATIONRELU ALPHA1E05 BATCHSIZEAUTO
BETA109 BETA20999 EARLYSTOPPINGFALSE
EPSILON1E08 HIDDENLAYERSIZES15
LEARNINGRATECONSTANT LEARNINGRATEINIT0001
MAXITER200 MOMENTUM09 NITERNOCHANGE10
NESTEROVSMOMENTUMTRUE POWERT05 RANDOMSTATE1
SHUFFLETRUE SOLVERLBFGS TOL00001
VALIDATIONFRACTION01 VERBOSEFALSE WARMSTARTFALSE
CLFPREDICT1 2
ARRAY1 1
CLFPREDICT0 0
ARRAY0 1
```

SEE THE EXAMPLES BELOW AND THE DOCSTRING OF MLPCLASSIFIERFIT FOR FURTHER INFORMATION

EXAMPLES

- COMPARE STOCHASTIC LEARNING STRATEGIES FOR MLPCLASSIFIER
- VISUALIZATION OF MLP WEIGHTS ON MNIST

REGRESSION

CLASSMLPREGRESSOR IMPLEMENTS A MULTILAYER PERCEPTRON MLP THAT TRAINS USING BACKPROPAGATION WITH NO ACTIVATION FUNCTION IN THE OUTPUT LAYER WHICH CAN ALSO BE SEEN AS USING THE IDENTITY FUNCTION AS ACTIVATION FUNCTION THEREFORE IT USES THE SQUARE ERROR AS THE LOSS FUNCTION AND THE OUTPUT IS A SET OF CONTINUOUS VALUES

MLPREGRESSOR ALSO SUPPORTS MULTIOUTPUT REGRESSION IN WHICH A SAMPLE CAN HAVE MORE THAN ONE TARGET

REGULARIZATION

BOTHMLPREGRESSOR ANDMLPCLASSIFIER USE PARAMETER ALPHA FOR REGULARIZATION L2 REGULARIZATION TERM WHICH HELPS IN AVOIDING OVERFITTING BY PENALIZING WEIGHTS WITH LARGE MAGNITUDES FOLLOWING PLOT DISPLAYS VARYING DECISION FUNCTION WITH VALUE OF ALPHA

SEE THE EXAMPLES BELOW FOR FURTHER INFORMATION
EXAMPLES
•VARYING REGULARIZATION IN MULTILAYER PERCEPTRON
ALGORITHMS
MLP TRAINS USING STOCHASTIC GRADIENT DESCENT ADAM OR LBFGS STOCHASTIC GRADIENT DESCENT SGD UPDATES PA
RAMETERS USING THE GRADIENT OF THE LOSS FUNCTION WITH RESPECT TO A PARAMETER THAT NEEDS ADAPTATION IE
□←□−□□□□□
□□□□□□□
□□
WHERE □IS THE LEARNING RATE WHICH CONTROLS THE STEPSIZE IN THE PARAMETER SPACE SEARCH □□□□ IS THE LOSS FUNCTION USED FOR THE NETWORK
MORE DETAILS CAN BE FOUND IN THE DOCUMENTATION OF SGD
ADAM IS SIMILAR TO SGD IN A SENSE THAT IT IS A STOCHASTIC OPTIMIZER BUT IT CAN AUTOMATICALLY ADJUST THE AMOUNT TO UPDATE PARAMETERS BASED ON ADAPTIVE ESTIMATES OF LOWERORDER MOMENTS
WITH SGD OR ADAM TRAINING SUPPORTS ONLINE AND MINIBATCH LEARNING
LBFGS IS A SOLVER THAT APPROXIMATES THE HESSIAN MATRIX WHICH REPRESENTS THE SECONDORDER PARTIAL DERIVATIVE OF A FUNCTION FURTHER IT APPROXIMATES THE INVERSE OF THE HESSIAN MATRIX TO PERFORM PARAMETER UPDATES THE IMPLEMENTATION USES THE SCIPY VERSION OF LBFGS
IF THE SELECTED SOLVER IS ‘LBFGS’ TRAINING DOES NOT SUPPORT ONLINE NOR MINIBATCH LEARNING

COMPLEXITY
SUPPOSE THERE ARE □TRAINING SAMPLES □FEATURES □HIDDEN LAYERS EACH CONTAINING *h*NEURONS FOR SIMPLICITY AND □ OUTPUT NEURONS THE TIME COMPLEXITY OF BACKPROPAGATION IS □□·□·*h*□·□·□ WHERE □IS THE NUMBER OF ITERATIONS SINCE BACKPROPAGATION HAS A HIGH TIME COMPLEXITY IT IS ADVISABLE TO START WITH SMALLER NUMBER OF HIDDEN NEURONS AND FEW HIDDEN LAYERS FOR TRAINING
MATHEMATICAL FORMULATION
GIVEN A SET OF TRAINING EXAMPLES □1 □1□2 □2 □□ □□WHERE □□∈R□AND□□∈01 A ONE HIDDEN LAYER ONE HIDDEN NEURON MLP LEARNS THE FUNCTION □□ □2□□□
1□□1 □2WHERE □1∈R□AND□2 □1 □2∈RARE
MODEL PARAMETERS □1 □2REPRESENT THE WEIGHTS OF THE INPUT LAYER AND HIDDEN LAYER RESPECTIVELY AND □1 □2REPRESENT THE BIAS ADDED TO THE HIDDEN LAYER AND THE OUTPUT LAYER RESPECTIVELY □· □→□IS THE ACTIVATION FUNCTION SET BY DEFAULT AS THE HYPERBOLIC TAN IT IS GIVEN AS
□□ □□−□−□
□□□−□
FOR BINARY CLASSIFICATION □□PASSES THROUGH THE LOGISTIC FUNCTION □□ 1 1□−□TO OBTAIN OUTPUT VALUES BETWEEN ZERO AND ONE A THRESHOLD SET TO 05 WOULD ASSIGN SAMPLES OF OUTPUTS LARGER OR EQUAL 05 TO THE POSITIVE CLASS AND THE REST TO THE NEGATIVE CLASS
IF THERE ARE MORE THAN TWO CLASSES □□ITSELF WOULD BE A VECTOR OF SIZE NCLASSES INSTEAD OF PASSING THROUGH LOGISTIC FUNCTION IT PASSES THROUGH THE SOFTMAX FUNCTION WHICH IS WRITTEN AS
SOFTMAX □□EXP□□
∑□
□1EXP□□
WHERE □□REPRESENTS THE □TH ELEMENT OF THE INPUT TO SOFTMAX WHICH CORRESPONDS TO CLASS □ AND □IS THE NUMBER OF CLASSES THE RESULT IS A VECTOR CONTAINING THE PROBABILITIES THAT SAMPLE □BELONG TO EACH CLASS THE OUTPUT IS THE CLASS WITH THE HIGHEST PROBABILITY
IN REGRESSION THE OUTPUT REMAINS AS □□ THEREFORE OUTPUT ACTIVATION FUNCTION IS JUST THE IDENTITY FUNCTION
MLP USES DIFFERENT LOSS FUNCTIONS DEPENDING ON THE PROBLEM TYPE THE LOSS FUNCTION FOR CLASSIFICATION IS CROSSENTROPY WHICH IN BINARY CASE IS GIVEN AS
□□□□ □ □ □ −□LN □−1−□ LN 1−□ □□2
2
WHERE □□2
2IS AN L2REGULARIZATION TERM AKA PENALTY THAT PENALIZES COMPLEX MODELS AND □ 0IS A NONNEGATIVE HYPERPARAMETER THAT CONTROLS THE MAGNITUDE OF THE PENALTY
FOR REGRESSION MLP USES THE SQUARE ERROR LOSS FUNCTION WRITTEN AS
□□□□ □ □ □ 1
2□−□2
2□
2□2
2
STARTING FROM INITIAL RANDOM WEIGHTS MULTILAYER PERCEPTRON MLP MINIMIZES THE LOSS FUNCTION BY REPEATEDLY UPDATING THESE WEIGHTS AFTER COMPUTING THE LOSS A BACKWARD PASS PROPAGATES IT FROM THE OUTPUT LAYER TO THE PREVIOUS LAYERS PROVIDING EACH WEIGHT PARAMETER WITH AN UPDATE VALUE MEANT TO DECREASE THE LOSS
IN GRADIENT DESCENT THE GRADIENT ∇□□□□ □OF THE LOSS WITH RESPECT TO THE WEIGHTS IS COMPUTED AND DEDUCTED FROM □ MORE FORMALLY THIS IS EXPRESSED AS
□□1□□−□∇□□□□□
□
WHERE □IS THE ITERATION STEP AND □IS THE LEARNING RATE WITH A VALUE LARGER THAN 0
THE ALGORITHM STOPS WHEN IT REACHES A PRESET MAXIMUM NUMBER OF ITERATIONS OR WHEN THE IMPROVEMENT IN LOSS IS BELOW A CERTAIN SMALL NUMBER

TIPS ON PRACTICAL USE

• MULTILAYER PERCEPTRON IS SENSITIVE TO FEATURE SCALING SO IT IS HIGHLY RECOMMENDED TO SCALE YOUR DATA FOR EXAMPLE SCALE EACH ATTRIBUTE ON THE INPUT VECTOR X TO 0 1 OR 1 1 OR STANDARDIZE IT TO HAVE MEAN 0 AND VARIANCE 1 NOTE THAT YOU MUST APPLY THE SAME SCALING TO THE TEST SET FOR MEANINGFUL RESULTS YOU CAN USE STANDARDSCALER FOR STANDARDIZATION

```
 FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
SCALER  STANDARDSCALER
 DONT CHEAT  FIT ONLY ON TRAINING DATA
SCALERFITXTRAIN
XTRAIN  SCALERTRANSFORMXTRAIN
 APPLY SAME TRANSFORMATION TO TEST DATA
XTEST  SCALERTRANSFORMXTEST
```

AN ALTERNATIVE AND RECOMMENDED APPROACH IS TO USE STANDARDSCALER IN APIPELINE

• FINDING A REASONABLE REGULARIZATION PARAMETER □IS BEST DONE USING GRIDSEARCHCV USUALLY IN THE RANGE 100 NPARANGE1 7

• EMPIRICALLY WE OBSERVED THAT LBFGS CONVERGES FASTER AND WITH BETTER SOLUTIONS ON SMALL DATASETS FOR RELA TIVELY LARGE DATASETS HOWEVER ADAM IS VERY ROBUST IT USUALLY CONVERGES QUICKLY AND GIVES PRETTY GOOD PERFOR MANCE STOCHASTIC GRADIENT DESCENT WITH MOMENTUM OR NESTEROV'S MOMENTUM ON THE OTHER HAND CAN PERFORM BETTER THAN THOSE TWO ALGORITHMS IF LEARNING RATE IS CORRECTLY TUNED

MORE CONTROL WITH WARMSTART

IF YOU WANT MORE CONTROL OVER STOPPING CRITERIA OR LEARNING RATE IN SGD OR WANT TO DO ADDITIONAL MONITORING USING WARMSTARTTRUE ANDMAXITER1 AND ITERATING YOURSELF CAN BE HELPFUL

```
X  0 0 1 1
Y  0 1
CLF  MLPCLASSIFIERHIDDENLAYERSIZES15 RANDOMSTATE1 MAXITER1 WARM
‹→STARTTRUE
 FOR IINRANGE10
 CLFFITX Y
  ADDITIONAL MONITORING  INSPECTION
```

MLPCLASSIFIER

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32 UNSUPERVISED LEARNING
321 GAUSSIAN MIXTURE MODELS
SKLEARNMIXTURE IS A PACKAGE WHICH ENABLES ONE TO LEARN GAUSSIAN MIXTURE MODELS DIAGONAL SPHERICAL TIED AND FULL COVARIANCE MATRICES SUPPORTED SAMPLE THEM AND ESTIMATE THEM FROM DATA FACILITIES TO HELP DETERMINE THE APPROPRIATE NUMBER OF COMPONENTS ARE ALSO PROVIDED

FIG 33 TWOCOMPONENT GAUSSIAN MIXTURE MODEL DATA POINTS AND EQUIPROBABILITY SURFACES OF THE MODEL

A GAUSSIAN MIXTURE MODEL IS A PROBABILISTIC MODEL THAT ASSUMES ALL THE DATA POINTS ARE GENERATED FROM A MIXTURE OF A FINITE NUMBER OF GAUSSIAN DISTRIBUTIONS WITH UNKNOWN PARAMETERS ONE CAN THINK OF MIXTURE MODELS AS GENERALIZING KMEANS CLUSTERING TO INCORPORATE INFORMATION ABOUT THE COVARIANCE STRUCTURE OF THE DATA AS WELL AS THE CENTERS OF THE LATENT GAUSSIANS

SCIKITLEARN IMPLEMENTS DIFFERENT CLASSES TO ESTIMATE GAUSSIAN MIXTURE MODELS THAT CORRESPOND TO DIFFERENT ESTIMATION STRATEGIES DETAILED BELOW

GAUSSIAN MIXTURE

THEGAUSSIANMIXTURE OBJECT IMPLEMENTS THE EXPECTATIONMAXIMIZATION EM ALGORITHM FOR FITTING MIXTUREOF GAUSSIAN MODELS IT CAN ALSO DRAW CONFIDENCE ELLIPSOIDS FOR MULTIVARIATE MODELS AND COMPUTE THE BAYESIAN INFOR MATION CRITERION TO ASSESS THE NUMBER OF CLUSTERS IN THE DATA A GAUSSIANMIXTUREFIT METHOD IS PROVIDED THAT LEARNS A GAUSSIAN MIXTURE MODEL FROM TRAIN DATA GIVEN TEST DATA IT CAN ASSIGN TO EACH SAMPLE THE GAUSSIAN IT MOSTLY PROBABLY BELONG TO USING THE GAUSSIANMIXTUREPREDICT METHOD

THEGAUSSIANMIXTURE COMES WITH DIFFERENT OPTIONS TO CONSTRAIN THE COVARIANCE OF THE DIFFERENCE CLASSES ESTIMATED SPHERICAL DIAGONAL TIED OR FULL COVARIANCE

EXAMPLES

• SEE GMM COVARIANCES FOR AN EXAMPLE OF USING THE GAUSSIAN MIXTURE AS CLUSTERING ON THE IRIS DATASET
• SEE DENSITY ESTIMATION FOR A GAUSSIAN MIXTURE FOR AN EXAMPLE ON PLOTTING THE DENSITY ESTIMATION

PROS AND CONS OF CLASS GAUSSIANMIXTURE
PROS
SPEED IT IS THE FASTEST ALGORITHM FOR LEARNING MIXTURE MODELS
AGNOSTIC AS THIS ALGORITHM MAXIMIZES ONLY THE LIKELIHOOD IT WILL NOT BIAS THE MEANS TOWARDS ZERO OR
BIAS THE CLUSTER SIZES TO HAVE SPECIFIC STRUCTURES THAT MIGHT OR MIGHT NOT APPLY
CONS
SINGULARITIES WHEN ONE HAS INSUFFICIENTLY MANY POINTS PER MIXTURE ESTIMATING THE COVARIANCE MATRICES
BECOMES DIFFICULT AND THE ALGORITHM IS KNOWN TO DIVERGE AND FIND SOLUTIONS WITH INFINITE LIKELIHOOD
UNLESS ONE REGULARIZES THE COVARIANCES ARTIFICIALLY
NUMBER OF COMPONENTS THIS ALGORITHM WILL ALWAYS USE ALL THE COMPONENTS IT HAS ACCESS TO NEEDING
HELDOUT DATA OR INFORMATION THEORETICAL CRITERIA TO DECIDE HOW MANY COMPONENTS TO USE IN THE AB
SENCE OF EXTERNAL CUES
SELECTING THE NUMBER OF COMPONENTS IN A CLASSICAL GAUSSIAN MIXTURE MODEL
THE BIC CRITERION CAN BE USED TO SELECT THE NUMBER OF COMPONENTS IN A GAUSSIAN MIXTURE IN AN EFFICIENT WAY IN THEORY
IT RECOVERS THE TRUE NUMBER OF COMPONENTS ONLY IN THE ASYMPTOTIC REGIME IE IF MUCH DATA IS AVAILABLE AND ASSUMING

THAT THE DATA WAS ACTUALLY GENERATED IID FROM A MIXTURE OF GAUSSIAN DISTRIBUTION NOTE THAT USING A VARIATIONAL BAYESIAN GAUSSIAN MIXTURE AVOIDS THE SPECIFICATION OF THE NUMBER OF COMPONENTS FOR A GAUSSIAN MIXTURE MODEL

EXAMPLES

• SEE GAUSSIAN MIXTURE MODEL SELECTION FOR AN EXAMPLE OF MODEL SELECTION PERFORMED WITH CLASSICAL GAUSSIAN MIXTURE

ESTIMATION ALGORITHM EXPECTATIONMAXIMIZATION

THE MAIN DIFFICULTY IN LEARNING GAUSSIAN MIXTURE MODELS FROM UNLABELED DATA IS THAT IT IS ONE USUALLY DOESN'T KNOW WHICH POINTS CAME FROM WHICH LATENT COMPONENT IF ONE HAS ACCESS TO THIS INFORMATION IT GETS VERY EASY TO FIT A SEPARATE GAUSSIAN DISTRIBUTION TO EACH SET OF POINTS EXPECTATIONMAXIMIZATION IS A WELLFOUNDED STATISTICAL ALGORITHM TO GET AROUND THIS PROBLEM BY AN ITERATIVE PROCESS FIRST ONE ASSUMES RANDOM COMPONENTS RANDOMLY CENTERED ON DATA POINTS LEARNED FROM KMEANS OR EVEN JUST NORMALLY DISTRIBUTED AROUND THE ORIGIN AND COMPUTES FOR EACH POINT A PROBABILITY OF BEING GENERATED BY EACH COMPONENT OF THE MODEL THEN ONE TWEAKS THE PARAMETERS TO MAXIMIZE THE LIKELIHOOD OF THE DATA GIVEN THOSE ASSIGNMENTS REPEATING THIS PROCESS IS GUARANTEED TO ALWAYS CONVERGE TO A LOCAL OPTIMUM

VARIATIONAL BAYESIAN GAUSSIAN MIXTURE

THEBAYESIANGAUSSIANMIXTURE OBJECT IMPLEMENTS A VARIANT OF THE GAUSSIAN MIXTURE MODEL WITH VARIATIONAL INFERENCE ALGORITHMS THE API IS SIMILAR AS THE ONE DEFINED BY GAUSSIANMIXTURE

ESTIMATION ALGORITHM VARIATIONAL INFERENCE

VARIATIONAL INFERENCE IS AN EXTENSION OF EXPECTATIONMAXIMIZATION THAT MAXIMIZES A LOWER BOUND ON MODEL EVIDENCE INCLUDING PRIORS INSTEAD OF DATA LIKELIHOOD THE PRINCIPLE BEHIND VARIATIONAL METHODS IS THE SAME AS EXPECTATION MAXIMIZATION THAT IS BOTH ARE ITERATIVE ALGORITHMS THAT ALTERNATE BETWEEN FINDING THE PROBABILITIES FOR EACH POINT TO

BE GENERATED BY EACH MIXTURE AND FITTING THE MIXTURE TO THESE ASSIGNED POINTS BUT VARIATIONAL METHODS ADD REGULAR IZATION BY INTEGRATING INFORMATION FROM PRIOR DISTRIBUTIONS THIS AVOIDS THE SINGULARITIES OFTEN FOUND IN EXPECTATION MAXIMIZATION SOLUTIONS BUT INTRODUCES SOME SUBTLE BIASES TO THE MODEL INFERENCE IS OFTEN NOTABLY SLOWER BUT NOT USUALLY AS MUCH SO AS TO RENDER USAGE UNPRACTICAL

DUE TO ITS BAYESIAN NATURE THE VARIATIONAL ALGORITHM NEEDS MORE HYPER PARAMETERS THAN EXPECTATIONMAXIMIZATION THE MOST IMPORTANT OF THESE BEING THE CONCENTRATION PARAMETER WEIGHTCONCENTRATIONPRIOR SPECIFYING A LOW VALUE FOR THE CONCENTRATION PRIOR WILL MAKE THE MODEL PUT MOST OF THE WEIGHT ON FEW COMPONENTS SET THE REMAIN ING COMPONENTS WEIGHTS VERY CLOSE TO ZERO HIGH VALUES OF THE CONCENTRATION PRIOR WILL ALLOW A LARGER NUMBER OF COMPONENTS TO BE ACTIVE IN THE MIXTURE

THE PARAMETERS IMPLEMENTATION OF THE BAYESIANGAUSSIANMIXTURE CLASS PROPOSES TWO TYPES OF PRIOR FOR THE WEIGHTS DISTRIBUTION A FINITE MIXTURE MODEL WITH DIRICHLET DISTRIBUTION AND AN INFINITE MIXTURE MODEL WITH THE DIRICHLET PROCESS IN PRACTICE DIRICHLET PROCESS INFERENCE ALGORITHM IS APPROXIMATED AND USES A TRUNCATED DISTRIBUTION WITH A FIXED MAXIMUM NUMBER OF COMPONENTS CALLED THE STICKBREAKING REPRESENTATION THE NUMBER OF COMPONENTS ACTUALLY USED ALMOST ALWAYS DEPENDS ON THE DATA

THE NEXT FIGURE COMPARES THE RESULTS OBTAINED FOR THE DIFFERENT TYPE OF THE WEIGHT CONCENTRATION PRIOR PARAMETER WEIGHTCONCENTRATIONPRIORTYPE FOR DIFFERENT VALUES OF WEIGHTCONCENTRATIONPRIOR HERE

WE CAN SEE THE VALUE OF THE WEIGHTCONCENTRATIONPRIOR PARAMETER HAS A STRONG IMPACT ON THE EFFECTIVE NUMBER OF ACTIVE COMPONENTS OBTAINED WE CAN ALSO NOTICE THAT LARGE VALUES FOR THE CONCENTRATION WEIGHT PRIOR LEAD TO MORE UNIFORM WEIGHTS WHEN THE TYPE OF PRIOR IS ‘DIRICHLETDISTRIBUTION’ WHILE THIS IS NOT NECESSARILY THE CASE FOR THE ‘DIRICHLETPROCESS’ TYPE USED BY DEFAULT

THE EXAMPLES BELOW COMPARE GAUSSIAN MIXTURE MODELS WITH A FIXED NUMBER OF COMPONENTS TO THE VARIATIONAL GAUS
SIAN MIXTURE MODELS WITH A DIRICHLET PROCESS PRIOR HERE A CLASSICAL GAUSSIAN MIXTURE IS FITTED WITH 5 COMPONENTS ON
A DATASET COMPOSED OF 2 CLUSTERS WE CAN SEE THAT THE VARIATIONAL GAUSSIAN MIXTURE WITH A DIRICHLET PROCESS PRIOR IS
ABLE TO LIMIT ITSELF TO ONLY 2 COMPONENTS WHEREAS THE GAUSSIAN MIXTURE FITS THE DATA WITH A FIXED NUMBER OF COMPONENTS
THAT HAS TO BE SET A PRIORI BY THE USER IN THIS CASE THE USER HAS SELECTED NCOMPONENTS5 WHICH DOES NOT MATCH THE
TRUE GENERATIVE DISTRIBUTION OF THIS TOY DATASET NOTE THAT WITH VERY LITTLE OBSERVATIONS THE VARIATIONAL GAUSSIAN MIXTURE
MODELS WITH A DIRICHLET PROCESS PRIOR CAN TAKE A CONSERVATIVE STAND AND FIT ONLY ONE COMPONENT
ON THE FOLLOWING FIGURE WE ARE FITTING A DATASET NOT WELLDEPICTED BY A GAUSSIAN MIXTURE ADJUSTING THE
WEIGHTCONCENTRATIONPRIOR PARAMETER OF THE BAYESIANGAUSSIANMIXTURE CONTROLS THE NUMBER OF

COMPONENTS USED TO FIT THIS DATA WE ALSO PRESENT ON THE LAST TWO PLOTS A RANDOM SAMPLING GENERATED FROM THE TWO RESULTING MIXTURES

EXAMPLES

• SEE GAUSSIAN MIXTURE MODEL ELLIPSOIDS FOR AN EXAMPLE ON PLOTTING THE CONFIDENCE ELLIPSOIDS FOR BOTH GAUSSIANMIXTURE ANDBAYESIANGAUSSIANMIXTURE

•GAUSSIAN MIXTURE MODEL SINE CURVE SHOWS USING GAUSSIANMIXTURE AND BAYESIANGAUSSIANMIXTURE TO FIT A SINE WAVE

• SEE CONCENTRATION PRIOR TYPE ANALYSIS OF VARIATION BAYESIAN GAUSSIAN MIXTURE FOR AN EX AMPLE PLOTTING THE CONFIDENCE ELLIPSOIDS FOR THE BAYESIANGAUSSIANMIXTURE WITH DIF

FERENTWEIGHTCONCENTRATIONPRIORTYPE FOR DIFFERENT VALUES OF THE PARAMETER
WEIGHTCONCENTRATIONPRIOR
PROS AND CONS OF VARIATIONAL INFERENCE WITH BAYESIANGAUSSIANMIXTURE
PROS
AUTOMATIC SELECTION WHENWEIGHTCONCENTRATIONPRIOR IS SMALL ENOUGH AND
NCOMPONENTS IS LARGER THAN WHAT IS FOUND NECESSARY BY THE MODEL THE VARIATIONAL BAYESIAN
MIXTURE MODEL HAS A NATURAL TENDENCY TO SET SOME MIXTURE WEIGHTS VALUES CLOSE TO ZERO THIS MAKES
IT POSSIBLE TO LET THE MODEL CHOOSE A SUITABLE NUMBER OF EFFECTIVE COMPONENTS AUTOMATICALLY ONLY AN
UPPER BOUND OF THIS NUMBER NEEDS TO BE PROVIDED NOTE HOWEVER THAT THE “IDEAL” NUMBER OF ACTIVE
COMPONENTS IS VERY APPLICATION SPECIFIC AND IS TYPICALLY ILLDEFINED IN A DATA EXPLORATION SETTING
LESS SENSITIVITY TO THE NUMBER OF PARAMETERS UNLIKE FINITE MODELS WHICH WILL ALMOST ALWAYS USE
ALL COMPONENTS AS MUCH AS THEY CAN AND HENCE WILL PRODUCE WILDLY DIFFERENT SOLUTIONS FOR
DIFFERENT NUMBERS OF COMPONENTS THE VARIATIONAL INFERENCE WITH A DIRICHLET PROCESS PRIOR
WEIGHTCONCENTRATIONPRIORTYPEDIRICHLETPROCESS WON’T CHANGE MUCH
WITH CHANGES TO THE PARAMETERS LEADING TO MORE STABILITY AND LESS TUNING
REGULARIZATION DUE TO THE INCORPORATION OF PRIOR INFORMATION VARIATIONAL SOLUTIONS HAVE LESS PATHOLOGICAL
SPECIAL CASES THAN EXPECTATIONMAXIMIZATION SOLUTIONS
CONS
SPEED THE EXTRA PARAMETRIZATION NECESSARY FOR VARIATIONAL INFERENCE MAKE INFERENCE SLOWER ALTHOUGH NOT
BY MUCH
HYPERPARAMETERS THIS ALGORITHM NEEDS AN EXTRA HYPERPARAMETER THAT MIGHT NEED EXPERIMENTAL TUNING VIA
CROSSVALIDATION
BIAS THERE ARE MANY IMPLICIT BIASES IN THE INFERENCE ALGORITHMS AND ALSO IN THE DIRICHLET PROCESS IF USED
AND WHENEVER THERE IS A MISMATCH BETWEEN THESE BIASES AND THE DATA IT MIGHT BE POSSIBLE TO FIT BETTER
MODELS USING A FINITE MIXTURE
THE DIRICHLET PROCESS
HERE WE DESCRIBE VARIATIONAL INFERENCE ALGORITHMS ON DIRICHLET PROCESS MIXTURE THE DIRICHLET PROCESS IS A PRIOR
PROBABILITY DISTRIBUTION ON CLUSTERINGS WITH AN INFINITE UNBOUNDED NUMBER OF PARTITIONS VARIATIONAL TECHNIQUES LET US
INCORPORATE THIS PRIOR STRUCTURE ON GAUSSIAN MIXTURE MODELS AT ALMOST NO PENALTY IN INFERENCE TIME COMPARING WITH A
FINITE GAUSSIAN MIXTURE MODEL
AN IMPORTANT QUESTION IS HOW CAN THE DIRICHLET PROCESS USE AN INFINITE UNBOUNDED NUMBER OF CLUSTERS AND STILL BE
CONSISTENT WHILE A FULL EXPLANATION DOESN’T FIT THIS MANUAL ONE CAN THINK OF ITS STICK BREAKING PROCESS ANALOGY TO HELP
UNDERSTANDING IT THE STICK BREAKING PROCESS IS A GENERATIVE STORY FOR THE DIRICHLET PROCESS WE START WITH A UNITLENGTH
STICK AND IN EACH STEP WE BREAK OFF A PORTION OF THE REMAINING STICK EACH TIME WE ASSOCIATE THE LENGTH OF THE PIECE OF
THE STICK TO THE PROPORTION OF POINTS THAT FALLS INTO A GROUP OF THE MIXTURE AT THE END TO REPRESENT THE INFINITE MIXTURE
WE ASSOCIATE THE LAST REMAINING PIECE OF THE STICK TO THE PROPORTION OF POINTS THAT DON’T FALL INTO ALL THE OTHER GROUPS THE
LENGTH OF EACH PIECE IS A RANDOM VARIABLE WITH PROBABILITY PROPORTIONAL TO THE CONCENTRATION PARAMETER SMALLER VALUE
OF THE CONCENTRATION WILL DIVIDE THE UNITLENGTH INTO LARGER PIECES OF THE STICK DEFINING MORE CONCENTRATED DISTRIBUTION
LARGER CONCENTRATION VALUES WILL CREATE SMALLER PIECES OF THE STICK INCREASING THE NUMBER OF COMPONENTS WITH NON
ZERO WEIGHTS

VARIATIONAL INFERENCE TECHNIQUES FOR THE DIRICHLET PROCESS STILL WORK WITH A FINITE APPROXIMATION TO THIS INFINITE MIXTURE MODEL BUT INSTEAD OF HAVING TO SPECIFY A PRIORI HOW MANY COMPONENTS ONE WANTS TO USE ONE JUST SPECIFIES THE CONCEN TRATION PARAMETER AND AN UPPER BOUND ON THE NUMBER OF MIXTURE COMPONENTS THIS UPPER BOUND ASSUMING IT IS HIGHER THAN THE “TRUE” NUMBER OF COMPONENTS AFFECTS ONLY ALGORITHMIC COMPLEXITY NOT THE ACTUAL NUMBER OF COMPONENTS USED

322 MANIFOLD LEARNING

LOOK FOR THE BARE NECESSITIES
THE SIMPLE BARE NECESSITIES
FORGET ABOUT YOUR WORRIES AND YOUR STRIFE
I MEAN THE BARE NECESSITIES
OLD MOTHER NATURE’S RECIPES
THAT BRING THE BARE NECESSITIES OF LIFE
– BALOO’S SONG THE JUNGLE BOOK

MANIFOLD LEARNING IS AN APPROACH TO NONLINEAR DIMENSIONALITY REDUCTION ALGORITHMS FOR THIS TASK ARE BASED ON THE IDEA THAT THE DIMENSIONALITY OF MANY DATA SETS IS ONLY ARTIFICIALLY HIGH

INTRODUCTION

HIGHDIMENSIONAL DATASETS CAN BE VERY DIFFICULT TO VISUALIZE WHILE DATA IN TWO OR THREE DIMENSIONS CAN BE PLOTTED TO SHOW THE INHERENT STRUCTURE OF THE DATA EQUIVALENT HIGHDIMENSIONAL PLOTS ARE MUCH LESS INTUITIVE TO AID VISUALIZATION OF THE STRUCTURE OF A DATASET THE DIMENSION MUST BE REDUCED IN SOME WAY

THE SIMPLEST WAY TO ACCOMPLISH THIS DIMENSIONALITY REDUCTION IS BY TAKING A RANDOM PROJECTION OF THE DATA THOUGH THIS ALLOWS SOME DEGREE OF VISUALIZATION OF THE DATA STRUCTURE THE RANDOMNESS OF THE CHOICE LEAVES MUCH TO BE DESIRED IN A RANDOM PROJECTION IT IS LIKELY THAT THE MORE INTERESTING STRUCTURE WITHIN THE DATA WILL BE LOST

TO ADDRESS THIS CONCERN A NUMBER OF SUPERVISED AND UNSUPERVISED LINEAR DIMENSIONALITY REDUCTION FRAMEWORKS HAVE BEEN DESIGNED SUCH AS PRINCIPAL COMPONENT ANALYSIS PCA INDEPENDENT COMPONENT ANALYSIS LINEAR DISCRIMINANT ANALYSIS AND OTHERS THESE ALGORITHMS DEFINE SPECIFIC RUBRICS TO CHOOSE AN “INTERESTING” LINEAR PROJECTION OF THE DATA THESE METHODS CAN BE POWERFUL BUT OFTEN MISS IMPORTANT NONLINEAR STRUCTURE IN THE DATA

MANIFOLD LEARNING CAN BE THOUGHT OF AS AN ATTEMPT TO GENERALIZE LINEAR FRAMEWORKS LIKE PCA TO BE SENSITIVE TO NON LINEAR STRUCTURE IN DATA THOUGH SUPERVISED VARIANTS EXIST THE TYPICAL MANIFOLD LEARNING PROBLEM IS UNSUPERVISED IT LEARNS THE HIGHDIMENSIONAL STRUCTURE OF THE DATA FROM THE DATA ITSELF WITHOUT THE USE OF PREDETERMINED CLASSIFICATIONS

EXAMPLES

• SEE MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP FOR AN EXAMPLE OF DIMENSIONALITY REDUCTION ON HANDWRITTEN DIGITS

• SEE COMPARISON OF MANIFOLD LEARNING METHODS FOR AN EXAMPLE OF DIMENSIONALITY REDUCTION ON A TOY “S CURVE” DATASET

THE MANIFOLD LEARNING IMPLEMENTATIONS AVAILABLE IN SCIKITLEARN ARE SUMMARIZED BELOW

ISOMAP

ONE OF THE EARLIEST APPROACHES TO MANIFOLD LEARNING IS THE ISOMAP ALGORITHM SHORT FOR ISOMETRIC MAPPING ISOMAP CAN BE VIEWED AS AN EXTENSION OF MULTIDIMENSIONAL SCALING MDS OR KERNEL PCA ISOMAP SEEKS A LOWERDIMENSIONAL

EMBEDDING WHICH MAINTAINS GEODESIC DISTANCES BETWEEN ALL POINTS ISOMAP CAN BE PERFORMED WITH THE OBJECT ISOMAP
COMPLEXITY
THE ISOMAP ALGORITHM COMPRISES THREE STAGES
1NEAREST NEIGHBOR SEARCH ISOMAP USES SKLEARNNEIGHBORSBALLTREE FOR EFFICIENT NEIGHBOR SEARCH
THE COST IS APPROXIMATELY □□LOG□□LOG□ FOR□NEAREST NEIGHBORS OF □POINTS IN □DIMENSIONS
2SHORTESTPATH GRAPH SEARCH THE MOST EFFICIENT KNOWN ALGORITHMS FOR THIS ARE DIJKSTRA'S ALGORITHM WHICH IS
APPROXIMATELY □□2□ LOG □ OR THE FLOYDWARSHALL ALGORITHM WHICH IS □□3 THE ALGORITHM CAN BE
SELECTED BY THE USER WITH THE PATHMETHOD KEYWORD OF ISOMAP IF UNSPECIFIED THE CODE ATTEMPTS TO CHOOSE
THE BEST ALGORITHM FOR THE INPUT DATA
3PARTIAL EIGENVALUE DECOMPOSITION THE EMBEDDING IS ENCODED IN THE EIGENVECTORS CORRESPONDING TO THE □
LARGEST EIGENVALUES OF THE □×□ISOMAP KERNEL FOR A DENSE SOLVER THE COST IS APPROXIMATELY □□□2 THIS
COST CAN OFTEN BE IMPROVED USING THE ARPACK SOLVER THE EIGENSOLVER CAN BE SPECIFIED BY THE USER WITH THE
PATHMETHOD KEYWORD OF ISOMAP IF UNSPECIFIED THE CODE ATTEMPTS TO CHOOSE THE BEST ALGORITHM FOR THE
INPUT DATA
THE OVERALL COMPLEXITY OF ISOMAP IS □□LOG□□LOG□ □□2□ LOG □ □□□2
- □ NUMBER OF TRAINING DATA POINTS
- □ INPUT DIMENSION
- □ NUMBER OF NEAREST NEIGHBORS
- □ OUTPUT DIMENSION

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• "A GLOBAL GEOMETRIC FRAMEWORK FOR NONLINEAR DIMENSIONALITY REDUCTION" TENENBAUM JB DE SILVA V
LANGFORD JC SCIENCE 290 5500

LOCALLY LINEAR EMBEDDING
LOCALLY LINEAR EMBEDDING LLE SEEKS A LOWERDIMENSIONAL PROJECTION OF THE DATA WHICH PRESERVES DISTANCES WITHIN LOCAL NEIGHBORHOODS IT CAN BE THOUGHT OF AS A SERIES OF LOCAL PRINCIPAL COMPONENT ANALYSES WHICH ARE GLOBALLY COMPARED TO FIND THE BEST NONLINEAR EMBEDDING
LOCALLY LINEAR EMBEDDING CAN BE PERFORMED WITH FUNCTION LOCALLYLINEAREMBEDDING OR ITS OBJECTORIENTED COUNTERPART LOCALLYLINEAREMBEDDING
COMPLEXITY
THE STANDARD LLE ALGORITHM COMPRISES THREE STAGES
1NEAREST NEIGHBORS SEARCH SEE DISCUSSION UNDER ISOMAP ABOVE
2WEIGHT MATRIX CONSTRUCTION □□□□3 THE CONSTRUCTION OF THE LLE WEIGHT MATRIX INVOLVES THE SOLUTION OF A□×□LINEAR EQUATION FOR EACH OF THE □LOCAL NEIGHBORHOODS
3PARTIAL EIGENVALUE DECOMPOSITION SEE DISCUSSION UNDER ISOMAP ABOVE
THE OVERALL COMPLEXITY OF STANDARD LLE IS □□LOG□□LOG□ □□□□3 □□□2
•□ NUMBER OF TRAINING DATA POINTS
•□ INPUT DIMENSION
•□ NUMBER OF NEAREST NEIGHBORS
•□ OUTPUT DIMENSION
REFERENCES
• “NONLINEAR DIMENSIONALITY REDUCTION BY LOCALLY LINEAR EMBEDDING” ROWEIS S SAUL L SCIENCE 2902323 2000
MODIFIED LOCALLY LINEAR EMBEDDING
ONE WELLKNOWN ISSUE WITH LLE IS THE REGULARIZATION PROBLEM WHEN THE NUMBER OF NEIGHBORS IS GREATER THAN THE NUMBER OF INPUT DIMENSIONS THE MATRIX DEFINING EACH LOCAL NEIGHBORHOOD IS RANKDEFICIENT TO ADDRESS THIS STANDARD

LLE APPLIES AN ARBITRARY REGULARIZATION PARAMETER □ WHICH IS CHOSEN RELATIVE TO THE TRACE OF THE LOCAL WEIGHT MATRIX THOUGH IT CAN BE SHOWN FORMALLY THAT AS □→0 THE SOLUTION CONVERGES TO THE DESIRED EMBEDDING THERE IS NO GUARANTEE THAT THE OPTIMAL SOLUTION WILL BE FOUND FOR □ 0 THIS PROBLEM MANIFESTS ITSELF IN EMBEDDINGS WHICH DISTORT THE UNDERLYING GEOMETRY OF THE MANIFOLD

ONE METHOD TO ADDRESS THE REGULARIZATION PROBLEM IS TO USE MULTIPLE WEIGHT VECTORS IN EACH NEIGHBORHOOD THIS IS THE ESSENCE OF MODIFIED LOCALLY LINEAR EMBEDDING MLLE MLLE CAN BE PERFORMED WITH FUNCTION LOCALLYLINEAREMBEDDING OR ITS OBJECTORIENTED COUNTERPART LOCALLYLINEAREMBEDDING WITH THE KEY WORDMETHOD MODIFIED IT REQUIRES NNEIGHBORS NCOMPONENTS

COMPLEXITY

THE MLLE ALGORITHM COMPRISES THREE STAGES

1NEAREST NEIGHBORS SEARCH SAME AS STANDARD LLE

2WEIGHT MATRIX CONSTRUCTION APPROXIMATELY □□□□3□□□−□□2 THE FIRST TERM IS EXACTLY EQUIVALENT TO THAT OF STANDARD LLE THE SECOND TERM HAS TO DO WITH CONSTRUCTING THE WEIGHT MATRIX FROM MULTIPLE WEIGHTS IN PRACTICE THE ADDED COST OF CONSTRUCTING THE MLLE WEIGHT MATRIX IS RELATIVELY SMALL COMPARED TO THE COST OF STEPS 1 AND 3

3PARTIAL EIGENVALUE DECOMPOSITION SAME AS STANDARD LLE

THE OVERALL COMPLEXITY OF MLLE IS □□LOG□□LOG□ □□□□3 □□□−□□2 □□□2

- □ NUMBER OF TRAINING DATA POINTS
- □ INPUT DIMENSION
- □ NUMBER OF NEAREST NEIGHBORS
- □ OUTPUT DIMENSION

REFERENCES

- “MLLE MODIFIED LOCALLY LINEAR EMBEDDING USING MULTIPLE WEIGHTS” ZHANG Z WANG J

HESSIAN EIGENMAPPING
HESSIAN EIGENMAPPING ALSO KNOWN AS HESSIANBASED LLE HLLE IS ANOTHER METHOD OF SOLVING THE REGULARIZATION PROBLEM OF LLE IT REVOLVES AROUND A HESSIANBASED QUADRATIC FORM AT EACH NEIGHBORHOOD WHICH IS USED TO RECOVER THE LOCALLY LINEAR STRUCTURE THOUGH OTHER IMPLEMENTATIONS NOTE ITS POOR SCALING WITH DATA SIZE SKLEARN IMPLEMENTS SOME ALGORITHMIC IMPROVEMENTS WHICH MAKE ITS COST COMPARABLE TO THAT OF OTHER LLE VARIANTS FOR SMALL OUTPUT DIMENSION HLLE CAN BE PERFORMED WITH FUNCTION LOCALLYLINEAREMBEDDING OR ITS OBJECTORIENTED COUNTERPARTLOCALLYLINEAREMBEDDING WITH THE KEYWORD METHOD HESSIAN IT REQUIRES NNEIGHBORS NCOMPONENTS NCOMPONENTS 3 2
COMPLEXITY
THE HLLE ALGORITHM COMPRISES THREE STAGES
1NEAREST NEIGHBORS SEARCH SAME AS STANDARD LLE
2WEIGHT MATRIX CONSTRUCTION APPROXIMATELY □□□□3 □□□6 THE FIRST TERM REFLECTS A SIMILAR COST TO THAT OF STANDARD LLE THE SECOND TERM COMES FROM A QR DECOMPOSITION OF THE LOCAL HESSIAN ESTIMATOR
3PARTIAL EIGENVALUE DECOMPOSITION SAME AS STANDARD LLE
THE OVERALL COMPLEXITY OF STANDARD HLLE IS □□LOG□□LOG□ □□□□3 □□□6 □□□2
•□ NUMBER OF TRAINING DATA POINTS
•□ INPUT DIMENSION
•□ NUMBER OF NEAREST NEIGHBORS
•□ OUTPUT DIMENSION
REFERENCES
• “HESSIAN EIGENMAPS LOCALLY LINEAR EMBEDDING TECHNIQUES FOR HIGHDIMENSIONAL DATA” DONOHO D GRIMES C PROC NATL ACAD SCI USA 1005591 2003

SPECTRAL EMBEDDING

SPECTRAL EMBEDDING IS AN APPROACH TO CALCULATING A NONLINEAR EMBEDDING SCIKITLEARN IMPLEMENTS LAPLACIAN EIGEN MAPS WHICH FINDS A LOW DIMENSIONAL REPRESENTATION OF THE DATA USING A SPECTRAL DECOMPOSITION OF THE GRAPH LAPLACIAN THE GRAPH GENERATED CAN BE CONSIDERED AS A DISCRETE APPROXIMATION OF THE LOW DIMENSIONAL MANIFOLD IN THE HIGH DIMEN SIONAL SPACE MINIMIZATION OF A COST FUNCTION BASED ON THE GRAPH ENSURES THAT POINTS CLOSE TO EACH OTHER ON THE MANIFOLD ARE MAPPED CLOSE TO EACH OTHER IN THE LOW DIMENSIONAL SPACE PRESERVING LOCAL DISTANCES SPECTRAL EMBEDDING CAN BE PERFORMED WITH THE FUNCTION SPECTRALEMBEDDING OR ITS OBJECTORIENTED COUNTERPART SPECTRALEMBEDDING

COMPLEXITY

THE SPECTRAL EMBEDDING LAPLACIAN EIGENMAPS ALGORITHM COMPRISES THREE STAGES

1WEIGHTED GRAPH CONSTRUCTION TRANSFORM THE RAW INPUT DATA INTO GRAPH REPRESENTATION USING AFFINITY ADJA CENCY MATRIX REPRESENTATION

2GRAPH LAPLACIAN CONSTRUCTION UNNORMALIZED GRAPH LAPLACIAN IS CONSTRUCTED AS □□−□FOR AND NORMAL IZED ONE AS □□−1
2□−□□−1
2

3PARTIAL EIGENVALUE DECOMPOSITION EIGENVALUE DECOMPOSITION IS DONE ON GRAPH LAPLACIAN

THE OVERALL COMPLEXITY OF SPECTRAL EMBEDDING IS □□LOG□□LOG□ □□□□3 □□□2

- □ NUMBER OF TRAINING DATA POINTS
- □ INPUT DIMENSION
- □ NUMBER OF NEAREST NEIGHBORS
- □ OUTPUT DIMENSION

REFERENCES

• “LAPLACIAN EIGENMAPS FOR DIMENSIONALITY REDUCTION AND DATA REPRESENTATION” M BELKIN P NIYOGI NEURAL COMPUTATION JUNE 2003 15 613731396

LOCAL TANGENT SPACE ALIGNMENT

THOUGH NOT TECHNICALLY A VARIANT OF LLE LOCAL TANGENT SPACE ALIGNMENT LTSA IS ALGORITHMICALLY SIMILAR ENOUGH TO LLE THAT IT CAN BE PUT IN THIS CATEGORY RATHER THAN FOCUSING ON PRESERVING NEIGHBORHOOD DISTANCES AS IN LLE LTSA SEEKS TO CHARACTERIZE THE LOCAL GEOMETRY AT EACH NEIGHBORHOOD VIA ITS TANGENT SPACE AND PERFORMS A GLOBAL OPTIMIZATION TO ALIGN THESE LOCAL TANGENT SPACES TO LEARN THE EMBEDDING LTSA CAN BE PERFORMED WITH FUNCTION LOCALLYLINEAREMBEDDING OR ITS OBJECTORIENTED COUNTERPART LOCALLYLINEAREMBEDDING WITH THE KEY WORDMETHOD LTSA

COMPLEXITY

THE LTSA ALGORITHM COMPRISES THREE STAGES

1NEAREST NEIGHBORS SEARCH SAME AS STANDARD LLE

2WEIGHT MATRIX CONSTRUCTION APPROXIMATELY □□□□3 □□2□ THE FIRST TERM REFLECTS A SIMILAR COST TO THAT OF STANDARD LLE

3PARTIAL EIGENVALUE DECOMPOSITION SAME AS STANDARD LLE

THE OVERALL COMPLEXITY OF STANDARD LTSA IS □□LOG□□LOG□ □□□□3 □□2□ □□□2
•□ NUMBER OF TRAINING DATA POINTS
•□ INPUT DIMENSION
•□ NUMBER OF NEAREST NEIGHBORS
•□ OUTPUT DIMENSION
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• “PRINCIPAL MANIFOLDS AND NONLINEAR DIMENSIONALITY REDUCTION VIA TANGENT SPACE ALIGNMENT” ZHANG Z ZHA
H JOURNAL OF SHANGHAI UNIV 8406 2004
MULTIDIMENSIONAL SCALING MDS
MULTIDIMENSIONAL SCALING MDS SEEKS A LOWDIMENSIONAL REPRESENTATION OF THE DATA IN WHICH THE DISTANCES RESPECT WELL THE DISTANCES IN THE ORIGINAL HIGHDIMENSIONAL SPACE
IN GENERAL IS A TECHNIQUE USED FOR ANALYZING SIMILARITY OR DISSIMILARITY DATA MDS ATTEMPTS TO MODEL SIMILARITY OR DISSIMILARITY DATA AS DISTANCES IN A GEOMETRIC SPACES THE DATA CAN BE RATINGS OF SIMILARITY BETWEEN OBJECTS INTERACTION FREQUENCIES OF MOLECULES OR TRADE INDICES BETWEEN COUNTRIES
THERE EXISTS TWO TYPES OF MDS ALGORITHM METRIC AND NON METRIC IN THE SCIKITLEARN THE CLASS MDS IMPLEMENTS BOTH IN METRIC MDS THE INPUT SIMILARITY MATRIX ARISES FROM A METRIC AND THUS RESPECTS THE TRIANGULAR INEQUALITY THE DISTANCES BETWEEN OUTPUT TWO POINTS ARE THEN SET TO BE AS CLOSE AS POSSIBLE TO THE SIMILARITY OR DISSIMILARITY DATA IN THE NONMETRIC VERSION THE ALGORITHMS WILL TRY TO PRESERVE THE ORDER OF THE DISTANCES AND HENCE SEEK FOR A MONOTONIC RELATIONSHIP BETWEEN THE DISTANCES IN THE EMBEDDED SPACE AND THE SIMILARITIESDISSIMILARITIES
LET□BE THE SIMILARITY MATRIX AND □THE COORDINATES OF THE □INPUT POINTS DISPARITIES □□□ARE TRANSFORMATION OF THE SIMILARITIES CHOSEN IN SOME OPTIMAL WAYS THE OBJECTIVE CALLED THE STRESS IS THEN DEFINED BY □□□ □□□□□□−□□□□
METRIC MDS
THE SIMPLEST METRIC MDS MODEL CALLED ABSOLUTE MDS DISPARITIES ARE DEFINED BY □□□□□□ WITH ABSOLUTE MDS THE VALUE □□□SHOULD THEN CORRESPOND EXACTLY TO THE DISTANCE BETWEEN POINT □AND□IN THE EMBEDDING POINT

MOST COMMONLY DISPARITIES ARE SET TO □□□□□□□
NONMETRIC MDS
NON METRIC MDS FOCUSES ON THE ORDINATION OF THE DATA IF □□□ □□□ THEN THE EMBEDDING SHOULD ENFORCE □□□ □□□
A SIMPLE ALGORITHM TO ENFORCE THAT IS TO USE A MONOTONIC REGRESSION OF □□□ON□□□ YIELDING DISPARITIES □□□IN THE SAME ORDER AS □□□
A TRIVIAL SOLUTION TO THIS PROBLEM IS TO SET ALL THE POINTS ON THE ORIGIN IN ORDER TO AVOID THAT THE DISPARITIES □□□ARE NORMALIZED
REFERENCES
• “MODERN MULTIDIMENSIONAL SCALING THEORY AND APPLICATIONS” BORG I GROENEN P SPRINGER SERIES IN STATIS TICS 1997
• “NONMETRIC MULTIDIMENSIONAL SCALING A NUMERICAL METHOD” KRUSKAL J PSYCHOMETRIKA 29 1964

• “MULTIDIMENSIONAL SCALING BY OPTIMIZING GOODNESS OF FIT TO A NONMETRIC HYPOTHESIS” KRUSKAL J PSYCHOME
TRIKA 29 1964
TDISTRIBUTED STOCHASTIC NEIGHBOR EMBEDDING TSNE
TSNE TSNE CONVERTS AFFINITIES OF DATA POINTS TO PROBABILITIES THE AFFINITIES IN THE ORIGINAL SPACE ARE REPRESENTED BY GAUSSIAN JOINT PROBABILITIES AND THE AFFINITIES IN THE EMBEDDED SPACE ARE REPRESENTED BY STUDENT’S TDISTRIBUTIONS THIS ALLOWS TSNE TO BE PARTICULARLY SENSITIVE TO LOCAL STRUCTURE AND HAS A FEW OTHER ADVANTAGES OVER EXISTING TECHNIQUES
• REVEALING THE STRUCTURE AT MANY SCALES ON A SINGLE MAP
• REVEALING DATA THAT LIE IN MULTIPLE DIFFERENT MANIFOLDS OR CLUSTERS
• REDUCING THE TENDENCY TO CROWD POINTS TOGETHER AT THE CENTER
WHILE ISOMAP LLE AND VARIANTS ARE BEST SUITED TO UNFOLD A SINGLE CONTINUOUS LOW DIMENSIONAL MANIFOLD TSNE WILL FOCUS ON THE LOCAL STRUCTURE OF THE DATA AND WILL TEND TO EXTRACT CLUSTERED LOCAL GROUPS OF SAMPLES AS HIGHLIGHTED ON THE SCURVE EXAMPLE THIS ABILITY TO GROUP SAMPLES BASED ON THE LOCAL STRUCTURE MIGHT BE BENEFICIAL TO VISUALLY DISENTANGLE A DATASET THAT COMPRISES SEVERAL MANIFOLDS AT ONCE AS IS THE CASE IN THE DIGITS DATASET
THE KULLBACKLEIBLER KL DIVERGENCE OF THE JOINT PROBABILITIES IN THE ORIGINAL SPACE AND THE EMBEDDED SPACE WILL BE MINIMIZED BY GRADIENT DESCENT NOTE THAT THE KL DIVERGENCE IS NOT CONVEX IE MULTIPLE RESTARTS WITH DIFFERENT INITIALIZATIONS WILL END UP IN LOCAL MINIMA OF THE KL DIVERGENCE HENCE IT IS SOMETIMES USEFUL TO TRY DIFFERENT SEEDS AND SELECT THE EMBEDDING WITH THE LOWEST KL DIVERGENCE
THE DISADVANTAGES TO USING TSNE ARE ROUGHLY
• TSNE IS COMPUTATIONALLY EXPENSIVE AND CAN TAKE SEVERAL HOURS ON MILLIONSAMPLE DATASETS WHERE PCA WILL FINISH IN SECONDS OR MINUTES
• THE BARNESHUT TSNE METHOD IS LIMITED TO TWO OR THREE DIMENSIONAL EMBEDDINGS
• THE ALGORITHM IS STOCHASTIC AND MULTIPLE RESTARTS WITH DIFFERENT SEEDS CAN YIELD DIFFERENT EMBEDDINGS HOWEVER IT IS PERFECTLY LEGITIMATE TO PICK THE EMBEDDING WITH THE LEAST ERROR
• GLOBAL STRUCTURE IS NOT EXPLICITLY PRESERVED THIS PROBLEM IS MITIGATED BY INITIALIZING POINTS WITH PCA USING INITPCA

OPTIMIZING TSNE

THE MAIN PURPOSE OF TSNE IS VISUALIZATION OF HIGHDIMENSIONAL DATA HENCE IT WORKS BEST WHEN THE DATA WILL BE EMBEDDED ON TWO OR THREE DIMENSIONS

OPTIMIZING THE KL DIVERGENCE CAN BE A LITTLE BIT TRICKY SOMETIMES THERE ARE FIVE PARAMETERS THAT CONTROL THE OPTIMIZATION OF TSNE AND THEREFORE POSSIBLY THE QUALITY OF THE RESULTING EMBEDDING

- PERPLEXITY
- EARLY EXAGGERATION FACTOR
- LEARNING RATE
- MAXIMUM NUMBER OF ITERATIONS
- ANGLE NOT USED IN THE EXACT METHOD

THE PERPLEXITY IS DEFINED AS 2WHERE IS THE SHANNON ENTROPY OF THE CONDITIONAL PROBABILITY DISTRIBUTION THE PERPLEXITY OF A SIDED DIE IS SO THAT IS EFFECTIVELY THE NUMBER OF NEAREST NEIGHBORS TSNE CONSIDERS WHEN GENERATING THE CONDITIONAL PROBABILITIES LARGER PERPLEXITIES LEAD TO MORE NEAREST NEIGHBORS AND LESS SENSITIVE TO SMALL STRUCTURE CONVERSELY A LOWER PERPLEXITY CONSIDERS A SMALLER NUMBER OF NEIGHBORS AND THUS IGNORES MORE GLOBAL INFORMATION IN FAVOUR OF THE LOCAL NEIGHBORHOOD AS DATASET SIZES GET LARGER MORE POINTS WILL BE REQUIRED TO GET A REASONABLE SAMPLE OF THE LOCAL NEIGHBORHOOD AND HENCE LARGER PERPLEXITIES MAY BE REQUIRED SIMILARLY NOISIER DATASETS WILL REQUIRE LARGER PERPLEXITY VALUES TO ENCOMPASS ENOUGH LOCAL NEIGHBORS TO SEE BEYOND THE BACKGROUND NOISE

THE MAXIMUM NUMBER OF ITERATIONS IS USUALLY HIGH ENOUGH AND DOES NOT NEED ANY TUNING THE OPTIMIZATION CONSISTS OF TWO PHASES THE EARLY EXAGGERATION PHASE AND THE FINAL OPTIMIZATION DURING EARLY EXAGGERATION THE JOINT PROBABILITIES IN THE ORIGINAL SPACE WILL BE ARTIFICIALLY INCREASED BY MULTIPLICATION WITH A GIVEN FACTOR LARGER FACTORS RESULT IN LARGER GAPS BETWEEN NATURAL CLUSTERS IN THE DATA IF THE FACTOR IS TOO HIGH THE KL DIVERGENCE COULD INCREASE DURING THIS PHASE USUALLY IT DOES NOT HAVE TO BE TUNED A CRITICAL PARAMETER IS THE LEARNING RATE IF IT IS TOO LOW GRADIENT DESCENT WILL GET STUCK IN A BAD LOCAL MINIMUM IF IT IS TOO HIGH THE KL DIVERGENCE WILL INCREASE DURING OPTIMIZATION MORE TIPS CAN BE FOUND IN LAURENS VAN DER MAATEN'S FAQ SEE REFERENCES THE LAST PARAMETER ANGLE IS A TRADEOFF BETWEEN PERFORMANCE AND ACCURACY LARGER ANGLES IMPLY THAT WE CAN APPROXIMATE LARGER REGIONS BY A SINGLE POINT LEADING TO BETTER SPEED BUT LESS ACCURATE RESULTS

"HOW TO USE TSNE EFFECTIVELY" PROVIDES A GOOD DISCUSSION OF THE EFFECTS OF THE VARIOUS PARAMETERS AS WELL AS INTERACTIVE PLOTS TO EXPLORE THE EFFECTS OF DIFFERENT PARAMETERS

BARNESHUT TSNE

THE BARNESHUT TSNE THAT HAS BEEN IMPLEMENTED HERE IS USUALLY MUCH SLOWER THAN OTHER MANIFOLD LEARNING ALGORITHMS THE OPTIMIZATION IS QUITE DIFFICULT AND THE COMPUTATION OF THE GRADIENT IS WHERE IS THE NUMBER OF OUTPUT DIMENSIONS AND IS THE NUMBER OF SAMPLES THE BARNESHUT METHOD IMPROVES ON THE EXACT METHOD WHERE TSNE COMPLEXITY IS 2 BUT HAS SEVERAL OTHER NOTABLE DIFFERENCES

- THE BARNESHUT IMPLEMENTATION ONLY WORKS WHEN THE TARGET DIMENSIONALITY IS 3 OR LESS THE 2D CASE IS TYPICAL WHEN BUILDING VISUALIZATIONS
- BARNESHUT ONLY WORKS WITH DENSE INPUT DATA SPARSE DATA MATRICES CAN ONLY BE EMBEDDED WITH THE EXACT METHOD OR CAN BE APPROXIMATED BY A DENSE LOW RANK PROJECTION FOR INSTANCE USING SKLEARNDECOMPOSITION TRUNCATEDSVD
- BARNESHUT IS AN APPROXIMATION OF THE EXACT METHOD THE APPROXIMATION IS PARAMETERIZED WITH THE ANGLE PARAMETER THEREFORE THE ANGLE PARAMETER IS UNUSED WHEN METHOD"EXACT"
- BARNESHUT IS SIGNIFICANTLY MORE SCALABLE BARNESHUT CAN BE USED TO EMBED HUNDRED OF THOUSANDS OF DATA POINTS WHILE THE EXACT METHOD CAN HANDLE THOUSANDS OF SAMPLES BEFORE BECOMING COMPUTATIONALLY INTRACTABLE

FOR VISUALIZATION PURPOSE WHICH IS THE MAIN USE CASE OF TSNE USING THE BARNESHUT METHOD IS STRONGLY RECOM
MENDED THE EXACT TSNE METHOD IS USEFUL FOR CHECKING THE THEORETICALLY PROPERTIES OF THE EMBEDDING POSSIBLY IN
HIGHER DIMENSIONAL SPACE BUT LIMIT TO SMALL DATASETS DUE TO COMPUTATIONAL CONSTRAINTS
ALSO NOTE THAT THE DIGITS LABELS ROUGHLY MATCH THE NATURAL GROUPING FOUND BY TSNE WHILE THE LINEAR 2D PROJECTION OF
THE PCA MODEL YIELDS A REPRESENTATION WHERE LABEL REGIONS LARGELY OVERLAP THIS IS A STRONG CLUE THAT THIS DATA CAN BE
WELL SEPARATED BY NON LINEAR METHODS THAT FOCUS ON THE LOCAL STRUCTURE EG AN SVM WITH A GAUSSIAN RBF KERNEL
HOWEVER FAILING TO VISUALIZE WELL SEPARATED HOMOGENEOUSLY LABELED GROUPS WITH TSNE IN 2D DOES NOT NECESSARILY
IMPLY THAT THE DATA CANNOT BE CORRECTLY CLASSIFIED BY A SUPERVISED MODEL IT MIGHT BE THE CASE THAT 2 DIMENSIONS ARE NOT
LOW ENOUGH TO ACCURATELY REPRESENTS THE INTERNAL STRUCTURE OF THE DATA
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• “ACCELERATING TSNE USING TREEBASED ALGORITHMS” LJP VAN DER MAATEN JOURNAL OF MACHINE LEARNING
RESEARCH 15OCT32213245 2014
TIPS ON PRACTICAL USE
• MAKE SURE THE SAME SCALE IS USED OVER ALL FEATURES BECAUSE MANIFOLD LEARNING METHODS ARE BASED ON A NEAREST
NEIGHBOR SEARCH THE ALGORITHM MAY PERFORM POORLY OTHERWISE SEE STANDARDSCALER FOR CONVENIENT WAYS OF
SCALING HETEROGENEOUS DATA
• THE RECONSTRUCTION ERROR COMPUTED BY EACH ROUTINE CAN BE USED TO CHOOSE THE OPTIMAL OUTPUT DIMENSION FOR A
□DIMENSIONAL MANIFOLD EMBEDDED IN A □DIMENSIONAL PARAMETER SPACE THE RECONSTRUCTION ERROR WILL DECREASE
ASNCOMPONENTS IS INCREASED UNTIL NCOMPONENTS D
• NOTE THAT NOISY DATA CAN “SHORTCIRCUIT” THE MANIFOLD IN ESSENCE ACTING AS A BRIDGE BETWEEN PARTS OF THE MANIFOLD
THAT WOULD OTHERWISE BE WELLSEPARATED MANIFOLD LEARNING ON NOISY ANDOR INCOMPLETE DATA IS AN ACTIVE AREA OF
RESEARCH
• CERTAIN INPUT CONFIGURATIONS CAN LEAD TO SINGULAR WEIGHT MATRICES FOR EXAMPLE WHEN MORE THAN TWO POINTS IN THE
DATASET ARE IDENTICAL OR WHEN THE DATA IS SPLIT INTO DISJOINTED GROUPS IN THIS CASE SOLVERARPACK WILL
FAIL TO FIND THE NULL SPACE THE EASIEST WAY TO ADDRESS THIS IS TO USE SOLVERDENSE WHICH WILL WORK ON A
SINGULAR MATRIX THOUGH IT MAY BE VERY SLOW DEPENDING ON THE NUMBER OF INPUT POINTS ALTERNATIVELY ONE CAN
ATTEMPT TO UNDERSTAND THE SOURCE OF THE SINGULARITY IF IT IS DUE TO DISJOINT SETS INCREASING NNEIGHBORS MAY
HELP IF IT IS DUE TO IDENTICAL POINTS IN THE DATASET REMOVING THESE POINTS MAY HELP
SEE ALSO
TOTALLY RANDOM TREES EMBEDDING CAN ALSO BE USEFUL TO DERIVE NONLINEAR REPRESENTATIONS OF FEATURE SPACE ALSO IT DOES
NOT PERFORM DIMENSIONALITY REDUCTION
323 CLUSTERING
CLUSTERING OF UNLABELED DATA CAN BE PERFORMED WITH THE MODULE SKLEARNCLUSTER
EACH CLUSTERING ALGORITHM COMES IN TWO VARIANTS A CLASS THAT IMPLEMENTS THE FIT METHOD TO LEARN THE CLUSTERS ON TRAIN
DATA AND A FUNCTION THAT GIVEN TRAIN DATA RETURNS AN ARRAY OF INTEGER LABELS CORRESPONDING TO THE DIFFERENT CLUSTERS FOR
THE CLASS THE LABELS OVER THE TRAINING DATA CAN BE FOUND IN THE LABELS ATTRIBUTE

INPUT DATA
ONE IMPORTANT THING TO NOTE IS THAT THE ALGORITHMS IMPLEMENTED IN THIS MODULE CAN TAKE DIFFERENT KINDS OF MATRIX AS INPUT ALL THE METHODS ACCEPT STANDARD DATA MATRICES OF SHAPE NSAMPLES NFEATURES THESE CAN BE OB
TAINED FROM THE CLASSES IN THE SKLEARNFEATUREEXTRACTION MODULE FOR AFFINITYPROPAGATION
SPECTRALCLUSTERING ANDDBSCAN ONE CAN ALSO INPUT SIMILARITY MATRICES OF SHAPE NSAMPLES
NSAMPLES THESE CAN BE OBTAINED FROM THE FUNCTIONS IN THE SKLEARNMETRICSPAIRWISE MODULE
OVERVIEW OF CLUSTERING METHODS
FIG 34 A COMPARISON OF THE CLUSTERING ALGORITHMS IN SCIKITLEARN

POINTS FROM ALTHOUGH THEY LIVE IN THE SAME SPACE
THE KMEANS ALGORITHM AIMS TO CHOOSE CENTROIDS THAT MINIMISE THE INERTIA ORWITHINCLUSTER SUMOFSQUARES CRITE
RION
Σ
0MIN
∈−2
INERTIA CAN BE RECOGNIZED AS A MEASURE OF HOW INTERNALLY COHERENT CLUSTERS ARE IT SUFFERS FROM VARIOUS DRAWBACKS
• INERTIA MAKES THE ASSUMPTION THAT CLUSTERS ARE CONVEX AND ISOTROPIC WHICH IS NOT ALWAYS THE CASE IT RESPONDS
POORLY TO ELONGATED CLUSTERS OR MANIFOLDS WITH IRREGULAR SHAPES
• INERTIA IS NOT A NORMALIZED METRIC WE JUST KNOW THAT LOWER VALUES ARE BETTER AND ZERO IS OPTIMAL BUT IN VERY
HIGHDIMENSIONAL SPACES EUCLIDEAN DISTANCES TEND TO BECOME INFLATED THIS IS AN INSTANCE OF THE SOCALLED “CURSE
OF DIMENSIONALITY” RUNNING A DIMENSIONALITY REDUCTION ALGORITHM SUCH AS PRINCIPAL COMPONENT ANALYSIS PCA
PRIOR TO KMEANS CLUSTERING CAN ALLEVIATE THIS PROBLEM AND SPEED UP THE COMPUTATIONS
K
MEANS IS OFTEN REFERRED TO AS LLOYD’S ALGORITHM IN BASIC TERMS THE ALGORITHM HAS THREE STEPS THE FIRST STEP CHOOSES
THE INITIAL CENTROIDS WITH THE MOST BASIC METHOD BEING TO CHOOSE SAMPLES FROM THE DATASET AFTER INITIALIZATION

KMEANS CONSISTS OF LOOPING BETWEEN THE TWO OTHER STEPS THE FIRST STEP ASSIGNS EACH SAMPLE TO ITS NEAREST CENTROID THE SECOND STEP CREATES NEW CENTROIDS BY TAKING THE MEAN VALUE OF ALL OF THE SAMPLES ASSIGNED TO EACH PREVIOUS CENTROID THE DIFFERENCE BETWEEN THE OLD AND THE NEW CENTROIDS ARE COMPUTED AND THE ALGORITHM REPEATS THESE LAST TWO STEPS UNTIL THIS VALUE IS LESS THAN A THRESHOLD IN OTHER WORDS IT REPEATS UNTIL THE CENTROIDS DO NOT MOVE SIGNIFICANTLY KMEANS IS EQUIVALENT TO THE EXPECTATIONMAXIMIZATION ALGORITHM WITH A
SMALL ALLEQUAL DIAGONAL COVARIANCE MATRIX
THE ALGORITHM CAN ALSO BE UNDERSTOOD THROUGH THE CONCEPT OF V ORONOI DIAGRAMS FIRST THE V ORONOI DIAGRAM OF THE POINTS IS CALCULATED USING THE CURRENT CENTROIDS EACH SEGMENT IN THE V ORONOI DIAGRAM BECOMES A SEPARATE CLUSTER SECONDLY THE CENTROIDS ARE UPDATED TO THE MEAN OF EACH SEGMENT THE ALGORITHM THEN REPEATS THIS UNTIL A STOPPING CRITERION IS FULFILLED USUALLY THE ALGORITHM STOPS WHEN THE RELATIVE DECREASE IN THE OBJECTIVE FUNCTION BETWEEN ITERATIONS IS LESS THAN THE GIVEN TOLERANCE VALUE THIS IS NOT THE CASE IN THIS IMPLEMENTATION ITERATION STOPS WHEN CENTROIDS MOVE LESS THAN THE TOLERANCE
GIVEN ENOUGH TIME KMEANS WILL ALWAYS CONVERGE HOWEVER THIS MAY BE TO A LOCAL MINIMUM THIS IS HIGHLY DEPEN
DENT ON THE INITIALIZATION OF THE CENTROIDS AS A RESULT THE COMPUTATION IS OFTEN DONE SEVERAL TIMES WITH DIFFERENT INITIALIZATIONS OF THE CENTROIDS ONE METHOD TO HELP ADDRESS THIS ISSUE IS THE KMEANS INITIALIZATION SCHEME WHICH HAS BEEN IMPLEMENTED IN SCIKITLEARN USE THE INITKMEANS PARAMETER THIS INITIALIZES THE CENTROIDS TO
BE GENERALLY DISTANT FROM EACH OTHER LEADING TO PROVABLY BETTER RESULTS THAN RANDOM INITIALIZATION AS SHOWN IN THE REFERENCE
THE ALGORITHM SUPPORTS SAMPLE WEIGHTS WHICH CAN BE GIVEN BY A PARAMETER SAMPLEWEIGHT THIS ALLOWS TO ASSIGN MORE WEIGHT TO SOME SAMPLES WHEN COMPUTING CLUSTER CENTERS AND VALUES OF INERTIA FOR EXAMPLE ASSIGNING A WEIGHT OF 2 TO A SAMPLE IS EQUIVALENT TO ADDING A DUPLICATE OF THAT SAMPLE TO THE DATASET
A PARAMETER CAN BE GIVEN TO ALLOW KMEANS TO BE RUN IN PARALLEL CALLED NJOBS GIVING THIS PARAMETER A POSITIVE VALUE USES THAT MANY PROCESSORS DEFAULT 1 A VALUE OF 1 USES ALL AVAILABLE PROCESSORS WITH 2 USING ONE LESS AND SO ON PARALLELIZATION GENERALLY SPEEDS UP COMPUTATION AT THE COST OF MEMORY IN THIS CASE MULTIPLE COPIES OF CENTROIDS NEED TO BE STORED ONE FOR EACH JOB
WARNING THE PARALLEL VERSION OF KMEANS IS BROKEN ON OS X WHEN NUMPY USES THEACCELERATE FRAMEWORK
THIS IS EXPECTED BEHAVIOR ACCELERATE CAN BE CALLED AFTER A FORK BUT YOU NEED TO EXECV THE SUBPROCESS WITH THE PYTHON BINARY WHICH MULTIPROCESSING DOES NOT DO UNDER POSIX
KMEANS CAN BE USED FOR VECTOR QUANTIZATION THIS IS ACHIEVED USING THE TRANSFORM METHOD OF A TRAINED MODEL OF KMEANS
EXAMPLES
•DEMONSTRATION OF KMEANS ASSUMPTIONS DEMONSTRATING WHEN KMEANS PERFORMS INTUITIVELY AND WHEN IT DOES NOT
•A DEMO OF KMEANS CLUSTERING ON THE HANDWRITTEN DIGITS DATA CLUSTERING HANDWRITTEN DIGITS

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THE EIGHTEENTH ANNUAL ACMSIAM SYMPOSIUM ON DISCRETE ALGORITHMS SOCIETY FOR INDUSTRIAL AND APPLIED
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MINI BATCH KMEANS
THEMINIBATCHKMEANS IS A VARIANT OF THE KMEANS ALGORITHM WHICH USES MINIBATCHES TO REDUCE THE COMPUTATION
TIME WHILE STILL ATTEMPTING TO OPTIMISE THE SAME OBJECTIVE FUNCTION MINIBATCHES ARE SUBSETS OF THE INPUT DATA RAN
DOMLY SAMPLED IN EACH TRAINING ITERATION THESE MINIBATCHES DRASTICALLY REDUCE THE AMOUNT OF COMPUTATION REQUIRED
TO CONVERGE TO A LOCAL SOLUTION IN CONTRAST TO OTHER ALGORITHMS THAT REDUCE THE CONVERGENCE TIME OF KMEANS MINIBATCH
KMEANS PRODUCES RESULTS THAT ARE GENERALLY ONLY SLIGHTLY WORSE THAN THE STANDARD ALGORITHM
THE ALGORITHM ITERATES BETWEEN TWO MAJOR STEPS SIMILAR TO VANILLA KMEANS IN THE FIRST STEP □SAMPLES ARE DRAWN
RANDOMLY FROM THE DATASET TO FORM A MINIBATCH THESE ARE THEN ASSIGNED TO THE NEAREST CENTROID IN THE SECOND STEP
THE CENTROIDS ARE UPDATED IN CONTRAST TO KMEANS THIS IS DONE ON A PERSAMPLE BASIS FOR EACH SAMPLE IN THE MINIBATCH
THE ASSIGNED CENTROID IS UPDATED BY TAKING THE STREAMING AVERAGE OF THE SAMPLE AND ALL PREVIOUS SAMPLES ASSIGNED TO
THAT CENTROID THIS HAS THE EFFECT OF DECREASING THE RATE OF CHANGE FOR A CENTROID OVER TIME THESE STEPS ARE PERFORMED
UNTIL CONVERGENCE OR A PREDETERMINED NUMBER OF ITERATIONS IS REACHED
MINIBATCHKMEANS CONVERGES FASTER THAN KMEANS BUT THE QUALITY OF THE RESULTS IS REDUCED IN PRACTICE THIS DIFFER
ENCE IN QUALITY CAN BE QUITE SMALL AS SHOWN IN THE EXAMPLE AND CITED REFERENCE
EXAMPLES
•COMPARISON OF THE KMEANS AND MINIBATCHKMEANS CLUSTERING ALGORITHMS COMPARISON OF KMEANS AND
MINIBATCHKMEANS
•CLUSTERING TEXT DOCUMENTS USING KMEANS DOCUMENT CLUSTERING USING SPARSE MINIBATCHKMEANS
•ONLINE LEARNING OF A DICTIONARY OF PARTS OF FACES

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AFFINITY PROPAGATION
AFFINITYPROPAGATION CREATES CLUSTERS BY SENDING MESSAGES BETWEEN PAIRS OF SAMPLES UNTIL CONVERGENCE A DATASET IS THEN DESCRIBED USING A SMALL NUMBER OF EXEMPLARS WHICH ARE IDENTIFIED AS THOSE MOST REPRESENTATIVE OF OTHER SAMPLES THE MESSAGES SENT BETWEEN PAIRS REPRESENT THE SUITABILITY FOR ONE SAMPLE TO BE THE EXEMPLAR OF THE OTHER WHICH IS UPDATED IN RESPONSE TO THE VALUES FROM OTHER PAIRS THIS UPDATING HAPPENS ITERATIVELY UNTIL CONVERGENCE AT WHICH POINT THE FINAL EXEMPLARS ARE CHOSEN AND HENCE THE FINAL CLUSTERING IS GIVEN
AFFINITY PROPAGATION CAN BE INTERESTING AS IT CHOOSES THE NUMBER OF CLUSTERS BASED ON THE DATA PROVIDED FOR THIS PUR POSE THE TWO IMPORTANT PARAMETERS ARE THE PREFERENCE WHICH CONTROLS HOW MANY EXEMPLARS ARE USED AND THE DAMPING FACTOR WHICH DAMPS THE RESPONSIBILITY AND AVAILABILITY MESSAGES TO AVOID NUMERICAL OSCILLATIONS WHEN UPDATING THESE MESSAGES
THE MAIN DRAWBACK OF AFFINITY PROPAGATION IS ITS COMPLEXITY THE ALGORITHM HAS A TIME COMPLEXITY OF THE ORDER □□2□ WHERE □IS THE NUMBER OF SAMPLES AND □IS THE NUMBER OF ITERATIONS UNTIL CONVERGENCE FURTHER THE MEMORY COMPLEXITY IS OF THE ORDER □□2IF A DENSE SIMILARITY MATRIX IS USED BUT REDUCIBLE IF A SPARSE SIMILARITY MATRIX IS USED THIS MAKES AFFINITY PROPAGATION MOST APPROPRIATE FOR SMALL TO MEDIUM SIZED DATASETS
EXAMPLES
•DEMO OF AFFINITY PROPAGATION CLUSTERING ALGORITHM AFFINITY PROPAGATION ON A SYNTHETIC 2D DATASETS WITH 3 CLASSES
•VISUALIZING THE STOCK MARKET STRUCTURE AFFINITY PROPAGATION ON FINANCIAL TIME SERIES TO FIND GROUPS OF COMPA NIES
ALGORITHM DESCRIPTION THE MESSAGES SENT BETWEEN POINTS BELONG TO ONE OF TWO CATEGORIES THE FIRST IS THE RESPONSI BILITY □□ □ WHICH IS THE ACCUMULATED EVIDENCE THAT SAMPLE □SHOULD BE THE EXEMPLAR FOR SAMPLE □ THE SECOND IS THE AVAILABILITY □□ □WHICH IS THE ACCUMULATED EVIDENCE THAT SAMPLE □SHOULD CHOOSE SAMPLE □TO BE ITS EXEMPLAR AND CONSIDERS THE VALUES FOR ALL OTHER SAMPLES THAT □SHOULD BE AN EXEMPLAR IN THIS WAY EXEMPLARS ARE CHOSEN BY SAMPLES IF THEY ARE 1 SIMILAR ENOUGH TO MANY SAMPLES AND 2 CHOSEN BY MANY SAMPLES TO BE REPRESENTATIVE OF THEMSELVES

MORE FORMALLY THE RESPONSIBILITY OF A SAMPLE □TO BE THE EXEMPLAR OF SAMPLE □IS GIVEN BY
□□ □←□□ □−□□□□□ □′ □□ □′∀□′□
WHERE □□ □IS THE SIMILARITY BETWEEN SAMPLES □AND□ THE AVAILABILITY OF SAMPLE □TO BE THE EXEMPLAR OF SAMPLE □IS GIVEN BY
□□ □←□□□0 □□ □ ∑
□′□□ □′∈□□□□′ □
TO BEGIN WITH ALL VALUES FOR □AND□ARE SET TO ZERO AND THE CALCULATION OF EACH ITERATES UNTIL CONVERGENCE AS DISCUSSED ABOVE IN ORDER TO AVOID NUMERICAL OSCILLATIONS WHEN UPDATING THE MESSAGES THE DAMPING FACTOR □IS INTRODUCED TO ITERATION PROCESS
□□1□ □ □·□□□ □ 1−□·□□1□ □
□□1□ □ □·□□□ □ 1−□·□□1□ □
WHERE □INDICATES THE ITERATION TIMES
MEAN SHIFT
MEANSHIFT CLUSTERING AIMS TO DISCOVER BLOBS IN A SMOOTH DENSITY OF SAMPLES IT IS A CENTROID BASED ALGORITHM WHICH WORKS BY UPDATING CANDIDATES FOR CENTROIDS TO BE THE MEAN OF THE POINTS WITHIN A GIVEN REGION THESE CANDIDATES ARE THEN FILTERED IN A POSTPROCESSING STAGE TO ELIMINATE NEARDUPLICATES TO FORM THE FINAL SET OF CENTROIDS
GIVEN A CANDIDATE CENTROID □□FOR ITERATION □ THE CANDIDATE IS UPDATED ACCORDING TO THE FOLLOWING EQUATION
□□1
□□□□
□
WHERE □□□IS THE NEIGHBORHOOD OF SAMPLES WITHIN A GIVEN DISTANCE AROUND □□AND□IS THE MEAN SHIFT VECTOR THAT IS COMPUTED FOR EACH CENTROID THAT POINTS TOWARDS A REGION OF THE MAXIMUM INCREASE IN THE DENSITY OF POINTS THIS IS COMPUTED USING THE FOLLOWING EQUATION EFFECTIVELY UPDATING A CENTROID TO BE THE MEAN OF THE SAMPLES WITHIN ITS NEIGHBORHOOD
□□□ ∑
□□∈□□□□□□−□□□□∑
□□∈□□□□□□−□□
THE ALGORITHM AUTOMATICALLY SETS THE NUMBER OF CLUSTERS INSTEAD OF RELYING ON A PARAMETER BANDWIDTH WHICH DICTATES THE SIZE OF THE REGION TO SEARCH THROUGH THIS PARAMETER CAN BE SET MANUALLY BUT CAN BE ESTIMATED USING THE PROVIDED ESTIMATEBANDWIDTH FUNCTION WHICH IS CALLED IF THE BANDWIDTH IS NOT SET
THE ALGORITHM IS NOT HIGHLY SCALABLE AS IT REQUIRES MULTIPLE NEAREST NEIGHBOR SEARCHES DURING THE EXECUTION OF THE ALGORITHM THE ALGORITHM IS GUARANTEED TO CONVERGE HOWEVER THE ALGORITHM WILL STOP ITERATING WHEN THE CHANGE IN CENTROIDS IS SMALL
LABELLING A NEW SAMPLE IS PERFORMED BY FINDING THE NEAREST CENTROID FOR A GIVEN SAMPLE
EXAMPLES
•A DEMO OF THE MEANSHIFT CLUSTERING ALGORITHM MEAN SHIFT CLUSTERING ON A SYNTHETIC 2D DATASETS WITH 3 CLASSES

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SPECTRAL CLUSTERING
SPECTRALCLUSTERING DOES A LOWDIMENSION EMBEDDING OF THE AFFINITY MATRIX BETWEEN SAMPLES FOLLOWED BY A KMEANS IN THE LOW DIMENSIONAL SPACE IT IS ESPECIALLY EFFICIENT IF THE AFFINITY MATRIX IS SPARSE AND THE PYAMG MODULE IS INSTALLED SPECTRALCLUSTERING REQUIRES THE NUMBER OF CLUSTERS TO BE SPECIFIED IT WORKS WELL FOR A SMALL NUMBER OF CLUSTERS BUT IS NOT ADVISED WHEN USING MANY CLUSTERS
FOR TWO CLUSTERS IT SOLVES A CONVEX RELAXATION OF THE NORMALISED CUTS PROBLEM ON THE SIMILARITY GRAPH CUTTING THE GRAPH IN TWO SO THAT THE WEIGHT OF THE EDGES CUT IS SMALL COMPARED TO THE WEIGHTS OF THE EDGES INSIDE EACH CLUSTER THIS CRITERIA IS ESPECIALLY INTERESTING WHEN WORKING ON IMAGES GRAPH VERTICES ARE PIXELS AND EDGES OF THE SIMILARITY GRAPH ARE A FUNCTION OF THE GRADIENT OF THE IMAGE
WARNING TRANSFORMING DISTANCE TO WELLBEHAVED SIMILARITIES
NOTE THAT IF THE VALUES OF YOUR SIMILARITY MATRIX ARE NOT WELL DISTRIBUTED EG WITH NEGATIVE VALUES OR WITH A DISTANCE

MATRIX RATHER THAN A SIMILARITY THE SPECTRAL PROBLEM WILL BE SINGULAR AND THE PROBLEM NOT SOLVABLE IN WHICH CASE IT IS ADVISED TO APPLY A TRANSFORMATION TO THE ENTRIES OF THE MATRIX FOR INSTANCE IN THE CASE OF A SIGNED DISTANCE MATRIX IS COMMON TO APPLY A HEAT KERNEL
SIMILARITY NPEXPBETA DISTANCE DISTANCESTD
SEE THE EXAMPLES FOR SUCH AN APPLICATION
EXAMPLES
•SPECTRAL CLUSTERING FOR IMAGE SEGMENTATION SEGMENTING OBJECTS FROM A NOISY BACKGROUND USING SPECTRAL CLUSTERING
•SEGMENTING THE PICTURE OF GREEK COINS IN REGIONS SPECTRAL CLUSTERING TO SPLIT THE IMAGE OF COINS IN REGIONS
DIFFERENT LABEL ASSIGNMENT STRATEGIES
DIFFERENT LABEL ASSIGNMENT STRATEGIES CAN BE USED CORRESPONDING TO THE ASSIGNLABELS PARAMETER OF SPECTRALCLUSTERING THEKMEANS STRATEGY CAN MATCH FINER DETAILS OF THE DATA BUT IT CAN BE MORE UNSTA BLE IN PARTICULAR UNLESS YOU CONTROL THE RANDOMSTATE IT MAY NOT BE REPRODUCIBLE FROM RUNTORUN AS IT DEPENDS ON A RANDOM INITIALIZATION ON THE OTHER HAND THE DISCRETIZE STRATEGY IS 100 REPRODUCIBLE BUT IT TENDS TO CREATE PARCELS OF FAIRLY EVEN AND GEOMETRICAL SHAPE
ASSIGNLABELSKMEANS ASSIGNLABELSDISCRETIZE
SPECTRAL CLUSTERING GRAPHS
SPECTRAL CLUSTERING CAN ALSO BE USED TO CLUSTER GRAPHS BY THEIR SPECTRAL EMBEDDINGS IN THIS CASE THE AFFINITY MATRIX IS THE ADJACENCY MATRIX OF THE GRAPH AND SPECTRALCLUSTERING IS INITIALIZED WITH AFFINITYPRECOMPUTED

FROM SKLEARNCLUSTER IMPORT SPECTRALCLUSTERING
SC SPECTRALCLUSTERING3 AFFINITYPRECOMPUTED NINIT100
ASSIGNLABELSDISCRETIZE
SCFITPREDICTADJACENCYMATRIX
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HIERARCHICAL CLUSTERING
HIERARCHICAL CLUSTERING IS A GENERAL FAMILY OF CLUSTERING ALGORITHMS THAT BUILD NESTED CLUSTERS BY MERGING OR SPLITTING THEM SUCCESSIVELY THIS HIERARCHY OF CLUSTERS IS REPRESENTED AS A TREE OR DENDROGRAM THE ROOT OF THE TREE IS THE UNIQUE CLUSTER THAT GATHERS ALL THE SAMPLES THE LEAVES BEING THE CLUSTERS WITH ONLY ONE SAMPLE SEE THE WIKIPEDIA PAGE FOR MORE DETAILS
THEAGGLOMERATIVECLUSTERING OBJECT PERFORMS A HIERARCHICAL CLUSTERING USING A BOTTOM UP APPROACH EACH OBSERVATION STARTS IN ITS OWN CLUSTER AND CLUSTERS ARE SUCCESSIVELY MERGED TOGETHER THE LINKAGE CRITERIA DETERMINES THE METRIC USED FOR THE MERGE STRATEGY
•WARD MINIMIZES THE SUM OF SQUARED DIFFERENCES WITHIN ALL CLUSTERS IT IS A VARIANCEMINIMIZING APPROACH AND IN THIS SENSE IS SIMILAR TO THE KMEANS OBJECTIVE FUNCTION BUT TACKLED WITH AN AGGLOMERATIVE HIERARCHICAL APPROACH
•MAXIMUM ORCOMPLETE LINKAGE MINIMIZES THE MAXIMUM DISTANCE BETWEEN OBSERVATIONS OF PAIRS OF CLUSTERS
•AVERAGE LINKAGE MINIMIZES THE AVERAGE OF THE DISTANCES BETWEEN ALL OBSERVATIONS OF PAIRS OF CLUSTERS
•SINGLE LINKAGE MINIMIZES THE DISTANCE BETWEEN THE CLOSEST OBSERVATIONS OF PAIRS OF CLUSTERS
AGGLOMERATIVECLUSTERING CAN ALSO SCALE TO LARGE NUMBER OF SAMPLES WHEN IT IS USED JOINTLY WITH A CONNECTIVITY MATRIX BUT IS COMPUTATIONALLY EXPENSIVE WHEN NO CONNECTIVITY CONSTRAINTS ARE ADDED BETWEEN SAMPLES IT CONSIDERS AT EACH STEP ALL THE POSSIBLE MERGES
FEATUREAGGLOMERATION
THEFEATUREAGGLOMERATION USES AGGLOMERATIVE CLUSTERING TO GROUP TOGETHER FEATURES THAT LOOK VERY SIMILAR THUS DECREASING THE NUMBER OF FEATURES IT IS A DIMENSIONALITY REDUCTION TOOL SEE UNSUPERVISED DIMENSIONALITY REDUCTION
DIFFERENT LINKAGE TYPE WARD COMPLETE AVERAGE AND SINGLE LINKAGE
AGGLOMERATIVECLUSTERING SUPPORTS WARD SINGLE AVERAGE AND COMPLETE LINKAGE STRATEGIES

AG
GLOMERATIVE CLUSTER HAS A “RICH GET RICHER” BEHAVIOR THAT LEADS TO UNEVEN CLUSTER SIZES IN THIS REGARD SINGLE LINKAGE IS THE WORST STRATEGY AND WARD GIVES THE MOST REGULAR SIZES HOWEVER THE AFFINITY OR DISTANCE USED IN CLUSTERING CANNOT BE VARIED WITH WARD THUS FOR NON EUCLIDEAN METRICS AVERAGE LINKAGE IS A GOOD ALTERNATIVE SINGLE LINKAGE WHILE NOT ROBUST TO NOISY DATA CAN BE COMPUTED VERY EFFICIENTLY AND CAN THEREFORE BE USEFUL TO PROVIDE HIERARCHICAL CLUSTERING OF LARGER DATASETS SINGLE LINKAGE CAN ALSO PERFORM WELL ON NONGLOBULAR DATA

EXAMPLES

•VARIOUS AGGLOMERATIVE CLUSTERING ON A 2D EMBEDDING OF DIGITS EXPLORATION OF THE DIFFERENT LINKAGE STRATEGIES IN A REAL DATASET

ADDING CONNECTIVITY CONSTRAINTS
AN INTERESTING ASPECT OF AGGLOMERATIVECLUSTERING IS THAT CONNECTIVITY CONSTRAINTS CAN BE ADDED TO THIS AL GORITHM ONLY ADJACENT CLUSTERS CAN BE MERGED TOGETHER THROUGH A CONNECTIVITY MATRIX THAT DEFINES FOR EACH SAMPLE THE NEIGHBORING SAMPLES FOLLOWING A GIVEN STRUCTURE OF THE DATA FOR INSTANCE IN THE SWISSROLL EXAMPLE BELOW THE CONNECTIVITY CONSTRAINTS FORBID THE MERGING OF POINTS THAT ARE NOT ADJACENT ON THE SWISS ROLL AND THUS AVOID FORMING CLUSTERS THAT EXTEND ACROSS OVERLAPPING FOLDS OF THE ROLL
THESE CONSTRAINT ARE USEFUL TO IMPOSE A CERTAIN LOCAL STRUCTURE BUT THEY ALSO MAKE THE ALGORITHM FASTER ESPECIALLY WHEN THE NUMBER OF THE SAMPLES IS HIGH
THE CONNECTIVITY CONSTRAINTS ARE IMPOSED VIA AN CONNECTIVITY MATRIX A SCIPY SPARSE MATRIX THAT HAS ELEMENTS ONLY AT THE INTERSECTION OF A ROW AND A COLUMN WITH INDICES OF THE DATASET THAT SHOULD BE CONNECTED THIS MATRIX CAN BE CONSTRUCTED FROM APRIORI INFORMATION FOR INSTANCE YOU MAY WISH TO CLUSTER WEB PAGES BY ONLY MERGING PAGES WITH A LINK POINTING FROM ONE TO ANOTHER IT CAN ALSO BE LEARNED FROM THE DATA FOR INSTANCE USING SKLEARN NEIGHBORSKNEIGHBORSGRAPH TO RESTRICT MERGING TO NEAREST NEIGHBORS AS IN THIS EXAMPLE OR USINGSKLEARN FEATUREEXTRACTIONIMAGEGRIDTOGRAPH TO ENABLE ONLY MERGING OF NEIGHBORING PIXELS ON AN IMAGE AS IN THE COIN EXAMPLE
EXAMPLES
•A DEMO OF STRUCTURED WARD HIERARCHICAL CLUSTERING ON AN IMAGE OF COINS WARD CLUSTERING TO SPLIT THE IMAGE OF COINS IN REGIONS
•HIERARCHICAL CLUSTERING STRUCTURED VS UNSTRUCTURED WARD EXAMPLE OF WARD ALGORITHM ON A SWISSROLL COM PARISON OF STRUCTURED APPROACHES VERSUS UNSTRUCTURED APPROACHES
•FEATURE AGGLOMERATION VS UNIVARIATE SELECTION EXAMPLE OF DIMENSIONALITY REDUCTION WITH FEATURE AGGLOMER ATION BASED ON WARD HIERARCHICAL CLUSTERING
•AGGLOMERATIVE CLUSTERING WITH AND WITHOUT STRUCTURE
WARNING CONNECTIVITY CONSTRAINTS WITH SINGLE AVERAGE AND COMPLETE LINKAGE
CONNECTIVITY CONSTRAINTS AND SINGLE COMPLETE OR AVERAGE LINKAGE CAN ENHANCE THE ‘RICH GETTING RICHER’ ASPECT OF AGGLOMERATIVE CLUSTERING PARTICULARLY SO IF THEY ARE BUILT WITH SKLEARNNEIGHBORSKNEIGHBORSGRAPH
IN THE LIMIT OF A SMALL NUMBER OF CLUSTERS THEY TEND TO GIVE A FEW MACROSCOPICALLY OCCUPIED CLUSTERS AND ALMOST EMPTY ONES SEE THE DISCUSSION IN AGGLOMERATIVE CLUSTERING WITH AND WITHOUT STRUCTURE SINGLE LINKAGE IS THE MOST BRITTLE LINKAGE OPTION WITH REGARD TO THIS ISSUE

VARYING THE METRIC
SINGLE AVERAGE AND COMPLETE LINKAGE CAN BE USED WITH A VARIETY OF DISTANCES OR AFFINITIES IN PARTICULAR EUCLIDEAN DISTANCE L2 MANHATTAN DISTANCE OR CITYBLOCK OR L1 COSINE DISTANCE OR ANY PRECOMPUTED AFFINITY MATRIX
•L1DISTANCE IS OFTEN GOOD FOR SPARSE FEATURES OR SPARSE NOISE IE MANY OF THE FEATURES ARE ZERO AS IN TEXT MINING USING OCCURRENCES OF RARE WORDS
•COSINE DISTANCE IS INTERESTING BECAUSE IT IS INVARIANT TO GLOBAL SCALINGS OF THE SIGNAL
THE GUIDELINES FOR CHOOSING A METRIC IS TO USE ONE THAT MAXIMIZES THE DIS
TANCE BETWEEN SAMPLES IN DIFFERENT CLASSES AND MINIMIZES THAT WITHIN EACH CLASS
EXAMPLES
•AGGLOMERATIVE CLUSTERING WITH DIFFERENT METRICS
DBSCAN
THEDBSCAN ALGORITHM VIEWS CLUSTERS AS AREAS OF HIGH DENSITY SEPARATED BY AREAS OF LOW DENSITY DUE TO THIS RATHER GENERIC VIEW CLUSTERS FOUND BY DBSCAN CAN BE ANY SHAPE AS OPPOSED TO KMEANS WHICH ASSUMES THAT CLUSTERS ARE CONVEX SHAPED THE CENTRAL COMPONENT TO THE DBSCAN IS THE CONCEPT OF CORE SAMPLES WHICH ARE SAMPLES THAT ARE IN AREAS OF HIGH DENSITY A CLUSTER IS THEREFORE A SET OF CORE SAMPLES EACH CLOSE TO EACH OTHER MEASURED BY SOME DISTANCE MEASURE AND A SET OF NONCORE SAMPLES THAT ARE CLOSE TO A CORE SAMPLE BUT ARE NOT THEMSELVES CORE SAMPLES THERE ARE TWO PARAMETERS TO THE ALGORITHM MINSAMPLES ANDEPS WHICH DEFINE FORMALLY WHAT WE MEAN WHEN WE SAY DENSE HIGHERMINSAMPLES OR LOWEREPS INDICATE HIGHER DENSITY NECESSARY TO FORM A CLUSTER
MORE FORMALLY WE DEFINE A CORE SAMPLE AS BEING A SAMPLE IN THE DATASET SUCH THAT THERE EXIST MINSAMPLES OTHER SAMPLES WITHIN A DISTANCE OF EPS WHICH ARE DEFINED AS NEIGHBORS OF THE CORE SAMPLE THIS TELLS US THAT THE CORE SAMPLE IS IN A DENSE AREA OF THE VECTOR SPACE A CLUSTER IS A SET OF CORE SAMPLES THAT CAN BE BUILT BY RECURSIVELY TAKING A CORE SAMPLE FINDING ALL OF ITS NEIGHBORS THAT ARE CORE SAMPLES FINDING ALL OF THEIR NEIGHBORS THAT ARE CORE SAMPLES AND SO ON A CLUSTER ALSO HAS A SET OF NONCORE SAMPLES WHICH ARE SAMPLES THAT ARE NEIGHBORS OF A CORE SAMPLE IN THE CLUSTER BUT ARE NOT THEMSELVES CORE SAMPLES INTUITIVELY THESE SAMPLES ARE ON THE FRINGES OF A CLUSTER

ANY CORE SAMPLE IS PART OF A CLUSTER BY DEFINITION ANY SAMPLE THAT IS NOT A CORE SAMPLE AND IS AT LEAST EPS IN DISTANCE FROM ANY CORE SAMPLE IS CONSIDERED AN OUTLIER BY THE ALGORITHM
WHILE THE PARAMETER MINSAMPLES PRIMARILY CONTROLS HOW TOLERANT THE ALGORITHM IS TOWARDS NOISE ON NOISY AND LARGE DATA SETS IT MAY BE DESIABLE TO INCREASE THIS PARAMETER THE PARAMETER EPS ISCRUCIAL TO CHOOSE APPROPRIATELY FOR THE DATA SET AND DISTANCE FUNCTION AND USUALLY CANNOT BE LEFT AT THE DEFAULT VALUE IT CONTROLS THE LOCAL NEIGHBORHOOD OF THE POINTS WHEN CHOSEN TOO SMALL MOST DATA WILL NOT BE CLUSTERED AT ALL AND LABELED AS 1FOR “NOISE” WHEN CHOSEN TOO LARGE IT CAUSES CLOSE CLUSTERS TO BE MERGED INTO ONE CLUSTER AND EVENTUALLY THE ENTIRE DATA SET TO BE RETURNED AS A SINGLE CLUSTER SOME HEURISTICS FOR CHOOSING THIS PARAMETER HAVE BEEN DISCUSSED IN LITERATURE FOR EXAMPLE BASED ON A KNEE IN THE NEAREST NEIGHBOR DISTANCES PLOT AS DISCUSSED IN THE REFERENCES BELOW
IN THE FIGURE BELOW THE COLOR INDICATES CLUSTER MEMBERSHIP WITH LARGE CIRCLES INDICATING CORE SAMPLES FOUND BY THE ALGORITHM SMALLER CIRCLES ARE NONCORE SAMPLES THAT ARE STILL PART OF A CLUSTER MOREOVER THE OUTLIERS ARE INDICATED BY BLACK POINTS BELOW
EXAMPLES
•DEMO OF DBSCAN CLUSTERING ALGORITHM
IMPLEMENTATION
THE DBSCAN ALGORITHM IS DETERMINISTIC ALWAYS GENERATING THE SAME CLUSTERS WHEN GIVEN THE SAME DATA IN THE SAME ORDER HOWEVER THE RESULTS CAN DIFFER WHEN DATA IS PROVIDED IN A DIFFERENT ORDER FIRST EVEN THOUGH THE CORE SAMPLES WILL ALWAYS BE ASSIGNED TO THE SAME CLUSTERS THE LABELS OF THOSE CLUSTERS WILL DEPEND ON THE ORDER IN WHICH THOSE SAMPLES ARE ENCOUNTERED IN THE DATA SECOND AND MORE IMPORTANTLY THE CLUSTERS TO WHICH NONCORE SAMPLES ARE ASSIGNED CAN DIFFER DEPENDING ON THE DATA ORDER THIS WOULD HAPPEN WHEN A NONCORE SAMPLE HAS A DISTANCE LOWER THANEPS TO TWO CORE SAMPLES IN DIFFERENT CLUSTERS BY THE TRIANGULAR INEQUALITY THOSE TWO CORE SAMPLES MUST BE MORE DISTANT THAN EPS FROM EACH OTHER OR THEY WOULD BE IN THE SAME CLUSTER THE NONCORE SAMPLE IS ASSIGNED TO WHICHEVER CLUSTER IS GENERATED FIRST IN A PASS THROUGH THE DATA AND SO THE RESULTS WILL DEPEND ON THE DATA ORDERING
THE CURRENT IMPLEMENTATION USES BALL TREES AND KDTREES TO DETERMINE THE NEIGHBORHOOD OF POINTS WHICH AVOIDS CALCULATING THE FULL DISTANCE MATRIX AS WAS DONE IN SCIKITLEARN VERSIONS BEFORE 014 THE POSSIBILITY TO USE CUSTOM METRICS IS RETAINED FOR DETAILS SEE NEARESTNEIGHBORS
MEMORY CONSUMPTION FOR LARGE SAMPLE SIZES

THIS IMPLEMENTATION IS BY DEFAULT NOT MEMORY EFFICIENT BECAUSE IT CONSTRUCTS A FULL PAIRWISE SIMILARITY MATRIX IN THE CASE WHERE KDTREES OR BALLTREES CANNOT BE USED EG WITH SPARSE MATRICES THIS MATRIX WILL CONSUME N2 FLOATS A COUPLE OF MECHANISMS FOR GETTING AROUND THIS ARE

- USE OPTICS CLUSTERING IN CONJUNCTION WITH THE EXTRACTDBSCAN METHOD OPTICS CLUSTERING ALSO CALCULATES THE FULL PAIRWISE MATRIX BUT ONLY KEEPS ONE ROW IN MEMORY AT A TIME MEMORY COMPLEXITY N
- A SPARSE RADIUS NEIGHBORHOOD GRAPH WHERE MISSING ENTRIES ARE PRESUMED TO BE OUT OF EPS CAN BE PRECOMPUTED IN A MEMORYEFFICIENT WAY AND DBSCAN CAN BE RUN OVER THIS WITH METRICPRECOMPUTED SEE SKLEARNNEIGHBORSNEARESTNEIGHBORSRADIUSNEIGHBORSGRAPH
- THE DATASET CAN BE COMPRESSED EITHER BY REMOVING EXACT DUPLICATES IF THESE OCCUR IN YOUR DATA OR BY USING BIRCH THEN YOU ONLY HAVE A RELATIVELY SMALL NUMBER OF REPRESENTATIVES FOR A LARGE NUMBER OF POINTS YOU CAN THEN PROVIDE A SAMPLEWEIGHT WHEN FITTING DBSCAN

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- “A DENSITYBASED ALGORITHM FOR DISCOVERING CLUSTERS IN LARGE SPATIAL DATABASES WITH NOISE” ESTER M H P KRIEGEL J SANDER AND X XU IN PROCEEDINGS OF THE 2ND INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING PORTLAND OR AAAI PRESS PP 226–231 1996
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OPTICS

THEOPTICS ALGORITHM SHARES MANY SIMILARITIES WITH THE DBSCAN ALGORITHM AND CAN BE CONSIDERED A GENERALIZATION OF DBSCAN THAT RELAXES THE EPS REQUIREMENT FROM A SINGLE VALUE TO A VALUE RANGE THE KEY DIFFERENCE BETWEEN DBSCAN AND OPTICS IS THAT THE OPTICS ALGORITHM BUILDS A REACHABILITY GRAPH WHICH ASSIGNS EACH SAMPLE BOTH AREACHABILITY DISTANCE AND A SPOT WITHIN THE CLUSTER ORDERING ATTRIBUTE THESE TWO ATTRIBUTES ARE ASSIGNED WHEN THE MODEL IS FITTED AND ARE USED TO DETERMINE CLUSTER MEMBERSHIP IF OPTICS IS RUN WITH THE DEFAULT VALUE OF INF SET FORMAXEPS THEN DBSCAN STYLE CLUSTER EXTRACTION CAN BE PERFORMED REPEATEDLY IN LINEAR TIME FOR ANY GIVEN EPS VALUE USING THE CLUSTEROPTICSDBSCAN METHOD SETTING MAXEPS TO A LOWER VALUE WILL RESULT IN SHORTER RUN TIMES AND CAN BE THOUGHT OF AS THE MAXIMUM NEIGHBORHOOD RADIUS FROM EACH POINT TO FIND OTHER POTENTIAL REACHABLE POINTS

THEREACHABILITY DISTANCES GENERATED BY OPTICS ALLOW FOR VARIABLE DENSITY EXTRACTION OF CLUSTERS WITHIN A SINGLE DATA SET AS SHOWN IN THE ABOVE PLOT COMBINING REACHABILITY DISTANCES AND DATA SET ORDERING PRODUCES A REACHABILITY PLOT WHERE POINT DENSITY IS REPRESENTED ON THE YAXIS AND POINTS ARE ORDERED SUCH THAT NEARBY POINTS ARE ADJACENT 'CUTTING' THE REACHABILITY PLOT AT A SINGLE VALUE PRODUCES DBSCAN LIKE RESULTS ALL POINTS ABOVE THE 'CUT' ARE CLASSIFIED AS NOISE AND EACH TIME THAT THERE IS A BREAK WHEN READING FROM LEFT TO RIGHT SIGNIFIES A NEW CLUSTER THE DEFAULT CLUSTER EXTRACTION WITH OPTICS LOOKS AT THE STEEP SLOPES WITHIN THE GRAPH TO FIND CLUSTERS AND THE USER CAN DEFINE WHAT COUNTS AS A STEEP SLOPE USING THE PARAMETER XI THERE ARE ALSO OTHER POSSIBILITIES FOR ANALYSIS ON THE GRAPH ITSELF SUCH AS GENERATING HIERARCHICAL REPRESENTATIONS OF THE DATA THROUGH REACHABILITYPLOT DENDROGRAMS AND THE HIERARCHY OF CLUSTERS DETECTED BY THE ALGORITHM CAN BE ACCESSED THROUGH THE CLUSTERHIERARCHY PARAMETER THE PLOT ABOVE HAS BEEN COLORCODED SO THAT CLUSTER COLORS IN PLANAR SPACE MATCH THE LINEAR SEGMENT CLUSTERS OF THE REACHABILITY PLOT NOTE THAT THE BLUE AND RED CLUSTERS ARE ADJACENT IN THE REACHABILITY PLOT AND CAN BE HIERARCHICALLY REPRESENTED AS CHILDREN OF A LARGER PARENT CLUSTER

EXAMPLES

•DEMO OF OPTICS CLUSTERING ALGORITHM

COMPARISON WITH DBSCAN

THE RESULTS FROM OPTICS CLUSTEROPTICSDBSCAN METHOD AND DBSCAN ARE VERY SIMILAR BUT NOT ALWAYS IDENTICAL SPECIFICALLY LABELING OF PERIPHERY AND NOISE POINTS THIS IS IN PART BECAUSE THE FIRST SAMPLES OF EACH DENSE AREA PROCESSED BY OPTICS HAVE A LARGE REACHABILITY VALUE WHILE BEING CLOSE TO OTHER POINTS IN THEIR AREA AND WILL THUS SOMETIMES BE MARKED AS NOISE RATHER THAN PERIPHERY THIS AFFECTS ADJACENT POINTS WHEN THEY ARE CONSIDERED AS CANDIDATES FOR BEING MARKED AS EITHER PERIPHERY OR NOISE

NOTE THAT FOR ANY SINGLE VALUE OF EPS DBSCAN WILL TEND TO HAVE A SHORTER RUN TIME THAN OPTICS HOWEVER FOR REPEATED RUNS AT VARYING EPS VALUES A SINGLE RUN OF OPTICS MAY REQUIRE LESS CUMULATIVE RUNTIME THAN DBSCAN

IT IS ALSO IMPORTANT TO NOTE THAT OPTICS' OUTPUT IS CLOSE TO DBSCAN'S ONLY IF EPS ANDMAXEPS ARE CLOSE

COMPUTATIONAL COMPLEXITY
SPATIAL INDEXING TREES ARE USED TO AVOID CALCULATING THE FULL DISTANCE MATRIX AND ALLOW FOR EFFICIENT MEMORY USAGE ON LARGE SETS OF SAMPLES DIFFERENT DISTANCE METRICS CAN BE SUPPLIED VIA THE METRIC KEYWORD
FOR LARGE DATASETS SIMILAR BUT NOT IDENTICAL RESULTS CAN BE OBTAINED VIA HDBSCAN THE HDBSCAN IMPLEMENTATION IS MULTITHREADED AND HAS BETTER ALGORITHMIC RUNTIME COMPLEXITY THAN OPTICS AT THE COST OF WORSE MEMORY SCALING FOR EXTREMELY LARGE DATASETS THAT EXHAUST SYSTEM MEMORY USING HDBSCAN OPTICS WILL MAINTAIN NAS OPPOSED TO N2 MEMORY SCALING HOWEVER TUNING OF THE MAXEPS PARAMETER WILL LIKELY NEED TO BE USED TO GIVE A SOLUTION IN A REASONABLE AMOUNT OF WALL TIME
REFERENCES
• “OPTICS ORDERING POINTS TO IDENTIFY THE CLUSTERING STRUCTURE” ANKERST MIHAEL MARKUS M BREUNIG HANS PETER KRIEGEL AND JÖRG SANDER IN ACM SIGMOD RECORD VOL 28 NO 2 PP 4960 ACM 1999
BIRCH
THEBIRCH BUILDS A TREE CALLED THE CHARACTERISTIC FEATURE TREE CFT FOR THE GIVEN DATA THE DATA IS ESSENTIALLY LOSSY COMPRESSED TO A SET OF CHARACTERISTIC FEATURE NODES CF NODES THE CF NODES HAVE A NUMBER OF SUBCLUSTERS CALLED CHARACTERISTIC FEATURE SUBCLUSTERS CF SUBCLUSTERS AND THESE CF SUBCLUSTERS LOCATED IN THE NONTERMINAL CF NODES CAN HAVE CF NODES AS CHILDREN
THE CF SUBCLUSTERS HOLD THE NECESSARY INFORMATION FOR CLUSTERING WHICH PREVENTS THE NEED TO HOLD THE ENTIRE INPUT DATA IN MEMORY THIS INFORMATION INCLUDES
• NUMBER OF SAMPLES IN A SUBCLUSTER
• LINEAR SUM A NDIMENSIONAL VECTOR HOLDING THE SUM OF ALL SAMPLES
• SQUARED SUM SUM OF THE SQUARED L2 NORM OF ALL SAMPLES
• CENTROIDS TO AVOID RECALCULATION LINEAR SUM NSAMPLES
• SQUARED NORM OF THE CENTROIDS
THE BIRCH ALGORITHM HAS TWO PARAMETERS THE THRESHOLD AND THE BRANCHING FACTOR THE BRANCHING FACTOR LIMITS THE NUMBER OF SUBCLUSTERS IN A NODE AND THE THRESHOLD LIMITS THE DISTANCE BETWEEN THE ENTERING SAMPLE AND THE EXISTING SUBCLUSTERS
THIS ALGORITHM CAN BE VIEWED AS AN INSTANCE OR DATA REDUCTION METHOD SINCE IT REDUCES THE INPUT DATA TO A SET OF SUBCLUSTERS WHICH ARE OBTAINED DIRECTLY FROM THE LEAVES OF THE CFT THIS REDUCED DATA CAN BE FURTHER PROCESSED BY FEEDING IT INTO A GLOBAL CLUSTERER THIS GLOBAL CLUSTERER CAN BE SET BY NCLUSTERS IFNCLUSTERS IS SET TO NONE
THE SUBCLUSTERS FROM THE LEAVES ARE DIRECTLY READ OFF OTHERWISE A GLOBAL CLUSTERING STEP LABELS THESE SUBCLUSTERS INTO GLOBAL CLUSTERS LABELS AND THE SAMPLES ARE MAPPED TO THE GLOBAL LABEL OF THE NEAREST SUBCLUSTER
ALGORITHM DESCRIPTION
• A NEW SAMPLE IS INSERTED INTO THE ROOT OF THE CF TREE WHICH IS A CF NODE IT IS THEN MERGED WITH THE SUBCLUSTER OF THE ROOT THAT HAS THE SMALLEST RADIUS AFTER MERGING CONSTRAINED BY THE THRESHOLD AND BRANCHING FACTOR CONDITIONS IF THE SUBCLUSTER HAS ANY CHILD NODE THEN THIS IS DONE REPEATEDLY TILL IT REACHES A LEAF AFTER FINDING THE NEAREST SUBCLUSTER IN THE LEAF THE PROPERTIES OF THIS SUBCLUSTER AND THE PARENT SUBCLUSTERS ARE RECURSIVELY UPDATED
• IF THE RADIUS OF THE SUBCLUSTER OBTAINED BY MERGING THE NEW SAMPLE AND THE NEAREST SUBCLUSTER IS GREATER THAN THE SQUARE OF THE THRESHOLD AND IF THE NUMBER OF SUBCLUSTERS IS GREATER THAN THE BRANCHING FACTOR THEN A SPACE IS TEMPORARILY ALLOCATED TO THIS NEW SAMPLE THE TWO FARTHEST SUBCLUSTERS ARE TAKEN AND THE SUBCLUSTERS ARE DIVIDED INTO TWO GROUPS ON THE BASIS OF THE DISTANCE BETWEEN THESE SUBCLUSTERS

• IF THIS SPLIT NODE HAS A PARENT SUBCLUSTER AND THERE IS ROOM FOR A NEW SUBCLUSTER THEN THE PARENT IS SPLIT INTO TWO IF THERE IS NO ROOM THEN THIS NODE IS AGAIN SPLIT INTO TWO AND THE PROCESS IS CONTINUED RECURSIVELY TILL IT REACHES THE ROOT

BIRCH OR MINIBATCHKMEANS

• BIRCH DOES NOT SCALE VERY WELL TO HIGH DIMENSIONAL DATA AS A RULE OF THUMB IF NFEATURES IS GREATER THAN TWENTY IT IS GENERALLY BETTER TO USE MINIBATCHKMEANS

• IF THE NUMBER OF INSTANCES OF DATA NEEDS TO BE REDUCED OR IF ONE WANTS A LARGE NUMBER OF SUBCLUSTERS EITHER AS A PREPROCESSING STEP OR OTHERWISE BIRCH IS MORE USEFUL THAN MINIBATCHKMEANS

HOW TO USE PARTIALFIT

TO AVOID THE COMPUTATION OF GLOBAL CLUSTERING FOR EVERY CALL OF PARTIALFIT THE USER IS ADVISED

1 TO SETNCLUSTERSNONE INITIALLY

2 TRAIN ALL DATA BY MULTIPLE CALLS TO PARTIALFIT

3 SETNCLUSTERS TO A REQUIRED VALUE USING BRCSETPARAMSNCLUSTERSNCLUSTERS

4 CALLPARTIALFIT FINALLY WITH NO ARGUMENTS IE BRCPARTIALFIT WHICH PERFORMS THE GLOBAL CLUS TERING

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• ROBERTO PERDISCI JBIRCH JAVA IMPLEMENTATION OF BIRCH CLUSTERING ALGORITHM HTTPSCODEGOOGLECOM ARCHIVEPJBIRCH

CLUSTERING PERFORMANCE EVALUATION

EVALUATING THE PERFORMANCE OF A CLUSTERING ALGORITHM IS NOT AS TRIVIAL AS COUNTING THE NUMBER OF ERRORS OR THE PRECISION AND RECALL OF A SUPERVISED CLASSIFICATION ALGORITHM IN PARTICULAR ANY EVALUATION METRIC SHOULD NOT TAKE THE ABSOLUTE VALUES OF THE CLUSTER LABELS INTO ACCOUNT BUT RATHER IF THIS CLUSTERING DEFINE SEPARATIONS OF THE DATA SIMILAR TO SOME GROUND TRUTH SET OF CLASSES OR SATISFYING SOME ASSUMPTION SUCH THAT MEMBERS BELONG TO THE SAME CLASS ARE MORE SIMILAR THAT MEMBERS OF DIFFERENT CLASSES ACCORDING TO SOME SIMILARITY METRIC

ADJUSTED RAND INDEX
GIVEN THE KNOWLEDGE OF THE GROUND TRUTH CLASS ASSIGNMENTS LABELSTRUE AND OUR CLUSTERING ALGORITHM ASSIGNMENTS OF THE SAME SAMPLES LABELSPRED THE ADJUSTED RAND INDEX IS A FUNCTION THAT MEASURES THE SIMILARITY OF THE TWO ASSIGNMENTS IGNORING PERMUTATIONS AND WITH CHANCE NORMALIZATION
FROM SKLEARN IMPORT METRICS
LABELSTRUE 0 0 0 1 1 1
LABELSPRED 0 0 1 1 2 2
METRICSADJUSTEDRANDSCORELABELSTRUE LABELSPRED
024
ONE CAN PERMUTE 0 AND 1 IN THE PREDICTED LABELS RENAME 2 TO 3 AND GET THE SAME SCORE
LABELSPRED 1 1 0 0 3 3
METRICSADJUSTEDRANDSCORELABELSTRUE LABELSPRED
024
FURTHERMORE ADJUSTEDRANDSCORE ISSYMMETRIC SWAPPING THE ARGUMENT DOES NOT CHANGE THE SCORE IT CAN THUS BE USED AS A CONSENSUS MEASURE
METRICSADJUSTEDRANDSCORELABELSPRED LABELSTRUE
024
PERFECT LABELING IS SCORED 10
LABELSPRED LABELSTRUE
METRICSADJUSTEDRANDSCORELABELSTRUE LABELSPRED
10
BAD EG INDEPENDENT LABELINGS HAVE NEGATIVE OR CLOSE TO 00 SCORES
LABELSTRUE 0 1 2 0 3 4 5 1
LABELSPRED 1 1 0 0 2 2 2 2
METRICSADJUSTEDRANDSCORELABELSTRUE LABELSPRED
012
ADVANTAGES
•RANDOM UNIFORM LABEL ASSIGNMENTS HAVE A ARI SCORE CLOSE TO 00 FOR ANY VALUE OF NCLUSTERS AND NSAMPLES WHICH IS NOT THE CASE FOR RAW RAND INDEX OR THE VMEASURE FOR INSTANCE
•BOUNDED RANGE 1 1 NEGATIVE VALUES ARE BAD INDEPENDENT LABELINGS SIMILAR CLUSTERINGS HAVE A POSITIVE ARI 10 IS THE PERFECT MATCH SCORE
•NO ASSUMPTION IS MADE ON THE CLUSTER STRUCTURE CAN BE USED TO COMPARE CLUSTERING ALGORITHMS SUCH AS K MEANS WHICH ASSUMES ISOTROPIC BLOB SHAPES WITH RESULTS OF SPECTRAL CLUSTERING ALGORITHMS WHICH CAN FIND CLUSTER WITH “FOLDED” SHAPES
DRAWBACKS
• CONTRARY TO INERTIA ARI REQUIRES KNOWLEDGE OF THE GROUND TRUTH CLASSES WHILE IS ALMOST NEVER AVAILABLE IN PRACTICE OR REQUIRES MANUAL ASSIGNMENT BY HUMAN ANNOTATORS AS IN THE SUPERVISED LEARNING SETTING

HOWEVER ARI CAN ALSO BE USEFUL IN A PURELY UNSUPERVISED SETTING AS A BUILDING BLOCK FOR A CONSENSUS INDEX THAT CAN BE USED FOR CLUSTERING MODEL SELECTION TODO

EXAMPLES

•ADJUSTMENT FOR CHANCE IN CLUSTERING PERFORMANCE EVALUATION ANALYSIS OF THE IMPACT OF THE DATASET SIZE ON THE VALUE OF CLUSTERING MEASURES FOR RANDOM ASSIGNMENTS

MATHEMATICAL FORMULATION

IF C IS A GROUND TRUTH CLASS ASSIGNMENT AND K THE CLUSTERING LET US DEFINE □AND□AS

•□ THE NUMBER OF PAIRS OF ELEMENTS THAT ARE IN THE SAME SET IN C AND IN THE SAME SET IN K

•□ THE NUMBER OF PAIRS OF ELEMENTS THAT ARE IN DIFFERENT SETS IN C AND IN DIFFERENT SETS IN K

THE RAW UNADJUSTED RAND INDEX IS THEN GIVEN BY

RI□□

□□□□□□□□□□

2

WHERE □□□□□□□□□□

2 IS THE TOTAL NUMBER OF POSSIBLE PAIRS IN THE DATASET WITHOUT ORDERING

HOWEVER THE RI SCORE DOES NOT GUARANTEE THAT RANDOM LABEL ASSIGNMENTS WILL GET A VALUE CLOSE TO ZERO ESP IF THE NUMBER OF CLUSTERS IS IN THE SAME ORDER OF MAGNITUDE AS THE NUMBER OF SAMPLES

TO COUNTER THIS EFFECT WE CAN DISCOUNT THE EXPECTED RI □RIOF RANDOM LABELINGS BY DEFINING THE ADJUSTED RAND INDEX AS FOLLOWS

ARIRI−□RI

MAX RI−□RI

REFERENCES

• COMPARING PARTITIONS L HUBERT AND P ARABIE JOURNAL OF CLASSIFICATION 1985

• WIKIPEDIA ENTRY FOR THE ADJUSTED RAND INDEX

MUTUAL INFORMATION BASED SCORES

GIVEN THE KNOWLEDGE OF THE GROUND TRUTH CLASS ASSIGNMENTS LABELSTRUE AND OUR CLUSTERING ALGORITHM ASSIGNMENTS OF THE SAME SAMPLES LABELSPRED THE MUTUAL INFORMATION IS A FUNCTION THAT MEASURES THE AGREEMENT OF THE TWO ASSIGNMENTS IGNORING PERMUTATIONS TWO DIFFERENT NORMALIZED VERSIONS OF THIS MEASURE ARE AVAILABLE NORMALIZED MUTUAL INFORMATION NMI ANDADJUSTED MUTUAL INFORMATION AMI NMI IS OFTEN USED IN THE LITERATURE WHILE AMI WAS PROPOSED MORE RECENTLY AND IS NORMALIZED AGAINST CHANCE

```
 FROM SKLEARN IMPORT METRICS
LABELSTRUE  0 0 0 1 1 1
LABELSPRED  0 0 1 1 2 2
METRICSADJUSTEDMUTUALINFOSCORELABELSTRUE LABELSPRED
022504
```

ONE CAN PERMUTE 0 AND 1 IN THE PREDICTED LABELS RENAME 2 TO 3 AND GET THE SAME SCORE

LABELSPRED 1 1 0 0 3 3
METRICSADJUSTEDMUTUALINFOSCORELABELSTRUE LABELSPRED
022504
ALLMUTUALINFOSCORE ADJUSTEDMUTUALINFOSCORE ANDNORMALIZEDMUTUALINFOSCORE
ARE SYMMETRIC SWAPPING THE ARGUMENT DOES NOT CHANGE THE SCORE THUS THEY CAN BE USED AS A CONSENSUS MEASURE
METRICSADJUSTEDMUTUALINFOSCORELABELSPRED LABELSTRUE
022504
PERFECT LABELING IS SCORED 10
LABELSPRED LABELSTRUE
METRICSADJUSTEDMUTUALINFOSCORELABELSTRUE LABELSPRED
10
METRICSNORMALIZEDMUTUALINFOSCORELABELSTRUE LABELSPRED
10
THIS IS NOT TRUE FOR MUTUALINFOSCORE WHICH IS THEREFORE HARDER TO JUDGE
METRICSMUTUALINFOSCORELABELSTRUE LABELSPRED
069
BAD EG INDEPENDENT LABELINGS HAVE NONPOSITIVE SCORES
LABELSTRUE 0 1 2 0 3 4 5 1
LABELSPRED 1 1 0 0 2 2 2 2
METRICSADJUSTEDMUTUALINFOSCORELABELSTRUE LABELSPRED
010526
ADVANTAGES
•RANDOM UNIFORM LABEL ASSIGNMENTS HAVE A AMI SCORE CLOSE TO 00 FOR ANY VALUE OF NCLUSTERS AND
NSAMPLES WHICH IS NOT THE CASE FOR RAW MUTUAL INFORMATION OR THE VMEASURE FOR INSTANCE
•UPPER BOUND OF 1 VALUES CLOSE TO ZERO INDICATE TWO LABEL ASSIGNMENTS THAT ARE LARGELY INDEPENDENT WHILE
VALUES CLOSE TO ONE INDICATE SIGNIFICANT AGREEMENT FURTHER AN AMI OF EXACTLY 1 INDICATES THAT THE TWO LABEL
ASSIGNMENTS ARE EQUAL WITH OR WITHOUT PERMUTATION
DRAWBACKS
• CONTRARY TO INERTIA MIBASED MEASURES REQUIRE THE KNOWLEDGE OF THE GROUND TRUTH CLASSES WHILE ALMOST
NEVER AVAILABLE IN PRACTICE OR REQUIRES MANUAL ASSIGNMENT BY HUMAN ANNOTATORS AS IN THE SUPERVISED LEARNING
SETTING
HOWEVER MIBASED MEASURES CAN ALSO BE USEFUL IN PURELY UNSUPERVISED SETTING AS A BUILDING BLOCK FOR A CONSEN
SUS INDEX THAT CAN BE USED FOR CLUSTERING MODEL SELECTION
• NMI AND MI ARE NOT ADJUSTED AGAINST CHANCE
EXAMPLES

•ADJUSTMENT FOR CHANCE IN CLUSTERING PERFORMANCE EVALUATION ANALYSIS OF THE IMPACT OF THE DATASET SIZE ON THE VALUE OF CLUSTERING MEASURES FOR RANDOM ASSIGNMENTS THIS EXAMPLE ALSO INCLUDES THE ADJUSTED RAND INDEX
MATHEMATICAL FORMULATION
ASSUME TWO LABEL ASSIGNMENTS OF THE SAME N OBJECTS □AND□ THEIR ENTROPY IS THE AMOUNT OF UNCERTAINTY FOR A PARTITION SET DEFINED BY
□□ −□∑
□1□□ LOG □□
WHERE □□ □□□IS THE PROBABILITY THAT AN OBJECT PICKED AT RANDOM FROM □FALLS INTO CLASS □□ LIKEWISE FOR □
□□ −□∑
□1□′□ LOG □′□
WITH □′□ □□□ THE MUTUAL INFORMATION MI BETWEEN □AND□IS CALCULATED BY
MI□ □ □∑
□1□□∑
□1□□ □ LOG□□ □
□□□′□
WHERE □□ □ □□∩□□□IS THE PROBABILITY THAT AN OBJECT PICKED AT RANDOM FALLS INTO BOTH CLASSES □□AND□□
IT ALSO CAN BE EXPRESSED IN SET CARDINALITY FORMULATION
MI□ □ □∑
□1□□∑
□1□□∩□□
□LOG□□□∩□□
□□□□
THE NORMALIZED MUTUAL INFORMATION IS DEFINED AS
NMI□ □ MI□ □
MEAN □□ □□
THIS VALUE OF THE MUTUAL INFORMATION AND ALSO THE NORMALIZED VARIANT IS NOT ADJUSTED FOR CHANCE AND WILL TEND TO INCREASE AS THE NUMBER OF DIFFERENT LABELS CLUSTERS INCREASES REGARDLESS OF THE ACTUAL AMOUNT OF “MUTUAL INFORMATION” BETWEEN THE LABEL ASSIGNMENTS
THE EXPECTED VALUE FOR THE MUTUAL INFORMATION CAN BE CALCULATED USING THE FOLLOWING EQUATION VEB2009 IN THIS EQUATION □□□□THE NUMBER OF ELEMENTS IN □□ AND □□□□THE NUMBER OF ELEMENTS IN □□
□MI□ □ □∑
□1□∑
□1MIN□□□□∑
□□□□□□□□−□□□□
□LOG□□□□
□□□□□□□□□□−□□□−□□
□□□□□□−□□□□□−□□□□−□□−□□□□□
USING THE EXPECTED VALUE THE ADJUSTED MUTUAL INFORMATION CAN THEN BE CALCULATED USING A SIMILAR FORM TO THAT OF THE ADJUSTED RAND INDEX
AMI MI−□MI
MEAN □□ □□−□MI
FOR NORMALIZED MUTUAL INFORMATION AND ADJUSTED MUTUAL INFORMATION THE NORMALIZING VALUE IS TYPICALLY SOME GENER ALIZED MEAN OF THE ENTROPIES OF EACH CLUSTERING VARIOUS GENERALIZED MEANS EXIST AND NO FIRM RULES EXIST FOR PREFERRING ONE OVER THE OTHERS THE DECISION IS LARGELY A FIELDBYFIELD BASIS FOR INSTANCE IN COMMUNITY DETECTION THE ARITHMETIC MEAN IS MOST COMMON EACH NORMALIZING METHOD PROVIDES “QUALITATIVELY SIMILAR BEHAVIOURS” YAT2016 IN OUR IMPLEMENTATION THIS IS CONTROLLED BY THE AVERAGEMETHOD PARAMETER
VINH ET AL 2010 NAMED VARIANTS OF NMI AND AMI BY THEIR AVERAGING METHOD VEB2010 THEIR ‘SQRT’ AND ‘SUM’ AVERAGES ARE THE GEOMETRIC AND ARITHMETIC MEANS WE USE THESE MORE BROADLY COMMON NAMES

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WORK FOR COMBINING MULTIPLE PARTITIONS” JOURNAL OF MACHINE LEARNING RESEARCH 3 583–617
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• WIKIPEDIA ENTRY FOR THE NORMALIZED MUTUAL INFORMATION
• WIKIPEDIA ENTRY FOR THE ADJUSTED MUTUAL INFORMATION
HOMOGENEITY COMPLETENESS AND VMEASURE
GIVEN THE KNOWLEDGE OF THE GROUND TRUTH CLASS ASSIGNMENTS OF THE SAMPLES IT IS POSSIBLE TO DEFINE SOME INTUITIVE METRIC
USING CONDITIONAL ENTROPY ANALYSIS
IN PARTICULAR ROSENBERG AND HIRSCHBERG 2007 DEFINE THE FOLLOWING TWO DESIRABLE OBJECTIVES FOR ANY CLUSTER ASSIGN
MENT
•HOMOGENEITY EACH CLUSTER CONTAINS ONLY MEMBERS OF A SINGLE CLASS
•COMPLETENESS ALL MEMBERS OF A GIVEN CLASS ARE ASSIGNED TO THE SAME CLUSTER
WE CAN TURN THOSE CONCEPT AS SCORES HOMOGENEITYSCORE ANDCOMPLETENESSSCORE BOTH ARE BOUNDED
BELOW BY 00 AND ABOVE BY 10 HIGHER IS BETTER
```
 FROM SKLEARN IMPORT METRICS
LABELSTRUE  0 0 0 1 1 1
LABELSPRED  0 0 1 1 2 2
METRICSHOMOGENEITYSCORELABELSTRUE LABELSPRED
066
METRICSCOMPLETENESSSCORELABELSTRUE LABELSPRED
042
```
THEIR HARMONIC MEAN CALLED VMEASURE IS COMPUTED BY VMEASURESCORE
```
METRICSVMEASURESCORELABELSTRUE LABELSPRED
051
```
THIS FUNCTION’S FORMULA IS AS FOLLOWS
```
 MATH V  FRAC1  BETA TIMES TEXTHOMOGENEITY TIMES TEXTCOMPLETENESS
‘→BETA TIMES TEXTHOMOGENEITY  TEXTCOMPLETENESS
```
BETA DEFAULTS TO A VALUE OF 10 BUT FOR USING A VALUE LESS THAN 1 FOR BETA
```
METRICSVMEASURESCORELABELSTRUE LABELSPRED BETA06
054
```
MORE WEIGHT WILL BE ATTRIBUTED TO HOMOGENEITY AND USING A VALUE GREATER THAN 1
```
METRICSVMEASURESCORELABELSTRUE LABELSPRED BETA18
048
```
MORE WEIGHT WILL BE ATTRIBUTED TO COMPLETENESS

THE VMEASURE IS ACTUALLY EQUIVALENT TO THE MUTUAL INFORMATION NMI DISCUSSED ABOVE WITH THE AGGREGATION FUNCTION BEING THE ARITHMETIC MEAN B2011
HOMOGENEITY COMPLETENESS AND VMEASURE CAN BE COMPUTED AT ONCE USING
HOMOGENEITYCOMPLETENESSVMEASURE AS FOLLOWS
METRICSHOMOGENEITYCOMPLETENESSVMEASURELABELSTRUE LABELSPRED

066 042 051
THE FOLLOWING CLUSTERING ASSIGNMENT IS SLIGHTLY BETTER SINCE IT IS HOMOGENEOUS BUT NOT COMPLETE
LABELSPRED 0 0 0 1 2 2
METRICSHOMOGENEITYCOMPLETENESSVMEASURELABELSTRUE LABELSPRED

10 068 081
NOTEVMEASURESCORE ISSYMMETRIC IT CAN BE USED TO EVALUATE THE AGREEMENT OF TWO INDEPENDENT ASSIGNMENTS ON THE SAME DATASET
THIS IS NOT THE CASE FOR COMPLETENESSSCORE ANDHOMOGENEITYSCORE BOTH ARE BOUND BY THE RELATIONSHIP
HOMOGENEITYSCOREA B COMPLETENESSSCOREB A
ADVANTAGES
•BOUNDED SCORES 00 IS AS BAD AS IT CAN BE 10 IS A PERFECT SCORE
• INTUITIVE INTERPRETATION CLUSTERING WITH BAD VMEASURE CAN BE QUALITATIVELY ANALYZED IN TERMS OF HOMOGENEITY AND COMPLETENESS TO BETTER FEEL WHAT ‘KIND’ OF MISTAKES IS DONE BY THE ASSIGNMENT
•NO ASSUMPTION IS MADE ON THE CLUSTER STRUCTURE CAN BE USED TO COMPARE CLUSTERING ALGORITHMS SUCH AS K MEANS WHICH ASSUMES ISOTROPIC BLOB SHAPES WITH RESULTS OF SPECTRAL CLUSTERING ALGORITHMS WHICH CAN FIND CLUSTER WITH “FOLDED” SHAPES
DRAWBACKS
• THE PREVIOUSLY INTRODUCED METRICS ARE NOT NORMALIZED WITH REGARDS TO RANDOM LABELING THIS MEANS THAT DEPENDING ON THE NUMBER OF SAMPLES CLUSTERS AND GROUND TRUTH CLASSES A COMPLETELY RANDOM LABELING WILL NOT ALWAYS YIELD THE SAME VALUES FOR HOMOGENEITY COMPLETENESS AND HENCE VMEASURE IN PARTICULAR RANDOM LABELING WON’T YIELD ZERO SCORES ESPECIALLY WHEN THE NUMBER OF CLUSTERS IS LARGE
THIS PROBLEM CAN SAFELY BE IGNORED WHEN THE NUMBER OF SAMPLES IS MORE THAN A THOUSAND AND THE NUMBER OF CLUSTERS IS LESS THAN 10 FOR SMALLER SAMPLE SIZES OR LARGER NUMBER OF CLUSTERS IT IS SAFER TO USE AN ADJUSTED INDEX SUCH AS THE ADJUSTED RAND INDEX ARI
• THESE METRICS REQUIRE THE KNOWLEDGE OF THE GROUND TRUTH CLASSES WHILE ALMOST NEVER AVAILABLE IN PRACTICE OR REQUIRES MANUAL ASSIGNMENT BY HUMAN ANNOTATORS AS IN THE SUPERVISED LEARNING SETTING
EXAMPLES
•ADJUSTMENT FOR CHANCE IN CLUSTERING PERFORMANCE EVALUATION ANALYSIS OF THE IMPACT OF THE DATASET SIZE ON THE VALUE OF CLUSTERING MEASURES FOR RANDOM ASSIGNMENTS

MATHEMATICAL FORMULATION
HOMOGENEITY AND COMPLETENESS SCORES ARE FORMALLY GIVEN BY
h 1−□□□
□□
□ 1−□□□
□□
WHERE □□□IS THE CONDITIONAL ENTROPY OF THE CLASSES GIVEN THE CLUSTER ASSIGNMENTS AND IS GIVEN BY
□□□ −□∑
□1□∑
□1□□□
□·LOG□□□
□□
AND□□IS THE ENTROPY OF THE CLASSES AND IS GIVEN BY
□□ −□∑
□1□□
□·LOG□□
□
WITH□THE TOTAL NUMBER OF SAMPLES □□AND□□THE NUMBER OF SAMPLES RESPECTIVELY BELONGING TO CLASS □AND CLUSTER □
AND FINALLY □□□THE NUMBER OF SAMPLES FROM CLASS □ASSIGNED TO CLUSTER □
THECONDITIONAL ENTROPY OF CLUSTERS GIVEN CLASS □□□AND THE ENTROPY OF CLUSTERS □□ARE DEFINED IN A SYM
METRIC MANNER
ROSENBERG AND HIRSCHBERG FURTHER DEFINE VMEASURE AS THE HARMONIC MEAN OF HOMOGENEITY AND COMPLETENESS
□ 2·*h*·□
h□
REFERENCES
• VMEASURE A CONDITIONAL ENTROPYBASED EXTERNAL CLUSTER EVALUATION MEASURE ANDREW ROSENBERG AND JULIA
HIRSCHBERG 2007
FOWLKESMALLOWS SCORES
THE FOWLKESMALLOWS INDEX SKLEARNMETRICSFOWLKESMALLOWSSCORE CAN BE USED WHEN THE GROUND
TRUTH CLASS ASSIGNMENTS OF THE SAMPLES IS KNOWN THE FOWLKESMALLOWS SCORE FMI IS DEFINED AS THE GEOMETRIC MEAN
OF THE PAIRWISE PRECISION AND RECALL
FMITP√
TPFPTPFN
WHERETPIS THE NUMBER OF TRUE POSITIVE IE THE NUMBER OF PAIR OF POINTS THAT BELONG TO THE SAME CLUSTERS IN BOTH THE
TRUE LABELS AND THE PREDICTED LABELS FPIS THE NUMBER OF FALSE POSITIVE IE THE NUMBER OF PAIR OF POINTS THAT BELONG
TO THE SAME CLUSTERS IN THE TRUE LABELS AND NOT IN THE PREDICTED LABELS AND FNIS THE NUMBER OF FALSE NEGATIVE IE THE
NUMBER OF PAIR OF POINTS THAT BELONGS IN THE SAME CLUSTERS IN THE PREDICTED LABELS AND NOT IN THE TRUE LABELS
THE SCORE RANGES FROM 0 TO 1 A HIGH VALUE INDICATES A GOOD SIMILARITY BETWEEN TWO CLUSTERS
```
 FROM SKLEARN IMPORT METRICS
LABELSTRUE  0 0 0 1 1 1
LABELSPRED  0 0 1 1 2 2
```

METRICSFOWLKESMALLOWSSCORELABELSTRUE LABELSPRED
047140
ONE CAN PERMUTE 0 AND 1 IN THE PREDICTED LABELS RENAME 2 TO 3 AND GET THE SAME SCORE
LABELSPRED 1 1 0 0 3 3
METRICSFOWLKESMALLOWSSCORELABELSTRUE LABELSPRED
047140
PERFECT LABELING IS SCORED 10
LABELSPRED LABELSTRUE
METRICSFOWLKESMALLOWSSCORELABELSTRUE LABELSPRED
10
BAD EG INDEPENDENT LABELINGS HAVE ZERO SCORES
LABELSTRUE 0 1 2 0 3 4 5 1
LABELSPRED 1 1 0 0 2 2 2 2
METRICSFOWLKESMALLOWSSCORELABELSTRUE LABELSPRED
00
ADVANTAGES
•RANDOM UNIFORM LABEL ASSIGNMENTS HAVE A FMI SCORE CLOSE TO 00 FOR ANY VALUE OF NCLUSTERS AND NSAMPLES WHICH IS NOT THE CASE FOR RAW MUTUAL INFORMATION OR THE VMEASURE FOR INSTANCE
•UPPERBOUNDED AT 1 VALUES CLOSE TO ZERO INDICATE TWO LABEL ASSIGNMENTS THAT ARE LARGELY INDEPENDENT WHILE VALUES CLOSE TO ONE INDICATE SIGNIFICANT AGREEMENT FURTHER VALUES OF EXACTLY 0 INDICATE PURELY INDEPENDENT LABEL ASSIGNMENTS AND A FMI OF EXACTLY 1 INDICATES THAT THE TWO LABEL ASSIGNMENTS ARE EQUAL WITH OR WITHOUT PERMUTATION
•NO ASSUMPTION IS MADE ON THE CLUSTER STRUCTURE CAN BE USED TO COMPARE CLUSTERING ALGORITHMS SUCH AS K MEANS WHICH ASSUMES ISOTROPIC BLOB SHAPES WITH RESULTS OF SPECTRAL CLUSTERING ALGORITHMS WHICH CAN FIND CLUSTER WITH “FOLDED” SHAPES
DRAWBACKS
• CONTRARY TO INERTIA FMIBASED MEASURES REQUIRE THE KNOWLEDGE OF THE GROUND TRUTH CLASSES WHILE ALMOST NEVER AVAILABLE IN PRACTICE OR REQUIRES MANUAL ASSIGNMENT BY HUMAN ANNOTATORS AS IN THE SUPERVISED LEARNING SETTING
REFERENCES
• E B FOWKLES AND C L MALLOWS 1983 “A METHOD FOR COMPARING TWO HIERARCHICAL CLUSTERINGS” JOURNAL OF THE AMERICAN STATISTICAL ASSOCIATION HTTPWILDFIRESTATUCLAEDUPDFLIBRARYFOWLKESPDF
• WIKIPEDIA ENTRY FOR THE FOWLKESMALLOWS INDEX

SILHOUETTE COEFFICIENT
IF THE GROUND TRUTH LABELS ARE NOT KNOWN EVALUATION MUST BE PERFORMED USING THE MODEL ITSELF THE SILHOUETTE COEFFICIENT SKLEARNMETRICSSILHOUETTESCORE IS AN EXAMPLE OF SUCH AN EVALUATION WHERE A HIGHER SILHOUETTE COEFFICIENT SCORE RELATES TO A MODEL WITH BETTER DEFINED CLUSTERS THE SILHOUETTE COEFFICIENT IS DEFINED FOR EACH SAMPLE AND IS COMPOSED OF TWO SCORES
•A THE MEAN DISTANCE BETWEEN A SAMPLE AND ALL OTHER POINTS IN THE SAME CLASS
•B THE MEAN DISTANCE BETWEEN A SAMPLE AND ALL OTHER POINTS IN THE NEXT NEAREST CLUSTER
THE SILHOUETTE COEFFICIENT SFOR A SINGLE SAMPLE IS THEN GIVEN AS
□□−□
□□□□ □
THE SILHOUETTE COEFFICIENT FOR A SET OF SAMPLES IS GIVEN AS THE MEAN OF THE SILHOUETTE COEFFICIENT FOR EACH SAMPLE
```
 FROM SKLEARN IMPORT METRICS
 FROM SKLEARNMETRICS IMPORT PAIRWISEDISTANCES
 FROM SKLEARN IMPORT DATASETS
DATASET  DATASETSLOADIRIS
X  DATASETDATA
Y  DATASETTARGET
```
IN NORMAL USAGE THE SILHOUETTE COEFFICIENT IS APPLIED TO THE RESULTS OF A CLUSTER ANALYSIS
```
 IMPORT NUMPY AS NP
 FROM SKLEARNCLUSTER IMPORT KMEANS
KMEANSMODEL  KMEANSNCLUSTERS3 RANDOMSTATE1FITX
LABELS  KMEANSMODELLABELS
METRICSSILHOUETTESCOREX LABELS METRICEUCLIDEAN

055
```
REFERENCES
• PETER J ROUSSEEUW 1987 “SILHOUETTES A GRAPHICAL AID TO THE INTERPRETATION AND VALIDATION OF CLUSTER ANALYSIS” COMPUTATIONAL AND APPLIED MATHEMATICS 20 53–65 DOI10101603770427879012 57
ADVANTAGES
• THE SCORE IS BOUNDED BETWEEN 1 FOR INCORRECT CLUSTERING AND 1 FOR HIGHLY DENSE CLUSTERING SCORES AROUND ZERO INDICATE OVERLAPPING CLUSTERS
• THE SCORE IS HIGHER WHEN CLUSTERS ARE DENSE AND WELL SEPARATED WHICH RELATES TO A STANDARD CONCEPT OF A CLUSTER
DRAWBACKS
• THE SILHOUETTE COEFFICIENT IS GENERALLY HIGHER FOR CONVEX CLUSTERS THAN OTHER CONCEPTS OF CLUSTERS SUCH AS DENSITY BASED CLUSTERS LIKE THOSE OBTAINED THROUGH DBSCAN

EXAMPLES
•SELECTING THE NUMBER OF CLUSTERS WITH SILHOUETTE ANALYSIS ON KMEANS CLUSTERING IN THIS EXAMPLE THE SILHOUETTE ANALYSIS IS USED TO CHOOSE AN OPTIMAL VALUE FOR NCLUSTERS
CALINSKIHARABASZ INDEX
IF THE GROUND TRUTH LABELS ARE NOT KNOWN THE CALINSKIHARABASZ INDEX SKLEARNMETRICS CALINSKIHARABASZSCORE ALSO KNOWN AS THE VARIANCE RATIO CRITERION CAN BE USED TO EVALUATE THE MODEL WHERE A HIGHER CALINSKIHARABASZ SCORE RELATES TO A MODEL WITH BETTER DEFINED CLUSTERS
FOR□CLUSTERS THE CALINSKIHARABASZ SCORE □IS GIVEN AS THE RATIO OF THE BETWEENCLUSTERS DISPERSION MEAN AND THE WITHINCLUSTER DISPERSION
□□ TR□□
TR□□×□−□
□−1
WHERE □□IS THE BETWEEN GROUP DISPERSION MATRIX AND □□IS THE WITHINCLUSTER DISPERSION MATRIX DEFINED BY
□□□∑
□1∑
□∈□□□−□□□−□□□
□□∑
□□□□□−□□□−□□
WITH□BE THE NUMBER OF POINTS IN OUR DATA □□BE THE SET OF POINTS IN CLUSTER □□□BE THE CENTER OF CLUSTER □□BE THE CENTER OF □□□BE THE NUMBER OF POINTS IN CLUSTER □

```
 FROM SKLEARN IMPORT METRICS
 FROM SKLEARNMETRICS IMPORT PAIRWISEDISTANCES
 FROM SKLEARN IMPORT DATASETS
DATASET  DATASETSLOADIRIS
X  DATASETDATA
Y  DATASETTARGET
```

IN NORMAL USAGE THE CALINSKIHARABASZ INDEX IS APPLIED TO THE RESULTS OF A CLUSTER ANALYSIS

```
 IMPORT NUMPY AS NP
 FROM SKLEARNCLUSTER IMPORT KMEANS
KMEANSMODEL  KMEANSNCLUSTERS3 RANDOMSTATE1FITX
LABELS  KMEANSMODELLABELS
METRICSCALINSKIHARABASZSCOREX LABELS
56162
```

ADVANTAGES
• THE SCORE IS HIGHER WHEN CLUSTERS ARE DENSE AND WELL SEPARATED WHICH RELATES TO A STANDARD CONCEPT OF A CLUSTER
• THE SCORE IS FAST TO COMPUTE

DRAWBACKS
• THE CALINSKIHARABASZ INDEX IS GENERALLY HIGHER FOR CONVEX CLUSTERS THAN OTHER CONCEPTS OF CLUSTERS SUCH AS DENSITY BASED CLUSTERS LIKE THOSE OBTAINED THROUGH DBSCAN
REFERENCES
• CALI ´NSKI T HARABASZ J 1974 “A DENDRITE METHOD FOR CLUSTER ANALYSIS” COMMUNICATIONS IN STATISTICS THEORY AND METHODS 3 127 DOI101080036109262011560741
DAVIESBOULDIN INDEX
IF THE GROUND TRUTH LABELS ARE NOT KNOWN THE DAVIESBOULDIN INDEX SKLEARNMETRICS DAVIESBOULDINSCORE CAN BE USED TO EVALUATE THE MODEL WHERE A LOWER DAVIESBOULDIN INDEX RELATES TO A MODEL WITH BETTER SEPARATION BETWEEN THE CLUSTERS
THE INDEX IS DEFINED AS THE AVERAGE SIMILARITY BETWEEN EACH CLUSTER □□FOR□ 1 □ AND ITS MOST SIMILAR ONE □□ IN THE CONTEXT OF THIS INDEX SIMILARITY IS DEFINED AS A MEASURE □□□THAT TRADES OFF
•□□ THE AVERAGE DISTANCE BETWEEN EACH POINT OF CLUSTER □AND THE CENTROID OF THAT CLUSTER – ALSO KNOW AS CLUSTER DIAMETER
•□□□ THE DISTANCE BETWEEN CLUSTER CENTROIDS □AND□
A SIMPLE CHOICE TO CONSTRUCT □□□SO THAT IT IS NONNEGATIVE AND SYMMETRIC IS
□□□□□□□
□□□
THEN THE DAVIESBOULDIN INDEX IS DEFINED AS
□□1
□□Σ
□1MAX
⁄□□□□
ZERO IS THE LOWEST POSSIBLE SCORE VALUES CLOSER TO ZERO INDICATE A BETTER PARTITION
IN NORMAL USAGE THE DAVIESBOULDIN INDEX IS APPLIED TO THE RESULTS OF A CLUSTER ANALYSIS AS FOLLOWS
```
 FROM SKLEARN IMPORT DATASETS
IRIS  DATASETSLOADIRIS
X  IRISDATA
 FROM SKLEARNCLUSTER IMPORT KMEANS
 FROM SKLEARNMETRICS IMPORT DAVIESBOULDINSCORE
KMEANS  KMEANSNCLUSTERS3 RANDOMSTATE1FITX
LABELS  KMEANSLABELS
DAVIESBOULDINSCOREX LABELS
06619
```
ADVANTAGES
• THE COMPUTATION OF DAVIESBOULDIN IS SIMPLER THAN THAT OF SILHOUETTE SCORES
• THE INDEX IS COMPUTED ONLY QUANTITIES AND FEATURES INHERENT TO THE DATASET

DRAWBACKS
• THE DAVIESBOULDING INDEX IS GENERALLY HIGHER FOR CONVEX CLUSTERS THAN OTHER CONCEPTS OF CLUSTERS SUCH AS DENSITY BASED CLUSTERS LIKE THOSE OBTAINED FROM DBSCAN
• THE USAGE OF CENTROID DISTANCE LIMITS THE DISTANCE METRIC TO EUCLIDEAN SPACE
• A GOOD VALUE REPORTED BY THIS METHOD DOES NOT IMPLY THE BEST INFORMATION RETRIEVAL
REFERENCES
• DAVIES DAVID L BOULDIN DONALD W 1979 “A CLUSTER SEPARATION MEASURE” IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE PAMI1 2 224227 DOI101109TPAMI19794766909
• HALKIDI MARIA BATISTAKIS YANNIS VAZIRGIANNIS MICHALIS 2001 “ON CLUSTERING VALIDATION TECHNIQUES” JOURNAL OF INTELLIGENT INFORMATION SYSTEMS 1723 107145 DOI101023A1012801612483
• WIKIPEDIA ENTRY FOR DAVIESBOULDIN INDEX
CONTINGENCY MATRIX
CONTINGENCY MATRIX SKLEARNMETRICSCLUSTERCONTINGENCYMATRIX REPORTS THE INTERSECTION CARDI NALITY FOR EVERY TRUEPREDICTED CLUSTER PAIR THE CONTINGENCY MATRIX PROVIDES SUFFICIENT STATISTICS FOR ALL CLUSTERING MET RICS WHERE THE SAMPLES ARE INDEPENDENT AND IDENTICALLY DISTRIBUTED AND ONE DOESN’T NEED TO ACCOUNT FOR SOME INSTANCES NOT BEING CLUSTERED
HERE IS AN EXAMPLE
```
 FROM SKLEARNMETRICSCLUSTER IMPORT CONTINGENCYMATRIX
X  A A A B B B
Y  0 0 1 1 2 2
CONTINGENCYMATRIXX Y
ARRAY2 1 0
0 1 2
```
THE FIRST ROW OF OUTPUT ARRAY INDICATES THAT THERE ARE THREE SAMPLES WHOSE TRUE CLUSTER IS “A” OF THEM TWO ARE IN PREDICTED CLUSTER 0 ONE IS IN 1 AND NONE IS IN 2 AND THE SECOND ROW INDICATES THAT THERE ARE THREE SAMPLES WHOSE TRUE CLUSTER IS “B” OF THEM NONE IS IN PREDICTED CLUSTER 0 ONE IS IN 1 AND TWO ARE IN 2
ACONFUSION MATRIX FOR CLASSIFICATION IS A SQUARE CONTINGENCY MATRIX WHERE THE ORDER OF ROWS AND COLUMNS CORRESPOND TO A LIST OF CLASSES
ADVANTAGES
• ALLOWS TO EXAMINE THE SPREAD OF EACH TRUE CLUSTER ACROSS PREDICTED CLUSTERS AND VICE VERSA
• THE CONTINGENCY TABLE CALCULATED IS TYPICALLY UTILIZED IN THE CALCULATION OF A SIMILARITY STATISTIC LIKE THE OTHERS LISTED IN THIS DOCUMENT BETWEEN THE TWO CLUSTERINGS
DRAWBACKS
• CONTINGENCY MATRIX IS EASY TO INTERPRET FOR A SMALL NUMBER OF CLUSTERS BUT BECOMES VERY HARD TO INTERPRET FOR A LARGE NUMBER OF CLUSTERS

• IT DOESN’T GIVE A SINGLE METRIC TO USE AS AN OBJECTIVE FOR CLUSTERING OPTIMISATION
REFERENCES
• WIKIPEDIA ENTRY FOR CONTINGENCY MATRIX
324 BICLUSTERING
BICLUSTERING CAN BE PERFORMED WITH THE MODULE SKLEARNCLUSTERBICLUSTER BICLUSTERING ALGORITHMS SIMUL
TANEOUSLY CLUSTER ROWS AND COLUMNS OF A DATA MATRIX THESE CLUSTERS OF ROWS AND COLUMNS ARE KNOWN AS BICLUSTERS
EACH DETERMINES A SUBMATRIX OF THE ORIGINAL DATA MATRIX WITH SOME DESIRED PROPERTIES
FOR INSTANCE GIVEN A MATRIX OF SHAPE 10 10 ONE POSSIBLE BICLUSTER WITH THREE ROWS AND TWO COLUMNS INDUCES A
SUBMATRIX OF SHAPE 3 2
IMPORT NUMPY AS NP
DATA NPARANGE100RESHAPE10 10
ROWS NPARRAY0 2 3 NPNEWAXIS
COLUMNS NPARRAY1 2
DATAROWS COLUMNS
ARRAY 1 2
21 22
31 32
FOR VISUALIZATION PURPOSES GIVEN A BICLUSTER THE ROWS AND COLUMNS OF THE DATA MATRIX MAY BE REARRANGED TO MAKE THE
BICLUSTER CONTIGUOUS
ALGORITHMS DIFFER IN HOW THEY DEFINE BICLUSTERS SOME OF THE COMMON TYPES INCLUDE
• CONSTANT VALUES CONSTANT ROWS OR CONSTANT COLUMNS
• UNUSUALLY HIGH OR LOW VALUES
• SUBMATRICES WITH LOW VARIANCE
• CORRELATED ROWS OR COLUMNS
ALGORITHMS ALSO DIFFER IN HOW ROWS AND COLUMNS MAY BE ASSIGNED TO BICLUSTERS WHICH LEADS TO DIFFERENT BICLUSTER
STRUCTURES BLOCK DIAGONAL OR CHECKERBOARD STRUCTURES OCCUR WHEN ROWS AND COLUMNS ARE DIVIDED INTO PARTITIONS
IF EACH ROW AND EACH COLUMN BELONGS TO EXACTLY ONE BICLUSTER THEN REARRANGING THE ROWS AND COLUMNS OF THE DATA MATRIX
REVEALS THE BICLUSTERS ON THE DIAGONAL HERE IS AN EXAMPLE OF THIS STRUCTURE WHERE BICLUSTERS HAVE HIGHER AVERAGE VALUES
THAN THE OTHER ROWS AND COLUMNS
IN THE CHECKERBOARD CASE EACH ROW BELONGS TO ALL COLUMN CLUSTERS AND EACH COLUMN BELONGS TO ALL ROW CLUSTERS HERE
IS AN EXAMPLE OF THIS STRUCTURE WHERE THE VARIANCE OF THE VALUES WITHIN EACH BICLUSTER IS SMALL
AFTER FITTING A MODEL ROW AND COLUMN CLUSTER MEMBERSHIP CAN BE FOUND IN THE ROWS ANDCOLUMNS ATTRIBUTES
ROWSI IS A BINARY VECTOR WITH NONZERO ENTRIES CORRESPONDING TO ROWS THAT BELONG TO BICLUSTER I SIMILARLY
COLUMNSI INDICATES WHICH COLUMNS BELONG TO BICLUSTER I
SOME MODELS ALSO HAVE ROWLABELS ANDCOLUMNLABELS ATTRIBUTES THESE MODELS PARTITION THE ROWS AND
COLUMNS SUCH AS IN THE BLOCK DIAGONAL AND CHECKERBOARD BICLUSTER STRUCTURES
NOTE BICLUSTERING HAS MANY OTHER NAMES IN DIFFERENT FIELDS INCLUDING COCLUSTERING TWOMODE CLUSTERING TWOWAY
CLUSTERING BLOCK CLUSTERING COUPLED TWOWAY CLUSTERING ETC THE NAMES OF SOME ALGORITHMS SUCH AS THE SPECTRAL
COCLUSTERING ALGORITHM REFLECT THESE ALTERNATE NAMES

SCIKITLEARN USER GUIDE RELEASE 0213
FIG 35 AN EXAMPLE OF BICLUSTERS FORMED BY PARTITIONING ROWS AND COLUMNS
FIG 36 AN EXAMPLE OF CHECKERBOARD BICLUSTERS
32 UNSUPERVISED LEARNING 387

SPECTRAL COCLUSTERING

THESPECTRALCOCLUSTERING ALGORITHM FINDS BICLUSTERS WITH VALUES HIGHER THAN THOSE IN THE CORRESPONDING OTHER ROWS AND COLUMNS EACH ROW AND EACH COLUMN BELONGS TO EXACTLY ONE BICLUSTER SO REARRANGING THE ROWS AND COLUMNS TO MAKE PARTITIONS CONTIGUOUS REVEALS THESE HIGH VALUES ALONG THE DIAGONAL

NOTE THE ALGORITHM TREATS THE INPUT DATA MATRIX AS A BIPARTITE GRAPH THE ROWS AND COLUMNS OF THE MATRIX CORRESPOND TO THE TWO SETS OF VERTICES AND EACH ENTRY CORRESPONDS TO AN EDGE BETWEEN A ROW AND A COLUMN THE ALGORITHM APPROXIMATES THE NORMALIZED CUT OF THIS GRAPH TO FIND HEAVY SUBGRAPHS

MATHEMATICAL FORMULATION

AN APPROXIMATE SOLUTION TO THE OPTIMAL NORMALIZED CUT MAY BE FOUND VIA THE GENERALIZED EIGENVALUE DECOMPOSITION OF THE LAPLACIAN OF THE GRAPH USUALLY THIS WOULD MEAN WORKING DIRECTLY WITH THE LAPLACIAN MATRIX IF THE ORIGINAL DATA MATRIX □HAS SHAPE □×□ THE LAPLACIAN MATRIX FOR THE CORRESPONDING BIPARTITE GRAPH HAS SHAPE □□×□□

HOWEVER IN THIS CASE IT IS POSSIBLE TO WORK DIRECTLY WITH □ WHICH IS SMALLER AND MORE EFFICIENT

THE INPUT MATRIX □IS PREPROCESSED AS FOLLOWS

□□□−12□□−12

WHERE □IS THE DIAGONAL MATRIX WITH ENTRY □EQUAL TO∑

□□□□AND□IS THE DIAGONAL MATRIX WITH ENTRY □EQUAL TO∑

□□□□

THE SINGULAR VALUE DECOMPOSITION □□□□□⊤ PROVIDES THE PARTITIONS OF THE ROWS AND COLUMNS OF □ A SUBSET OF THE LEFT SINGULAR VECTORS GIVES THE ROW PARTITIONS AND A SUBSET OF THE RIGHT SINGULAR VECTORS GIVES THE COLUMN PARTITIONS THEℓ⌈LOG2□⌉SINGULAR VECTORS STARTING FROM THE SECOND PROVIDE THE DESIRED PARTITIONING INFORMATION THEY ARE USED TO FORM THE MATRIX □

□⌈
⌊□−12□
□−12□⌉
⌋

WHERE THE COLUMNS OF □ARE□2 □ ℓ1 AND SIMILARLY FOR □

THEN THE ROWS OF □ARE CLUSTERED USING KMEANS THE FIRST NROWS LABELS PROVIDE THE ROW PARTITIONING AND THE REMAININGNCOLUMNS LABELS PROVIDE THE COLUMN PARTITIONING

EXAMPLES

•A DEMO OF THE SPECTRAL COCLUSTERING ALGORITHM A SIMPLE EXAMPLE SHOWING HOW TO GENERATE A DATA MATRIX WITH BICLUSTERS AND APPLY THIS METHOD TO IT

•BICLUSTERING DOCUMENTS WITH THE SPECTRAL COCLUSTERING ALGORITHM AN EXAMPLE OF FINDING BICLUSTERS IN THE TWENTY NEWSGROUP DATASET

REFERENCES

• DHILLON INDERJIT S 2001 COCLUSTERING DOCUMENTS AND WORDS USING BIPARTITE SPECTRAL GRAPH PARTITIONING

SPECTRAL BICLUSTERING
THESPECTRALBICLUSTERING ALGORITHM ASSUMES THAT THE INPUT DATA MATRIX HAS A HIDDEN CHECKERBOARD STRUCTURE THE ROWS AND COLUMNS OF A MATRIX WITH THIS STRUCTURE MAY BE PARTITIONED SO THAT THE ENTRIES OF ANY BICLUSTER IN THE CARTESIAN PRODUCT OF ROW CLUSTERS AND COLUMN CLUSTERS ARE APPROXIMATELY CONSTANT FOR INSTANCE IF THERE ARE TWO ROW PARTITIONS AND THREE COLUMN PARTITIONS EACH ROW WILL BELONG TO THREE BICLUSTERS AND EACH COLUMN WILL BELONG TO TWO BICLUSTERS
THE ALGORITHM PARTITIONS THE ROWS AND COLUMNS OF A MATRIX SO THAT A CORRESPONDING BLOCKWISECONSTANT CHECKERBOARD MATRIX PROVIDES A GOOD APPROXIMATION TO THE ORIGINAL MATRIX
MATHEMATICAL FORMULATION
THE INPUT MATRIX □IS FIRST NORMALIZED TO MAKE THE CHECKERBOARD PATTERN MORE OBVIOUS THERE ARE THREE POSSIBLE METHODS
1INDEPENDENT ROW AND COLUMN NORMALIZATION AS IN SPECTRAL COCLUSTERING THIS METHOD MAKES THE ROWS SUM TO A CONSTANT AND THE COLUMNS SUM TO A DIFFERENT CONSTANT
2BISTOCHASTIZATION REPEATED ROW AND COLUMN NORMALIZATION UNTIL CONVERGENCE THIS METHOD MAKES BOTH ROWS AND COLUMNS SUM TO THE SAME CONSTANT
3LOG NORMALIZATION THE LOG OF THE DATA MATRIX IS COMPUTED □ LOG □ THEN THE COLUMN MEAN □□· ROW MEAN □·□ AND OVERALL MEAN □··OF□ARE COMPUTED THE FINAL MATRIX IS COMPUTED ACCORDING TO THE FORMULA □□□□□□−□□·−□·□□··
AFTER NORMALIZING THE FIRST FEW SINGULAR VECTORS ARE COMPUTED JUST AS IN THE SPECTRAL COCLUSTERING ALGORITHM IF LOG NORMALIZATION WAS USED ALL THE SINGULAR VECTORS ARE MEANINGFUL HOWEVER IF INDEPENDENT NORMALIZATION OR BISTOCHASTIZATION WERE USED THE FIRST SINGULAR VECTORS □1AND□1 ARE DISCARDED FROM NOW ON THE “FIRST” SINGULAR VECTORS REFERS TO □2 □ □1AND□2 □ □1EXCEPT IN THE CASE OF LOG NORMALIZATION
GIVEN THESE SINGULAR VECTORS THEY ARE RANKED ACCORDING TO WHICH CAN BE BEST APPROXIMATED BY A PIECEWISECONSTANT VECTOR THE APPROXIMATIONS FOR EACH VECTOR ARE FOUND USING ONEDIMENSIONAL KMEANS AND SCORED USING THE EUCLIDEAN DISTANCE SOME SUBSET OF THE BEST LEFT AND RIGHT SINGULAR VECTOR ARE SELECTED NEXT THE DATA IS PROJECTED TO THIS BEST SUBSET OF SINGULAR VECTORS AND CLUSTERED
FOR INSTANCE IF □SINGULAR VECTORS WERE CALCULATED THE □BEST ARE FOUND AS DESCRIBED WHERE □ □ LET□BE THE MATRIX WITH COLUMNS THE □BEST LEFT SINGULAR VECTORS AND SIMILARLY □FOR THE RIGHT TO PARTITION THE ROWS THE ROWS OF □ARE PROJECTED TO A □DIMENSIONAL SPACE □□ TREATING THE □ROWS OF THIS □×□MATRIX AS SAMPLES AND CLUSTERING USING KMEANS YIELDS THE ROW LABELS SIMILARLY PROJECTING THE COLUMNS TO □⊤□AND CLUSTERING THIS □×□MATRIX YIELDS THE COLUMN LABELS
EXAMPLES
•A DEMO OF THE SPECTRAL BICLUSTERING ALGORITHM A SIMPLE EXAMPLE SHOWING HOW TO GENERATE A CHECKERBOARD MATRIX AND BICLUSTER IT
REFERENCES
• KLUGER YUVAL ET AL 2003 SPECTRAL BICLUSTERING OF MICROARRAY DATA COCLUSTERING GENES AND CONDITIONS

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BICLUSTERING EVALUATION
THERE ARE TWO WAYS OF EVALUATING A BICLUSTERING RESULT INTERNAL AND EXTERNAL INTERNAL MEASURES SUCH AS CLUSTER STABILITY RELY ONLY ON THE DATA AND THE RESULT THEMSELVES CURRENTLY THERE ARE NO INTERNAL BICLUSTER MEASURES IN SCIKIT LEARN EXTERNAL MEASURES REFER TO AN EXTERNAL SOURCE OF INFORMATION SUCH AS THE TRUE SOLUTION WHEN WORKING WITH REAL DATA THE TRUE SOLUTION IS USUALLY UNKNOWN BUT BICLUSTERING ARTIFICIAL DATA MAY BE USEFUL FOR EVALUATING ALGORITHMS PRECISELY BECAUSE THE TRUE SOLUTION IS KNOWN
TO COMPARE A SET OF FOUND BICLUSTERS TO THE SET OF TRUE BICLUSTERS TWO SIMILARITY MEASURES ARE NEEDED A SIMILARITY MEASURE FOR INDIVIDUAL BICLUSTERS AND A WAY TO COMBINE THESE INDIVIDUAL SIMILARITIES INTO AN OVERALL SCORE
TO COMPARE INDIVIDUAL BICLUSTERS SEVERAL MEASURES HAVE BEEN USED FOR NOW ONLY THE JACCARD INDEX IS IMPLEMENTED
□□ □ □∩□
□□−□∩□
WHERE □AND□ARE BICLUSTERS□∩□IS THE NUMBER OF ELEMENTS IN THEIR INTERSECTION THE JACCARD INDEX ACHIEVES ITS MINIMUM OF 0 WHEN THE BICLUSTERS TO NOT OVERLAP AT ALL AND ITS MAXIMUM OF 1 WHEN THEY ARE IDENTICAL
SEVERAL METHODS HAVE BEEN DEVELOPED TO COMPARE TWO SETS OF BICLUSTERS FOR NOW ONLY CONSENSUSSCORE HOCHRE ITER ET AL 2010 IS AVAILABLE
1 COMPUTE BICLUSTER SIMILARITIES FOR PAIRS OF BICLUSTERS ONE IN EACH SET USING THE JACCARD INDEX OR A SIMILAR MEASURE
2 ASSIGN BICLUSTERS FROM ONE SET TO ANOTHER IN A ONETOONE FASHION TO MAXIMIZE THE SUM OF THEIR SIMILARITIES THIS STEP IS PERFORMED USING THE HUNGARIAN ALGORITHM
3 THE FINAL SUM OF SIMILARITIES IS DIVIDED BY THE SIZE OF THE LARGER SET
THE MINIMUM CONSENSUS SCORE 0 OCCURS WHEN ALL PAIRS OF BICLUSTERS ARE TOTALLY DISSIMILAR THE MAXIMUM SCORE 1 OCCURS WHEN BOTH SETS ARE IDENTICAL
REFERENCES
• HOCHREITER BODENHOFER ET AL 2010 FABIA FACTOR ANALYSIS FOR BICLUSTER ACQUISITION
325 DECOMPOSING SIGNALS IN COMPONENTS MATRIX FACTORIZATION PROBLEMS
PRINCIPAL COMPONENT ANALYSIS PCA
EXACT PCA AND PROBABILISTIC INTERPRETATION
PCA IS USED TO DECOMPOSE A MULTIVARIATE DATASET IN A SET OF SUCCESSIVE ORTHOGONAL COMPONENTS THAT EXPLAIN A MAXIMUM AMOUNT OF THE VARIANCE IN SCIKITLEARN PCA IS IMPLEMENTED AS A TRANSFORMER OBJECT THAT LEARNS □COMPONENTS IN ITS FIT METHOD AND CAN BE USED ON NEW DATA TO PROJECT IT ON THESE COMPONENTS
PCA CENTERS BUT DOES NOT SCALE THE INPUT DATA FOR EACH FEATURE BEFORE APPLYING THE SVD THE OPTIONAL PARAMETER PARAMETERWHITENTRUE MAKES IT POSSIBLE TO PROJECT THE DATA ONTO THE SINGULAR SPACE WHILE SCALING EACH COMPONENT TO UNIT VARIANCE THIS IS OFTEN USEFUL IF THE MODELS DOWNSTREAM MAKE STRONG ASSUMPTIONS ON THE ISOTROPY OF THE SIGNAL THIS IS FOR EXAMPLE THE CASE FOR SUPPORT VECTOR MACHINES WITH THE RBF KERNEL AND THE KMEANS CLUSTERING ALGORITHM BELOW IS AN EXAMPLE OF THE IRIS DATASET WHICH IS COMPRISED OF 4 FEATURES PROJECTED ON THE 2 DIMENSIONS THAT EXPLAIN MOST VARIANCE
THEPCA OBJECT ALSO PROVIDES A PROBABILISTIC INTERPRETATION OF THE PCA THAT CAN GIVE A LIKELIHOOD OF DATA BASED ON THE AMOUNT OF VARIANCE IT EXPLAINS AS SUCH IT IMPLEMENTS A SCORE METHOD THAT CAN BE USED IN CROSSVALIDATION
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EXAMPLES
•COMPARISON OF LDA AND PCA 2D PROJECTION OF IRIS DATASET
•MODEL SELECTION WITH PROBABILISTIC PCA AND FACTOR ANALYSIS FA
INCREMENTAL PCA
THEPCA OBJECT IS VERY USEFUL BUT HAS CERTAIN LIMITATIONS FOR LARGE DATASETS THE BIGGEST LIMITATION IS THAT PCA ONLY SUP PORTS BATCH PROCESSING WHICH MEANS ALL OF THE DATA TO BE PROCESSED MUST FIT IN MAIN MEMORY THE INCREMENTALPCA OBJECT USES A DIFFERENT FORM OF PROCESSING AND ALLOWS FOR PARTIAL COMPUTATIONS WHICH ALMOST EXACTLY MATCH THE RESULTS OFPCA WHILE PROCESSING THE DATA IN A MINIBATCH FASHION INCREMENTALPCA MAKES IT POSSIBLE TO IMPLEMENT OUTOF CORE PRINCIPAL COMPONENT ANALYSIS EITHER BY
• USING ITS PARTIALFIT METHOD ON CHUNKS OF DATA FETCHED SEQUENTIALLY FROM THE LOCAL HARD DRIVE OR A NETWORK DATABASE
• CALLING ITS FIT METHOD ON A MEMORY MAPPED FILE USING NUMPYMEMMAP
INCREMENTALPCA ONLY STORES ESTIMATES OF COMPONENT AND NOISE VARIANCES IN ORDER UPDATE EXPLAINEDVARIANCERATIO INCREMENTALLY THIS IS WHY MEMORY USAGE DEPENDS ON THE NUMBER OF SAMPLES PER BATCH RATHER THAN THE NUMBER OF SAMPLES TO BE PROCESSED IN THE DATASET
AS INPCAINCREMENTALPCA CENTERS BUT DOES NOT SCALE THE INPUT DATA FOR EACH FEATURE BEFORE APPLYING THE SVD
EXAMPLES
•INCREMENTAL PCA
PCA USING RANDOMIZED SVD
IT IS OFTEN INTERESTING TO PROJECT DATA TO A LOWERDIMENSIONAL SPACE THAT PRESERVES MOST OF THE VARIANCE BY DROPPING THE SINGULAR VECTOR OF COMPONENTS ASSOCIATED WITH LOWER SINGULAR VALUES
FOR INSTANCE IF WE WORK WITH 64X64 PIXEL GRAYLEVEL PICTURES FOR FACE RECOGNITION THE DIMENSIONALITY OF THE DATA IS 4096 AND IT IS SLOW TO TRAIN AN RBF SUPPORT VECTOR MACHINE ON SUCH WIDE DATA FURTHERMORE WE KNOW THAT THE INTRINSIC DIMENSIONALITY OF THE DATA IS MUCH LOWER THAN 4096 SINCE ALL PICTURES OF HUMAN FACES LOOK SOMEWHAT ALIKE THE SAMPLES LIE ON A MANIFOLD OF MUCH LOWER DIMENSION SAY AROUND 200 FOR INSTANCE THE PCA ALGORITHM CAN BE USED TO LINEARLY TRANSFORM THE DATA WHILE BOTH REDUCING THE DIMENSIONALITY AND PRESERVE MOST OF THE EXPLAINED VARIANCE AT THE SAME TIME
THE CLASSPCA USED WITH THE OPTIONAL PARAMETER SVDSOLVERRANDOMIZED IS VERY USEFUL IN THAT CASE SINCE WE ARE GOING TO DROP MOST OF THE SINGULAR VECTORS IT IS MUCH MORE EFFICIENT TO LIMIT THE COMPUTATION TO AN APPROXIMATED ESTIMATE OF THE SINGULAR VECTORS WE WILL KEEP TO ACTUALLY PERFORM THE TRANSFORM
FOR INSTANCE THE FOLLOWING SHOWS 16 SAMPLE PORTRAITS CENTERED AROUND 00 FROM THE OLIVETTI DATASET ON THE RIGHT HAND SIDE ARE THE FIRST 16 SINGULAR VECTORS RESHAPED AS PORTRAITS SINCE WE ONLY REQUIRE THE TOP 16 SINGULAR VECTORS OF A DATASET WITH SIZE □□□□□□□□ 400 AND□□□□□□□□□ 64×64 4096 THE COMPUTATION TIME IS LESS THAN 1S

IF WE NOTE □MAX MAX □SAMPLES □FEATURES AND□MIN MIN □SAMPLES □FEATURES THE TIME COMPLEXITY OF THE RANDOM IZEDPCA IS□□2
MAX·□COMPONENTS INSTEAD OF □□2
MAX·□MINFOR THE EXACT METHOD IMPLEMENTED IN PCA
THE MEMORY FOOTPRINT OF RANDOMIZED PCA IS ALSO PROPORTIONAL TO 2·□MAX·□COMPONENTS INSTEAD OF □MAX·□MINFOR THE EXACT METHOD
NOTE THE IMPLEMENTATION OF INVERSETRANSFORM INPCA WITHSVDSOLVERRANDOMIZED IS NOT THE EXACT INVERSE TRANSFORM OF TRANSFORM EVEN WHEN WHITENFALSE DEFAULT
EXAMPLES
•FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
•FACES DATASET DECOMPOSITIONS
REFERENCES
• “FINDING STRUCTURE WITH RANDOMNESS STOCHASTIC ALGORITHMS FOR CONSTRUCTING APPROXIMATE MATRIX DECOMPOSITIONS” HALKO ET AL 2009

KERNEL PCA
KERNELPCA IS AN EXTENSION OF PCA WHICH ACHIEVES NONLINEAR DIMENSIONALITY REDUCTION THROUGH THE USE OF KERNELS SEE PAIRWISE METRICS AFFINITIES AND KERNELS IT HAS MANY APPLICATIONS INCLUDING DENOISING COMPRES SION AND STRUCTURED PREDICTION KERNEL DEPENDENCY ESTIMATION KERNELPCA SUPPORTS BOTH TRANSFORM AND INVERSETRANSFORM
EXAMPLES
•KERNEL PCA
SPARSE PRINCIPAL COMPONENTS ANALYSIS SPARSEPCA AND MINIBATCHSPARSEPCA
SPARSEPCA IS A VARIANT OF PCA WITH THE GOAL OF EXTRACTING THE SET OF SPARSE COMPONENTS THAT BEST RECONSTRUCT THE DATA
MINIBATCH SPARSE PCA MINIBATCHSPARSEPCA IS A VARIANT OF SPARSEPCA THAT IS FASTER BUT LESS ACCURATE THE INCREASED SPEED IS REACHED BY ITERATING OVER SMALL CHUNKS OF THE SET OF FEATURES FOR A GIVEN NUMBER OF ITERATIONS
PRINCIPAL COMPONENT ANALYSIS PCA HAS THE DISADVANTAGE THAT THE COMPONENTS EXTRACTED BY THIS METHOD HAVE EXCLU SIVELY DENSE EXPRESSIONS IE THEY HAVE NONZERO COEFFICIENTS WHEN EXPRESSED AS LINEAR COMBINATIONS OF THE ORIGINAL VARIABLES THIS CAN MAKE INTERPRETATION DIFFICULT IN MANY CASES THE REAL UNDERLYING COMPONENTS CAN BE MORE NATURALLY IMAGINED AS SPARSE VECTORS FOR EXAMPLE IN FACE RECOGNITION COMPONENTS MIGHT NATURALLY MAP TO PARTS OF FACES
SPARSE PRINCIPAL COMPONENTS YIELDS A MORE PARSIMONIOUS INTERPRETABLE REPRESENTATION CLEARLY EMPHASIZING WHICH OF THE ORIGINAL FEATURES CONTRIBUTE TO THE DIFFERENCES BETWEEN SAMPLES
THE FOLLOWING EXAMPLE ILLUSTRATES 16 COMPONENTS EXTRACTED USING SPARSE PCA FROM THE OLIVETTI FACES DATASET IT CAN BE SEEN HOW THE REGULARIZATION TERM INDUCES MANY ZEROS FURTHERMORE THE NATURAL STRUCTURE OF THE DATA CAUSES THE NONZERO COEFFICIENTS TO BE VERTICALLY ADJACENT THE MODEL DOES NOT ENFORCE THIS MATHEMATICALLY EACH COMPONENT IS

A VECTOR $h \in R4096$ AND THERE IS NO NOTION OF VERTICAL ADJACENCY EXCEPT DURING THE HUMANFRIENDLY VISUALIZATION AS 64X64 PIXEL IMAGES THE FACT THAT THE COMPONENTS SHOWN BELOW APPEAR LOCAL IS THE EFFECT OF THE INHERENT STRUCTURE OF THE DATA WHICH MAKES SUCH LOCAL PATTERNS MINIMIZE RECONSTRUCTION ERROR THERE EXIST SPARSITYINDUCING NORMS THAT TAKE INTO ACCOUNT ADJACENCY AND DIFFERENT KINDS OF STRUCTURE SEE JEN09 FOR A REVIEW OF SUCH METHODS FOR MORE DETAILS ON HOW TO USE SPARSE PCA SEE THE EXAMPLES SECTION BELOW

NOTE THAT THERE ARE MANY DIFFERENT FORMULATIONS FOR THE SPARSE PCA PROBLEM THE ONE IMPLEMENTED HERE IS BASED ONMRL09 THE OPTIMIZATION PROBLEM SOLVED IS A PCA PROBLEM DICTIONARY LEARNING WITH AN ℓ1PENALTY ON THE COMPONENTS

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THE SPARSITYINDUCING ℓ1NORM ALSO PREVENTS LEARNING COMPONENTS FROM NOISE WHEN FEW TRAINING SAMPLES ARE AVAILABLE THE DEGREE OF PENALIZATION AND THUS SPARSITY CAN BE ADJUSTED THROUGH THE HYPERPARAMETER ALPHA SMALL VALUES LEAD TO A GENTLY REGULARIZED FACTORIZATION WHILE LARGER VALUES SHRINK MANY COEFFICIENTS TO ZERO

NOTE WHILE IN THE SPIRIT OF AN ONLINE ALGORITHM THE CLASS MINIBATCHSPARSEPCA DOES NOT IMPLEMENT PARTIALFIT BECAUSE THE ALGORITHM IS ONLINE ALONG THE FEATURES DIRECTION NOT THE SAMPLES DIRECTION

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EXAMPLES
•FACES DATASET DECOMPOSITIONS
REFERENCES
TRUNCATED SINGULAR VALUE DECOMPOSITION AND LATENT SEMANTIC ANALYSIS
TRUNCATEDSVD IMPLEMENTS A VARIANT OF SINGULAR VALUE DECOMPOSITION SVD THAT ONLY COMPUTES THE □LARGEST SINGULAR VALUES WHERE □IS A USERSPECIFIED PARAMETER
WHEN TRUNCATED SVD IS APPLIED TO TERMDOCUMENT MATRICES AS RETURNED BY COUNTVECTORIZER OR TFIDFVECTORIZER THIS TRANSFORMATION IS KNOWN AS LATENT SEMANTIC ANALYSIS LSA BECAUSE IT TRANSFORMS SUCH MATRICES TO A “SEMANTIC” SPACE OF LOW DIMENSIONALITY IN PARTICULAR LSA IS KNOWN TO COMBAT THE EFFECTS OF SYNONYMY AND POLYSEMY BOTH OF WHICH ROUGHLY MEAN THERE ARE MULTIPLE MEANINGS PER WORD WHICH CAUSE TERMDOCUMENT MATRICES TO BE OVERLY SPARSE AND EXHIBIT POOR SIMILARITY UNDER MEASURES SUCH AS COSINE SIMILARITY
NOTE LSA IS ALSO KNOWN AS LATENT SEMANTIC INDEXING LSI THOUGH STRICTLY THAT REFERS TO ITS USE IN PERSISTENT INDEXES FOR INFORMATION RETRIEVAL PURPOSES
MATHEMATICALLY TRUNCATED SVD APPLIED TO TRAINING SAMPLES □PRODUCES A LOWRANK APPROXIMATION □
□≈□□□□□□□⊤
□
AFTER THIS OPERATION □□□⊤
□IS THE TRANSFORMED TRAINING SET WITH □FEATURES CALLED NCOMPONENTS IN THE API
TO ALSO TRANSFORM A TEST SET □ WE MULTIPLY IT WITH □□
□′□□□
NOTE MOST TREATMENTS OF LSA IN THE NATURAL LANGUAGE PROCESSING NLP AND INFORMATION RETRIEVAL IR LITERATURE SWAP THE AXES OF THE MATRIX □SO THAT IT HAS SHAPE NFEATURES ×NSAMPLES WE PRESENT LSA IN A DIFFERENT WAY THAT MATCHES THE SCIKITLEARN API BETTER BUT THE SINGULAR VALUES FOUND ARE THE SAME
TRUNCATEDSVD IS VERY SIMILAR TO PCA BUT DIFFERS IN THAT IT WORKS ON SAMPLE MATRICES □DIRECTLY INSTEAD OF THEIR COVARIANCE MATRICES WHEN THE COLUMNWISE PERFEATURE MEANS OF □ARE SUBTRACTED FROM THE FEATURE VALUES TRUNCATED SVD ON THE RESULTING MATRIX IS EQUIVALENT TO PCA IN PRACTICAL TERMS THIS MEANS THAT THE TRUNCATEDSVD TRANSFORMER ACCEPTSSCIPYSPARSE MATRICES WITHOUT THE NEED TO DENSIFY THEM AS DENSIFYING MAY FILL UP MEMORY EVEN FOR MEDIUMSIZED DOCUMENT COLLECTIONS
WHILE THETRUNCATEDSVD TRANSFORMER WORKS WITH ANY SPARSE FEATURE MATRIX USING IT ON TF–IDF MATRICES IS RECOMMENDED OVER RAW FREQUENCY COUNTS IN AN LSADOCUMENT PROCESSING SETTING IN PARTICULAR SUBLINEAR SCALING AND INVERSE DOCUMENT FREQUENCY SHOULD BE TURNED ON SUBLINEARTFTRUE USEIDFTRUE TO BRING THE FEATURE VALUES CLOSER TO A GAUSSIAN DISTRIBUTION COMPENSATING FOR LSA’S ERRONEOUS ASSUMPTIONS ABOUT TEXTUAL DATA
EXAMPLES
•CLUSTERING TEXT DOCUMENTS USING KMEANS

REFERENCES
• CHRISTOPHER D MANNING PRABHAKAR RAGHAVAN AND HINRICH SCHÜTZE 2008 INTRODUCTION TO INFORMATION RE TRIEVAL CAMBRIDGE UNIVERSITY PRESS CHAPTER 18 MATRIX DECOMPOSITIONS LATENT SEMANTIC INDEXING
DICTIONARY LEARNING
SPARSE CODING WITH A PRECOMPUTED DICTIONARY
THESPARSECODER OBJECT IS AN ESTIMATOR THAT CAN BE USED TO TRANSFORM SIGNALS INTO SPARSE LINEAR COMBINATION OF ATOMS FROM A FIXED PRECOMPUTED DICTIONARY SUCH AS A DISCRETE WAVELET BASIS THIS OBJECT THEREFORE DOES NOT IMPLEMENT AFIT METHOD THE TRANSFORMATION AMOUNTS TO A SPARSE CODING PROBLEM FINDING A REPRESENTATION OF THE DATA AS A LINEAR COMBINATION OF AS FEW DICTIONARY ATOMS AS POSSIBLE ALL VARIATIONS OF DICTIONARY LEARNING IMPLEMENT THE FOLLOWING TRANSFORM METHODS CONTROLLABLE VIA THE TRANSFORMMETHOD INITIALIZATION PARAMETER
• ORTHOGONAL MATCHING PURSUIT ORTHOGONAL MATCHING PURSUIT OMP
• LEASTANGLE REGRESSION LEAST ANGLE REGRESSION
• LASSO COMPUTED BY LEASTANGLE REGRESSION
• LASSO USING COORDINATE DESCENT LASSO
• THRESHOLDING
THRESHOLDING IS VERY FAST BUT IT DOES NOT YIELD ACCURATE RECONSTRUCTIONS THEY HAVE BEEN SHOWN USEFUL IN LITERATURE FOR CLASSIFICATION TASKS FOR IMAGE RECONSTRUCTION TASKS ORTHOGONAL MATCHING PURSUIT YIELDS THE MOST ACCURATE UNBIASED RECONSTRUCTION
THE DICTIONARY LEARNING OBJECTS OFFER VIA THE SPLITCODE PARAMETER THE POSSIBILITY TO SEPARATE THE POSITIVE AND NEGATIVE VALUES IN THE RESULTS OF SPARSE CODING THIS IS USEFUL WHEN DICTIONARY LEARNING IS USED FOR EXTRACTING FEATURES THAT WILL BE USED FOR SUPERVISED LEARNING BECAUSE IT ALLOWS THE LEARNING ALGORITHM TO ASSIGN DIFFERENT WEIGHTS TO NEGATIVE LOADINGS OF A PARTICULAR ATOM FROM TO THE CORRESPONDING POSITIVE LOADING
THE SPLIT CODE FOR A SINGLE SAMPLE HAS LENGTH 2NCOMPONENTS AND IS CONSTRUCTED USING THE FOLLOWING RULE FIRST THE REGULAR CODE OF LENGTH NCOMPONENTS IS COMPUTED THEN THE FIRST NCOMPONENTS ENTRIES OF THE SPLITCODE ARE FILLED WITH THE POSITIVE PART OF THE REGULAR CODE VECTOR THE SECOND HALF OF THE SPLIT CODE IS FILLED WITH THE NEGATIVE PART OF THE CODE VECTOR ONLY WITH A POSITIVE SIGN THEREFORE THE SPLITCODE IS NONNEGATIVE
EXAMPLES
•SPARSE CODING WITH A PRECOMPUTED DICTIONARY
GENERIC DICTIONARY LEARNING
DICTIONARY LEARNING DICTIONARYLEARNING IS A MATRIX FACTORIZATION PROBLEM THAT AMOUNTS TO FINDING A USUALLY OVERCOMPLETE DICTIONARY THAT WILL PERFORM WELL AT SPARSELY ENCODING THE FITTED DATA
REPRESENTING DATA AS SPARSE COMBINATIONS OF ATOMS FROM AN OVERCOMPLETE DICTIONARY IS SUGGESTED TO BE THE WAY THE MAMMALIAN PRIMARY VISUAL CORTEX WORKS CONSEQUENTLY DICTIONARY LEARNING APPLIED ON IMAGE PATCHES HAS BEEN SHOWN TO GIVE GOOD RESULTS IN IMAGE PROCESSING TASKS SUCH AS IMAGE COMPLETION INPAINTING AND DENOISING AS WELL AS FOR SUPERVISED RECOGNITION TASKS

DICTIONARY LEARNING IS AN OPTIMIZATION PROBLEM SOLVED BY ALTERNATIVELY UPDATING THE SPARSE CODE AS A SOLUTION TO MULTIPLE LASSO PROBLEMS CONSIDERING THE DICTIONARY FIXED AND THEN UPDATING THE DICTIONARY TO BEST FIT THE SPARSE CODE
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SUBJECT TO□□2 1FOR ALL 0≤□ □ ATOMS
AFTER USING SUCH A PROCEDURE TO FIT THE DICTIONARY THE TRANSFORM IS SIMPLY A SPARSE CODING STEP THAT SHARES THE SAME IMPLEMENTATION WITH ALL DICTIONARY LEARNING OBJECTS SEE SPARSE CODING WITH A PRECOMPUTED DICTIONARY
IT IS ALSO POSSIBLE TO CONSTRAIN THE DICTIONARY ANDOR CODE TO BE POSITIVE TO MATCH CONSTRAINTS THAT MAY BE PRESENT IN THE DATA BELOW ARE THE FACES WITH DIFFERENT POSITIVITY CONSTRAINTS APPLIED RED INDICATES NEGATIVE VALUES BLUE INDICATES POSITIVE VALUES AND WHITE REPRESENTS ZEROS

THE FOLLOWING IMAGE SHOWS HOW A DICTIONARY LEARNED FROM 4X4 PIXEL IMAGE PATCHES EXTRACTED FROM PART OF THE IMAGE OF A RACCOON FACE LOOKS LIKE

EXAMPLES

•IMAGE DENOISING USING DICTIONARY LEARNING

REFERENCES

• “ONLINE DICTIONARY LEARNING FOR SPARSE CODING” J MAIRAL F BACH J PONCE G SAPIRO 2009

MINIBATCH DICTIONARY LEARNING

MINIBATCHDICTIONARYLEARNING IMPLEMENTS A FASTER BUT LESS ACCURATE VERSION OF THE DICTIONARY LEARNING ALGO RITHM THAT IS BETTER SUITED FOR LARGE DATASETS

BY DEFAULT MINIBATCHDICTIONARYLEARNING DIVIDES THE DATA INTO MINIBATCHES AND OPTIMIZES IN AN ONLINE MANNER BY CYCLING OVER THE MINIBATCHES FOR THE SPECIFIED NUMBER OF ITERATIONS HOWEVER AT THE MOMENT IT DOES NOT IMPLEMENT A STOPPING CONDITION

THE ESTIMATOR ALSO IMPLEMENTS PARTIALFIT WHICH UPDATES THE DICTIONARY BY ITERATING ONLY ONCE OVER A MINIBATCH
THIS CAN BE USED FOR ONLINE LEARNING WHEN THE DATA IS NOT READILY AVAILABLE FROM THE START OR FOR WHEN THE DATA DOES NOT FIT INTO THE MEMORY
CLUSTERING FOR DICTIONARY LEARNING
NOTE THAT WHEN USING DICTIONARY LEARNING TO EXTRACT A REPRESENTATION EG FOR SPARSE CODING CLUSTERING CAN BE A GOOD PROXY TO LEARN THE DICTIONARY FOR INSTANCE THE MINIBATCHKMEANS ESTIMATOR IS COMPUTATIONALLY EFFICIENT AND IMPLEMENTS ONLINE LEARNING WITH A PARTIALFIT METHOD
EXAMPLE ONLINE LEARNING OF A DICTIONARY OF PARTS OF FACES
FACTOR ANALYSIS
IN UNSUPERVISED LEARNING WE ONLY HAVE A DATASET □□1 □2 □ □ HOW CAN THIS DATASET BE DESCRIBED MATHEMATICALLY A VERY SIMPLE CONTINUOUS LATENT VARIABLE MODEL FOR □IS
□□□*h*□□□
THE VECTOR *h*□IS CALLED “LATENT” BECAUSE IT IS UNOBSERVED □IS CONSIDERED A NOISE TERM DISTRIBUTED ACCORDING TO A GAUSSIAN WITH MEAN 0 AND COVARIANCE □IE□~□0□□IS SOME ARBITRARY OFFSET VECTOR SUCH A MODEL IS CALLED “GENERATIVE” AS IT DESCRIBES HOW □□IS GENERATED FROM *h*□ IF WE USE ALL THE □□‘S AS COLUMNS TO FORM A MATRIX XAND ALL THE*h*□‘S AS COLUMNS OF A MATRIX HTHEN WE CAN WRITE WITH SUITABLY DEFINED MANDE
X□HME
IN OTHER WORDS WE DECOMPOSED MATRIX X
IF*h*□IS GIVEN THE ABOVE EQUATION AUTOMATICALLY IMPLIES THE FOLLOWING PROBABILISTIC INTERPRETATION
□□□*h*□ □□*h*□□□
FOR A COMPLETE PROBABILISTIC MODEL WE ALSO NEED A PRIOR DISTRIBUTION FOR THE LATENT VARIABLE *h* THE MOST STRAIGHTFORWARD ASSUMPTION BASED ON THE NICE PROPERTIES OF THE GAUSSIAN DISTRIBUTION IS *h*~□0I THIS YIELDS A GAUSSIAN AS THE MARGINAL DISTRIBUTION OF □
□□ □□ □□□ □
NOW WITHOUT ANY FURTHER ASSUMPTIONS THE IDEA OF HAVING A LATENT VARIABLE *h*WOULD BE SUPERFLUOUS – □CAN BE COMPLETELY MODELLED WITH A MEAN AND A COVARIANCE WE NEED TO IMPOSE SOME MORE SPECIFIC STRUCTURE ON ONE OF THESE TWO PARAMETERS A SIMPLE ADDITIONAL ASSUMPTION REGARDS THE STRUCTURE OF THE ERROR COVARIANCE □
•□ □2I THIS ASSUMPTION LEADS TO THE PROBABILISTIC MODEL OF PCA

• DIAG 1 2 THIS MODEL IS CALLED FACTORANALYSIS A CLASSICAL STATISTICAL MODEL THE MATRIX
W IS SOMETIMES CALLED THE “FACTOR LOADING MATRIX”
BOTH MODELS ESSENTIALLY ESTIMATE A GAUSSIAN WITH A LOWRANK COVARIANCE MATRIX BECAUSE BOTH MODELS ARE PROBABILISTIC
THEY CAN BE INTEGRATED IN MORE COMPLEX MODELS EG MIXTURE OF FACTOR ANALYSERS ONE GETS VERY DIFFERENT MODELS EG
FASTICA IF NONGAUSSIAN PRIORS ON THE LATENT VARIABLES ARE ASSUMED
FACTOR ANALYSIS CANPRODUCE SIMILAR COMPONENTS THE COLUMNS OF ITS LOADING MATRIX TO PCA HOWEVER ONE CAN NOT
MAKE ANY GENERAL STATEMENTS ABOUT THESE COMPONENTS EG WHETHER THEY ARE ORTHOGONAL
THE MAIN ADVANTAGE FOR FACTOR ANALYSIS OVER PCA IS THAT IT CAN MODEL THE VARIANCE IN EVERY DIRECTION OF THE INPUT SPACE
INDEPENDENTLY HETEROSCEDASTIC NOISE
THIS ALLOWS BETTER MODEL SELECTION THAN PROBABILISTIC PCA IN THE PRESENCE OF HETEROSCEDASTIC NOISE
EXAMPLES
•MODEL SELECTION WITH PROBABILISTIC PCA AND FACTOR ANALYSIS FA

INDEPENDENT COMPONENT ANALYSIS ICA
INDEPENDENT COMPONENT ANALYSIS SEPARATES A MULTIVARIATE SIGNAL INTO ADDITIVE SUBCOMPONENTS THAT ARE MAXIMALLY IN DEPENDENT IT IS IMPLEMENTED IN SCIKITLEARN USING THE FAST ICA ALGORITHM TYPICALLY ICA IS NOT USED FOR REDUCING DIMENSIONALITY BUT FOR SEPARATING SUPERIMPOSED SIGNALS SINCE THE ICA MODEL DOES NOT INCLUDE A NOISE TERM FOR THE MODEL TO BE CORRECT WHITENING MUST BE APPLIED THIS CAN BE DONE INTERNALLY USING THE WHITEN ARGUMENT OR MANUALLY USING ONE OF THE PCA VARIANTS
IT IS CLASSICALLY USED TO SEPARATE MIXED SIGNALS A PROBLEM KNOWN AS BLIND SOURCE SEPARATION AS IN THE EXAMPLE BELOW ICA CAN ALSO BE USED AS YET ANOTHER NON LINEAR DECOMPOSITION THAT FINDS COMPONENTS WITH SOME SPARSITY

EXAMPLES
•BLIND SOURCE SEPARATION USING FASTICA
•FASTICA ON 2D POINT CLOUDS
•FACES DATASET DECOMPOSITIONS
NONNEGATIVE MATRIX FACTORIZATION NMF OR NNMF
NMF WITH THE FROBENIUS NORM
NMF1IS AN ALTERNATIVE APPROACH TO DECOMPOSITION THAT ASSUMES THAT THE DATA AND THE COMPONENTS ARE NONNEGATIVE NMF CAN BE PLUGGED IN INSTEAD OF PCA OR ITS VARIANTS IN THE CASES WHERE THE DATA MATRIX DOES NOT CONTAIN NEGATIVE VALUES IT FINDS A DECOMPOSITION OF SAMPLES □INTO TWO MATRICES □AND□OF NONNEGATIVE ELEMENTS BY OPTIMIZING THE DISTANCE □BETWEEN □AND THE MATRIX PRODUCT □□ THE MOST WIDELY USED DISTANCE FUNCTION IS THE SQUARED FROBENIUS NORM WHICH IS AN OBVIOUS EXTENSION OF THE EUCLIDEAN NORM TO MATRICES
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FRO1
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UNLIKEPCA THE REPRESENTATION OF A VECTOR IS OBTAINED IN AN ADDITIVE FASHION BY SUPERIMPOSING THE COMPONENTS WITHOUT SUBTRACTING SUCH ADDITIVE MODELS ARE EFFICIENT FOR REPRESENTING IMAGES AND TEXT
IT HAS BEEN OBSERVED IN HOYER 20042THAT WHEN CAREFULLY CONSTRAINED NMF CAN PRODUCE A PARTSBASED REPRESENTATION OF THE DATASET RESULTING IN INTERPRETABLE MODELS THE FOLLOWING EXAMPLE DISPLAYS 16 SPARSE COMPONENTS FOUND BY NMF FROM THE IMAGES IN THE OLIVETTI FACES DATASET IN COMPARISON WITH THE PCA EIGENFACES
1“LEARNING THE PARTS OF OBJECTS BY NONNEGATIVE MATRIX FACTORIZATION” D LEE S SEUNG 1999
2“NONNEGATIVE MATRIX FACTORIZATION WITH SPARSENESS CONSTRAINTS” P HOYER 2004

THEINIT ATTRIBUTE DETERMINES THE INITIALIZATION METHOD APPLIED WHICH HAS A GREAT IMPACT ON THE PERFORMANCE OF THE METHODNMF IMPLEMENTS THE METHOD NONNEGATIVE DOUBLE SINGULAR VALUE DECOMPOSITION NNDSVD4IS BASED ON TWO SVD PROCESSES ONE APPROXIMATING THE DATA MATRIX THE OTHER APPROXIMATING POSITIVE SECTIONS OF THE RESULTING PARTIAL SVD FACTORS UTILIZING AN ALGEBRAIC PROPERTY OF UNIT RANK MATRICES THE BASIC NNDSVD ALGORITHM IS BETTER FIT FOR SPARSE FACTORIZATION ITS VARIANTS NNDSVDA IN WHICH ALL ZEROS ARE SET EQUAL TO THE MEAN OF ALL ELEMENTS OF THE DATA AND NNDSVDAR IN WHICH THE ZEROS ARE SET TO RANDOM PERTURBATIONS LESS THAN THE MEAN OF THE DATA DIVIDED BY 100 ARE RECOMMENDED IN THE DENSE CASE

NOTE THAT THE MULTIPLICATIVE UPDATE 'MU' SOLVER CANNOT UPDATE ZEROS PRESENT IN THE INITIALIZATION SO IT LEADS TO POORER RESULTS WHEN USED JOINTLY WITH THE BASIC NNDSVD ALGORITHM WHICH INTRODUCES A LOT OF ZEROS IN THIS CASE NNDSVDA OR NNDSVDAR SHOULD BE PREFERRED

NMF CAN ALSO BE INITIALIZED WITH CORRECTLY SCALED RANDOM NONNEGATIVE MATRICES BY SETTING INITRANDOM AN INTEGER SEED OR A RANDOMSTATE CAN ALSO BE PASSED TO RANDOMSTATE TO CONTROL REPRODUCIBILITY

INNMF L1 AND L2 PRIORS CAN BE ADDED TO THE LOSS FUNCTION IN ORDER TO REGULARIZE THE MODEL THE L2 PRIOR USES THE FROBENIUS NORM WHILE THE L1 PRIOR USES AN ELEMENTWISE L1 NORM AS IN ELASTICNET WE CONTROL THE COMBINATION OF L1 AND L2 WITH THE L1RATIO □ PARAMETER AND THE INTENSITY OF THE REGULARIZATION WITH THE ALPHA □ PARAMETER THEN THE PRIORS TERMS ARE

□□□1□□□1□1−□

2□2

FRO□1−□

2□2

FRO

4"SVD BASED INITIALIZATION A HEAD START FOR NONNEGATIVE MATRIX FACTORIZATION" C BOUTSIDIS E GALLOPOULOS 2008

AND THE REGULARIZED OBJECTIVE FUNCTION IS
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2□2
FRO□1−□
2□2
FRO
NMF REGULARIZES BOTH W AND H THE PUBLIC FUNCTION NONNEGATIVEFACTORIZATION ALLOWS A FINER CONTROL THROUGH THE REGULARIZATION ATTRIBUTE AND MAY REGULARIZE ONLY W ONLY H OR BOTH
NMF WITH A BETADIVERGENCE
AS DESCRIBED PREVIOUSLY THE MOST WIDELY USED DISTANCE FUNCTION IS THE SQUARED FROBENIUS NORM WHICH IS AN OBVIOUS EXTENSION OF THE EUCLIDEAN NORM TO MATRICES
□FRO□ □ 1
2□−□2
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OTHER DISTANCE FUNCTIONS CAN BE USED IN NMF AS FOR EXAMPLE THE GENERALIZED KULLBACKLEIBLER KL DIVERGENCE ALSO REFERRED AS IDIVERGENCE
□□□□ □ ∑
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□□□−□□□□□□
OR THE ITAKURASAITO IS DIVERGENCE
□□□□ □ ∑
□□□□□
□□□−LOG□□□
□□□−1
THESE THREE DISTANCES ARE SPECIAL CASES OF THE BETADIVERGENCE FAMILY WITH □ 210RESPECTIVELY6 THE BETA DIVERGENCE ARE DEFINED BY
□□□ □ ∑
□□1
□□−1□□
□□ □−1□□
□□−□□□□□−1
□□
NOTE THAT THIS DEFINITION IS NOT VALID IF □∈0 1 YET IT CAN BE CONTINUOUSLY EXTENDED TO THE DEFINITIONS OF □□□AND □□□RESPECTIVELY
NMF IMPLEMENTS TWO SOLVERS USING COORDINATE DESCENT ‘CD’5 AND MULTIPLICATIVE UPDATE ‘MU’6 THE ‘MU’ SOLVER CAN OPTIMIZE EVERY BETADIVERGENCE INCLUDING OF COURSE THE FROBENIUS NORM □ 2 THE GENERALIZED KULLBACK LEIBLER DIVERGENCE □ 1 AND THE ITAKURASAITO DIVERGENCE □ 0 NOTE THAT FOR □∈1 2 THE ‘MU’ SOLVER IS SIGNIFICANTLY FASTER THAN FOR OTHER VALUES OF □ NOTE ALSO THAT WITH A NEGATIVE OR 0 IE ‘ITAKURASAITO’ □ THE INPUT MATRIX CANNOT CONTAIN ZERO VALUES
THE ‘CD’ SOLVER CAN ONLY OPTIMIZE THE FROBENIUS NORM DUE TO THE UNDERLYING NONCONVEXITY OF NMF THE DIFFERENT SOLVERS MAY CONVERGE TO DIFFERENT MINIMA EVEN WHEN OPTIMIZING THE SAME DISTANCE FUNCTION
NMF IS BEST USED WITH THE FITTRANSFORM METHOD WHICH RETURNS THE MATRIX W THE MATRIX H IS STORED INTO THE FITTED MODEL IN THE COMPONENTS ATTRIBUTE THE METHOD TRANSFORM WILL DECOMPOSE A NEW MATRIX XNEW BASED ON THESE STORED COMPONENTS
```
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 3 12 4 1 5 08 6 1
 FROM SKLEARNDECOMPOSITION IMPORT NMF
MODEL  NMFNCOMPONENTS2 INITRANDOM RANDOMSTATE0
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6“ALGORITHMS FOR NONNEGATIVE MATRIX FACTORIZATION WITH THE BETADIVERGENCE” C FEVOTTE J IDIER 2011
5“FAST LOCAL ALGORITHMS FOR LARGE SCALE NONNEGATIVE MATRIX AND TENSOR FACTORIZATIONS” A CICHOCKI A PHAN 2009

W MODELFITTRANSFORMX
H MODELCOMPONENTS
XNEW NPARRAY1 0 1 61 1 0 1 4 32 1 0 4
WNEW MODELTRANSFORMXNEW
EXAMPLES
•FACES DATASET DECOMPOSITIONS
•TOPIC EXTRACTION WITH NONNEGATIVE MATRIX FACTORIZATION AND LATENT DIRICHLET ALLOCATION
•BETADIVERGENCE LOSS FUNCTIONS
REFERENCES
LATENT DIRICHLET ALLOCATION LDA
LATENT DIRICHLET ALLOCATION IS A GENERATIVE PROBABILISTIC MODEL FOR COLLECTIONS OF DISCRETE DATASET SUCH AS TEXT CORPORA
IT IS ALSO A TOPIC MODEL THAT IS USED FOR DISCOVERING ABSTRACT TOPICS FROM A COLLECTION OF DOCUMENTS
THE GRAPHICAL MODEL OF LDA IS A THREELEVEL GENERATIVE MODEL

NOTE ON NOTATIONS PRESENTED IN THE GRAPHICAL MODEL ABOVE WHICH CAN BE FOUND IN HOFFMAN ET AL 2013
• THE CORPUS IS A COLLECTION OF □DOCUMENTS
• A DOCUMENT IS A SEQUENCE OF □WORDS
• THERE ARE □TOPICS IN THE CORPUS
• THE BOXES REPRESENT REPEATED SAMPLING
IN THE GRAPHICAL MODEL EACH NODE IS A RANDOM VARIABLE AND HAS A ROLE IN THE GENERATIVE PROCESS A SHADED NODE INDICATES AN OBSERVED VARIABLE AND AN UNSHADED NODE INDICATES A HIDDEN LATENT VARIABLE IN THIS CASE WORDS IN THE CORPUS ARE THE ONLY DATA THAT WE OBSERVE THE LATENT VARIABLES DETERMINE THE RANDOM MIXTURE OF TOPICS IN THE CORPUS AND THE DISTRIBUTION OF WORDS IN THE DOCUMENTS THE GOAL OF LDA IS TO USE THE OBSERVED WORDS TO INFER THE HIDDEN TOPIC STRUCTURE
WHEN MODELING TEXT CORPORA THE MODEL ASSUMES THE FOLLOWING GENERATIVE PROCESS FOR A CORPUS WITH □DOCUMENTS AND □TOPICS WITH □CORRESPONDING TO NCOMPONENTS IN THE API
1 FOR EACH TOPIC □∈□ DRAW □□~DIRICHLET □ THIS PROVIDES A DISTRIBUTION OVER THE WORDS IE THE PROBABILITY OF A WORD APPEARING IN TOPIC □□CORRESPONDS TO TOPICWORDPRIOR
2 FOR EACH DOCUMENT □∈□ DRAW THE TOPIC PROPORTIONS □□~DIRICHLET □□CORRESPONDS TO DOCTOPICPRIOR
3 FOR EACH WORD □IN DOCUMENT □
1 DRAW THE TOPIC ASSIGNMENT □□□~MULTINOMIAL □□
2 DRAW THE OBSERVED WORD □□□~MULTINOMIAL □□□□
FOR PARAMETER ESTIMATION THE POSTERIOR DISTRIBUTION IS
□□ □ □□ □ □ □□ □ □□ □
□□□ □
SINCE THE POSTERIOR IS INTRACTABLE VARIATIONAL BAYESIAN METHOD USES A SIMPLER DISTRIBUTION □□ □ □□ □ □ TO APPROX IMATE IT AND THOSE VARIATIONAL PARAMETERS □□□ARE OPTIMIZED TO MAXIMIZE THE EVIDENCE LOWER BOUND ELBO LOG□□□ □≥□□ □ □ □ △□□LOG□□ □ □ □□ □−□□LOG□□ □ □
MAXIMIZING ELBO IS EQUIVALENT TO MINIMIZING THE KULLBACKLEIBLERKL DIVERGENCE BETWEEN □□ □ □ AND THE TRUE POSTERIOR □□ □ □□ □ □
LATENTDIRICHLETALLOCATION IMPLEMENTS THE ONLINE VARIATIONAL BAYES ALGORITHM AND SUPPORTS BOTH ONLINE AND BATCH UPDATE METHODS WHILE THE BATCH METHOD UPDATES VARIATIONAL VARIABLES AFTER EACH FULL PASS THROUGH THE DATA THE ONLINE METHOD UPDATES VARIATIONAL VARIABLES FROM MINIBATCH DATA POINTS
NOTE ALTHOUGH THE ONLINE METHOD IS GUARANTEED TO CONVERGE TO A LOCAL OPTIMUM POINT THE QUALITY OF THE OPTIMUM POINT AND THE SPEED OF CONVERGENCE MAY DEPEND ON MINIBATCH SIZE AND ATTRIBUTES RELATED TO LEARNING RATE SETTING

WHENLATENTDIRICHLETALLOCATION IS APPLIED ON A “DOCUMENTTERM” MATRIX THE MATRIX WILL BE DECOMPOSED INTO A “TOPICTERM” MATRIX AND A “DOCUMENTTOPIC” MATRIX WHILE “TOPICTERM” MATRIX IS STORED AS COMPONENTS IN THE MODEL “DOCUMENTTOPIC” MATRIX CAN BE CALCULATED FROM TRANSFORM METHOD
LATENTDIRICHLETALLOCATION ALSO IMPLEMENTS PARTIALFIT METHOD THIS IS USED WHEN DATA CAN BE FETCHED SEQUENTIALLY
EXAMPLES
•TOPIC EXTRACTION WITH NONNEGATIVE MATRIX FACTORIZATION AND LATENT DIRICHLET ALLOCATION
REFERENCES
• “LATENT DIRICHLET ALLOCATION” D BLEI A NG M JORDAN 2003
• “ONLINE LEARNING FOR LATENT DIRICHLET ALLOCATION” M HOFFMAN D BLEI F BACH 2010
• “STOCHASTIC VARIATIONAL INFERENCE” M HOFFMAN D BLEI C WANG J PAISLEY 2013
SEE ALSO DIMENSIONALITY REDUCTION FOR DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
326 COVARIANCE ESTIMATION
MANY STATISTICAL PROBLEMS REQUIRE THE ESTIMATION OF A POPULATION’S COVARIANCE MATRIX WHICH CAN BE SEEN AS AN ESTIMATION OF DATA SET SCATTER PLOT SHAPE MOST OF THE TIME SUCH AN ESTIMATION HAS TO BE DONE ON A SAMPLE WHOSE PROPERTIES SIZE STRUCTURE HOMOGENEITY HAVE A LARGE INFLUENCE ON THE ESTIMATION’S QUALITY THE SKLEARNCOVARIANCE PACKAGE PROVIDES TOOLS FOR ACCURATELY ESTIMATING A POPULATION’S COVARIANCE MATRIX UNDER VARIOUS SETTINGS
WE ASSUME THAT THE OBSERVATIONS ARE INDEPENDENT AND IDENTICALLY DISTRIBUTED IID
EMPIRICAL COVARIANCE
THE COVARIANCE MATRIX OF A DATA SET IS KNOWN TO BE WELL APPROXIMATED BY THE CLASSICAL MAXIMUM LIKELIHOOD ESTIMATOR OR “EMPIRICAL COVARIANCE” PROVIDED THE NUMBER OF OBSERVATIONS IS LARGE ENOUGH COMPARED TO THE NUMBER OF FEATURES THE VARIABLES DESCRIBING THE OBSERVATIONS MORE PRECISELY THE MAXIMUM LIKELIHOOD ESTIMATOR OF A SAMPLE IS AN UNBIASED ESTIMATOR OF THE CORRESPONDING POPULATION’S COVARIANCE MATRIX
THE EMPIRICAL COVARIANCE MATRIX OF A SAMPLE CAN BE COMPUTED USING THE EMPIRICALCOVARIANCE FUNCTION OF THE PACKAGE OR BY FITTING AN EMPIRICALCOVARIANCE OBJECT TO THE DATA SAMPLE WITH THE EMPIRICALCOVARIANCE FIT METHOD BE CAREFUL THAT RESULTS DEPEND ON WHETHER THE DATA ARE CENTERED SO ONE MAY WANT TO USE THE ASSUMECENTERED PARAMETER ACCURATELY MORE PRECISELY IF ASSUMECENTEREDFALSE THEN THE TEST SET IS SUPPOSED TO HAVE THE SAME MEAN VECTOR AS THE TRAINING SET IF NOT BOTH SHOULD BE CENTERED BY THE USER AND ASSUMECENTEREDTRUE SHOULD BE USED
EXAMPLES
• SEE SHRINKAGE COVARIANCE ESTIMATION LEDOITWOLF VS OAS AND MAXLIKELIHOOD FOR AN EXAMPLE ON HOW TO FIT AN EMPIRICALCOVARIANCE OBJECT TO DATA

SHRUNK COVARIANCE

BASIC SHRINKAGE

DESPITE BEING AN UNBIASED ESTIMATOR OF THE COVARIANCE MATRIX THE MAXIMUM LIKELIHOOD ESTIMATOR IS NOT A GOOD ESTI MATOR OF THE EIGENVALUES OF THE COVARIANCE MATRIX SO THE PRECISION MATRIX OBTAINED FROM ITS INVERSION IS NOT ACCURATE SOMETIMES IT EVEN OCCURS THAT THE EMPIRICAL COVARIANCE MATRIX CANNOT BE INVERTED FOR NUMERICAL REASONS TO AVOID SUCH AN INVERSION PROBLEM A TRANSFORMATION OF THE EMPIRICAL COVARIANCE MATRIX HAS BEEN INTRODUCED THE SHRINKAGE IN SCIKITLEARN THIS TRANSFORMATION WITH A USERDEFINED SHRINKAGE COEFFICIENT CAN BE DIRECTLY APPLIED TO A PRECOMPUTED COVARIANCE WITH THE SHRUNKCOVARIANCE METHOD ALSO A SHRUNK ESTIMATOR OF THE COVARIANCE CAN BE FITTED TO DATA WITH ASHRUNKCOVARIANCE OBJECT AND ITS SHRUNKCOVARIANCEFIT METHOD AGAIN RESULTS DEPEND ON WHETHER THE DATA ARE CENTERED SO ONE MAY WANT TO USE THE ASSUMECENTERED PARAMETER ACCURATELY

MATHEMATICALLY THIS SHRINKAGE CONSISTS IN REDUCING THE RATIO BETWEEN THE SMALLEST AND THE LARGEST EIGENVALUES OF THE EMPIRICAL COVARIANCE MATRIX IT CAN BE DONE BY SIMPLY SHIFTING EVERY EIGENVALUE ACCORDING TO A GIVEN OFFSET WHICH IS EQUIVALENT OF FINDING THE L2PENALIZED MAXIMUM LIKELIHOOD ESTIMATOR OF THE COVARIANCE MATRIX IN PRACTICE SHRINKAGE BOILS DOWN TO A SIMPLE A CONVEX TRANSFORMATION $\Sigma_{\text{SHRUNK}} = (1-\alpha)\hat{\Sigma} + \alpha\frac{\text{Tr}\hat{\Sigma}}{p}\text{Id}$

CHOOSING THE AMOUNT OF SHRINKAGE αAMOUNTS TO SETTING A BIASVARIANCE TRADEOFF AND IS DISCUSSED BELOW

EXAMPLES

• SEE SHRINKAGE COVARIANCE ESTIMATION LEDOITWOLF VS OAS AND MAXLIKELIHOOD FOR AN EXAMPLE ON HOW TO FIT A SHRUNKCOVARIANCE OBJECT TO DATA

LEDOITWOLF SHRINKAGE

IN THEIR 2004 PAPER1 O LEDOIT AND M WOLF PROPOSE A FORMULA TO COMPUTE THE OPTIMAL SHRINKAGE COEFFICIENT αTHAT MINIMIZES THE MEAN SQUARED ERROR BETWEEN THE ESTIMATED AND THE REAL COVARIANCE MATRIX

THE LEDOITWOLF ESTIMATOR OF THE COVARIANCE MATRIX CAN BE COMPUTED ON A SAMPLE WITH THE LEDOITWOLF FUNCTION OF THESKLEARNCOVARIANCE PACKAGE OR IT CAN BE OTHERWISE OBTAINED BY FITTING A LEDOITWOLF OBJECT TO THE SAME SAMPLE

NOTE CASE WHEN POPULATION COVARIANCE MATRIX IS ISOTROPIC

IT IS IMPORTANT TO NOTE THAT WHEN THE NUMBER OF SAMPLES IS MUCH LARGER THAN THE NUMBER OF FEATURES ONE WOULD EXPECT THAT NO SHRINKAGE WOULD BE NECESSARY THE INTUITION BEHIND THIS IS THAT IF THE POPULATION COVARIANCE IS FULL RANK WHEN THE NUMBER OF SAMPLE GROWS THE SAMPLE COVARIANCE WILL ALSO BECOME POSITIVE DEFINITE AS A RESULT NO SHRINKAGE WOULD NECESSARY AND THE METHOD SHOULD AUTOMATICALLY DO THIS

THIS HOWEVER IS NOT THE CASE IN THE LEDOITWOLF PROCEDURE WHEN THE POPULATION COVARIANCE HAPPENS TO BE A MULTIPLE OF THE IDENTITY MATRIX IN THIS CASE THE LEDOITWOLF SHRINKAGE ESTIMATE APPROACHES 1 AS THE NUMBER OF SAMPLES INCREASES THIS INDICATES THAT THE OPTIMAL ESTIMATE OF THE COVARIANCE MATRIX IN THE LEDOITWOLF SENSE IS MULTIPLE OF THE IDENTITY SINCE THE POPULATION COVARIANCE IS ALREADY A MULTIPLE OF THE IDENTITY MATRIX THE LEDOITWOLF SOLUTION IS INDEED A REASONABLE ESTIMATE

1O LEDOIT AND M WOLF “A WELLCONDITIONED ESTIMATOR FOR LARGEDIMENSIONAL COVARIANCE MATRICES” JOURNAL OF MULTIVARIATE ANALY UME 88 ISSUE 2 FEBRUARY 2004 PAGES 365411

EXAMPLES
• SEE SHRINKAGE COVARIANCE ESTIMATION LEDOITWOLF VS OAS AND MAXLIKELIHOOD FOR AN EXAMPLE ON HOW TO FIT A LEDOITWOLF OBJECT TO DATA AND FOR VISUALIZING THE PERFORMANCES OF THE LEDOITWOLF ESTIMATOR IN TERMS OF LIKELIHOOD
REFERENCES
ORACLE APPROXIMATING SHRINKAGE
UNDER THE ASSUMPTION THAT THE DATA ARE GAUSSIAN DISTRIBUTED CHEN ET AL2DERIVED A FORMULA AIMED AT CHOOSING A SHRINKAGE COEFFICIENT THAT YIELDS A SMALLER MEAN SQUARED ERROR THAN THE ONE GIVEN BY LEDOIT AND WOLF'S FORMULA THE RESULTING ESTIMATOR IS KNOWN AS THE ORACLE SHRINKAGE APPROXIMATING ESTIMATOR OF THE COVARIANCE
THE OAS ESTIMATOR OF THE COVARIANCE MATRIX CAN BE COMPUTED ON A SAMPLE WITH THE OAS FUNCTION OF THE SKLEARN COVARIANCE PACKAGE OR IT CAN BE OTHERWISE OBTAINED BY FITTING AN OAS OBJECT TO THE SAME SAMPLE
FIG 37 BIASVARIANCE TRADEOFF WHEN SETTING THE SHRINKAGE COMPARING THE CHOICES OF LEDOITWOLF AND OAS ESTIMA TORS
REFERENCES
EXAMPLES
• SEE SHRINKAGE COVARIANCE ESTIMATION LEDOITWOLF VS OAS AND MAXLIKELIHOOD FOR AN EXAMPLE ON HOW TO FIT AN OAS OBJECT TO DATA
2CHEN ET AL "SHRINKAGE ALGORITHMS FOR MMSE COVARIANCE ESTIMATION" IEEE TRANS ON SIGN PROC V OLUME 58 ISSUE 10 OCTOBER 2010

• SEE LEDOITWOLF VS OAS ESTIMATION TO VISUALIZE THE MEAN SQUARED ERROR DIFFERENCE BETWEEN A LEDOITWOLF AND ANOAS ESTIMATOR OF THE COVARIANCE

SPARSE INVERSE COVARIANCE

THE MATRIX INVERSE OF THE COVARIANCE MATRIX OFTEN CALLED THE PRECISION MATRIX IS PROPORTIONAL TO THE PARTIAL CORRELATION MATRIX IT GIVES THE PARTIAL INDEPENDENCE RELATIONSHIP IN OTHER WORDS IF TWO FEATURES ARE INDEPENDENT CONDITIONALLY ON THE OTHERS THE CORRESPONDING COEFFICIENT IN THE PRECISION MATRIX WILL BE ZERO THIS IS WHY IT MAKES SENSE TO ESTIMATE A SPARSE PRECISION MATRIX THE ESTIMATION OF THE COVARIANCE MATRIX IS BETTER CONDITIONED BY LEARNING INDEPENDENCE RELATIONS FROM THE DATA THIS IS KNOWN AS COVARIANCE SELECTION

IN THE SMALLSAMPLES SITUATION IN WHICH NSAMPLES IS ON THE ORDER OF NFEATURES OR SMALLER SPARSE INVERSE COVARIANCE ESTIMATORS TEND TO WORK BETTER THAN SHRUNK COVARIANCE ESTIMATORS HOWEVER IN THE OPPOSITE SITUATION OR FOR VERY CORRELATED DATA THEY CAN BE NUMERICALLY UNSTABLE IN ADDITION UNLIKE SHRINKAGE ESTIMATORS SPARSE ESTIMATORS ARE ABLE TO RECOVER OFFDIAGONAL STRUCTURE

THEGRAPHICALLASSO ESTIMATOR USES AN L1 PENALTY TO ENFORCE SPARSITY ON THE PRECISION MATRIX THE HIGHER ITS ALPHA PARAMETER THE MORE SPARSE THE PRECISION MATRIX THE CORRESPONDING GRAPHICALLASSOCV OBJECT USES CROSSVALIDATION TO AUTOMATICALLY SET THE ALPHA PARAMETER

NOTE STRUCTURE RECOVERY

RECOVERING A GRAPHICAL STRUCTURE FROM CORRELATIONS IN THE DATA IS A CHALLENGING THING IF YOU ARE INTERESTED IN SUCH RECOVERY KEEP IN MIND THAT

• RECOVERY IS EASIER FROM A CORRELATION MATRIX THAN A COVARIANCE MATRIX STANDARDIZE YOUR OBSERVATIONS BEFORE RUNNINGGRAPHICALLASSO

• IF THE UNDERLYING GRAPH HAS NODES WITH MUCH MORE CONNECTIONS THAN THE AVERAGE NODE THE ALGORITHM WILL MISS SOME OF THESE CONNECTIONS

FIG 38 A COMPARISON OF MAXIMUM LIKELIHOOD SHRINKAGE AND SPARSE ESTIMATES OF THE COVARIANCE AND PRECISION MATRIX IN THE VERY SMALL SAMPLES SETTINGS

• IF YOUR NUMBER OF OBSERVATIONS IS NOT LARGE COMPARED TO THE NUMBER OF EDGES IN YOUR UNDERLYING GRAPH YOU WILL NOT RECOVER IT

• EVEN IF YOU ARE IN FAVORABLE RECOVERY CONDITIONS THE ALPHA PARAMETER CHOSEN BY CROSSVALIDATION EG USING THE GRAPHICALLASSOCV OBJECT WILL LEAD TO SELECTING TOO MANY EDGES HOWEVER THE RELEVANT EDGES WILL HAVE HEAVIER WEIGHTS THAN THE IRRELEVANT ONES

THE MATHEMATICAL FORMULATION IS THE FOLLOWING

□ ARGMIN□

TR□□−LOGDET □□‖□‖1

WHERE □IS THE PRECISION MATRIX TO BE ESTIMATED AND □IS THE SAMPLE COVARIANCE MATRIX ‖□‖1IS THE SUM OF THE ABSO LUTE VALUES OF OFFDIAGONAL COEFFICIENTS OF □ THE ALGORITHM EMPLOYED TO SOLVE THIS PROBLEM IS THE GLASSO ALGORITHM FROM THE FRIEDMAN 2008 BIOSTATISTICS PAPER IT IS THE SAME ALGORITHM AS IN THE R GLASSO PACKAGE

EXAMPLES

•SPARSE INVERSE COVARIANCE ESTIMATION EXAMPLE ON SYNTHETIC DATA SHOWING SOME RECOVERY OF A STRUCTURE AND COMPARING TO OTHER COVARIANCE ESTIMATORS

•VISUALIZING THE STOCK MARKET STRUCTURE EXAMPLE ON REAL STOCK MARKET DATA FINDING WHICH SYMBOLS ARE MOST LINKED

REFERENCES

• FRIEDMAN ET AL “SPARSE INVERSE COVARIANCE ESTIMATION WITH THE GRAPHICAL LASSO” BIOSTATISTICS 9 PP 432 2008

ROBUST COVARIANCE ESTIMATION

REAL DATA SETS ARE OFTEN SUBJECT TO MEASUREMENT OR RECORDING ERRORS REGULAR BUT UNCOMMON OBSERVATIONS MAY ALSO APPEAR FOR A VARIETY OF REASONS OBSERVATIONS WHICH ARE VERY UNCOMMON ARE CALLED OUTLIERS THE EMPIRICAL COVARIANCE ESTIMATOR AND THE SHRUNK COVARIANCE ESTIMATORS PRESENTED ABOVE ARE VERY SENSITIVE TO THE PRESENCE OF OUTLIERS IN THE DATA THEREFORE ONE SHOULD USE ROBUST COVARIANCE ESTIMATORS TO ESTIMATE THE COVARIANCE OF ITS REAL DATA SETS ALTERNATIVELY ROBUST COVARIANCE ESTIMATORS CAN BE USED TO PERFORM OUTLIER DETECTION AND DISCARDDOWNWEIGHT SOME OBSERVATIONS ACCORDING TO FURTHER PROCESSING OF THE DATA

THESKLEARNCOVARIANCE PACKAGE IMPLEMENTS A ROBUST ESTIMATOR OF COVARIANCE THE MINIMUM COVARIANCE DE TERMINANT3

MINIMUM COVARIANCE DETERMINANT

THE MINIMUM COVARIANCE DETERMINANT ESTIMATOR IS A ROBUST ESTIMATOR OF A DATA SET'S COVARIANCE INTRODUCED BY PJ ROUSSEEUW IN3 THE IDEA IS TO FIND A GIVEN PROPORTION H OF "GOOD" OBSERVATIONS WHICH ARE NOT OUTLIERS AND COMPUTE THEIR EMPIRICAL COVARIANCE MATRIX THIS EMPIRICAL COVARIANCE MATRIX IS THEN RESCALED TO COMPENSATE THE PERFORMED SELECTION OF OBSERVATIONS "CONSISTENCY STEP" HAVING COMPUTED THE MINIMUM COVARIANCE DETERMINANT ESTIMATOR ONE CAN GIVE WEIGHTS TO OBSERVATIONS ACCORDING TO THEIR MAHALANOBIS DISTANCE LEADING TO A REWEIGHTED ESTIMATE OF THE COVARIANCE MATRIX OF THE DATA SET "REWEIGHTING STEP"

ROUSSEEUW AND VAN DRIESSEN4DEVELOPED THE FASTMCD ALGORITHM IN ORDER TO COMPUTE THE MINIMUM COVARIANCE DETERMINANT THIS ALGORITHM IS USED IN SCIKITLEARN WHEN FITTING AN MCD OBJECT TO DATA THE FASTMCD ALGORITHM ALSO COMPUTES A ROBUST ESTIMATE OF THE DATA SET LOCATION AT THE SAME TIME

RAW ESTIMATES CAN BE ACCESSED AS RAWLOCATION ANDRAWCOVARIANCE ATTRIBUTES OF A MINCOVDET ROBUST COVARIANCE ESTIMATOR OBJECT

REFERENCES

EXAMPLES

• SEE ROBUST VS EMPIRICAL COVARIANCE ESTIMATE FOR AN EXAMPLE ON HOW TO FIT A MINCOVDET OBJECT TO DATA AND SEE HOW THE ESTIMATE REMAINS ACCURATE DESPITE THE PRESENCE OF OUTLIERS

• SEE ROBUST COVARIANCE ESTIMATION AND MAHALANOBIS DISTANCES RELEVANCE TO VISUALIZE THE DIFFERENCE BETWEEN EMPIRICALCOVARIANCE ANDMINCOVDET COVARIANCE ESTIMATORS IN TERMS OF MAHALANOBIS DISTANCE SO WE GET A BETTER ESTIMATE OF THE PRECISION MATRIX TOO

3P J ROUSSEEUW LEAST MEDIAN OF SQUARES REGRESSION J AM STAT ASS 79871 1984

4A FAST ALGORITHM FOR THE MINIMUM COVARIANCE DETERMINANT ESTIMATOR 1999 AMERICAN STATISTICAL ASSOCIATION AND THE AMERICAN QUALITY TECHNOMETRICS

INFLUENCE OF OUTLIERS ON LOCATION AND COVARIANCE
ESTIMATESSEPARATING INLIERS FROM OUTLIERS USING A MAHALANOBIS
DISTANCE
327 NOVELTY AND OUTLIER DETECTION
MANY APPLICATIONS REQUIRE BEING ABLE TO DECIDE WHETHER A NEW OBSERVATION BELONGS TO THE SAME DISTRIBUTION AS EXISTING OBSERVATIONS IT IS AN INLIER OR SHOULD BE CONSIDERED AS DIFFERENT IT IS AN OUTLIER OFTEN THIS ABILITY IS USED TO CLEAN REAL DATA SETS TWO IMPORTANT DISTINCTIONS MUST BE MADE
OUTLIER DETECTION THE TRAINING DATA CONTAINS OUTLIERS WHICH ARE DEFINED AS OBSERVATIONS THAT ARE FAR FROM THE OTHERS OUTLIER DETECTION ESTIMATORS THUS TRY TO FIT THE REGIONS WHERE THE TRAINING DATA IS THE MOST CONCENTRATED IGNORING THE DEVIANT OBSERVATIONS
NOVELTY DETECTION THE TRAINING DATA IS NOT POLLUTED BY OUTLIERS AND WE ARE INTERESTED IN DETECTING WHETHER ANEW OBSERVATION IS AN OUTLIER IN THIS CONTEXT AN OUTLIER IS ALSO CALLED A NOVELTY
OUTLIER DETECTION AND NOVELTY DETECTION ARE BOTH USED FOR ANOMALY DETECTION WHERE ONE IS INTERESTED IN DETECTING ABNORMAL OR UNUSUAL OBSERVATIONS OUTLIER DETECTION IS THEN ALSO KNOWN AS UNSUPERVISED ANOMALY DETECTION AND NOVELTY DETECTION AS SEMISUPERVISED ANOMALY DETECTION IN THE CONTEXT OF OUTLIER DETECTION THE OUTLIERSANOMALIES CANNOT FORM A DENSE CLUSTER AS AVAILABLE ESTIMATORS ASSUME THAT THE OUTLIERSANOMALIES ARE LOCATED IN LOW DENSITY REGIONS ON THE CONTRARY IN THE CONTEXT OF NOVELTY DETECTION NOVELTIESANOMALIES CAN FORM A DENSE CLUSTER AS LONG AS THEY ARE IN A LOW DENSITY REGION OF THE TRAINING DATA CONSIDERED AS NORMAL IN THIS CONTEXT
THE SCIKITLEARN PROJECT PROVIDES A SET OF MACHINE LEARNING TOOLS THAT CAN BE USED BOTH FOR NOVELTY OR OUTLIER DETECTION THIS STRATEGY IS IMPLEMENTED WITH OBJECTS LEARNING IN AN UNSUPERVISED WAY FROM THE DATA
ESTIMATORFITXTRAIN
NEW OBSERVATIONS CAN THEN BE SORTED AS INLIERS OR OUTLIERS WITH A PREDICT METHOD
ESTIMATORPREDICTXTEST
INLIERS ARE LABELED 1 WHILE OUTLIERS ARE LABELED 1 THE PREDICT METHOD MAKES USE OF A THRESHOLD ON THE RAW SCORING FUNCTION COMPUTED BY THE ESTIMATOR THIS SCORING FUNCTION IS ACCESSIBLE THROUGH THE SCORESAMPLES METHOD WHILE THE THRESHOLD CAN BE CONTROLLED BY THE CONTAMINATION PARAMETER
THEDECISIONFUNCTION METHOD IS ALSO DEFINED FROM THE SCORING FUNCTION IN SUCH A WAY THAT NEGATIVE VALUES ARE OUTLIERS AND NONNEGATIVE ONES ARE INLIERS
ESTIMATORDECISIONFUNCTIONXTEST

NOTE THAT NEIGHBORSLOCALOUTLIERFACTOR DOES NOT SUPPORT PREDICT DECISIONFUNCTION AND
SCORESAMPLES METHODS BY DEFAULT BUT ONLY A FITPREDICT METHOD AS THIS ESTIMATOR WAS ORIGINALLY MEANT
TO BE APPLIED FOR OUTLIER DETECTION THE SCORES OF ABNORMALITY OF THE TRAINING SAMPLES ARE ACCESSIBLE THROUGH THE
NEGATIVEOUTLIERFACTOR ATTRIBUTE
IF YOU REALLY WANT TO USE NEIGHBORSLOCALOUTLIERFACTOR FOR NOVELTY DETECTION IE PREDICT LABELS OR COMPUTE
THE SCORE OF ABNORMALITY OF NEW UNSEEN DATA YOU CAN INSTANTIATE THE ESTIMATOR WITH THE NOVELTY PARAMETER SET TO
TRUE BEFORE FITTING THE ESTIMATOR IN THIS CASE FITPREDICT IS NOT AVAILABLE
WARNING NOVELTY DETECTION WITH LOCAL OUTLIER FACTOR
WHENNOVELTY IS SET TOTRUE BE AWARE THAT YOU MUST ONLY USE PREDICT DECISIONFUNCTION
ANDSCORESAMPLES ON NEW UNSEEN DATA AND NOT ON THE TRAINING SAMPLES AS THIS WOULD LEAD TO
WRONG RESULTS THE SCORES OF ABNORMALITY OF THE TRAINING SAMPLES ARE ALWAYS ACCESSIBLE THROUGH THE
NEGATIVEOUTLIERFACTOR ATTRIBUTE
THE BEHAVIOR OF NEIGHBORSLOCALOUTLIERFACTOR IS SUMMARIZED IN THE FOLLOWING TABLE
METHOD OUTLIER DETECTION NOVELTY DETECTION
FITPREDICT OK NOT AVAILABLE
PREDICT NOT AVAILABLE USE ONLY ON NEW DATA
DECISIONFUNCTION NOT AVAILABLE USE ONLY ON NEW DATA
SCORESAMPLES USENEGATIVEOUTLIERFACTOR USE ONLY ON NEW DATA
OVERVIEW OF OUTLIER DETECTION METHODS
A COMPARISON OF THE OUTLIER DETECTION ALGORITHMS IN SCIKITLEARN LOCAL OUTLIER FACTOR LOF DOES NOT SHOW A DECISION
BOUNDARY IN BLACK AS IT HAS NO PREDICT METHOD TO BE APPLIED ON NEW DATA WHEN IT IS USED FOR OUTLIER DETECTION
ENSEMBLEISOLATIONFOREST ANDNEIGHBORSLOCALOUTLIERFACTOR PERFORM REASONABLY WELL ON THE
DATA SETS CONSIDERED HERE THE SVMONECLASSSVM IS KNOWN TO BE SENSITIVE TO OUTLIERS AND THUS DOES NOT PERFORM
VERY WELL FOR OUTLIER DETECTION FINALLY COVARIANCEELLIPTICENVELOPE ASSUMES THE DATA IS GAUSSIAN AND
LEARNS AN ELLIPSE FOR MORE DETAILS ON THE DIFFERENT ESTIMATORS REFER TO THE EXAMPLE COMPARING ANOMALY DETECTION
ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS AND THE SECTIONS HEREUNDER
EXAMPLES
• SEE COMPARING ANOMALY DETECTION ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS FOR A COM
PARISON OF THE SVMONECLASSSVM THEENSEMBLEISOLATIONFOREST THENEIGHBORS
LOCALOUTLIERFACTOR ANDCOVARIANCEELLIPTICENVELOPE
NOVELTY DETECTION
CONSIDER A DATA SET OF □OBSERVATIONS FROM THE SAME DISTRIBUTION DESCRIBED BY □FEATURES CONSIDER NOW THAT WE ADD ONE
MORE OBSERVATION TO THAT DATA SET IS THE NEW OBSERVATION SO DIFFERENT FROM THE OTHERS THAT WE CAN DOUBT IT IS REGULAR
IE DOES IT COME FROM THE SAME DISTRIBUTION OR ON THE CONTRARY IS IT SO SIMILAR TO THE OTHER THAT WE CANNOT DISTINGUISH
IT FROM THE ORIGINAL OBSERVATIONS THIS IS THE QUESTION ADDRESSED BY THE NOVELTY DETECTION TOOLS AND METHODS
IN GENERAL IT IS ABOUT TO LEARN A ROUGH CLOSE FRONTIER DELIMITING THE CONTOUR OF THE INITIAL OBSERVATIONS DISTRIBUTION
PLOTTED IN EMBEDDING □DIMENSIONAL SPACE THEN IF FURTHER OBSERVATIONS LAY WITHIN THE FRONTIERDELIMITED SUBSPACE

THEY ARE CONSIDERED AS COMING FROM THE SAME POPULATION THAN THE INITIAL OBSERVATIONS OTHERWISE IF THEY LAY OUTSIDE THE FRONTIER WE CAN SAY THAT THEY ARE ABNORMAL WITH A GIVEN CONFIDENCE IN OUR ASSESSMENT

THE ONECLASS SVM HAS BEEN INTRODUCED BY SCHÖLKOPF ET AL FOR THAT PURPOSE AND IMPLEMENTED IN THE SUPPORT VECTOR MACHINES MODULE IN THE SVMONECLASSSVM OBJECT IT REQUIRES THE CHOICE OF A KERNEL AND A SCALAR PARAMETER TO DEFINE A FRONTIER THE RBF KERNEL IS USUALLY CHOSEN ALTHOUGH THERE EXISTS NO EXACT FORMULA OR ALGORITHM TO SET ITS BANDWIDTH PARAMETER THIS IS THE DEFAULT IN THE SCIKITLEARN IMPLEMENTATION THE PARAMETER ALSO KNOWN AS THE MARGIN OF THE ONECLASS SVM CORRESPONDS TO THE PROBABILITY OF FINDING A NEW BUT REGULAR OBSERVATION OUTSIDE THE FRONTIER

REFERENCES

• ESTIMATING THE SUPPORT OF A HIGHDIMENSIONAL DISTRIBUTION SCHÖLKOPF BERNHARD ET AL NEURAL COMPUTATION 137 2001 14431471

EXAMPLES

• SEE ONECLASS SVM WITH NONLINEAR KERNEL RBF FOR VISUALIZING THE FRONTIER LEARNED AROUND SOME DATA BY A SVMONECLASSSVM OBJECT

•SPECIES DISTRIBUTION MODELING

OUTLIER DETECTION

OUTLIER DETECTION IS SIMILAR TO NOVELTY DETECTION IN THE SENSE THAT THE GOAL IS TO SEPARATE A CORE OF REGULAR OBSERVATIONS FROM SOME POLLUTING ONES CALLED OUTLIERS YET IN THE CASE OF OUTLIER DETECTION WE DON’T HAVE A CLEAN DATA SET REPRESENTING THE POPULATION OF REGULAR OBSERVATIONS THAT CAN BE USED TO TRAIN ANY TOOL

FITTING AN ELLIPTIC ENVELOPE
ONE COMMON WAY OF PERFORMING OUTLIER DETECTION IS TO ASSUME THAT THE REGULAR DATA COME FROM A KNOWN DISTRIBUTION EG DATA ARE GAUSSIAN DISTRIBUTED FROM THIS ASSUMPTION WE GENERALLY TRY TO DEFINE THE “SHAPE” OF THE DATA AND CAN DEFINE OUTLYING OBSERVATIONS AS OBSERVATIONS WHICH STAND FAR ENOUGH FROM THE FIT SHAPE
THE SCIKITLEARN PROVIDES AN OBJECT COVARIANCEELLIPTICENVELOPE THAT FITS A ROBUST COVARIANCE ESTIMATE TO THE DATA AND THUS FITS AN ELLIPSE TO THE CENTRAL DATA POINTS IGNORING POINTS OUTSIDE THE CENTRAL MODE
FOR INSTANCE ASSUMING THAT THE INLIER DATA ARE GAUSSIAN DISTRIBUTED IT WILL ESTIMATE THE INLIER LOCATION AND COVARIANCE IN A ROBUST WAY IE WITHOUT BEING INFLUENCED BY OUTLIERS THE MAHALANOBIS DISTANCES OBTAINED FROM THIS ESTIMATE IS USED TO DERIVE A MEASURE OF OUTLYINGNESS THIS STRATEGY IS ILLUSTRATED BELOW
EXAMPLES
• SEE ROBUST COVARIANCE ESTIMATION AND MAHALANOBIS DISTANCES RELEVANCE FOR AN ILLUSTRATION OF THE DIF FERENCE BETWEEN USING A STANDARD COVARIANCEEMPIRICALCOVARIANCE OR A ROBUST ESTIMATE COVARIANCEMINCOVDET OF LOCATION AND COVARIANCE TO ASSESS THE DEGREE OF OUTLYINGNESS OF AN OB SERVATION
REFERENCES
• ROUSSEEUW PJ VAN DRIESSEN K “A FAST ALGORITHM FOR THE MINIMUM COVARIANCE DETERMINANT ESTIMATOR” TECHNOMETRICS 413 212 1999

ISOLATION FOREST
ONE EFFICIENT WAY OF PERFORMING OUTLIER DETECTION IN HIGHDIMENSIONAL DATASETS IS TO USE RANDOM FORESTS THE ENSEMBLEISOLATIONFOREST 'ISOLATES' OBSERVATIONS BY RANDOMLY SELECTING A FEATURE AND THEN RANDOMLY SE LECTING A SPLIT VALUE BETWEEN THE MAXIMUM AND MINIMUM VALUES OF THE SELECTED FEATURE
SINCE RECURSIVE PARTITIONING CAN BE REPRESENTED BY A TREE STRUCTURE THE NUMBER OF SPLITTINGS REQUIRED TO ISOLATE A SAMPLE IS EQUIVALENT TO THE PATH LENGTH FROM THE ROOT NODE TO THE TERMINATING NODE
THIS PATH LENGTH AVERAGED OVER A FOREST OF SUCH RANDOM TREES IS A MEASURE OF NORMALITY AND OUR DECISION FUNCTION RANDOM PARTITIONING PRODUCES NOTICEABLY SHORTER PATHS FOR ANOMALIES HENCE WHEN A FOREST OF RANDOM TREES COLLEC TIVELY PRODUCE SHORTER PATH LENGTHS FOR PARTICULAR SAMPLES THEY ARE HIGHLY LIKELY TO BE ANOMALIES
THE IMPLEMENTATION OF ENSEMBLEISOLATIONFOREST IS BASED ON AN ENSEMBLE OF TREE EXTRATREEREGRESSOR FOLLOWING ISOLATION FOREST ORIGINAL PAPER THE MAXIMUM DEPTH OF EACH TREE IS SET TO⌈LOG2□⌉WHERE □IS THE NUMBER OF SAMPLES USED TO BUILD THE TREE SEE LIU ET AL 2008 FOR MORE DETAILS
THIS ALGORITHM IS ILLUSTRATED BELOW THE ENSEMBLEISOLATIONFOREST SUPPORTSWARMSTARTTRUE WHICH ALLOWS YOU TO ADD MORE TREES TO AN ALREADY FITTED MODEL

```
 FROM SKLEARNENSEMBLE IMPORT ISOLATIONFOREST
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 3 2 0 0 20 50 3 5
CLF  ISOLATIONFORESTNESTIMATORS10 WARMSTART TRUE
CLFFITX  FIT 10 TREES
CLFSETPARAMSNESTIMATORS20  ADD 10 MORE TREES
CLFFITX  FIT THE ADDED TREES
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EXAMPLES
• SEE ISOLATIONFOREST EXAMPLE FOR AN ILLUSTRATION OF THE USE OF ISOLATIONFOREST

• SEE COMPARING ANOMALY DETECTION ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS FOR A COMPARISON OF ENSEMBLEISOLATIONFOREST WITHNEIGHBORSLOCALOUTLIERFACTOR SVMONECLASSSVM TUNED TO PERFORM LIKE AN OUTLIER DETECTION METHOD AND A COVARIANCEBASED OUTLIER DETECTION WITH COVARIANCEELLIPTICENVELOPE

REFERENCES

• LIU FEI TONY TING KAI MING AND ZHOU ZHIHUA “ISOLATION FOREST” DATA MINING 2008 ICDM’08 EIGHTH IEEE INTERNATIONAL CONFERENCE ON

LOCAL OUTLIER FACTOR

ANOTHER EFFICIENT WAY TO PERFORM OUTLIER DETECTION ON MODERATELY HIGH DIMENSIONAL DATASETS IS TO USE THE LOCAL OUTLIER FACTOR LOF ALGORITHM

THENEIGHBORSLOCALOUTLIERFACTOR LOF ALGORITHM COMPUTES A SCORE CALLED LOCAL OUTLIER FACTOR REFLECTING THE DEGREE OF ABNORMALITY OF THE OBSERVATIONS IT MEASURES THE LOCAL DENSITY DEVIATION OF A GIVEN DATA POINT WITH RESPECT TO ITS NEIGHBORS THE IDEA IS TO DETECT THE SAMPLES THAT HAVE A SUBSTANTIALLY LOWER DENSITY THAN THEIR NEIGHBORS IN PRACTICE THE LOCAL DENSITY IS OBTAINED FROM THE KNEAREST NEIGHBORS THE LOF SCORE OF AN OBSERVATION IS EQUAL TO THE RATIO OF THE AVERAGE LOCAL DENSITY OF HIS KNEAREST NEIGHBORS AND ITS OWN LOCAL DENSITY A NORMAL INSTANCE IS EXPECTED TO HAVE A LOCAL DENSITY SIMILAR TO THAT OF ITS NEIGHBORS WHILE ABNORMAL DATA ARE EXPECTED TO HAVE MUCH SMALLER LOCAL DENSITY

THE NUMBER K OF NEIGHBORS CONSIDERED ALIAS PARAMETER NNEIGHBORS IS TYPICALLY CHOSEN 1 GREATER THAN THE MINIMUM NUMBER OF OBJECTS A CLUSTER HAS TO CONTAIN SO THAT OTHER OBJECTS CAN BE LOCAL OUTLIERS RELATIVE TO THIS CLUSTER AND 2 SMALLER THAN THE MAXIMUM NUMBER OF CLOSE BY OBJECTS THAT CAN POTENTIALLY BE LOCAL OUTLIERS IN PRACTICE SUCH INFORMATIONS ARE GENERALLY NOT AVAILABLE AND TAKING NNEIGHBORS20 APPEARS TO WORK WELL IN GENERAL WHEN THE PROPORTION OF OUTLIERS IS HIGH IE GREATER THAN 10 AS IN THE EXAMPLE BELOW NNEIGHBORS SHOULD BE GREATER NNEIGHBORS35 IN THE EXAMPLE BELOW

THE STRENGTH OF THE LOF ALGORITHM IS THAT IT TAKES BOTH LOCAL AND GLOBAL PROPERTIES OF DATASETS INTO CONSIDERATION IT CAN PERFORM WELL EVEN IN DATASETS WHERE ABNORMAL SAMPLES HAVE DIFFERENT UNDERLYING DENSITIES THE QUESTION IS NOT HOW ISOLATED THE SAMPLE IS BUT HOW ISOLATED IT IS WITH RESPECT TO THE SURROUNDING NEIGHBORHOOD

WHEN APPLYING LOF FOR OUTLIER DETECTION THERE ARE NO PREDICT DECISIONFUNCTION ANDSCORESAMPLES METHODS BUT ONLY A FITPREDICT METHOD THE SCORES OF ABNORMALITY OF THE TRAINING SAMPLES ARE ACCESSIBLE THROUGH THE NEGATIVEOUTLIERFACTOR ATTRIBUTE NOTE THAT PREDICT DECISIONFUNCTION AND SCORESAMPLES CAN BE USED ON NEW UNSEEN DATA WHEN LOF IS APPLIED FOR NOVELTY DETECTION IE WHEN THE NOVELTY PARAMETER IS SET TO TRUE SEE NOVELTY DETECTION WITH LOCAL OUTLIER FACTOR

THIS STRATEGY IS ILLUSTRATED BELOW

EXAMPLES

• SEE OUTLIER DETECTION WITH LOCAL OUTLIER FACTOR LOF FOR AN ILLUSTRATION OF THE USE OF NEIGHBORS LOCALOUTLIERFACTOR
• SEE COMPARING ANOMALY DETECTION ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS FOR A COMPARISON WITH OTHER ANOMALY DETECTION METHODS

REFERENCES
• BREUNIG KRIEGEL NG AND SANDER 2000 LOF IDENTIFYING DENSITYBASED LOCAL OUTLIERS PROC ACM SIGMOD
NOVELTY DETECTION WITH LOCAL OUTLIER FACTOR
TO USENEIGHBORSLOCALOUTLIERFACTOR FOR NOVELTY DETECTION IE PREDICT LABELS OR COMPUTE THE SCORE OF
ABNORMALITY OF NEW UNSEEN DATA YOU NEED TO INSTANTIATE THE ESTIMATOR WITH THE NOVELTY PARAMETER SET TO TRUE
BEFORE FITTING THE ESTIMATOR
LOF LOCALOUTLIERFACTORNOVELTY TRUE
LOFFITXTRAIN
NOTE THATFITPREDICT IS NOT AVAILABLE IN THIS CASE
WARNING NOVELTY DETECTION WITH LOCAL OUTLIER FACTOR‘
WHENNOVELTY IS SET TOTRUE BE AWARE THAT YOU MUST ONLY USE PREDICT DECISIONFUNCTION
ANDSCORESAMPLES ON NEW UNSEEN DATA AND NOT ON THE TRAINING SAMPLES AS THIS WOULD LEAD TO
WRONG RESULTS THE SCORES OF ABNORMALITY OF THE TRAINING SAMPLES ARE ALWAYS ACCESSIBLE THROUGH THE
NEGATIVEOUTLIERFACTOR ATTRIBUTE
NOVELTY DETECTION WITH LOCAL OUTLIER FACTOR IS ILLUSTRATED BELOW

328 DENSITY ESTIMATION
DENSITY ESTIMATION WALKS THE LINE BETWEEN UNSUPERVISED LEARNING FEATURE ENGINEERING AND DATA MODELING SOME OF THE MOST POPULAR AND USEFUL DENSITY ESTIMATION TECHNIQUES ARE MIXTURE MODELS SUCH AS GAUSSIAN MIXTURES SKLEARN MIXTUREGAUSSIANMIXTURE AND NEIGHBORBASED APPROACHES SUCH AS THE KERNEL DENSITY ESTIMATE SKLEARN NEIGHBORSKERNELDENSITY GAUSSIAN MIXTURES ARE DISCUSSED MORE FULLY IN THE CONTEXT OF CLUSTERING BECAUSE THE TECHNIQUE IS ALSO USEFUL AS AN UNSUPERVISED CLUSTERING SCHEME
DENSITY ESTIMATION IS A VERY SIMPLE CONCEPT AND MOST PEOPLE ARE ALREADY FAMILIAR WITH ONE COMMON DENSITY ESTIMATION TECHNIQUE THE HISTOGRAM
DENSITY ESTIMATION HISTOGRAMS
A HISTOGRAM IS A SIMPLE VISUALIZATION OF DATA WHERE BINS ARE DEFINED AND THE NUMBER OF DATA POINTS WITHIN EACH BIN IS TALLIED AN EXAMPLE OF A HISTOGRAM CAN BE SEEN IN THE UPPERLEFT PANEL OF THE FOLLOWING FIGURE

A MAJOR PROBLEM WITH HISTOGRAMS HOWEVER IS THAT THE CHOICE OF BINNING CAN HAVE A DISPROPORTIONATE EFFECT ON THE RESULTING VISUALIZATION CONSIDER THE UPPERRIGHT PANEL OF THE ABOVE FIGURE IT SHOWS A HISTOGRAM OVER THE SAME DATA WITH THE BINS SHIFTED RIGHT THE RESULTS OF THE TWO VISUALIZATIONS LOOK ENTIRELY DIFFERENT AND MIGHT LEAD TO DIFFERENT INTERPRETATIONS OF THE DATA

INTUITIVELY ONE CAN ALSO THINK OF A HISTOGRAM AS A STACK OF BLOCKS ONE BLOCK PER POINT BY STACKING THE BLOCKS IN THE APPROPRIATE GRID SPACE WE RECOVER THE HISTOGRAM BUT WHAT IF INSTEAD OF STACKING THE BLOCKS ON A REGULAR GRID WE CENTER EACH BLOCK ON THE POINT IT REPRESENTS AND SUM THE TOTAL HEIGHT AT EACH LOCATION THIS IDEA LEADS TO THE LOWERLEFT VISUALIZATION IT IS PERHAPS NOT AS CLEAN AS A HISTOGRAM BUT THE FACT THAT THE DATA DRIVE THE BLOCK LOCATIONS MEAN THAT IT IS A MUCH BETTER REPRESENTATION OF THE UNDERLYING DATA

THIS VISUALIZATION IS AN EXAMPLE OF A KERNEL DENSITY ESTIMATION IN THIS CASE WITH A TOPHAT KERNEL IE A SQUARE BLOCK AT EACH POINT WE CAN RECOVER A SMOOTHER DISTRIBUTION BY USING A SMOOTHER KERNEL THE BOTTOMRIGHT PLOT SHOWS A GAUSSIAN KERNEL DENSITY ESTIMATE IN WHICH EACH POINT CONTRIBUTES A GAUSSIAN CURVE TO THE TOTAL THE RESULT IS A SMOOTH DENSITY ESTIMATE WHICH IS DERIVED FROM THE DATA AND FUNCTIONS AS A POWERFUL NONPARAMETRIC MODEL OF THE DISTRIBUTION OF POINTS

KERNEL DENSITY ESTIMATION

KERNEL DENSITY ESTIMATION IN SCIKITLEARN IS IMPLEMENTED IN THE SKLEARNNEIGHBORSKERNELDENSITY ESTI MATOR WHICH USES THE BALL TREE OR KD TREE FOR EFFICIENT QUERIES SEE NEAREST NEIGHBORS FOR A DISCUSSION OF THESE THOUGH THE ABOVE EXAMPLE USES A 1D DATA SET FOR SIMPLICITY KERNEL DENSITY ESTIMATION CAN BE PERFORMED IN ANY NUMBER OF DIMENSIONS THOUGH IN PRACTICE THE CURSE OF DIMENSIONALITY CAUSES ITS PERFORMANCE TO DEGRADE IN HIGH DIMENSIONS IN THE FOLLOWING FIGURE 100 POINTS ARE DRAWN FROM A BIMODAL DISTRIBUTION AND THE KERNEL DENSITY ESTIMATES ARE SHOWN FOR THREE CHOICES OF KERNELS

IT’S CLEAR HOW THE KERNEL SHAPE AFFECTS THE SMOOTHNESS OF THE RESULTING DISTRIBUTION THE SCIKITLEARN KERNEL DENSITY ESTIMATOR CAN BE USED AS FOLLOWS

```
 FROM SKLEARNNEIGHBORSKDE IMPORT KERNELDENSITY
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
KDE  KERNELDENSITYKERNELGAUSSIAN BANDWIDTH02FITX
KDESCORESAMPLESX
ARRAY041075698 041075698 041076071 041075698 041075698
041076071
```

HERE WE HAVE USED KERNELGAUSSIAN AS SEEN ABOVE MATHEMATICALLY A KERNEL IS A POSITIVE FUNCTION □□*h* WHICH IS CONTROLLED BY THE BANDWIDTH PARAMETER *h* GIVEN THIS KERNEL FORM THE DENSITY ESTIMATE AT A POINT □WITHIN A GROUP OF POINTS □□□ 1⋯□IS GIVEN BY

□□□ □∑
□1□□−□□*h*

THE BANDWIDTH HERE ACTS AS A SMOOTHING PARAMETER CONTROLLING THE TRADEOFF BETWEEN BIAS AND VARIANCE IN THE RESULT A LARGE BANDWIDTH LEADS TO A VERY SMOOTH IE HIGHBIAS DENSITY DISTRIBUTION A SMALL BANDWIDTH LEADS TO AN UNSMOOTH IE HIGHVARIANCE DENSITY DISTRIBUTION

SKLEARNNEIGHBORSKERNELDENSITY IMPLEMENTS SEVERAL COMMON KERNEL FORMS WHICH ARE SHOWN IN THE FOLLOWING FIGURE

THE FORM OF THESE KERNELS IS AS FOLLOWS
• GAUSSIAN KERNEL KERNEL GAUSSIAN
□□*h*∝EXP−□2
2*h*2
• TOPHAT KERNEL KERNEL TOPHAT
□□*h*∝1IF□ *h*
• EPANECHNIKOV KERNEL KERNEL EPANECHNIKOV
□□*h*∝1−□2
*h*2
• EXPONENTIAL KERNEL KERNEL EXPONENTIAL
□□*h*∝EXP−□*h*
• LINEAR KERNEL KERNEL LINEAR
□□*h*∝1−□*h* IF□ *h*
• COSINE KERNEL KERNEL COSINE
□□*h*∝COS□□
2*h*IF□ *h*
THE KERNEL DENSITY ESTIMATOR CAN BE USED WITH ANY OF THE VALID DISTANCE METRICS SEE SKLEARNNEIGHBORS DISTANCEMETRIC FOR A LIST OF AVAILABLE METRICS THOUGH THE RESULTS ARE PROPERLY NORMALIZED ONLY FOR THE EUCLIDEAN METRIC ONE PARTICULARLY USEFUL METRIC IS THE HAVERSINE DISTANCE WHICH MEASURES THE ANGULAR DISTANCE BETWEEN POINTS ON A SPHERE HERE IS AN EXAMPLE OF USING A KERNEL DENSITY ESTIMATE FOR A VISUALIZATION OF GEOSPATIAL DATA IN THIS CASE THE DISTRIBUTION OF OBSERVATIONS OF TWO DIFFERENT SPECIES ON THE SOUTH AMERICAN CONTINENT

ONE OTHER USEFUL APPLICATION OF KERNEL DENSITY ESTIMATION IS TO LEARN A NONPARAMETRIC GENERATIVE MODEL OF A DATASET IN ORDER TO EFFICIENTLY DRAW NEW SAMPLES FROM THIS GENERATIVE MODEL HERE IS AN EXAMPLE OF USING THIS PROCESS TO CREATE A NEW SET OF HANDWRITTEN DIGITS USING A GAUSSIAN KERNEL LEARNED ON A PCA PROJECTION OF THE DATA
THE “NEW” DATA CONSISTS OF LINEAR COMBINATIONS OF THE INPUT DATA WITH WEIGHTS PROBABILISTICALLY DRAWN GIVEN THE KDE MODEL

EXAMPLES
•SIMPLE 1D KERNEL DENSITY ESTIMATION COMPUTATION OF SIMPLE KERNEL DENSITY ESTIMATES IN ONE DIMENSION
•KERNEL DENSITY ESTIMATION AN EXAMPLE OF USING KERNEL DENSITY ESTIMATION TO LEARN A GENERATIVE MODEL OF THE HANDWRITTEN DIGITS DATA AND DRAWING NEW SAMPLES FROM THIS MODEL
•KERNEL DENSITY ESTIMATE OF SPECIES DISTRIBUTIONS AN EXAMPLE OF KERNEL DENSITY ESTIMATION USING THE HAVER SINE DISTANCE METRIC TO VISUALIZE GEOSPATIAL DATA
329 NEURAL NETWORK MODELS UNSUPERVISED
RESTRICTED BOLTZMANN MACHINES
RESTRICTED BOLTZMANN MACHINES RBM ARE UNSUPERVISED NONLINEAR FEATURE LEARNERS BASED ON A PROBABILISTIC MODEL THE FEATURES EXTRACTED BY AN RBM OR A HIERARCHY OF RBMS OFTEN GIVE GOOD RESULTS WHEN FED INTO A LINEAR CLASSIFIER SUCH AS A LINEAR SVM OR A PERCEPTRON
THE MODEL MAKES ASSUMPTIONS REGARDING THE DISTRIBUTION OF INPUTS AT THE MOMENT SCIKITLEARN ONLY PROVIDES BERNOULLIRBM WHICH ASSUMES THE INPUTS ARE EITHER BINARY VALUES OR VALUES BETWEEN 0 AND 1 EACH ENCODING THE PROBABILITY THAT THE SPECIFIC FEATURE WOULD BE TURNED ON
THE RBM TRIES TO MAXIMIZE THE LIKELIHOOD OF THE DATA USING A PARTICULAR GRAPHICAL MODEL THE PARAMETER LEARNING ALGORITHM USED STOCHASTIC MAXIMUM LIKELIHOOD PREVENTS THE REPRESENTATIONS FROM STRAYING FAR FROM THE INPUT DATA WHICH MAKES THEM CAPTURE INTERESTING REGULARITIES BUT MAKES THE MODEL LESS USEFUL FOR SMALL DATASETS AND USUALLY NOT USEFUL FOR DENSITY ESTIMATION
THE METHOD GAINED POPULARITY FOR INITIALIZING DEEP NEURAL NETWORKS WITH THE WEIGHTS OF INDEPENDENT RBMS THIS METHOD IS KNOWN AS UNSUPERVISED PRETRAINING
EXAMPLES
•RESTRICTED BOLTZMANN MACHINE FEATURES FOR DIGIT CLASSIFICATION
GRAPHICAL MODEL AND PARAMETRIZATION
THE GRAPHICAL MODEL OF AN RBM IS A FULLYCONNECTED BIPARTITE GRAPH

THE NODES ARE RANDOM VARIABLES WHOSE STATES DEPEND ON THE STATE OF THE OTHER NODES THEY ARE CONNECTED TO THE MODEL IS THEREFORE PARAMETERIZED BY THE WEIGHTS OF THE CONNECTIONS AS WELL AS ONE INTERCEPT BIAS TERM FOR EACH VISIBLE AND HIDDEN UNIT OMITTED FROM THE IMAGE FOR SIMPLICITY

THE ENERGY FUNCTION MEASURES THE QUALITY OF A JOINT ASSIGNMENT

□VH −∑

□∑

□□□□□□*h*□−∑

□□□□□−∑

□□□*h*□

IN THE FORMULA ABOVE BANDCARE THE INTERCEPT VECTORS FOR THE VISIBLE AND HIDDEN LAYERS RESPECTIVELY THE JOINT

PROBABILITY OF THE MODEL IS DEFINED IN TERMS OF THE ENERGY
□VH □−□VH
□
THE WORD RESTRICTED REFERS TO THE BIPARTITE STRUCTURE OF THE MODEL WHICH PROHIBITS DIRECT INTERACTION BETWEEN HIDDEN UNITS OR BETWEEN VISIBLE UNITS THIS MEANS THAT THE FOLLOWING CONDITIONAL INDEPENDENCIES ARE ASSUMED
h□⊥*h*□V
□□⊥□□H
THE BIPARTITE STRUCTURE ALLOWS FOR THE USE OF EFFICIENT BLOCK GIBBS SAMPLING FOR INFERENCE
BERNOULLI RESTRICTED BOLTZMANN MACHINES
IN THEBERNOULLIRBM ALL UNITS ARE BINARY STOCHASTIC UNITS THIS MEANS THAT THE INPUT DATA SHOULD EITHER BE BINARY OR REALVALUED BETWEEN 0 AND 1 SIGNIFYING THE PROBABILITY THAT THE VISIBLE UNIT WOULD TURN ON OR OFF THIS IS A GOOD MODEL FOR CHARACTER RECOGNITION WHERE THE INTEREST IS ON WHICH PIXELS ARE ACTIVE AND WHICH AREN'T FOR IMAGES OF NATURAL SCENES IT NO LONGER FITS BECAUSE OF BACKGROUND DEPTH AND THE TENDENCY OF NEIGHBOURING PIXELS TO TAKE THE SAME VALUES THE CONDITIONAL PROBABILITY DISTRIBUTION OF EACH UNIT IS GIVEN BY THE LOGISTIC SIGMOID ACTIVATION FUNCTION OF THE INPUT IT RECEIVES
□□□ 1H □∑
□□□□*h*□□□
□*h*□ 1V □∑
□□□□□□□□
WHERE □IS THE LOGISTIC SIGMOID FUNCTION
□□ 1
1 □−□
STOCHASTIC MAXIMUM LIKELIHOOD LEARNING
THE TRAINING ALGORITHM IMPLEMENTED IN BERNOULLIRBM IS KNOWN AS STOCHASTIC MAXIMUM LIKELIHOOD SML OR PERSISTENT CONTRASTIVE DIVERGENCE PCD OPTIMIZING MAXIMUM LIKELIHOOD DIRECTLY IS INFEASIBLE BECAUSE OF THE FORM OF THE DATA LIKELIHOOD
LOG□□ LOG∑
h□−□□*h*−LOG∑
□□□−□□□
FOR SIMPLICITY THE EQUATION ABOVE IS WRITTEN FOR A SINGLE TRAINING EXAMPLE THE GRADIENT WITH RESPECT TO THE WEIGHTS IS FORMED OF TWO TERMS CORRESPONDING TO THE ONES ABOVE THEY ARE USUALLY KNOWN AS THE POSITIVE GRADIENT AND THE NEGATIVE GRADIENT BECAUSE OF THEIR RESPECTIVE SIGNS IN THIS IMPLEMENTATION THE GRADIENTS ARE ESTIMATED OVER MINIBATCHES OF SAMPLES
IN MAXIMIZING THE LOGLIKELIHOOD THE POSITIVE GRADIENT MAKES THE MODEL PREFER HIDDEN STATES THAT ARE COMPATIBLE WITH THE OBSERVED TRAINING DATA BECAUSE OF THE BIPARTITE STRUCTURE OF RBMS IT CAN BE COMPUTED EFFICIENTLY THE NEGATIVE GRADIENT HOWEVER IS INTRACTABLE ITS GOAL IS TO LOWER THE ENERGY OF JOINT STATES THAT THE MODEL PREFERS THEREFORE MAKING IT STAY TRUE TO THE DATA IT CAN BE APPROXIMATED BY MARKOV CHAIN MONTE CARLO USING BLOCK GIBBS SAMPLING BY ITERATIVELY SAMPLING EACH OF □AND*h*GIVEN THE OTHER UNTIL THE CHAIN MIXES SAMPLES GENERATED IN THIS WAY ARE SOMETIMES REFERRED AS FANTASY PARTICLES THIS IS INEFFICIENT AND IT IS DIFFICULT TO DETERMINE WHETHER THE MARKOV CHAIN MIXES
THE CONTRASTIVE DIVERGENCE METHOD SUGGESTS TO STOP THE CHAIN AFTER A SMALL NUMBER OF ITERATIONS □ USUALLY EVEN 1 THIS METHOD IS FAST AND HAS LOW VARIANCE BUT THE SAMPLES ARE FAR FROM THE MODEL DISTRIBUTION

PERSISTENT CONTRASTIVE DIVERGENCE ADDRESSES THIS INSTEAD OF STARTING A NEW CHAIN EACH TIME THE GRADIENT IS NEEDED AND PERFORMING ONLY ONE GIBBS SAMPLING STEP IN PCD WE KEEP A NUMBER OF CHAINS FANTASY PARTICLES THAT ARE UPDATED GIBBS STEPS AFTER EACH WEIGHT UPDATE THIS ALLOWS THE PARTICLES TO EXPLORE THE SPACE MORE THOROUGHLY

REFERENCES

• “A FAST LEARNING ALGORITHM FOR DEEP BELIEF NETS” G HINTON S OSINDERO Y W TEH 2006
• “TRAINING RESTRICTED BOLTZMANN MACHINES USING APPROXIMATIONS TO THE LIKELIHOOD GRADIENT” T TIELEMAN 2008

33 MODEL SELECTION AND EVALUATION

331 CROSSVALIDATION EVALUATING ESTIMATOR PERFORMANCE

LEARNING THE PARAMETERS OF A PREDICTION FUNCTION AND TESTING IT ON THE SAME DATA IS A METHODOLOGICAL MISTAKE A MODEL THAT WOULD JUST REPEAT THE LABELS OF THE SAMPLES THAT IT HAS JUST SEEN WOULD HAVE A PERFECT SCORE BUT WOULD FAIL TO PREDICT ANYTHING USEFUL ON YETUNSEEN DATA THIS SITUATION IS CALLED OVERFITTING TO AVOID IT IT IS COMMON PRACTICE WHEN PERFORMING A SUPERVISED MACHINE LEARNING EXPERIMENT TO HOLD OUT PART OF THE AVAILABLE DATA AS A TEST SETXTEST YTEST NOTE THAT THE WORD “EXPERIMENT” IS NOT INTENDED TO DENOTE ACADEMIC USE ONLY BECAUSE EVEN IN COMMERCIAL SETTINGS MACHINE LEARNING USUALLY STARTS OUT EXPERIMENTALLY HERE IS A FLOWCHART OF TYPICAL CROSS VALIDATION WORKFLOW IN MODEL TRAINING THE BEST PARAMETERS CAN BE DETERMINED BY GRID SEARCH TECHNIQUES

IN SCIKITLEARN A RANDOM SPLIT INTO TRAINING AND TEST SETS CAN BE QUICKLY COMPUTED WITH THE TRAINTESTSPLIT HELPER FUNCTION LET’S LOAD THE IRIS DATA SET TO FIT A LINEAR SUPPORT VECTOR MACHINE ON IT

```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
 FROM SKLEARN IMPORT DATASETS
 FROM SKLEARN IMPORT SVM
IRIS  DATASETSLOADIRIS
IRISDATASHAPE IRISTARGETSHAPE
150 4 150
```

WE CAN NOW QUICKLY SAMPLE A TRAINING SET WHILE HOLDING OUT 40 OF THE DATA FOR TESTING EVALUATING OUR CLASSIFIER

```
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLIT
 IRISDATA IRISTARGET TESTSIZE04 RANDOMSTATE0
XTRAINSHAPE YTRAINSHAPE
90 4 90
XTESTSHAPE YTESTSHAPE
60 4 60
CLF  SVMSVCKERNELLINEAR C1FITXTRAIN YTRAIN
CLFSCOREXTEST YTEST
096
```

WHEN EVALUATING DIFFERENT SETTINGS “HYPERPARAMETERS” FOR ESTIMATORS SUCH AS THE CSETTING THAT MUST BE MANUALLY SET FOR AN SVM THERE IS STILL A RISK OF OVERFITTING ON THE TEST SET BECAUSE THE PARAMETERS CAN BE TWEAKED UNTIL THE ESTIMATOR PERFORMS OPTIMALLY THIS WAY KNOWLEDGE ABOUT THE TEST SET CAN “LEAK” INTO THE MODEL AND EVALUATION METRICS NO LONGER REPORT ON GENERALIZATION PERFORMANCE TO SOLVE THIS PROBLEM YET ANOTHER PART OF THE DATASET CAN BE HELD OUT AS A SO CALLED “VALIDATION SET” TRAINING PROCEEDS ON THE TRAINING SET AFTER WHICH EVALUATION IS DONE ON THE VALIDATION SET AND WHEN THE EXPERIMENT SEEMS TO BE SUCCESSFUL FINAL EVALUATION CAN BE DONE ON THE TEST SET

HOWEVER BY PARTITIONING THE AVAILABLE DATA INTO THREE SETS WE DRASTICALLY REDUCE THE NUMBER OF SAMPLES WHICH CAN BE USED FOR LEARNING THE MODEL AND THE RESULTS CAN DEPEND ON A PARTICULAR RANDOM CHOICE FOR THE PAIR OF TRAIN VALIDATION SETS

A SOLUTION TO THIS PROBLEM IS A PROCEDURE CALLED CROSSVALIDATION CV FOR SHORT A TEST SET SHOULD STILL BE HELD OUT FOR FINAL EVALUATION BUT THE VALIDATION SET IS NO LONGER NEEDED WHEN DOING CV IN THE BASIC APPROACH CALLED KFOLD CV THE TRAINING SET IS SPLIT INTO KSMALLER SETS OTHER APPROACHES ARE DESCRIBED BELOW BUT GENERALLY FOLLOW THE SAME PRINCIPLES THE FOLLOWING PROCEDURE IS FOLLOWED FOR EACH OF THE K“FOLDS”

• A MODEL IS TRAINED USING □−1OF THE FOLDS AS TRAINING DATA

• THE RESULTING MODEL IS VALIDATED ON THE REMAINING PART OF THE DATA IE IT IS USED AS A TEST SET TO COMPUTE A PERFORMANCE MEASURE SUCH AS ACCURACY

THE PERFORMANCE MEASURE REPORTED BY KFOLD CROSSVALIDATION IS THEN THE AVERAGE OF THE VALUES COMPUTED IN THE LOOP THIS APPROACH CAN BE COMPUTATIONALLY EXPENSIVE BUT DOES NOT WASTE TOO MUCH DATA AS IS THE CASE WHEN FIXING AN ARBITRARY VALIDATION SET WHICH IS A MAJOR ADVANTAGE IN PROBLEMS SUCH AS INVERSE INFERENCE WHERE THE NUMBER OF SAMPLES IS VERY SMALL

COMPUTING CROSSVALIDATED METRICS
THE SIMPLEST WAY TO USE CROSSVALIDATION IS TO CALL THE CROSSVALSCORE HELPER FUNCTION ON THE ESTIMATOR AND THE DATASET
THE FOLLOWING EXAMPLE DEMONSTRATES HOW TO ESTIMATE THE ACCURACY OF A LINEAR KERNEL SUPPORT VECTOR MACHINE ON THE IRIS DATASET BY SPLITTING THE DATA FITTING A MODEL AND COMPUTING THE SCORE 5 CONSECUTIVE TIMES WITH DIFFERENT SPLITS EACH TIME

```
 FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
CLF  SVMSVCKERNELLINEAR C1
SCORES  CROSSVALSCORECLF IRISDATA IRISTARGET CV5
SCORES
ARRAY096 1  096 096 1
```

THE MEAN SCORE AND THE 95 CONFIDENCE INTERVAL OF THE SCORE ESTIMATE ARE HENCE GIVEN BY

```
PRINTACCURACY 02F02F  SCORESMEAN SCORESSTD 2
ACCURACY 098  003
```

BY DEFAULT THE SCORE COMPUTED AT EACH CV ITERATION IS THE SCORE METHOD OF THE ESTIMATOR IT IS POSSIBLE TO CHANGE THIS BY USING THE SCORING PARAMETER

```
 FROM SKLEARN IMPORT METRICS
SCORES  CROSSVALSCORE
 CLF IRISDATA IRISTARGET CV5 SCORINGF1MACRO
SCORES
ARRAY096 1  096 096 1
```

SEETHE SCORING PARAMETER DEFINING MODEL EVALUATION RULES FOR DETAILS IN THE CASE OF THE IRIS DATASET THE SAMPLES ARE BALANCED ACROSS TARGET CLASSES HENCE THE ACCURACY AND THE F1SCORE ARE ALMOST EQUAL
WHEN THECVARGUMENT IS AN INTEGER CROSSVALSCORE USES THEKFOLD ORSTRATIFIEDKFOLD STRATEGIES BY DEFAULT THE LATTER BEING USED IF THE ESTIMATOR DERIVES FROM CLASSIFIERMIXIN
IT IS ALSO POSSIBLE TO USE OTHER CROSS VALIDATION STRATEGIES BY PASSING A CROSS VALIDATION ITERATOR INSTEAD FOR INSTANCE

```
 FROM SKLEARNMODELSELECTION IMPORT SHUFFLESPLIT
NSAMPLES  IRISDATASHAPE0
CV  SHUFFLESPLITNSPLITS5 TESTSIZE03 RANDOMSTATE0
CROSSVALSCORECLF IRISDATA IRISTARGET CVCV
ARRAY0977 0977 1  0955 1
```

ANOTHER OPTION IS TO USE AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES FOR EXAMPLE

```
 DEF CUSTOMCV2FOLDSX
 N  XSHAPE0
 I  1
 WHILE I  2
 IDX  NPARANGEN I  1  2 N I  2 DTYPEINT
 YIELD IDX IDX
 I  1

CUSTOMCV  CUSTOMCV2FOLDSIRISDATA
CROSSVALSCORECLF IRISDATA IRISTARGET CVCUSTOMCV
ARRAY1  0973
```

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DATA TRANSFORMATION WITH HELD OUT DATA
JUST AS IT IS IMPORTANT TO TEST A PREDICTOR ON DATA HELDOUT FROM TRAINING PREPROCESSING SUCH AS STANDARDIZATION FEATURE SELECTION ETC AND SIMILAR DATA TRANSFORMATIONS SIMILARLY SHOULD BE LEARNT FROM A TRAINING SET AND APPLIED TO HELDOUT DATA FOR PREDICTION

```
 FROM SKLEARN IMPORT PREPROCESSING
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLIT
 IRISDATA IRISTARGET TESTSIZE04 RANDOMSTATE0
SCALER  PREPROCESSINGSTANDARDSCALERFITXTRAIN
XTRAINTRANSFORMED  SCALERTRANSFORMXTRAIN
CLF  SVMSVCC1FITXTRAINTRANSFORMED YTRAIN
XTESTTRANSFORMED  SCALERTRANSFORMXTEST
CLFSCOREXTESTTRANSFORMED YTEST
09333
```

APIPELINE MAKES IT EASIER TO COMPOSE ESTIMATORS PROVIDING THIS BEHAVIOR UNDER CROSSVALIDATION

```
 FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
CLF  MAKEPIPELINEPREPROCESSINGSTANDARDSCALER SVMSVCC1
CROSSVALSCORECLF IRISDATA IRISTARGET CVCV

ARRAY0977 0933 0955 0933 0977
```

SEEPIPELINES AND COMPOSITE ESTIMATORS
THE CROSSVALIDATE FUNCTION AND MULTIPLE METRIC EVALUATION
THECROSSVALIDATE FUNCTION DIFFERS FROM CROSSVALSCORE IN TWO WAYS
• IT ALLOWS SPECIFYING MULTIPLE METRICS FOR EVALUATION
• IT RETURNS A DICT CONTAINING FITTIMES SCORETIMES AND OPTIONALLY TRAINING SCORES AS WELL AS FITTED ESTIMATORS IN ADDITION TO THE TEST SCORE
FOR SINGLE METRIC EVALUATION WHERE THE SCORING PARAMETER IS A STRING CALLABLE OR NONE THE KEYS WILL BE
TESTSCORE FITTIME SCORETIME
AND FOR MULTIPLE METRIC EVALUATION THE RETURN VALUE IS A DICT WITH THE FOLLOWING KEYS
TESTSCORER1NAME TESTSCORER2NAME TESTSCORER FITTIME
SCORETIME
RETURNTRAINSCORE IS SET TOFALSE BY DEFAULT TO SAVE COMPUTATION TIME TO EVALUATE THE SCORES ON THE TRAINING SET AS WELL YOU NEED TO BE SET TO TRUE
YOU MAY ALSO RETAIN THE ESTIMATOR FITTED ON EACH TRAINING SET BY SETTING RETURNESTIMATORTRUE
THE MULTIPLE METRICS CAN BE SPECIFIED EITHER AS A LIST TUPLE OR SET OF PREDEFINED SCORER NAMES

```
 FROM SKLEARNMODELSELECTION IMPORT CROSSVALIDATE
 FROM SKLEARNMETRICS IMPORT RECALLSCORE
SCORING  PRECISIONMACRO RECALLMACRO
CLF  SVMSVCKERNELLINEAR C1 RANDOMSTATE0
SCORES  CROSSVALIDATECLF IRISDATA IRISTARGET SCORINGSCORING
 CV5
SORTEDSCORESKEYS
FITTIME SCORETIME TESTPRECISIONMACRO TESTRECALLMACRO
SCORESTESTRECALLMACRO
ARRAY096 1  096 096 1
```

OR AS A DICT MAPPING SCORER NAME TO A PREDEFINED OR CUSTOM SCORING FUNCTION
```
 FROM SKLEARNMETRICSSCORER IMPORT MAKESCORER
SCORING  PRECMACRO PRECISIONMACRO
 RECMACRO MAKESCORERRECALLSCORE AVERAGEMACRO
SCORES  CROSSVALIDATECLF IRISDATA IRISTARGET SCORINGSCORING
 CV5 RETURNTRAINSCORE TRUE
SORTEDSCORESKEYS
FITTIME SCORETIME TESTPRECMACRO TESTRECMACRO
TRAINPRECMACRO TRAINRECMACRO
SCORESTRAINRECMACRO
ARRAY097 097 099 098 098
```
HERE IS AN EXAMPLE OF CROSSVALIDATE USING A SINGLE METRIC
```
SCORES  CROSSVALIDATECLF IRISDATA IRISTARGET
 SCORINGPRECISIONMACRO CV5
 RETURNESTIMATOR TRUE
SORTEDSCORESKEYS
ESTIMATOR FITTIME SCORETIME TESTSCORE
```
OBTAINING PREDICTIONS BY CROSSVALIDATION

THE FUNCTION CROSSVALPREDICT HAS A SIMILAR INTERFACE TO CROSSVALSCORE BUT RETURNS FOR EACH ELEMENT IN THE INPUT THE PREDICTION THAT WAS OBTAINED FOR THAT ELEMENT WHEN IT WAS IN THE TEST SET ONLY CROSSVALIDATION STRATEGIES THAT ASSIGN ALL ELEMENTS TO A TEST SET EXACTLY ONCE CAN BE USED OTHERWISE AN EXCEPTION IS RAISED

WARNING NOTE ON INAPPROPRIATE USAGE OF CROSSVALPREDICT

THE RESULT OF CROSSVALPREDICT MAY BE DIFFERENT FROM THOSE OBTAINED USING CROSSVALSCORE AS THE ELEMENTS ARE GROUPED IN DIFFERENT WAYS THE FUNCTION CROSSVALSCORE TAKES AN AVERAGE OVER CROSSVALIDATION FOLDS WHEREAS CROSSVALPREDICT SIMPLY RETURNS THE LABELS OR PROBABILITIES FROM SEVERAL DISTINCT MODELS UNDISTINGUISHED THUS CROSSVALPREDICT IS NOT AN APPROPRIATE MEASURE OF GENERALISATION ERROR

THE FUNCTION CROSSVALPREDICT IS APPROPRIATE FOR

• VISUALIZATION OF PREDICTIONS OBTAINED FROM DIFFERENT MODELS
• MODEL BLENDING WHEN PREDICTIONS OF ONE SUPERVISED ESTIMATOR ARE USED TO TRAIN ANOTHER ESTIMATOR IN ENSEMBLE METHODS

THE AVAILABLE CROSS VALIDATION ITERATORS ARE INTRODUCED IN THE FOLLOWING SECTION

EXAMPLES

•RECEIVER OPERATING CHARACTERISTIC ROC WITH CROSS VALIDATION
•RECURSIVE FEATURE ELIMINATION WITH CROSSVALIDATION
•PARAMETER ESTIMATION USING GRID SEARCH WITH CROSSVALIDATION
•SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
•PLOTTING CROSSVALIDATED PREDICTIONS
•NESTED VERSUS NONNESTED CROSSVALIDATION

CROSS VALIDATION ITERATORS
THE FOLLOWING SECTIONS LIST UTILITIES TO GENERATE INDICES THAT CAN BE USED TO GENERATE DATASET SPLITS ACCORDING TO DIFFERENT CROSS VALIDATION STRATEGIES
CROSSVALIDATION ITERATORS FOR IID DATA
ASSUMING THAT SOME DATA IS INDEPENDENT AND IDENTICALLY DISTRIBUTED IID IS MAKING THE ASSUMPTION THAT ALL SAMPLES STEM FROM THE SAME GENERATIVE PROCESS AND THAT THE GENERATIVE PROCESS IS ASSUMED TO HAVE NO MEMORY OF PAST GENERATED SAMPLES
THE FOLLOWING CROSSVALIDATORS CAN BE USED IN SUCH CASES
NOTE
WHILE IID DATA IS A COMMON ASSUMPTION IN MACHINE LEARNING THEORY IT RARELY HOLDS IN PRACTICE IF ONE KNOWS THAT THE SAMPLES HAVE BEEN GENERATED USING A TIMEDEPENDENT PROCESS IT'S SAFER TO USE A TIMESERIES AWARE CROSSVALIDATION SCHEME SIMILARLY IF WE KNOW THAT THE GENERATIVE PROCESS HAS A GROUP STRUCTURE SAMPLES FROM COLLECTED FROM DIFFERENT SUBJECTS EXPERIMENTS MEASUREMENT DEVICES IT SAFER TO USE GROUPWISE CROSSVALIDATION
KFOLD
KFOLD DIVIDES ALL THE SAMPLES IN □GROUPS OF SAMPLES CALLED FOLDS IF □□ THIS IS EQUIVALENT TO THE LEAVE ONE OUT STRATEGY OF EQUAL SIZES IF POSSIBLE THE PREDICTION FUNCTION IS LEARNED USING □−1FOLDS AND THE FOLD LEFT OUT IS USED FOR TEST
EXAMPLE OF 2FOLD CROSSVALIDATION ON A DATASET WITH 4 SAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT KFOLD
X  A B C D
KF  KFOLDNSPLITS2
 FOR TRAIN TEST INKFSPLITX
 PRINTS S  TRAIN TEST
2 3 0 1
0 1 2 3
```
HERE IS A VISUALIZATION OF THE CROSSVALIDATION BEHAVIOR NOTE THAT KFOLD IS NOT AFFECTED BY CLASSES OR GROUPS

EACH FOLD IS CONSTITUTED BY TWO ARRAYS THE FIRST ONE IS RELATED TO THE TRAINING SET AND THE SECOND ONE TO THE TEST SET
THUS ONE CAN CREATE THE TRAININGTEST SETS USING NUMPY INDEXING

```
X  NPARRAY0 0 1 1 1 1 2 2
Y  NPARRAY0 1 0 1
XTRAIN XTEST YTRAIN YTEST  XTRAIN XTEST YTRAIN YTEST
```

REPEATED KFOLD
REPEATEDKFOLD REPEATS KFOLD N TIMES IT CAN BE USED WHEN ONE REQUIRES TO RUN KFOLD N TIMES PRODUCING
DIFFERENT SPLITS IN EACH REPETITION
EXAMPLE OF 2FOLD KFOLD REPEATED 2 TIMES

```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT REPEATEDKFOLD
X  NPARRAY1 2 3 4 1 2 3 4
RANDOMSTATE  12883823
RKF  REPEATEDKFOLDNSPLITS2 NREPEATS2 RANDOMSTATERANDOMSTATE
 FOR TRAIN TEST INRKFSPLITX
 PRINTS S  TRAIN TEST

2 3 0 1
0 1 2 3
0 2 1 3
1 3 0 2
```

SIMILARLYREPEATEDSTRATIFIEDKFOLD REPEATS STRATIFIED KFOLD N TIMES WITH DIFFERENT RANDOMIZATION IN EACH
REPETITION
LEAVE ONE OUT LOO
LEAVEONEOUT OR LOO IS A SIMPLE CROSSVALIDATION EACH LEARNING SET IS CREATED BY TAKING ALL THE SAMPLES EXCEPT
ONE THE TEST SET BEING THE SAMPLE LEFT OUT THUS FOR □SAMPLES WE HAVE □DIFFERENT TRAINING SETS AND □DIFFERENT TESTS
SET THIS CROSSVALIDATION PROCEDURE DOES NOT WASTE MUCH DATA AS ONLY ONE SAMPLE IS REMOVED FROM THE TRAINING SET

```
 FROM SKLEARNMODELSELECTION IMPORT LEAVEONEOUT
X  1 2 3 4
LOO  LEAVEONEOUT
 FOR TRAIN TEST INLOOSPLITX
 PRINTS S  TRAIN TEST
1 2 3 0
0 2 3 1
0 1 3 2
0 1 2 3
```

POTENTIAL USERS OF LOO FOR MODEL SELECTION SHOULD WEIGH A FEW KNOWN CAVEATS WHEN COMPARED WITH □FOLD CROSS
VALIDATION ONE BUILDS □MODELS FROM □SAMPLES INSTEAD OF □MODELS WHERE □ □ MOREOVER EACH IS TRAINED ON □−1
SAMPLES RATHER THAN □−1□□ IN BOTH WAYS ASSUMING □IS NOT TOO LARGE AND □ □ LOO IS MORE COMPUTATIONALLY
EXPENSIVE THAN □FOLD CROSS VALIDATION
IN TERMS OF ACCURACY LOO OFTEN RESULTS IN HIGH VARIANCE AS AN ESTIMATOR FOR THE TEST ERROR INTUITIVELY SINCE □−1OF
THE□SAMPLES ARE USED TO BUILD EACH MODEL MODELS CONSTRUCTED FROM FOLDS ARE VIRTUALLY IDENTICAL TO EACH OTHER AND TO
THE MODEL BUILT FROM THE ENTIRE TRAINING SET

HOWEVER IF THE LEARNING CURVE IS STEEP FOR THE TRAINING SIZE IN QUESTION THEN 5 OR 10 FOLD CROSS VALIDATION CAN OVERESTIMATE THE GENERALIZATION ERROR

AS A GENERAL RULE MOST AUTHORS AND EMPIRICAL EVIDENCE SUGGEST THAT 5 OR 10 FOLD CROSS VALIDATION SHOULD BE PREFERRED TO LOO

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LEAVE P OUT LPO

LEAVEPOUT IS VERY SIMILAR TO LEAVEONEOUT AS IT CREATES ALL THE POSSIBLE TRAININGTEST SETS BY REMOVING □SAMPLES FROM THE COMPLETE SET FOR □SAMPLES THIS PRODUCES□

□

TRAINTEST PAIRS UNLIKE LEAVEONEOUT ANDKFOLD THE TEST SETS WILL OVERLAP FOR □ 1

EXAMPLE OF LEAVE2OUT ON A DATASET WITH 4 SAMPLES

```
 FROM SKLEARNMODELSELECTION IMPORT LEAVEPOUT
X  NPONES4
LPO  LEAVEPOUTP2
 FOR TRAIN TEST INLPOSPLITX
 PRINTS S  TRAIN TEST
2 3 0 1
1 3 0 2
1 2 0 3
0 3 1 2
0 2 1 3
0 1 2 3
```

RANDOM PERMUTATIONS CROSSVALIDATION AKA SHUFFLE SPLIT

SHUFFLESPLIT

THESHUFFLESPLIT ITERATOR WILL GENERATE A USER DEFINED NUMBER OF INDEPENDENT TRAIN TEST DATASET SPLITS SAMPLES ARE FIRST SHUFFLED AND THEN SPLIT INTO A PAIR OF TRAIN AND TEST SETS

IT IS POSSIBLE TO CONTROL THE RANDOMNESS FOR REPRODUCIBILITY OF THE RESULTS BY EXPLICITLY SEEDING THE RANDOMSTATE PSEUDO RANDOM NUMBER GENERATOR

HERE IS A USAGE EXAMPLE

```
 FROM SKLEARNMODELSELECTION IMPORT SHUFFLESPLIT
X  NPARANGE10
SS  SHUFFLESPLITNSPLITS5 TESTSIZE025
 RANDOMSTATE0
 FOR TRAININDEX TESTINDEX INSSSPLITX
 PRINTS S  TRAININDEX TESTINDEX
9 1 6 7 3 0 5 2 8 4
2 9 8 0 6 7 4 3 5 1
4 5 1 0 6 9 7 2 3 8
2 7 5 8 0 3 4 6 1 9
4 1 0 6 8 9 3 5 2 7
```

HERE IS A VISUALIZATION OF THE CROSSVALIDATION BEHAVIOR NOTE THAT SHUFFLESPLIT IS NOT AFFECTED BY CLASSES OR GROUPS

SHUFFLESPLIT IS THUS A GOOD ALTERNATIVE TO KFOLD CROSS VALIDATION THAT ALLOWS A FINER CONTROL ON THE NUMBER OF ITERATIONS AND THE PROPORTION OF SAMPLES ON EACH SIDE OF THE TRAIN TEST SPLIT

CROSSVALIDATION ITERATORS WITH STRATIFICATION BASED ON CLASS LABELS

SOME CLASSIFICATION PROBLEMS CAN EXHIBIT A LARGE IMBALANCE IN THE DISTRIBUTION OF THE TARGET CLASSES FOR INSTANCE THERE COULD BE SEVERAL TIMES MORE NEGATIVE SAMPLES THAN POSITIVE SAMPLES IN SUCH CASES IT IS RECOMMENDED TO USE STRATIFIED SAMPLING AS IMPLEMENTED IN STRATIFIEDKFOLD ANDSTRATIFIEDSHUFFLESPLIT TO ENSURE THAT RELATIVE CLASS FREQUENCIES IS APPROXIMATELY PRESERVED IN EACH TRAIN AND VALIDATION FOLD

STRATIFIED KFOLD

STRATIFIEDKFOLD IS A VARIATION OF KFOLD WHICH RETURNS STRATIFIED FOLDS EACH SET CONTAINS APPROXIMATELY THE SAME PERCENTAGE OF SAMPLES OF EACH TARGET CLASS AS THE COMPLETE SET

EXAMPLE OF STRATIFIED 3FOLD CROSSVALIDATION ON A DATASET WITH 10 SAMPLES FROM TWO SLIGHTLY UNBALANCED CLASSES

```
 FROM SKLEARNMODELSELECTION IMPORT STRATIFIEDKFOLD
X  NPONES10
Y  0 0 0 0 1 1 1 1 1 1
SKF  STRATIFIEDKFOLDNSPLITS3
 FOR TRAIN TEST INSKFSPLITX Y
```

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PRINTS S TRAIN TEST
2 3 6 7 8 9 0 1 4 5
0 1 3 4 5 8 9 2 6 7
0 1 2 4 5 6 7 3 8 9
HERE IS A VISUALIZATION OF THE CROSSVALIDATION BEHAVIOR
REPEATEDSTRATIFIEDKFOLD CAN BE USED TO REPEAT STRATIFIED KFOLD N TIMES WITH DIFFERENT RANDOMIZATION IN EACH REPETITION
STRATIFIED SHUFFLE SPLIT
STRATIFIEDSHUFFLESPLIT IS A VARIATION OF SHUFFLESPLIT WHICH RETURNS STRATIFIED SPLITS IEWHICH CREATES SPLITS BY PRESERVING THE SAME PERCENTAGE FOR EACH TARGET CLASS AS IN THE COMPLETE SET
HERE IS A VISUALIZATION OF THE CROSSVALIDATION BEHAVIOR
CROSSVALIDATION ITERATORS FOR GROUPED DATA
THE IID ASSUMPTION IS BROKEN IF THE UNDERLYING GENERATIVE PROCESS YIELD GROUPS OF DEPENDENT SAMPLES
33 MODEL SELECTION AND EVALUATION 443

SUCH A GROUPING OF DATA IS DOMAIN SPECIFIC AN EXAMPLE WOULD BE WHEN THERE IS MEDICAL DATA COLLECTED FROM MULTIPLE PATIENTS WITH MULTIPLE SAMPLES TAKEN FROM EACH PATIENT AND SUCH DATA IS LIKELY TO BE DEPENDENT ON THE INDIVIDUAL GROUP IN OUR EXAMPLE THE PATIENT ID FOR EACH SAMPLE WILL BE ITS GROUP IDENTIFIER
IN THIS CASE WE WOULD LIKE TO KNOW IF A MODEL TRAINED ON A PARTICULAR SET OF GROUPS GENERALIZES WELL TO THE UNSEEN GROUPS TO MEASURE THIS WE NEED TO ENSURE THAT ALL THE SAMPLES IN THE VALIDATION FOLD COME FROM GROUPS THAT ARE NOT REPRESENTED AT ALL IN THE PAIRED TRAINING FOLD
THE FOLLOWING CROSSVALIDATION SPLITTERS CAN BE USED TO DO THAT THE GROUPING IDENTIFIER FOR THE SAMPLES IS SPECIFIED VIA THEGROUPS PARAMETER
GROUP KFOLD
GROUPKFOLD IS A VARIATION OF KFOLD WHICH ENSURES THAT THE SAME GROUP IS NOT REPRESENTED IN BOTH TESTING AND TRAINING SETS FOR EXAMPLE IF THE DATA IS OBTAINED FROM DIFFERENT SUBJECTS WITH SEVERAL SAMPLES PERSUBJECT AND IF THE MODEL IS FLEXIBLE ENOUGH TO LEARN FROM HIGHLY PERSON SPECIFIC FEATURES IT COULD FAIL TO GENERALIZE TO NEW SUBJECTS GROUPKFOLD MAKES IT POSSIBLE TO DETECT THIS KIND OF OVERFITTING SITUATIONS
IMAGINE YOU HAVE THREE SUBJECTS EACH WITH AN ASSOCIATED NUMBER FROM 1 TO 3
```
 FROM SKLEARNMODELSELECTION IMPORT GROUPKFOLD
X  01 02 22 24 23 455 58 88 9 10
Y  A B B B C C C D D D
GROUPS  1 1 1 2 2 2 3 3 3 3
GKF  GROUPKFOLDNSPLITS3
 FOR TRAIN TEST INGKFSPLITX Y GROUPSGROUPS
 PRINTS S  TRAIN TEST
0 1 2 3 4 5 6 7 8 9
0 1 2 6 7 8 9 3 4 5
3 4 5 6 7 8 9 0 1 2
```
EACH SUBJECT IS IN A DIFFERENT TESTING FOLD AND THE SAME SUBJECT IS NEVER IN BOTH TESTING AND TRAINING NOTICE THAT THE FOLDS DO NOT HAVE EXACTLY THE SAME SIZE DUE TO THE IMBALANCE IN THE DATA
HERE IS A VISUALIZATION OF THE CROSSVALIDATION BEHAVIOR

LEAVE ONE GROUP OUT
LEAVEONEGROUPOUT IS A CROSSVALIDATION SCHEME WHICH HOLDS OUT THE SAMPLES ACCORDING TO A THIRDPARTY PROVIDED ARRAY OF INTEGER GROUPS THIS GROUP INFORMATION CAN BE USED TO ENCODE ARBITRARY DOMAIN SPECIFIC PREDEFINED CROSS VALIDATION FOLDS
EACH TRAINING SET IS THUS CONSTITUTED BY ALL THE SAMPLES EXCEPT THE ONES RELATED TO A SPECIFIC GROUP
FOR EXAMPLE IN THE CASES OF MULTIPLE EXPERIMENTS LEAVEONEGROUPOUT CAN BE USED TO CREATE A CROSSVALIDATION BASED ON THE DIFFERENT EXPERIMENTS WE CREATE A TRAINING SET USING THE SAMPLES OF ALL THE EXPERIMENTS EXCEPT ONE

```
 FROM SKLEARNMODELSELECTION IMPORT LEAVEONEGROUPOUT
X  1 5 10 50 60 70 80
Y  0 1 1 2 2 2 2
GROUPS  1 1 2 2 3 3 3
LOGO  LEAVEONEGROUPOUT
 FOR TRAIN TEST INLOGOSPLITX Y GROUPSGROUPS
 PRINTS S  TRAIN TEST
2 3 4 5 6 0 1
0 1 4 5 6 2 3
0 1 2 3 4 5 6
```

ANOTHER COMMON APPLICATION IS TO USE TIME INFORMATION FOR INSTANCE THE GROUPS COULD BE THE YEAR OF COLLECTION OF THE SAMPLES AND THUS ALLOW FOR CROSSVALIDATION AGAINST TIMEBASED SPLITS
LEAVE P GROUPS OUT
LEAVEPGROUPSOUT IS SIMILAR AS LEAVEONEGROUPOUT BUT REMOVES SAMPLES RELATED TO □GROUPS FOR EACH TRAIN INGTEST SET
EXAMPLE OF LEAVE2GROUP OUT

```
 FROM SKLEARNMODELSELECTION IMPORT LEAVEPGROUPSOUT
X  NPARANGE6
Y  1 1 1 2 2 2
GROUPS  1 1 2 2 3 3
LPGO  LEAVEPGROUPSOUTNGROUPS2
 FOR TRAIN TEST INLPGOSPLITX Y GROUPSGROUPS
 PRINTS S  TRAIN TEST
4 5 0 1 2 3
2 3 0 1 4 5
0 1 2 3 4 5
```

GROUP SHUFFLE SPLIT
THEGROUPSHUFFLESPLIT ITERATOR BEHAVES AS A COMBINATION OF SHUFFLESPLIT ANDLEAVEPGROUPSOUT AND GENERATES A SEQUENCE OF RANDOMIZED PARTITIONS IN WHICH A SUBSET OF GROUPS ARE HELD OUT FOR EACH SPLIT
HERE IS A USAGE EXAMPLE

```
 FROM SKLEARNMODELSELECTION IMPORT GROUPSHUFFLESPLIT
X  01 02 22 24 23 455 58 0001
Y  A B B B C C C A
```

GROUPS 1 1 2 2 3 3 4 4
GSS GROUPSHUFFLESPLITNSPLITS4 TESTSIZE05 RANDOMSTATE0
 FOR TRAIN TEST INGSSSPLITX Y GROUPSGROUPS
 PRINTS S TRAIN TEST

0 1 2 3 4 5 6 7
2 3 6 7 0 1 4 5
2 3 4 5 0 1 6 7
4 5 6 7 0 1 2 3
HERE IS A VISUALIZATION OF THE CROSSVALIDATION BEHAVIOR
THIS CLASS IS USEFUL WHEN THE BEHAVIOR OF LEAVEPGROUPSOUT IS DESIRED BUT THE NUMBER OF GROUPS IS LARGE ENOUGH
THAT GENERATING ALL POSSIBLE PARTITIONS WITH GROUPS WITHHELD WOULD BE PROHIBITIVELY EXPENSIVE IN SUCH A SCE
NARIOGROUPSHUFFLESPLIT PROVIDES A RANDOM SAMPLE WITH REPLACEMENT OF THE TRAIN TEST SPLITS GENERATED BY
LEAVEPGROUPSOUT
PREDEFINED FOLDSPLITS VALIDATIONSETS
FOR SOME DATASETS A PREDEFINED SPLIT OF THE DATA INTO TRAINING AND VALIDATION FOLD OR INTO SEVERAL CROSSVALIDATION FOLDS
ALREADY EXISTS USING PREDEFINEDSPLIT IT IS POSSIBLE TO USE THESE FOLDS EG WHEN SEARCHING FOR HYPERPARAMETERS
FOR EXAMPLE WHEN USING A VALIDATION SET SET THE TESTFOLD TO 0 FOR ALL SAMPLES THAT ARE PART OF THE VALIDATION SET
AND TO 1 FOR ALL OTHER SAMPLES
CROSS VALIDATION OF TIME SERIES DATA
TIME SERIES DATA IS CHARACTERISED BY THE CORRELATION BETWEEN OBSERVATIONS THAT ARE NEAR IN TIME AUTOCORRELATION HOW
EVER CLASSICAL CROSSVALIDATION TECHNIQUES SUCH AS KFOLD ANDSHUFFLESPLIT ASSUME THE SAMPLES ARE INDEPENDENT
AND IDENTICALLY DISTRIBUTED AND WOULD RESULT IN UNREASONABLE CORRELATION BETWEEN TRAINING AND TESTING INSTANCES YIELD
ING POOR ESTIMATES OF GENERALISATION ERROR ON TIME SERIES DATA THEREFORE IT IS VERY IMPORTANT TO EVALUATE OUR MODEL
FOR TIME SERIES DATA ON THE “FUTURE” OBSERVATIONS LEAST LIKE THOSE THAT ARE USED TO TRAIN THE MODEL TO ACHIEVE THIS ONE
SOLUTION IS PROVIDED BY TIMESERIESSPLIT

TIME SERIES SPLIT

TIMESERIESSPLIT IS A VARIATION OF KFOLD WHICH RETURNS FIRST FOLDS AS TRAIN SET AND THE 1 TH FOLD AS TEST SET NOTE THAT UNLIKE STANDARD CROSSVALIDATION METHODS SUCCESSIVE TRAINING SETS ARE SUPERSETS OF THOSE THAT COME BEFORE THEM ALSO IT ADDS ALL SURPLUS DATA TO THE FIRST TRAINING PARTITION WHICH IS ALWAYS USED TO TRAIN THE MODEL

THIS CLASS CAN BE USED TO CROSSVALIDATE TIME SERIES DATA SAMPLES THAT ARE OBSERVED AT FIXED TIME INTERVALS

EXAMPLE OF 3SPLIT TIME SERIES CROSSVALIDATION ON A DATASET WITH 6 SAMPLES

```
 FROM SKLEARNMODELSELECTION IMPORT TIMESERIESSPLIT
X  NPARRAY1 2 3 4 1 2 3 4 1 2 3 4
Y  NPARRAY1 2 3 4 5 6
TSCV  TIMESERIESSPLITNSPLITS3
PRINTTSCV
TIMESERIESSPLITMAXTRAINSIZENONE NSPLITS3
 FOR TRAIN TEST INTSCVSPLITX
 PRINTS S  TRAIN TEST
0 1 2 3
0 1 2 3 4
0 1 2 3 4 5
```

HERE IS A VISUALIZATION OF THE CROSSVALIDATION BEHAVIOR

A NOTE ON SHUFFLING

IF THE DATA ORDERING IS NOT ARBITRARY EG SAMPLES WITH THE SAME CLASS LABEL ARE CONTIGUOUS SHUFFLING IT FIRST MAY BE ESSENTIAL TO GET A MEANINGFUL CROSS VALIDATION RESULT HOWEVER THE OPPOSITE MAY BE TRUE IF THE SAMPLES ARE NOT INDEPENDENTLY AND IDENTICALLY DISTRIBUTED FOR EXAMPLE IF SAMPLES CORRESPOND TO NEWS ARTICLES AND ARE ORDERED BY THEIR TIME OF PUBLICATION THEN SHUFFLING THE DATA WILL LIKELY LEAD TO A MODEL THAT IS OVERFIT AND AN INFLATED VALIDATION SCORE IT WILL BE TESTED ON SAMPLES THAT ARE ARTIFICIALLY SIMILAR CLOSE IN TIME TO TRAINING SAMPLES

SOME CROSS VALIDATION ITERATORS SUCH AS KFOLD HAVE AN INBUILT OPTION TO SHUFFLE THE DATA INDICES BEFORE SPLITTING THEM NOTE THAT

• THIS CONSUMES LESS MEMORY THAN SHUFFLING THE DATA DIRECTLY
• BY DEFAULT NO SHUFFLING OCCURS INCLUDING FOR THE STRATIFIED K FOLD CROSS VALIDATION PERFORMED BY SPECIFYING CVSOMEINTEGER TOCROSSVALSCORE GRID SEARCH ETC KEEP IN MIND THAT TRAINTESTSPLIT STILL RETURNS A RANDOM SPLIT

• THERANDOMSTATE PARAMETER DEFAULTS TO NONE MEANING THAT THE SHUFFLING WILL BE DIFFERENT EVERY TIME KFOLD SHUFFLETRUE IS ITERATED HOWEVER GRIDSEARCHCV WILL USE THE SAME SHUFFLING FOR EACH SET OF PARAMETERS VALIDATED BY A SINGLE CALL TO ITS FIT METHOD
• TO GET IDENTICAL RESULTS FOR EACH SPLIT SET RANDOMSTATE TO AN INTEGER

CROSS VALIDATION AND MODEL SELECTION

CROSS VALIDATION ITERATORS CAN ALSO BE USED TO DIRECTLY PERFORM MODEL SELECTION USING GRID SEARCH FOR THE OPTIMAL HYPERPARAMETERS OF THE MODEL THIS IS THE TOPIC OF THE NEXT SECTION TUNING THE HYPERPARAMETERS OF AN ESTIMATOR

332 TUNING THE HYPERPARAMETERS OF AN ESTIMATOR

HYPERPARAMETERS ARE PARAMETERS THAT ARE NOT DIRECTLY LEARNT WITHIN ESTIMATORS IN SCIKITLEARN THEY ARE PASSED AS ARGUMENTS TO THE CONSTRUCTOR OF THE ESTIMATOR CLASSES TYPICAL EXAMPLES INCLUDE CKERNEL ANDGAMMA FOR SUPPORT VECTOR CLASSIFIER ALPHA FOR LASSO ETC

IT IS POSSIBLE AND RECOMMENDED TO SEARCH THE HYPERPARAMETER SPACE FOR THE BEST CROSS VALIDATION SCORE

ANY PARAMETER PROVIDED WHEN CONSTRUCTING AN ESTIMATOR MAY BE OPTIMIZED IN THIS MANNER SPECIFICALLY TO FIND THE NAMES AND CURRENT VALUES FOR ALL PARAMETERS FOR A GIVEN ESTIMATOR USE

ESTIMATORGETPARAMS

A SEARCH CONSISTS OF

• AN ESTIMATOR REGRESSOR OR CLASSIFIER SUCH AS SKLEARNSVMSVC
• A PARAMETER SPACE
• A METHOD FOR SEARCHING OR SAMPLING CANDIDATES
• A CROSSVALIDATION SCHEME AND
• ASCORE FUNCTION

SOME MODELS ALLOW FOR SPECIALIZED EFFICIENT PARAMETER SEARCH STRATEGIES OUTLINED BELOW TWO GENERIC APPROACHES TO SAMPLING SEARCH CANDIDATES ARE PROVIDED IN SCIKITLEARN FOR GIVEN VALUES GRIDSEARCHCV EXHAUSTIVELY CONSIDERS ALL PARAMETER COMBINATIONS WHILE RANDOMIZEDSEARCHCV CAN SAMPLE A GIVEN NUMBER OF CANDIDATES FROM A PARAMETER SPACE WITH A SPECIFIED DISTRIBUTION AFTER DESCRIBING THESE TOOLS WE DETAIL BEST PRACTICE APPLICABLE TO BOTH APPROACHES NOTE THAT IT IS COMMON THAT A SMALL SUBSET OF THOSE PARAMETERS CAN HAVE A LARGE IMPACT ON THE PREDICTIVE OR COMPUTATION PERFORMANCE OF THE MODEL WHILE OTHERS CAN BE LEFT TO THEIR DEFAULT VALUES IT IS RECOMMENDED TO READ THE DOCSTRING OF THE ESTIMATOR CLASS TO GET A FINER UNDERSTANDING OF THEIR EXPECTED BEHAVIOR POSSIBLY BY READING THE ENCLOSED REFERENCE TO THE LITERATURE

EXHAUSTIVE GRID SEARCH

THE GRID SEARCH PROVIDED BY GRIDSEARCHCV EXHAUSTIVELY GENERATES CANDIDATES FROM A GRID OF PARAMETER VALUES SPECIFIED WITH THE PARAMGRID PARAMETER FOR INSTANCE THE FOLLOWING PARAMGRID

PARAMGRID

C 1 10 100 1000 KERNEL LINEAR
C 1 10 100 1000 GAMMA 0001 00001 KERNEL RBF

SPECIFIES THAT TWO GRIDS SHOULD BE EXPLORED ONE WITH A LINEAR KERNEL AND C VALUES IN 1 10 100 1000 AND THE SECOND ONE WITH AN RBF KERNEL AND THE CROSSPRODUCT OF C VALUES RANGING IN 1 10 100 1000 AND GAMMA VALUES IN 0001 00001

THEGRIDSEARCHCV INSTANCE IMPLEMENTS THE USUAL ESTIMATOR API WHEN “FITTING” IT ON A DATASET ALL THE POSSIBLE COMBINATIONS OF PARAMETER VALUES ARE EVALUATED AND THE BEST COMBINATION IS RETAINED

EXAMPLES

• SEE PARAMETER ESTIMATION USING GRID SEARCH WITH CROSSVALIDATION FOR AN EXAMPLE OF GRID SEARCH COMPUTATION ON THE DIGITS DATASET

• SEE SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION FOR AN EXAMPLE OF GRID SEARCH COUPLING PARAMETERS FROM A TEXT DOCUMENTS FEATURE EXTRACTOR NGRAM COUNT VECTORIZER AND TFIDF TRANSFORMER WITH A CLASSIFIER HERE A LINEAR SVM TRAINED WITH SGD WITH EITHER ELASTIC NET OR L2 PENALTY USING A PIPELINE PIPELINE INSTANCE

• SEE NESTED VERSUS NONNESTED CROSSVALIDATION FOR AN EXAMPLE OF GRID SEARCH WITHIN A CROSS VALIDATION LOOP ON THE IRIS DATASET THIS IS THE BEST PRACTICE FOR EVALUATING THE PERFORMANCE OF A MODEL WITH GRID SEARCH

• SEE DEMONSTRATION OF MULTIMETRIC EVALUATION ON CROSSVALSCORE AND GRIDSEARCHCV FOR AN EXAMPLE OF GRIDSEARCHCV BEING USED TO EVALUATE MULTIPLE METRICS SIMULTANEOUSLY

• SEE BALANCE MODEL COMPLEXITY AND CROSSVALIDATED SCORE FOR AN EXAMPLE OF USING REFITCALLABLE IN TERFACE INGRIDSEARCHCV THE EXAMPLE SHOWS HOW THIS INTERFACE ADDS CERTAIN AMOUNT OF FLEXIBILITY IN IDENTIFYING THE “BEST” ESTIMATOR THIS INTERFACE CAN ALSO BE USED IN MULTIPLE METRICS EVALUATION

RANDOMIZED PARAMETER OPTIMIZATION

WHILE USING A GRID OF PARAMETER SETTINGS IS CURRENTLY THE MOST WIDELY USED METHOD FOR PARAMETER OPTIMIZATION OTHER SEARCH METHODS HAVE MORE FAVOURABLE PROPERTIES RANDOMIZEDSEARCHCV IMPLEMENTS A RANDOMIZED SEARCH OVER PARAMETERS WHERE EACH SETTING IS SAMPLED FROM A DISTRIBUTION OVER POSSIBLE PARAMETER VALUES THIS HAS TWO MAIN BENEFITS OVER AN EXHAUSTIVE SEARCH

• A BUDGET CAN BE CHOSEN INDEPENDENT OF THE NUMBER OF PARAMETERS AND POSSIBLE VALUES

• ADDING PARAMETERS THAT DO NOT INFLUENCE THE PERFORMANCE DOES NOT DECREASE EFFICIENCY

SPECIFYING HOW PARAMETERS SHOULD BE SAMPLED IS DONE USING A DICTIONARY VERY SIMILAR TO SPECIFYING PARAMETERS FOR GRIDSEARCHCV ADDITIONALLY A COMPUTATION BUDGET BEING THE NUMBER OF SAMPLED CANDIDATES OR SAMPLING ITERATIONS IS SPECIFIED USING THE NITER PARAMETER FOR EACH PARAMETER EITHER A DISTRIBUTION OVER POSSIBLE VALUES OR A LIST OF DISCRETE CHOICES WHICH WILL BE SAMPLED UNIFORMLY CAN BE SPECIFIED

C SCIPYSTATSEXPONSCALE100 GAMMA SCIPYSTATSEXPONSCALE1

KERNEL RBF CLASSWEIGHTBALANCED NONE

THIS EXAMPLE USES THE SCIPYSTATS MODULE WHICH CONTAINS MANY USEFUL DISTRIBUTIONS FOR SAMPLING PARAMETERS SUCH ASEXPON GAMMA UNIFORM ORRANDINT IN PRINCIPLE ANY FUNCTION CAN BE PASSED THAT PROVIDES A RVS RANDOM VARIATE SAMPLE METHOD TO SAMPLE A VALUE A CALL TO THE RVS FUNCTION SHOULD PROVIDE INDEPENDENT RANDOM SAMPLES FROM POSSIBLE PARAMETER VALUES ON CONSECUTIVE CALLS

WARNING THE DISTRIBUTIONS IN SCIPYSTATS PRIOR TO VERSION SCIPY 016 DO NOT ALLOW SPECIFYING A RANDOM STATE INSTEAD THEY USE THE GLOBAL NUMPY RANDOM STATE THAT CAN BE SEEDED VIA NPRANDOM SEED OR SET USING NPRANDOMSETSTATE HOWEVER BEGINNING SCIKITLEARN 018 THE SKLEARN

MODELSELECTION MODULE SETS THE RANDOM STATE PROVIDED BY THE USER IF SCIPY 016 IS ALSO
AVAILABLE
FOR CONTINUOUS PARAMETERS SUCH AS CABOVE IT IS IMPORTANT TO SPECIFY A CONTINUOUS DISTRIBUTION TO TAKE FULL ADVANTAGE OF THE RANDOMIZATION THIS WAY INCREASING NITER WILL ALWAYS LEAD TO A FINER SEARCH
EXAMPLES
•COMPARING RANDOMIZED SEARCH AND GRID SEARCH FOR HYPERPARAMETER ESTIMATION COMPARES THE USAGE AND EFFI
CIENCY OF RANDOMIZED SEARCH AND GRID SEARCH
REFERENCES
• BERGSTRA J AND BENGIO Y RANDOM SEARCH FOR HYPERPARAMETER OPTIMIZATION THE JOURNAL OF MACHINE LEARN
ING RESEARCH 2012
TIPS FOR PARAMETER SEARCH
SPECIFYING AN OBJECTIVE METRIC
BY DEFAULT PARAMETER SEARCH USES THE SCORE FUNCTION OF THE ESTIMATOR TO EVALUATE A PARAMETER SETTING THESE ARE THESKLEARNMETRICSACCURACYSCORE FOR CLASSIFICATION AND SKLEARNMETRICSR2SCORE FOR REGRES
SION FOR SOME APPLICATIONS OTHER SCORING FUNCTIONS ARE BETTER SUITED FOR EXAMPLE IN UNBALANCED CLASSIFICATION THE ACCURACY SCORE IS OFTEN UNINFORMATIVE AN ALTERNATIVE SCORING FUNCTION CAN BE SPECIFIED VIA THE SCORING PARAMETER TOGRIDSEARCHCV RANDOMIZEDSEARCHCV AND MANY OF THE SPECIALIZED CROSSVALIDATION TOOLS DESCRIBED BELOW
SEETHE SCORING PARAMETER DEFINING MODEL EVALUATION RULES FOR MORE DETAILS
SPECIFYING MULTIPLE METRICS FOR EVALUATION
GRIDSEARCHCV ANDRANDOMIZEDSEARCHCV ALLOW SPECIFYING MULTIPLE METRICS FOR THE SCORING PARAMETER
MULTIMETRIC SCORING CAN EITHER BE SPECIFIED AS A LIST OF STRINGS OF PREDEFINED SCORES NAMES OR A DICT MAPPING THE SCORER NAME TO THE SCORER FUNCTION ANDOR THE PREDEFINED SCORER NAMES SEE USING MULTIPLE METRIC EVALUATION FOR MORE DETAILS
WHEN SPECIFYING MULTIPLE METRICS THE REFIT PARAMETER MUST BE SET TO THE METRIC STRING FOR WHICH THE BESTPARAMS WILL BE FOUND AND USED TO BUILD THE BESTESTIMATOR ON THE WHOLE DATASET IF THE SEARCH SHOULD NOT BE REFIT SET REFITFALSE LEAVING REFIT TO THE DEFAULT VALUE NONE WILL RESULT IN AN ERROR WHEN USING MULTIPLE METRICS
SEEDEMONSTRATION OF MULTIMETRIC EVALUATION ON CROSSVALSCORE AND GRIDSEARCHCV FOR AN EXAMPLE USAGE
COMPOSITE ESTIMATORS AND PARAMETER SPACES
PIPELINE CHAINING ESTIMATORS DESCRIBES BUILDING COMPOSITE ESTIMATORS WHOSE PARAMETER SPACE CAN BE SEARCHED WITH THESE TOOLS

MODEL SELECTION DEVELOPMENT AND EVALUATION
MODEL SELECTION BY EVALUATING VARIOUS PARAMETER SETTINGS CAN BE SEEN AS A WAY TO USE THE LABELED DATA TO “TRAIN” THE PARAMETERS OF THE GRID
WHEN EVALUATING THE RESULTING MODEL IT IS IMPORTANT TO DO IT ON HELDOUT SAMPLES THAT WERE NOT SEEN DURING THE GRID SEARCH PROCESS IT IS RECOMMENDED TO SPLIT THE DATA INTO A DEVELOPMENT SET TO BE FED TO THE GRIDSEARCHCV INSTANCE AND AN EVALUATION SET TO COMPUTE PERFORMANCE METRICS
THIS CAN BE DONE BY USING THE TRAINTESTSPLIT UTILITY FUNCTION
PARALLELISM
GRIDSEARCHCV ANDRANDOMIZEDSEARCHCV EVALUATE EACH PARAMETER SETTING INDEPENDENTLY COMPUTATIONS CAN BE RUN IN PARALLEL IF YOUR OS SUPPORTS IT BY USING THE KEYWORD NJOBS1 SEE FUNCTION SIGNATURE FOR MORE DETAILS
ROBUSTNESS TO FAILURE
SOME PARAMETER SETTINGS MAY RESULT IN A FAILURE TO FIT ONE OR MORE FOLDS OF THE DATA BY DEFAULT THIS WILL CAUSE THE ENTIRE SEARCH TO FAIL EVEN IF SOME PARAMETER SETTINGS COULD BE FULLY EVALUATED SETTING ERRORSCORE0 ORNP NAN WILL MAKE THE PROCEDURE ROBUST TO SUCH FAILURE ISSUING A WARNING AND SETTING THE SCORE FOR THAT FOLD TO 0 OR NAN BUT COMPLETING THE SEARCH
ALTERNATIVES TO BRUTE FORCE PARAMETER SEARCH
MODEL SPECIFIC CROSSVALIDATION
SOME MODELS CAN FIT DATA FOR A RANGE OF VALUES OF SOME PARAMETER ALMOST AS EFFICIENTLY AS FITTING THE ESTIMATOR FOR A SINGLE VALUE OF THE PARAMETER THIS FEATURE CAN BE LEVERAGED TO PERFORM A MORE EFFICIENT CROSSVALIDATION USED FOR MODEL SELECTION OF THIS PARAMETER
THE MOST COMMON PARAMETER AMENABLE TO THIS STRATEGY IS THE PARAMETER ENCODING THE STRENGTH OF THE REGULARIZER IN THIS CASE WE SAY THAT WE COMPUTE THE REGULARIZATION PATH OF THE ESTIMATOR
HERE IS THE LIST OF SUCH MODELS
LINEARMODELELASTICNETCV L1RATIO EPS ELASTIC NET MODEL WITH ITERATIVE FITTING ALONG A REGULARIZATION PATH
LINEARMODELLARSCV FITINTERCEPT CROSSVALIDATED LEAST ANGLE REGRESSION MODEL
LINEARMODELLASSOCV EPS NALPHAS LASSO LINEAR MODEL WITH ITERATIVE FITTING ALONG A REGULARIZATION PATH
LINEARMODELLASSOLARSCV FITINTERCEPT CROSSVALIDATED LASSO USING THE LARS ALGORITHM
LINEARMODELLOGISTICREGRESSIONCV CS
LOGISTIC REGRESSION CV AKA LOGIT MAXENT CLASSIFIER
LINEARMODELMULTITASKELASTICNETCV MULTITASK L1L2 ELASTICNET WITH BUILTIN CROSSVALIDATION
LINEARMODELMULTITASKLASSOCV EPS MULTITASK LASSO MODEL TRAINED WITH L1L2 MIXEDNORM AS REGULARIZER
LINEARMODELORTHOGONALMATCHINGPURSUITCV CROSSVALIDATED ORTHOGONAL MATCHING PURSUIT MODEL OMP
LINEARMODELRIDGECV ALPHAS RIDGE REGRESSION WITH BUILTIN CROSSVALIDATION
CONTINUED ON NEXT PAGE

TABLE 31 – CONTINUED FROM PREVIOUS PAGE
LINEARMODELRIDGECLASSIFIERCV ALPHAS
RIDGE CLASSIFIER WITH BUILTIN CROSSVALIDATION
SKLEARNLINEARMODEL ELASTICNETCV
CLASSSKLEARNLINEARMODEL ELASTICNETCV L1RATIO05 EPS0001 NALPHAS100 AL
PHASNONE FITINTERCEPTTRUE NORMALIZEFALSE
PRECOMPUTE'AUTO' MAXITER1000 TOL00001
CV'WARN' COPYXTRUE VERBOSE0 NJOBSNONE
POSITIVEFALSE RANDOMSTATENONE SELEC
TION'CYCLIC'
ELASTIC NET MODEL WITH ITERATIVE FITTING ALONG A REGULARIZATION PATH
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
READ MORE IN THE USER GUIDE
PARAMETERS
L1RATIO FLOAT OR ARRAY OF FLOATS OPTIONAL FLOAT BETWEEN 0 AND 1 PASSED TO ELASTICNET SCAL
ING BETWEEN L1 AND L2 PENALTIES FOR L1RATIO 0 THE PENALTY IS AN L2 PENALTY FOR
L1RATIO 1 IT IS AN L1 PENALTY FOR 0 L1RATIO 1 THE PENALTY IS A COM
BINATION OF L1 AND L2 THIS PARAMETER CAN BE A LIST IN WHICH CASE THE DIFFERENT VALUES ARE
TESTED BY CROSSVALIDATION AND THE ONE GIVING THE BEST PREDICTION SCORE IS USED NOTE THAT A
GOOD CHOICE OF LIST OF VALUES FOR L1RATIO IS OFTEN TO PUT MORE VALUES CLOSE TO 1 IE LASSO
AND LESS CLOSE TO 0 IE RIDGE AS IN 1 5 7 9 95 99 1
EPS FLOAT OPTIONAL LENGTH OF THE PATH EPS1E3 MEANS THATALPHAMIN ALPHAMAX
1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH USED FOR EACH L1RATIO
ALPHAS NUMPY ARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE
SET AUTOMATICALLY
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
PRECOMPUTE TRUE FALSE 'AUTO' ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO
SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE PASSED
AS ARGUMENT
MAXITER INT OPTIONAL THE MAXIMUM NUMBER OF ITERATIONS
TOLFLOAT OPTIONAL THE TOLERANCE FOR THE OPTIMIZATION IF THE UPDATES ARE SMALLER THAN TOL THE
OPTIMIZATION CODE CHECKS THE DUAL GAP FOR OPTIMALITY AND CONTINUES UNTIL IT IS SMALLER THAN
TOL
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION

• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CPUS TO USE DURING THE CROSS VALIDA
TIONNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING
ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
POSITIVE BOOL OPTIONAL WHEN SET TO TRUE FORCES THE COEFFICIENTS TO BE POSITIVE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR THAT SELECTS A RANDOM FEATURE TO UPDATE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SELECTION ‘RANDOM’
SELECTION STR DEFAULT ‘CYCLIC’ IF SET TO ‘RANDOM’ A RANDOM COEFFICIENT IS UPDATED EVERY ITERATION
RATHER THAN LOOPING OVER FEATURES SEQUENTIALLY BY DEFAULT THIS SETTING TO ‘RANDOM’ OFTEN
LEADS TO SIGNIFICANTLY FASTER CONVERGENCE ESPECIALLY WHEN TOL IS HIGHER THAN 1E4
ATTRIBUTES
ALPHA FLOAT THE AMOUNT OF PENALIZATION CHOSEN BY CROSS VALIDATION
L1RATIO FLOAT THE COMPROMISE BETWEEN L1 AND L2 PENALIZATION CHOSEN BY CROSS VALIDATION
COEF ARRAY SHAPE NFEATURES NTARGETS NFEATURES PARAMETER VECTOR W IN THE COST FUNC
TION FORMULA
INTERCEPT FLOAT ARRAY SHAPE NTARGETS NFEATURES INDEPENDENT TERM IN THE DECISION FUNC
TION
MSEPATH ARRAY SHAPE NL1RATIO NALPHA NFOLDS MEAN SQUARE ERROR FOR THE TEST SET ON
EACH FOLD VARYING L1RATIO AND ALPHA
ALPHAS NUMPY ARRAY SHAPE NALPHAS OR NL1RATIO NALPHAS THE GRID OF ALPHAS USED FOR
FITTING FOR EACH L1RATIO
NITER INT NUMBER OF ITERATIONS RUN BY THE COORDINATE DESCENT SOLVER TO REACH THE SPECIFIED
TOLERANCE FOR THE OPTIMAL ALPHA
SEE ALSO
ENETPATH
ELASTICNET
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOMODELSELECTIONPY

SCIKITLEARN USER GUIDE RELEASE 0213
TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A FORTRANCONTIGUOUS NUMPY ARRAY
THE PARAMETER L1RATIO CORRESPONDS TO ALPHA IN THE GLMNET R PACKAGE WHILE ALPHA CORRESPONDS TO THE LAMBDA PARAMETER IN GLMNET MORE SPECIFICALLY THE OPTIMIZATION OBJECTIVE IS
1 2NSAMPLES Y XW22
 ALPHA L1RATIO W1
 05ALPHA1 L1RATIO W22
IF YOU ARE INTERESTED IN CONTROLLING THE L1 AND L2 PENALTY SEPARATELY KEEP IN MIND THAT THIS IS EQUIVALENT TO
AL1 BL2
FOR
ALPHA A B ANDL1RATIO A A B
EXAMPLES
 FROM SKLEARNLINEARMODEL IMPORT ELASTICNETCV
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y MAKEREGRESSIONNFEATURES2 RANDOMSTATE0
REGR ELASTICNETCVCV5 RANDOMSTATE0
REGRFITX Y
ELASTICNETCVALPHASNONE COPYXTRUE CV5 EPS0001 FITINTERCEPTTRUE
L1RATIO05 MAXITER1000 NALPHAS100 NJOBSNONE
NORMALIZEFALSE POSITIVEFALSE PRECOMPUTEAUTO RANDOMSTATE0
SELECTIONCYCLIC TOL00001 VERBOSE0
PRINTREGRALPHA
0199
PRINTREGRINTERCEPT
0398
PRINTREGRPREDICT0 0
0398
METHODS
FITSELF X Y FIT LINEAR MODEL WITH COORDINATE DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PATH X Y L1RATIO EPS NALPHAS   COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFL1RATIO05 EPS0001 NALPHAS100 ALPHASNONE FITINTERCEPTTRUE NORMAL
IZEFALSE PRECOMPUTE'AUTO' MAXITER1000 TOL00001 CV'WARN' COPYXTRUE VER
BOSE0 NJOBSNONE POSITIVEFALSE RANDOMSTATENONE SELECTION'CYCLIC'
FITSELFXY
FIT LINEAR MODEL WITH COORDINATE DESCENT

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FIT IS ON GRID OF ALPHAS AND BEST ALPHA ESTIMATED BY CROSSVALIDATION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN
CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF Y IS MONOOUTPUT X CAN
BE SPARSE
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
STATICPATHXYL1RATIO05 EPS0001 NALPHAS100 ALPHASNONE PRECOMPUTE’AUTO’
XYNONE COPYXTRUE COEFINITNONE VERBOSEFALSE RETURNNITERFALSE POSI
TIVEFALSE CHECKINPUTTRUE PARAMS
COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
THE ELASTIC NET OPTIMIZATION FUNCTION VARIES FOR MONO AND MULTIOUTPUTS
FOR MONOOUTPUT TASKS IT IS
1 2NSAMPLES Y XW22
 ALPHA L1RATIO W1
 05ALPHA1 L1RATIO W22
FOR MULTIOUTPUT TASKS IT IS
1 2 NSAMPLES Y XWFRO2
 ALPHA L1RATIO W21
 05ALPHA1 L1RATIO WFRO2
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN
CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF YIS MONOOUTPUT THEN X
CAN BE SPARSE
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
L1RATIO FLOAT OPTIONAL FLOAT BETWEEN 0 AND 1 PASSED TO ELASTIC NET SCALING BETWEEN L1 AND
L2 PENALTIES L1RATIO1 CORRESPONDS TO THE LASSO
EPS FLOAT LENGTH OF THE PATH EPS1E3 MEANS THAT ALPHAMIN ALPHAMAX
1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH

ALPHAS NDARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE SET AUTOMATICALLY
PRECOMPUTE TRUE FALSE 'AUTO' ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE PASSED AS ARGUMENT
XYARRAYLIKE OPTIONAL XY NPDOTXT Y THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY WHEN THE GRAM MATRIX IS PRECOMPUTED
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVER WRITTEN
COEFINIT ARRAY SHAPE NFEATURES NONE THE INITIAL VALUES OF THE COEFFICIENTS
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
RETURNNITER BOOL WHETHER TO RETURN THE NUMBER OF ITERATIONS OR NOT
POSITIVE BOOL DEFAULT FALSE IF SET TO TRUE FORCES COEFFICIENTS TO BE POSITIVE ONLY ALLOWED WHENYNDIM 1
CHECKINPUT BOOL DEFAULT TRUE SKIP INPUT VALIDATION CHECKS INCLUDING THE GRAM MATRIX WHEN PROVIDED ASSUMING THERE ARE HANDLED BY THE CALLER WHEN CHECKINPUTFALSE
PARAMS KWARGS KEYWORD ARGUMENTS PASSED TO THE COORDINATE DESCENT SOLVER
RETURNS
ALPHAS ARRAY SHAPE NALPHAS THE ALPHAS ALONG THE PATH WHERE MODELS ARE COMPUTED
COEFS ARRAY SHAPE NFEATURES NALPHAS OR NOUTPUTS NFEATURES NALPHAS COEFFICIENTS ALONG THE PATH
DUALGAPS ARRAY SHAPE NALPHAS THE DUAL GAPS AT THE END OF THE OPTIMIZATION FOR EACH ALPHA
NITERS ARRAYLIKE SHAPE NALPHAS THE NUMBER OF ITERATIONS TAKEN BY THE COORDINATE DESCENT OPTIMIZER TO REACH THE SPECIFIED TOLERANCE FOR EACH ALPHA IS RETURNED WHEN RETURNNITER IS SET TO TRUE
SEE ALSO
MULTITASKELASTICNET
MULTITASKELASTICNETCV
ELASTICNET
ELASTICNETCV
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOCOORDINATEDESCENTPATHPY
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS

SCIKITLEARN USER GUIDE RELEASE 0213
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SKLEARNLINEARMODEL LARSCV
CLASSSKLEARNLINEARMODEL LARSCVFITINTERCEPTTRUE VERBOSEFALSE MAXITER500
NORMALIZETRUE PRECOMPUTE’AUTO’
CV’WARN’ MAXNALPHAS1000 NJOBSNONE
EPS2220446049250313E16 COPYXTRUE POSITIVEFALSE
CROSSVALIDATED LEAST ANGLE REGRESSION MODEL
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
READ MORE IN THE USER GUIDE
PARAMETERS
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED

VERBOSE BOOLEAN OR INTEGER OPTIONAL SETS THE VERBOSITY AMOUNT
MAXITER INTEGER OPTIONAL MAXIMUM NUMBER OF ITERATIONS TO PERFORM
NORMALIZE BOOLEAN OPTIONAL DEFAULT TRUE THIS PARAMETER IS IGNORED WHEN FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BEFORE REGRESSION BY SUB TRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE CALLING FIT ON AN ESTIMATOR WITHNORMALIZEFALSE
PRECOMPUTE TRUE FALSE 'AUTO' ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CANNOT BE PASSED AS ARGUMENT SINCE WE WILL USE ONLY SUBSETS OF X
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN V022
MAXNALPHAS INTEGER OPTIONAL THE MAXIMUM NUMBER OF POINTS ON THE PATH USED TO COMPUTE THE RESIDUALS IN THE CROSSVALIDATION
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CPUS TO USE DURING THE CROSS VALIDA TIONNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
EPS FLOAT OPTIONAL THE MACHINEPRECISION REGULARIZATION IN THE COMPUTATION OF THE CHOLESKY DIAGONAL FACTORS INCREASE THIS FOR VERY ILLCONDITIONED SYSTEMS
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
POSITIVE BOOLEAN DEFAULTFALSE RESTRICT COEFFICIENTS TO BE 0 BE AWARE THAT YOU MIGHT WANT TO REMOVE FITINTERCEPT WHICH IS SET TRUE BY DEFAULT
DEPRECATED SINCE VERSION 020 THE OPTION IS BROKEN AND DEPRECATED IT WILL BE REMOVED IN V022
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES PARAMETER VECTOR W IN THE FORMULATION FORMULA
INTERCEPT FLOAT INDEPENDENT TERM IN DECISION FUNCTION
COEFPATH ARRAY SHAPE NFEATURES NALPHAS THE VARYING VALUES OF THE COEFFICIENTS ALONG THE PATH
ALPHA FLOAT THE ESTIMATED REGULARIZATION PARAMETER ALPHA
ALPHAS ARRAY SHAPE NALPHAS THE DIFFERENT VALUES OF ALPHA ALONG THE PATH
CVALPHAS ARRAY SHAPE NCVALPHAS ALL THE VALUES OF ALPHA ALONG THE PATH FOR THE DIFFERENT FOLDS

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MSEPATH ARRAY SHAPE NFOLDS NCVALPHAS THE MEAN SQUARE ERROR ON LEFTOUT FOR EACH FOLD
ALONG THE PATH ALPHA VALUES GIVEN BY CVALPHAS
NITER ARRAYLIKE OR INT THE NUMBER OF ITERATIONS RUN BY LARS WITH THE OPTIMAL ALPHA
SEE ALSO
LARSPATH LASSOLARS LASSOLARSCV
EXAMPLES
FROM SKLEARNLINEARMODEL IMPORT LARSCV
FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y MAKEREGRESSIONNSAMPLES200 NOISE40 RANDOMSTATE0
REG LARSCVCV5FITX Y
REGSCOREX Y
09996
REGALPHA
00254
REGPREDICTX1
ARRAY1540842
METHODS
FITSELF X Y FIT THE MODEL USING X Y AS TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFFITINTERCEPTTRUE VERBOSEFALSE MAXITER500 NORMALIZETRUE PRECOM
PUTE’AUTO’ CV’WARN’ MAXNALPHAS1000 NJOBSNONE EPS2220446049250313E
16COPYXTRUE POSITIVEFALSE
FITSELFXY
FIT THE MODEL USING X Y AS TRAINING DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES
RETURNS
SELF OBJECT RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS

PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF

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SKLEARNLINEARMODEL LASSOCV
CLASSSKLEARNLINEARMODEL LASSOCVEPS0001 NALPHAS100 ALPHASNONE FITINTERCEPTTRUE
NORMALIZEFALSE PRECOMPUTE'AUTO' MAXITER1000
TOL00001 COPYXTRUE CV'WARN' VERBOSEFALSE
NJOBSNONE POSITIVEFALSE RANDOMSTATENONE SELEC
TION'CYCLIC'
LASSO LINEAR MODEL WITH ITERATIVE FITTING ALONG A REGULARIZATION PATH
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
THE BEST MODEL IS SELECTED BY CROSSVALIDATION
THE OPTIMIZATION OBJECTIVE FOR LASSO IS
1 2 NSAMPLES Y XW22 ALPHA W1
READ MORE IN THE USER GUIDE
PARAMETERS
EPS FLOAT OPTIONAL LENGTH OF THE PATH EPS1E3 MEANS THATALPHAMIN ALPHAMAX
 1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS NUMPY ARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS
ARE SET AUTOMATICALLY
FITINTERCEPT BOOLEAN DEFAULT TRUE WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO
FALSE NO INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
PRECOMPUTE TRUE FALSE 'AUTO' ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO
SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE PASSED
AS ARGUMENT
MAXITER INT OPTIONAL THE MAXIMUM NUMBER OF ITERATIONS
TOLFLOAT OPTIONAL THE TOLERANCE FOR THE OPTIMIZATION IF THE UPDATES ARE SMALLER THAN TOL THE
OPTIMIZATION CODE CHECKS THE DUAL GAP FOR OPTIMALITY AND CONTINUES UNTIL IT IS SMALLER THAN
TOL
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE

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CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CPUS TO USE DURING THE CROSS VALIDA
TIONNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING
ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
POSITIVE BOOL OPTIONAL IF POSITIVE RESTRICT REGRESSION COEFFICIENTS TO BE POSITIVE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR THAT SELECTS A RANDOM FEATURE TO UPDATE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SELECTION ‘RANDOM’
SELECTION STR DEFAULT ‘CYCLIC’ IF SET TO ‘RANDOM’ A RANDOM COEFFICIENT IS UPDATED EVERY ITERATION
RATHER THAN LOOPING OVER FEATURES SEQUENTIALLY BY DEFAULT THIS SETTING TO ‘RANDOM’ OFTEN
LEADS TO SIGNIFICANTLY FASTER CONVERGENCE ESPECIALLY WHEN TOL IS HIGHER THAN 1E4
ATTRIBUTES
ALPHA FLOAT THE AMOUNT OF PENALIZATION CHOSEN BY CROSS VALIDATION
COEF ARRAY SHAPE NFEATURES NTARGETS NFEATURES PARAMETER VECTOR W IN THE COST FUNC
TION FORMULA
INTERCEPT FLOAT ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION
MSEPATH ARRAY SHAPE NALPHAS NFOLDS MEAN SQUARE ERROR FOR THE TEST SET ON EACH FOLD
VARYING ALPHA
ALPHAS NUMPY ARRAY SHAPE NALPHAS THE GRID OF ALPHAS USED FOR FITTING
DUALGAP NDARRAY SHAPE THE DUAL GAP AT THE END OF THE OPTIMIZATION FOR THE OPTIMAL ALPHA
ALPHA
NITER INT NUMBER OF ITERATIONS RUN BY THE COORDINATE DESCENT SOLVER TO REACH THE SPECIFIED
TOLERANCE FOR THE OPTIMAL ALPHA
SEE ALSO
LARSPATH
LASSOPATH
LASSOLARS
LASSO
LASSOLARSCV
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOMODELSELECTIONPY
TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A
FORTRANCONTIGUOUS NUMPY ARRAY

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EXAMPLES
FROM SKLEARNLINEARMODEL IMPORT LASSOCV
FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y MAKEREGRESSIONNOISE4 RANDOMSTATE0
REG LASSOCVCV5 RANDOMSTATE0FITX Y
REGSCOREX Y
09993
REGPREDICTX1
ARRAY784951
METHODS
FITSELF X Y FIT LINEAR MODEL WITH COORDINATE DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PATH X Y EPS NALPHAS ALPHAS COMPUTE LASSO PATH WITH COORDINATE DESCENT
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFEPS0001 NALPHAS100 ALPHASNONE FITINTERCEPTTRUE NORMALIZEFALSE PRE
COMPUTE'AUTO' MAXITER1000 TOL00001 COPYXTRUE CV'WARN' VERBOSEFALSE
NJOBSNONE POSITIVEFALSE RANDOMSTATENONE SELECTION'CYCLIC'
FITSELFXY
FIT LINEAR MODEL WITH COORDINATE DESCENT
FIT IS ON GRID OF ALPHAS AND BEST ALPHA ESTIMATED BY CROSSVALIDATION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN
CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF Y IS MONOOUTPUT X CAN
BE SPARSE
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
STATICPATHXYEPS0001 NALPHAS100 ALPHASNONE PRECOMPUTE'AUTO' XYNONE
COPYXTRUE COEFINITNONE VERBOSEFALSE RETURNNITERFALSE POSITIVEFALSE
PARAMS
COMPUTE LASSO PATH WITH COORDINATE DESCENT
THE LASSO OPTIMIZATION FUNCTION VARIES FOR MONO AND MULTIOUTPUTS
FOR MONOOUTPUT TASKS IT IS

1 2 NSAMPLES Y XW22 ALPHA W1
FOR MULTIOUTPUT TASKS IT IS
1 2 NSAMPLES Y XW2FRO ALPHA W21
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY
AS FORTRANCONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF YIS MONOOUTPUT
THENXCAN BE SPARSE
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
EPS FLOAT OPTIONAL LENGTH OF THE PATH EPS1E3 MEANS THAT ALPHAMIN
ALPHAMAX 1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS NDARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE
SET AUTOMATICALLY
PRECOMPUTE TRUE FALSE ‘AUTO’ ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX
TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE
PASSED AS ARGUMENT
XYARRAYLIKE OPTIONAL XY NPDOTXT Y THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY
WHEN THE GRAM MATRIX IS PRECOMPUTED
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVER
WRITTEN
COEFINIT ARRAY SHAPE NFEATURES   NONE THE INITIAL VALUES OF THE COEFFICIENTS
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
RETURNNITER BOOL WHETHER TO RETURN THE NUMBER OF ITERATIONS OR NOT
POSITIVE BOOL DEFAULT FALSE IF SET TO TRUE FORCES COEFFICIENTS TO BE POSITIVE ONLY ALLOWED
WHENYNDIM 1
PARAMS KWARGS KEYWORD ARGUMENTS PASSED TO THE COORDINATE DESCENT SOLVER
RETURNS
ALPHAS ARRAY SHAPE NALPHAS THE ALPHAS ALONG THE PATH WHERE MODELS ARE COMPUTED
COEFS ARRAY SHAPE NFEATURES NALPHAS OR NOUTPUTS NFEATURES NALPHAS COEFFICIENTS
ALONG THE PATH
DUALGAPS ARRAY SHAPE NALPHAS THE DUAL GAPS AT THE END OF THE OPTIMIZATION FOR EACH
ALPHA
NITERS ARRAYLIKE SHAPE NALPHAS THE NUMBER OF ITERATIONS TAKEN BY THE COORDINATE DE
SCENT OPTIMIZER TO REACH THE SPECIFIED TOLERANCE FOR EACH ALPHA

SEE ALSO
LARSPATH
LASSO
LASSOLARS
LASSOCV
LASSOLARSCV
SKLEARNDECOMPOSITIONSPARSEENCODE
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOCOORDINATEDESCENTPATHPY
TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A FORTRANCONTIGUOUS NUMPY ARRAY
NOTE THAT IN CERTAIN CASES THE LARS SOLVER MAY BE SIGNIFICANTLY FASTER TO IMPLEMENT THIS FUNCTIONALITY IN PARTICULAR LINEAR INTERPOLATION CAN BE USED TO RETRIEVE MODEL COEFFICIENTS BETWEEN THE VALUES OUTPUT BY LARSPATH
EXAMPLES
COMPARING LASSOPATH AND LARSPATH WITH INTERPOLATION
X NPARRAY1 2 31 23 54 43T
Y NPARRAY1 2 31
 USE LASSOPATH TO COMPUTE A COEFFICIENT PATH
 COEFPATH   LASSOPATHX Y ALPHAS5 1 5
PRINTCOEFPATH
0 0 046874778
02159048 04425765 023689075
 NOW USE LARSPATH AND 1D LINEAR INTERPOLATION TO COMPUTE THE
 SAME PATH
 FROM SKLEARNLINEARMODEL IMPORT LARSPATH
ALPHAS ACTIVE COEFPATHLARS LARSPATHX Y METHODLASSO
 FROM SCIPY IMPORT INTERPOLATE
COEFPATHCONTINUOUS INTERPOLATEINTERP1DALPHAS1
 COEFPATHLARS 1
PRINTCOEFPATHCONTINUOUS5 1 5
0 0 046915237
02159048 04425765 023668876
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES

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SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELLASSOCV
•CROSSVALIDATION ON DIABETES DATASET EXERCISE
•FEATURE SELECTION USING SELECTFROMMODEL AND LASSOCV
•LASSO MODEL SELECTION CROSSVALIDATION AIC BIC
SKLEARNLINEARMODEL LASSOLARSCV
CLASSSKLEARNLINEARMODEL LASSOLARSCV FITINTERCEPTTRUE VERBOSEFALSE MAXITER500
NORMALIZETRUE PRECOMPUTE’AUTO’
CV’WARN’ MAXNALPHAS1000 NJOBSNONE
EPS2220446049250313E16 COPYXTRUE POSI
TIVEFALSE
CROSSVALIDATED LASSO USING THE LARS ALGORITHM

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SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
THE OPTIMIZATION OBJECTIVE FOR LASSO IS
1 2 NSAMPLES Y XW22 ALPHA W1
READ MORE IN THE USER GUIDE
PARAMETERS
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
VERBOSE BOOLEAN OR INTEGER OPTIONAL SETS THE VERBOSITY AMOUNT
MAXITER INTEGER OPTIONAL MAXIMUM NUMBER OF ITERATIONS TO PERFORM
NORMALIZE BOOLEAN OPTIONAL DEFAULT TRUE THIS PARAMETER IS IGNORED WHEN FITINTERCEPT
IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BEFORE REGRESSION BY SUB
TRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO STANDARDIZE PLEASE USE
SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE CALLING FIT ON AN ESTIMATOR
WITHNORMALIZEFALSE
PRECOMPUTE TRUE FALSE ‘AUTO’ WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO SPEED UP
CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CANNOT BE PASSED AS ARGUMENT
SINCE WE WILL USE ONLY SUBSETS OF X
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
MAXNALPHAS INTEGER OPTIONAL THE MAXIMUM NUMBER OF POINTS ON THE PATH USED TO COMPUTE
THE RESIDUALS IN THE CROSSVALIDATION
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CPUS TO USE DURING THE CROSS VALIDA
TIONNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING
ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
EPS FLOAT OPTIONAL THE MACHINEPRECISION REGULARIZATION IN THE COMPUTATION OF THE CHOLESKY
DIAGONAL FACTORS INCREASE THIS FOR VERY ILLCONDITIONED SYSTEMS
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
POSITIVE BOOLEAN DEFAULTFALSE RESTRICT COEFFICIENTS TO BE 0 BE AWARE THAT YOU MIGHT
WANT TO REMOVE FITINTERCEPT WHICH IS SET TRUE BY DEFAULT UNDER THE POSITIVE RESTRICTION THE
MODEL COEFFICIENTS DO NOT CONVERGE TO THE ORDINARYLEASTSQUARES SOLUTION FOR SMALL VALUES
OF ALPHA ONLY COEFFICIENTS UP TO THE SMALLEST ALPHA VALUE ALPHASALPHAS 0
MIN WHEN FITPATHTRUE REACHED BY THE STEPWISE LARSLASSO ALGORITHM ARE TYPICALLY IN
CONGRUENCE WITH THE SOLUTION OF THE COORDINATE DESCENT LASSO ESTIMATOR AS A CONSEQUENCE

USING LASSOLARSCV ONLY MAKES SENSE FOR PROBLEMS WHERE A SPARSE SOLUTION IS EXPECTED
ANDOR REACHED
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES PARAMETER VECTOR W IN THE FORMULATION FORMULA
INTERCEPT FLOAT INDEPENDENT TERM IN DECISION FUNCTION
COEFPATH ARRAY SHAPE NFEATURES NALPHAS THE VARYING VALUES OF THE COEFFICIENTS ALONG THE
PATH
ALPHA FLOAT THE ESTIMATED REGULARIZATION PARAMETER ALPHA
ALPHAS ARRAY SHAPE NALPHAS THE DIFFERENT VALUES OF ALPHA ALONG THE PATH
CVALPHAS ARRAY SHAPE NCVALPHAS ALL THE VALUES OF ALPHA ALONG THE PATH FOR THE DIFFERENT
FOLDS
MSEPATH ARRAY SHAPE NFOLDS NCVALPHAS THE MEAN SQUARE ERROR ON LEFTOUT FOR EACH FOLD
ALONG THE PATH ALPHA VALUES GIVEN BY CVALPHAS
NITER ARRAYLIKE OR INT THE NUMBER OF ITERATIONS RUN BY LARS WITH THE OPTIMAL ALPHA
SEE ALSO
LARSPATH LASSOLARS LARSCV LASSOCV
NOTES
THE OBJECT SOLVES THE SAME PROBLEM AS THE LASSOCV OBJECT HOWEVER UNLIKE THE LASSOCV IT FIND THE RELEVANT
ALPHAS VALUES BY ITSELF IN GENERAL BECAUSE OF THIS PROPERTY IT WILL BE MORE STABLE HOWEVER IT IS MORE FRAGILE TO
HEAVILY MULTICOLLINEAR DATASETS
IT IS MORE EFFICIENT THAN THE LASSOCV IF ONLY A SMALL NUMBER OF FEATURES ARE SELECTED COMPARED TO THE TOTAL
NUMBER FOR INSTANCE IF THERE ARE VERY FEW SAMPLES COMPARED TO THE NUMBER OF FEATURES
EXAMPLES
```
 FROM SKLEARNLINEARMODEL IMPORT LASSOLARSCV
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y  MAKEREGRESSIONNOISE40 RANDOMSTATE0
REG  LASSOLARSCVCV5FITX Y
REGSCOREX Y
09992
REGALPHA
00484
REGPREDICTX1
ARRAY778723
```
METHODS
FITSELF X Y FIT THE MODEL USING X Y AS TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
CONTINUED ON NEXT PAGE

TABLE 35 – CONTINUED FROM PREVIOUS PAGE
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFFITINTERCEPTTRUE VERBOSEFALSE MAXITER500 NORMALIZETRUE PRECOM
PUTE'AUTO' CV'WARN' MAXNALPHAS1000 NJOBSNONE EPS2220446049250313E
16COPYXTRUE POSITIVEFALSE
FITSELFXY
FIT THE MODEL USING X Y AS TRAINING DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES
RETURNS
SELF OBJECT RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y

NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELLASSOLARSCV
•LASSO MODEL SELECTION CROSSVALIDATION AIC BIC
SKLEARNLINEARMODEL LOGISTICREGRESSIONCV
CLASSSKLEARNLINEARMODEL LOGISTICREGRESSIONCV CS10 FITINTERCEPTTRUE CV’WARN’
DUALFALSE PENALTY’L2’ SCOR
INGNONE SOLVER’LBFGS’ TOL00001
MAXITER100 CLASSWEIGHTNONE
NJOBSNONE VERBOSE0 REFITTRUE IN
TERCEPTSCALING10 MULTICLASS’WARN’
RANDOMSTATENONE L1RATIOSNONE
LOGISTIC REGRESSION CV AKA LOGIT MAXENT CLASSIFIER
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
THIS CLASS IMPLEMENTS LOGISTIC REGRESSION USING LIBLINEAR NEWTONCG SAG OF LBFGS OPTIMIZER THE NEWTONCG SAG
AND LBFGS SOLVERS SUPPORT ONLY L2 REGULARIZATION WITH PRIMAL FORMULATION THE LIBLINEAR SOLVER SUPPORTS BOTH L1
AND L2 REGULARIZATION WITH A DUAL FORMULATION ONLY FOR THE L2 PENALTY ELASTICNET PENALTY IS ONLY SUPPORTED BY
THE SAGA SOLVER
FOR THE GRID OF CSVALUES AND L1RATIOS VALUES THE BEST HYPERPARAMETER IS SELECTED BY THE CROSSVALIDATOR
STRATIFIEDKFOLD BUT IT CAN BE CHANGED USING THE CVPARAMETER THE ‘NEWTONCG’ ‘SAG’ ‘SAGA’ AND ‘LBFGS’
SOLVERS CAN WARMSTART THE COEFFICIENTS SEE GLOSSARY
READ MORE IN THE USER GUIDE
PARAMETERS
CSLIST OF FLOATS OR INT OPTIONAL DEFAULT10 EACH OF THE VALUES IN CS DESCRIBES THE INVERSE OF
REGULARIZATION STRENGTH IF CS IS AS AN INT THEN A GRID OF CS VALUES ARE CHOSEN IN A LOGARITH
MIC SCALE BETWEEN 1E4 AND 1E4 LIKE IN SUPPORT VECTOR MACHINES SMALLER VALUES SPECIFY
STRONGER REGULARIZATION
FITINTERCEPT BOOL OPTIONAL DEFAULTTRUE SPECIFIES IF A CONSTANT AKA BIAS OR INTERCEPT
SHOULD BE ADDED TO THE DECISION FUNCTION

CVINT OR CROSSVALIDATION GENERATOR OPTIONAL DEFAULTNONE THE DEFAULT CROSSVALIDATION GEN
ERATOR USED IS STRATIFIED KFOLDS IF AN INTEGER IS PROVIDED THEN IT IS THE NUMBER OF FOLDS
USED SEE THE MODULE SKLEARNMODELSELECTION MODULE FOR THE LIST OF POSSIBLE
CROSSVALIDATION OBJECTS
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
DUAL BOOL OPTIONAL DEFAULTFALSE DUAL OR PRIMAL FORMULATION DUAL FORMULATION IS ONLY
IMPLEMENTED FOR L2 PENALTY WITH LIBLINEAR SOLVER PREFER DUALFALSE WHEN NSAMPLES
NFEATURES
PENALTY STR ‘L1’ ‘L2’ OR ‘ELASTICNET’ OPTIONAL DEFAULT’L2’ USED TO SPECIFY THE NORM USED
IN THE PENALIZATION THE ‘NEWTONCG’ ‘SAG’ AND ‘LBFGS’ SOLVERS SUPPORT ONLY L2 PENALTIES
‘ELASTICNET’ IS ONLY SUPPORTED BY THE ‘SAGA’ SOLVER
SCORING STRING CALLABLE OR NONE OPTIONAL DEFAULTNONE A STRING SEE MODEL EVALUATION DOC
UMENTATION OR A SCORER CALLABLE OBJECT FUNCTION WITH SIGNATURE SCORERESTIMATOR
X Y FOR A LIST OF SCORING FUNCTIONS THAT CAN BE USED LOOK AT SKLEARNMETRICS THE
DEFAULT SCORING OPTION USED IS ‘ACCURACY’
SOLVER STR ‘NEWTONCG’ ‘LBFGS’ ‘LIBLINEAR’ ‘SAG’ ‘SAGA’ OPTIONAL DEFAULT’LBFGS’ ALGO
RITHM TO USE IN THE OPTIMIZATION PROBLEM
• FOR SMALL DATASETS ‘LIBLINEAR’ IS A GOOD CHOICE WHEREAS ‘SAG’ AND ‘SAGA’ ARE FASTER FOR
LARGE ONES
• FOR MULTICLASS PROBLEMS ONLY ‘NEWTONCG’ ‘SAG’ ‘SAGA’ AND ‘LBFGS’ HANDLE MULTINOMIAL
LOSS ‘LIBLINEAR’ IS LIMITED TO ONEVERSUSREST SCHEMES
• ‘NEWTONCG’ ‘LBFGS’ AND ‘SAG’ ONLY HANDLE L2 PENALTY WHEREAS ‘LIBLINEAR’ AND ‘SAGA’
HANDLE L1 PENALTY
• ‘LIBLINEAR’ MIGHT BE SLOWER IN LOGISTICREGRESSIONCV BECAUSE IT DOES NOT HANDLE WARM
STARTING
NOTE THAT ‘SAG’ AND ‘SAGA’ FAST CONVERGENCE IS ONLY GUARANTEED ON FEATURES WITH APPROXI
MATELY THE SAME SCALE YOU CAN PREPROCESS THE DATA WITH A SCALER FROM SKLEARNPREPROCESSING
NEW IN VERSION 017 STOCHASTIC AVERAGE GRADIENT DESCENT SOLVER
NEW IN VERSION 019 SAGA SOLVER
TOLFLOAT OPTIONAL DEFAULT1E4 TOLERANCE FOR STOPPING CRITERIA
MAXITER INT OPTIONAL DEFAULT100 MAXIMUM NUMBER OF ITERATIONS OF THE OPTIMIZATION AL
GORITHM
CLASSWEIGHT DICT OR ‘BALANCED’ OPTIONAL DEFAULTNONE WEIGHTS ASSOCIATED WITH CLASSES IN
THE FORMCLASSLABEL WEIGHT IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE
WEIGHT ONE
THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP
BINCOUNTY
NOTE THAT THESE WEIGHTS WILL BE MULTIPLIED WITH SAMPLEWEIGHT PASSED THROUGH THE FIT
METHOD IF SAMPLEWEIGHT IS SPECIFIED
NEW IN VERSION 017 CLASSWEIGHT ‘BALANCED’

NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CPU CORES USED DURING THE CROSS
VALIDATION LOOP NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1
MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
VERBOSE INT OPTIONAL DEFAULT0 FOR THE 'LIBLINEAR' 'SAG' AND 'LBFGS' SOLVERS SET VERBOSE TO
ANY POSITIVE NUMBER FOR VERBOSITY
REFIT BOOL OPTIONAL DEFAULTTRUE IF SET TO TRUE THE SCORES ARE AVERAGED ACROSS ALL FOLDS AND
THE COEFS AND THE C THAT CORRESPONDS TO THE BEST SCORE IS TAKEN AND A FINAL REFIT IS DONE USING
THESE PARAMETERS OTHERWISE THE COEFS INTERCEPTS AND C THAT CORRESPOND TO THE BEST SCORES
ACROSS FOLDS ARE AVERAGED
INTERCEPTSCALING FLOAT OPTIONAL DEFAULT1 USEFUL ONLY WHEN THE SOLVER 'LIBLINEAR' IS USED
AND SELFFITINTERCEPT IS SET TO TRUE IN THIS CASE X BECOMES X SELFINTERCEPTSCALING
IE A "SYNTHETIC" FEATURE WITH CONSTANT VALUE EQUAL TO INTERCEPTSCALING IS AP
PENDED TO THE INSTANCE VECTOR THE INTERCEPT BECOMES INTERCEPTSCALING
SYNTHETICFEATUREWEIGHT
NOTE THE SYNTHETIC FEATURE WEIGHT IS SUBJECT TO L1L2 REGULARIZATION AS ALL OTHER FEATURES TO
LESSEN THE EFFECT OF REGULARIZATION ON SYNTHETIC FEATURE WEIGHT AND THEREFORE ON THE INTERCEPT
INTERCEPTSCALING HAS TO BE INCREASED
MULTICLASS STR 'OVR' 'MULTINOMIAL' 'AUTO' OPTIONAL DEFAULT'OVR' IF THE OPTION CHOSEN
IS 'OVR' THEN A BINARY PROBLEM IS FIT FOR EACH LABEL FOR 'MULTINOMIAL' THE LOSS MINIMISED
IS THE MULTINOMIAL LOSS FIT ACROSS THE ENTIRE PROBABILITY DISTRIBUTION EVEN WHEN THE DATA IS
BINARY 'MULTINOMIAL' IS UNAVAILABLE WHEN SOLVER'LIBLINEAR' 'AUTO' SELECTS 'OVR' IF THE DATA
IS BINARY OR IF SOLVER'LIBLINEAR' AND OTHERWISE SELECTS 'MULTINOMIAL'
NEW IN VERSION 018 STOCHASTIC AVERAGE GRADIENT DESCENT SOLVER FOR 'MULTINOMIAL' CASE
CHANGED IN VERSION 020 DEFAULT WILL CHANGE FROM 'OVR' TO 'AUTO' IN 022
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
L1RATIOS LIST OF FLOAT OR NONE OPTIONAL DEFAULTNONE THE LIST OF ELASTICNET MIXING PARAME
TER WITH0 L1RATIO 1 ONLY USED IF PENALTYELASTICNET A VALUE OF
0 IS EQUIVALENT TO USING PENALTYL2 WHILE 1 IS EQUIVALENT TO USING PENALTYL1
FOR0 L1RATIO 1 THE PENALTY IS A COMBINATION OF L1 AND L2
ATTRIBUTES
CLASSES ARRAY SHAPE NCLASSES A LIST OF CLASS LABELS KNOWN TO THE CLASSIFIER
COEF ARRAY SHAPE 1 NFEATURES OR NCLASSES NFEATURES COEFFICIENT OF THE FEATURES IN THE
DECISION FUNCTION
COEF IS OF SHAPE 1 NFEATURES WHEN THE GIVEN PROBLEM IS BINARY
INTERCEPT ARRAY SHAPE 1 OR NCLASSES INTERCEPT AKA BIAS ADDED TO THE DECISION FUNC
TION
IFFITINTERCEPT IS SET TO FALSE THE INTERCEPT IS SET TO ZERO INTERCEPT IS OF
SHAPE1 WHEN THE PROBLEM IS BINARY
CS ARRAY SHAPE NCS ARRAY OF C IE INVERSE OF REGULARIZATION PARAMETER VALUES USED FOR
CROSSVALIDATION
L1RATIOS ARRAY SHAPE NL1RATIOS ARRAY OF L1RATIOS USED FOR CROSSVALIDATION IF NO
L1RATIO IS USED IE PENALTY IS NOT 'ELASTICNET' THIS IS SET TO NONE

COEFSPATHS ARRAY SHAPE NFOLDS NCS NFEATURES OR NFOLDS NCS NFEATURES 1 DICT
WITH CLASSES AS THE KEYS AND THE PATH OF COEFFICIENTS OBTAINED DURING CROSSVALIDATING
ACROSS EACH FOLD AND THEN ACROSS EACH CS AFTER DOING AN OVR FOR THE CORRESPOND
ING CLASS AS VALUES IF THE ‘MULTICLASS’ OPTION IS SET TO ‘MULTINOMIAL’ THEN THE CO
EFSPATHS ARE THE COEFFICIENTS CORRESPONDING TO EACH CLASS EACH DICT VALUE HAS SHAPE
NFOLDS NCS NFEATURES ORNFOLDS NCS NFEATURES 1
DEPENDING ON WHETHER THE INTERCEPT IS FIT OR NOT IF PENALTYELASTICNET THE SHAPE
ISNFOLDS NCS NL1RATIOS NFEATURES ORNFOLDS NCS
NL1RATIOS NFEATURES 1
SCORES DICT DICT WITH CLASSES AS THE KEYS AND THE VALUES AS THE GRID OF SCORES OBTAINED DUR
ING CROSSVALIDATING EACH FOLD AFTER DOING AN OVR FOR THE CORRESPONDING CLASS IF THE
‘MULTICLASS’ OPTION GIVEN IS ‘MULTINOMIAL’ THEN THE SAME SCORES ARE REPEATED ACROSS ALL
CLASSES SINCE THIS IS THE MULTINOMIAL CLASS EACH DICT VALUE HAS SHAPE NFOLDS NCS
ORNFOLDS NCS NL1RATIOS IFPENALTYELASTICNET
CARRAY SHAPE NCLASSES OR NCLASSES 1 ARRAY OF C THAT MAPS TO THE BEST SCORES ACROSS
EVERY CLASS IF REFIT IS SET TO FALSE THEN FOR EACH CLASS THE BEST C IS THE AVERAGE OF THE C’S THAT
CORRESPOND TO THE BEST SCORES FOR EACH FOLD CIS OF SHAPENCLASSES WHEN THE PROBLEM IS
BINARY
L1RATIO ARRAY SHAPE NCLASSES OR NCLASSES 1 ARRAY OF L1RATIO THAT MAPS TO THE BEST
SCORES ACROSS EVERY CLASS IF REFIT IS SET TO FALSE THEN FOR EACH CLASS THE BEST L1RATIO IS THE
AVERAGE OF THE L1RATIO’S THAT CORRESPOND TO THE BEST SCORES FOR EACH FOLD L1RATIO IS OF
SHAPENCLASSES WHEN THE PROBLEM IS BINARY
NITER ARRAY SHAPE NCLASSES NFOLDS NCS OR 1 NFOLDS NCS ACTUAL NUMBER OF ITERA
TIONS FOR ALL CLASSES FOLDS AND CS IN THE BINARY OR MULTINOMIAL CASES THE FIRST DIMENSION
IS EQUAL TO 1 IF PENALTYELASTICNET THE SHAPE IS NCLASSES NFOLDS
NCS NL1RATIOS OR1 NFOLDS NCS NL1RATIOS
SEE ALSO
LOGISTICREGRESSION
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSIONCV
X Y  LOADIRISRETURNXY TRUE
CLF  LOGISTICREGRESSIONCVCV5 RANDOMSTATE0
 MULTICLASSMULTINOMIALFITX Y
CLFPREDICTX2
ARRAY0 0
CLFPREDICTPROBAX2 SHAPE
2 3
CLFSCOREX Y
098
```
METHODS
DECISIONFUNCTION SELF X PREDICT CONFIDENCE SCORES FOR SAMPLES
DENSIFY SELF CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
CONTINUED ON NEXT PAGE

TABLE 36 – CONTINUED FROM PREVIOUS PAGE
FITSELF X Y SAMPLEWEIGHT FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASS LABELS FOR SAMPLES IN X
PREDICTLOGPROBA SELF X LOG OF PROBABILITY ESTIMATES
PREDICTPROBA SELF X PROBABILITY ESTIMATES
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE SCORE USING THE SCORING OPTION ON THE GIVEN
TEST DATA AND LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
SPARSIFY SELF CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
INIT SELFCS10 FITINTERCEPTTRUE CV'WARN' DUALFALSE PENALTY'L2' SCORINGNONE
SOLVER'LBFGS' TOL00001 MAXITER100 CLASSWEIGHTNONE NJOBSNONE VER
BOSE0 REFITTRUE INTERCEPTSCALING10 MULTICLASS'WARN' RANDOMSTATENONE
L1RATIOSNONE
DECISIONFUNCTION SELFX
PREDICT CONFIDENCE SCORES FOR SAMPLES
THE CONFIDENCE SCORE FOR A SAMPLE IS THE SIGNED DISTANCE OF THAT SAMPLE TO THE HYPERPLANE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
ARRAY SHAPENSAMPLES IF NCLASSES 2 ELSE NSAMPLES NCLASSES CONFIDENCE
SCORES PER SAMPLE CLASS COMBINATION IN THE BINARY CASE CONFIDENCE SCORE FOR
SELFCLASSES1 WHERE 0 MEANS THIS CLASS WOULD BE PREDICTED
DENSIFYSELF
CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
CONVERTS THE COEF MEMBER BACK TO A NUMPYNDARRAY THIS IS THE DEFAULT FORMAT OF COEF AND IS
REQUIRED FOR FITTING SO CALLING THIS METHOD IS ONLY REQUIRED ON MODELS THAT HAVE PREVIOUSLY BEEN SPARSIFIED
OTHERWISE IT IS A NOOP
RETURNS
SELF ESTIMATOR
FITSELFXYSAMPLEWEIGHTNONE
FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES TARGET VECTOR RELATIVE TO X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL ARRAY OF WEIGHTS THAT ARE ASSIGNED
TO INDIVIDUAL SAMPLES IF NOT PROVIDED THEN EACH SAMPLE IS GIVEN UNIT WEIGHT
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT CLASS LABELS FOR SAMPLES IN X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES PREDICTED CLASS LABEL PER SAMPLE
PREDICTLOGPROBA SELFX
LOG OF PROBABILITY ESTIMATES
THE RETURNED ESTIMATES FOR ALL CLASSES ARE ORDERED BY THE LABEL OF CLASSES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
TARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE LOGPROBABILITY OF THE SAMPLE FOR
EACH CLASS IN THE MODEL WHERE CLASSES ARE ORDERED AS THEY ARE IN SELFCLASSES
PREDICTPROBA SELFX
PROBABILITY ESTIMATES
THE RETURNED ESTIMATES FOR ALL CLASSES ARE ORDERED BY THE LABEL OF CLASSES
FOR A MULTICLASS PROBLEM IF MULTICLASS IS SET TO BE “MULTINOMIAL” THE SOFTMAX FUNCTION IS USED TO FIND
THE PREDICTED PROBABILITY OF EACH CLASS ELSE USE A ONEVSREST APPROACH IE CALCULATE THE PROBABILITY OF
EACH CLASS ASSUMING IT TO BE POSITIVE USING THE LOGISTIC FUNCTION AND NORMALIZE THESE VALUES ACROSS ALL THE
CLASSES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
TARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE PROBABILITY OF THE SAMPLE FOR EACH
CLASS IN THE MODEL WHERE CLASSES ARE ORDERED AS THEY ARE IN SELFCLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE SCORE USING THE SCORING OPTION ON THE GIVEN TEST DATA AND LABELS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT SCORE OF SELFPREDICTX WRT Y

SCIKITLEARN USER GUIDE RELEASE 0213
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SPARSIFY SELF
CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
CONVERTS THE COEF MEMBER TO A SCIPYSPARSE MATRIX WHICH FOR L1REGULARIZED MODELS CAN BE MUCH MORE
MEMORY AND STORAGEEFFICIENT THAN THE USUAL NUMPYNDARRAY REPRESENTATION
THEINTERCEPT MEMBER IS NOT CONVERTED
RETURNS
SELF ESTIMATOR
NOTES
FOR NONSPARSE MODELS IE WHEN THERE ARE NOT MANY ZEROS IN COEF THIS MAY ACTUALLY INCREASE MEMORY
USAGE SO USE THIS METHOD WITH CARE A RULE OF THUMB IS THAT THE NUMBER OF ZERO ELEMENTS WHICH CAN BE
COMPUTED WITH COEF 0SUM MUST BE MORE THAN 50 FOR THIS TO PROVIDE SIGNIFICANT BENEFITS
AFTER CALLING THIS METHOD FURTHER FITTING WITH THE PARTIALFIT METHOD IF ANY WILL NOT WORK UNTIL YOU CALL
DENSIFY
SKLEARNLINEARMODEL MULTITASKELASTICNETCV
CLASSSKLEARNLINEARMODEL MULTITASKELASTICNETCV L1RATIO05 EPS0001 NALPHAS100
ALPHASNONE FITINTERCEPTTRUE
NORMALIZEFALSE MAXITER1000
TOL00001 CV'WARN' COPYXTRUE
VERBOSE0 NJOBSNONE RAN
DOMSTATENONE SELECTION'CYCLIC'
MULTITASK L1L2 ELASTICNET WITH BUILTIN CROSSVALIDATION
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
THE OPTIMIZATION OBJECTIVE FOR MULTITASKELASTICNET IS
1 2 NSAMPLES Y XWFRO2
 ALPHA L1RATIO W21
 05ALPHA1 L1RATIO WFRO2
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS

L1RATIO FLOAT OR ARRAY OF FLOATS THE ELASTICNET MIXING PARAMETER WITH 0 L1RATIO 1 FOR
L1RATIO 1 THE PENALTY IS AN L1L2 PENALTY FOR L1RATIO 0 IT IS AN L2 PENALTY FOR 0
L1RATIO 1 THE PENALTY IS A COMBINATION OF L1L2 AND L2 THIS PARAMETER CAN BE A
LIST IN WHICH CASE THE DIFFERENT VALUES ARE TESTED BY CROSSVALIDATION AND THE ONE GIVING THE
BEST PREDICTION SCORE IS USED NOTE THAT A GOOD CHOICE OF LIST OF VALUES FOR L1RATIO IS OFTEN
TO PUT MORE VALUES CLOSE TO 1 IE LASSO AND LESS CLOSE TO 0 IE RIDGE AS IN 1 5
7 9 95 99 1
EPS FLOAT OPTIONAL LENGTH OF THE PATH EPS1E3 MEANS THATALPHAMIN ALPHAMAX
 1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS ARRAYLIKE OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NOT PROVIDED SET
AUTOMATICALLY
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
MAXITER INT OPTIONAL THE MAXIMUM NUMBER OF ITERATIONS
TOLFLOAT OPTIONAL THE TOLERANCE FOR THE OPTIMIZATION IF THE UPDATES ARE SMALLER THAN TOL THE
OPTIMIZATION CODE CHECKS THE DUAL GAP FOR OPTIMALITY AND CONTINUES UNTIL IT IS SMALLER THAN
TOL
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CPUS TO USE DURING THE CROSS VALI
DATION NOTE THAT THIS IS USED ONLY IF MULTIPLE VALUES FOR L1RATIO ARE GIVEN NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR THAT SELECTS A RANDOM FEATURE TO UPDATE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SELECTION ‘RANDOM’

SELECTION STR DEFAULT ‘CYCLIC’ IF SET TO ‘RANDOM’ A RANDOM COEFFICIENT IS UPDATED EVERY ITERATION
RATHER THAN LOOPING OVER FEATURES SEQUENTIALLY BY DEFAULT THIS SETTING TO ‘RANDOM’ OFTEN
LEADS TO SIGNIFICANTLY FASTER CONVERGENCE ESPECIALLY WHEN TOL IS HIGHER THAN 1E4
ATTRIBUTES
INTERCEPT ARRAY SHAPE NTASKS INDEPENDENT TERM IN DECISION FUNCTION
COEF ARRAY SHAPE NTASKS NFEATURES PARAMETER VECTOR W IN THE COST FUNCTION FORMULA
NOTE THATCOEF STORES THE TRANSPOSE OF WWT
ALPHA FLOAT THE AMOUNT OF PENALIZATION CHOSEN BY CROSS VALIDATION
MSEPATH ARRAY SHAPE NALPHAS NFOLDS OR NL1RATIO NALPHAS NFOLDS MEAN SQUARE
ERROR FOR THE TEST SET ON EACH FOLD VARYING ALPHA
ALPHAS NUMPY ARRAY SHAPE NALPHAS OR NL1RATIO NALPHAS THE GRID OF ALPHAS USED FOR
FITTING FOR EACH L1RATIO
L1RATIO FLOAT BEST L1RATIO OBTAINED BY CROSSVALIDATION
NITER INT NUMBER OF ITERATIONS RUN BY THE COORDINATE DESCENT SOLVER TO REACH THE SPECIFIED
TOLERANCE FOR THE OPTIMAL ALPHA
SEE ALSO
MULTITASKELASTICNET
ELASTICNETCV
MULTITASKLASSOCV
NOTES
THE ALGORITHM USED TO FIT THE MODEL IS COORDINATE DESCENT
TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A
FORTRANCONTIGUOUS NUMPY ARRAY
EXAMPLES
FROM SKLEARN IMPORT LINEARMODEL
CLF LINEARMODELMULTITASKELASTICNETCVCV3
CLFFIT00 1 1 2 2
0 0 1 1 2 2

MULTITASKELASTICNETCVALPHASNONE COPYXTRUE CV3 EPS0001
FITINTERCEPTTRUE L1RATIO05 MAXITER1000 NALPHAS100
NJOBSNONE NORMALIZEFALSE RANDOMSTATENONE SELECTIONCYCLIC
TOL00001 VERBOSE0
PRINTCLFCOEF
052875032 046958558
052875032 046958558
PRINTCLFINTERCEPT
000166409 000166409

METHODS
FITSELF X Y FIT LINEAR MODEL WITH COORDINATE DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PATH X Y L1RATIO EPS NALPHAS COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFL1RATIO05 EPS0001 NALPHAS100 ALPHASNONE FITINTERCEPTTRUE NOR
MALIZEFALSE MAXITER1000 TOL00001 CV'WARN' COPYXTRUE VERBOSE0
NJOBSNONE RANDOMSTATENONE SELECTION'CYCLIC'
FITSELFXY
FIT LINEAR MODEL WITH COORDINATE DESCENT
FIT IS ON GRID OF ALPHAS AND BEST ALPHA ESTIMATED BY CROSSVALIDATION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN
CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF Y IS MONOOUTPUT X CAN
BE SPARSE
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
STATICPATHXYL1RATIO05 EPS0001 NALPHAS100 ALPHASNONE PRECOMPUTE'AUTO'
XYNONE COPYXTRUE COEFINITNONE VERBOSEFALSE RETURNNITERFALSE POSI
TIVEFALSE CHECKINPUTTRUE PARAMS
COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
THE ELASTIC NET OPTIMIZATION FUNCTION VARIES FOR MONO AND MULTIOUTPUTS
FOR MONOOUTPUT TASKS IT IS
1 2NSAMPLES Y XW22
 ALPHA L1RATIO W1
 05ALPHA1 L1RATIO W22
FOR MULTIOUTPUT TASKS IT IS
1 2 NSAMPLES Y XWFRO2
 ALPHA L1RATIO W21
 05ALPHA1 L1RATIO WFRO2
WHERE

W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF YIS MONOOUTPUT THEN X CAN BE SPARSE
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
L1RATIO FLOAT OPTIONAL FLOAT BETWEEN 0 AND 1 PASSED TO ELASTIC NET SCALING BETWEEN L1 AND L2 PENALTIES L1RATIO1 CORRESPONDS TO THE LASSO
EPS FLOAT LENGTH OF THE PATH EPS1E3 MEANS THAT ALPHAMIN ALPHAMAX 1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS NDARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE SET AUTOMATICALLY
PRECOMPUTE TRUE FALSE 'AUTO' ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE PASSED AS ARGUMENT
XYARRAYLIKE OPTIONAL XY NPDOTXT Y THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY WHEN THE GRAM MATRIX IS PRECOMPUTED
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVER WRITTEN
COEFINIT ARRAY SHAPE NFEATURES   NONE THE INITIAL VALUES OF THE COEFFICIENTS
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
RETURNNITER BOOL WHETHER TO RETURN THE NUMBER OF ITERATIONS OR NOT
POSITIVE BOOL DEFAULT FALSE IF SET TO TRUE FORCES COEFFICIENTS TO BE POSITIVE ONLY ALLOWED WHENYNDIM 1
CHECKINPUT BOOL DEFAULT TRUE SKIP INPUT VALIDATION CHECKS INCLUDING THE GRAM MATRIX WHEN PROVIDED ASSUMING THERE ARE HANDLED BY THE CALLER WHEN CHECKINPUTFALSE
PARAMS KWARGS KEYWORD ARGUMENTS PASSED TO THE COORDINATE DESCENT SOLVER
RETURNS
ALPHAS ARRAY SHAPE NALPHAS THE ALPHAS ALONG THE PATH WHERE MODELS ARE COMPUTED
COEFS ARRAY SHAPE NFEATURES NALPHAS OR NOUTPUTS NFEATURES NALPHAS COEFFICIENTS ALONG THE PATH
DUALGAPS ARRAY SHAPE NALPHAS THE DUAL GAPS AT THE END OF THE OPTIMIZATION FOR EACH ALPHA
NITERS ARRAYLIKE SHAPE NALPHAS THE NUMBER OF ITERATIONS TAKEN BY THE COORDINATE DESCENT OPTIMIZER TO REACH THE SPECIFIED TOLERANCE FOR EACH ALPHA IS RETURNED WHEN RETURNNITER IS SET TO TRUE
SEE ALSO

MULTITASKELASTICNET
MULTITASKELASTICNETCV
ELASTICNET
ELASTICNETCV
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOCOORDINATEDESCENTPATHPY
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT

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RETURNS
SELF
SKLEARNLINEARMODEL MULTITASKLASSOCV
CLASSSKLEARNLINEARMODEL MULTITASKLASSOCV EPS0001 NALPHAS100 ALPHASNONE
FITINTERCEPTTRUE NORMALIZEFALSE
MAXITER1000 TOL00001 COPYXTRUE
CV'WARN' VERBOSEFALSE NJOBSNONE
RANDOMSTATENONE SELECTION'CYCLIC'
MULTITASK LASSO MODEL TRAINED WITH L1L2 MIXEDNORM AS REGULARIZER
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
THE OPTIMIZATION OBJECTIVE FOR MULTITASKLASSO IS
1 2 NSAMPLES Y XWFRO2 ALPHA W21
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
EPS FLOAT OPTIONAL LENGTH OF THE PATH EPS1E3 MEANS THATALPHAMIN ALPHAMAX
 1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS ARRAYLIKE OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NOT PROVIDED SET
AUTOMATICALLY
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
MAXITER INT OPTIONAL THE MAXIMUM NUMBER OF ITERATIONS
TOLFLOAT OPTIONAL THE TOLERANCE FOR THE OPTIMIZATION IF THE UPDATES ARE SMALLER THAN TOL THE
OPTIMIZATION CODE CHECKS THE DUAL GAP FOR OPTIMALITY AND CONTINUES UNTIL IT IS SMALLER THAN
TOL
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER

• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CPUS TO USE DURING THE CROSS VALI
DATION NOTE THAT THIS IS USED ONLY IF MULTIPLE VALUES FOR L1RATIO ARE GIVEN NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR THAT SELECTS A RANDOM FEATURE TO UPDATE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SELECTION ‘RANDOM’
SELECTION STR DEFAULT ‘CYCLIC’ IF SET TO ‘RANDOM’ A RANDOM COEFFICIENT IS UPDATED EVERY ITERATION
RATHER THAN LOOPING OVER FEATURES SEQUENTIALLY BY DEFAULT THIS SETTING TO ‘RANDOM’ OFTEN
LEADS TO SIGNIFICANTLY FASTER CONVERGENCE ESPECIALLY WHEN TOL IS HIGHER THAN 1E4
ATTRIBUTES
INTERCEPT ARRAY SHAPE NTASKS INDEPENDENT TERM IN DECISION FUNCTION
COEF ARRAY SHAPE NTASKS NFEATURES PARAMETER VECTOR W IN THE COST FUNCTION FORMULA
NOTE THATCOEF STORES THE TRANSPOSE OF WWT
ALPHA FLOAT THE AMOUNT OF PENALIZATION CHOSEN BY CROSS VALIDATION
MSEPATH ARRAY SHAPE NALPHAS NFOLDS MEAN SQUARE ERROR FOR THE TEST SET ON EACH FOLD
VARYING ALPHA
ALPHAS NUMPY ARRAY SHAPE NALPHAS THE GRID OF ALPHAS USED FOR FITTING
NITER INT NUMBER OF ITERATIONS RUN BY THE COORDINATE DESCENT SOLVER TO REACH THE SPECIFIED
TOLERANCE FOR THE OPTIMAL ALPHA
SEE ALSO
MULTITASKELASTICNET
ELASTICNETCV
MULTITASKELASTICNETCV
NOTES
THE ALGORITHM USED TO FIT THE MODEL IS COORDINATE DESCENT
TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A
FORTRANCONTIGUOUS NUMPY ARRAY

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EXAMPLES
FROM SKLEARNLINEARMODEL IMPORT MULTITASKLASSOCV
FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
FROM SKLEARNMETRICS IMPORT R2SCORE
X Y MAKEREGRESSIONNTARGETS2 NOISE4 RANDOMSTATE0
REG MULTITASKLASSOCVCV5 RANDOMSTATE0FITX Y
R2SCOREY REGPREDICTX
09994
REGALPHA
05713
REGPREDICTX1
ARRAY1537971 949015
METHODS
FITSELF X Y FIT LINEAR MODEL WITH COORDINATE DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PATH X Y EPS NALPHAS ALPHAS COMPUTE LASSO PATH WITH COORDINATE DESCENT
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFEPS0001 NALPHAS100 ALPHASNONE FITINTERCEPTTRUE NORMALIZEFALSE
MAXITER1000 TOL00001 COPYXTRUE CV'WARN' VERBOSEFALSE NJOBSNONE RAN
DOMSTATENONE SELECTION'CYCLIC'
FITSELFXY
FIT LINEAR MODEL WITH COORDINATE DESCENT
FIT IS ON GRID OF ALPHAS AND BEST ALPHA ESTIMATED BY CROSSVALIDATION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN
CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF Y IS MONOOUTPUT X CAN
BE SPARSE
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
STATICPATHXYEPS0001 NALPHAS100 ALPHASNONE PRECOMPUTE'AUTO' XYNONE
COPYXTRUE COEFINITNONE VERBOSEFALSE RETURNNITERFALSE POSITIVEFALSE
PARAMS
COMPUTE LASSO PATH WITH COORDINATE DESCENT

THE LASSO OPTIMIZATION FUNCTION VARIES FOR MONO AND MULTIOUTPUTS
FOR MONOOUTPUT TASKS IT IS
1 2 NSAMPLES Y XW22 ALPHA W1
FOR MULTIOUTPUT TASKS IT IS
1 2 NSAMPLES Y XW2FRO ALPHA W21
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY
AS FORTRANCONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF YIS MONOOUTPUT
THENXCAN BE SPARSE
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
EPS FLOAT OPTIONAL LENGTH OF THE PATH EPS1E3 MEANS THAT ALPHAMIN
ALPHAMAX 1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS NDARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE
SET AUTOMATICALLY
PRECOMPUTE TRUE FALSE ‘AUTO’ ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX
TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE
PASSED AS ARGUMENT
XYARRAYLIKE OPTIONAL XY NPDOTXT Y THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY
WHEN THE GRAM MATRIX IS PRECOMPUTED
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVER
WRITTEN
COEFINIT ARRAY SHAPE NFEATURES   NONE THE INITIAL VALUES OF THE COEFFICIENTS
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
RETURNNITER BOOL WHETHER TO RETURN THE NUMBER OF ITERATIONS OR NOT
POSITIVE BOOL DEFAULT FALSE IF SET TO TRUE FORCES COEFFICIENTS TO BE POSITIVE ONLY ALLOWED
WHENYNDIM 1
PARAMS KWARGS KEYWORD ARGUMENTS PASSED TO THE COORDINATE DESCENT SOLVER
RETURNS
ALPHAS ARRAY SHAPE NALPHAS THE ALPHAS ALONG THE PATH WHERE MODELS ARE COMPUTED
COEFS ARRAY SHAPE NFEATURES NALPHAS OR NOUTPUTS NFEATURES NALPHAS COEFFICIENTS
ALONG THE PATH
DUALGAPS ARRAY SHAPE NALPHAS THE DUAL GAPS AT THE END OF THE OPTIMIZATION FOR EACH
ALPHA

NITERS ARRAYLIKE SHAPE NALPHAS THE NUMBER OF ITERATIONS TAKEN BY THE COORDINATE DE
SCENT OPTIMIZER TO REACH THE SPECIFIED TOLERANCE FOR EACH ALPHA
SEE ALSO
LARSPATH
LASSO
LASSOLARS
LASSOCV
LASSOLARSCV
SKLEARNDECOMPOSITIONSPARSEENCODE
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOCOORDINATEDESCENTPATHPY
TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A
FORTRANCONTIGUOUS NUMPY ARRAY
NOTE THAT IN CERTAIN CASES THE LARS SOLVER MAY BE SIGNIFICANTLY FASTER TO IMPLEMENT THIS FUNCTIONALITY IN
PARTICULAR LINEAR INTERPOLATION CAN BE USED TO RETRIEVE MODEL COEFFICIENTS BETWEEN THE VALUES OUTPUT BY
LARSPATH
EXAMPLES
COMPARING LASSOPATH AND LARSPATH WITH INTERPOLATION
X NPARRAY1 2 31 23 54 43T
Y NPARRAY1 2 31
 USE LASSOPATH TO COMPUTE A COEFFICIENT PATH
 COEFPATH   LASSOPATHX Y ALPHAS5 1 5
PRINTCOEFPATH
0 0 046874778
02159048 04425765 023689075
 NOW USE LARSPATH AND 1D LINEAR INTERPOLATION TO COMPUTE THE
 SAME PATH
 FROM SKLEARNLINEARMODEL IMPORT LARSPATH
ALPHAS ACTIVE COEFPATHLARS LARSPATHX Y METHODLASSO
 FROM SCIPY IMPORT INTERPOLATE
COEFPATHCONTINUOUS INTERPOLATEINTERP1DALPHAS1
 COEFPATHLARS 1
PRINTCOEFPATHCONTINUOUS5 1 5
0 0 046915237
02159048 04425765 023668876
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS

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CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SKLEARNLINEARMODEL ORTHOGONALMATCHINGPURSUITCV
CLASSSKLEARNLINEARMODEL ORTHOGONALMATCHINGPURSUITCV COPYTRUE FITINTERCEPTTRUE
NORMALIZETRUE
MAXITERNONE CV’WARN’
NJOBSNONE VERBOSEFALSE
CROSSVALIDATED ORTHOGONAL MATCHING PURSUIT MODEL OMP
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
READ MORE IN THE USER GUIDE
PARAMETERS
COPY BOOL OPTIONAL WHETHER THE DESIGN MATRIX X MUST BE COPIED BY THE ALGORITHM A FALSE
VALUE IS ONLY HELPFUL IF X IS ALREADY FORTRANORDERED OTHERWISE A COPY IS MADE ANYWAY

FITINTERCEPT BOOLEAN OPTIONAL WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE
NO INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT TRUE THIS PARAMETER IS IGNORED WHEN FITINTERCEPT
IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BEFORE REGRESSION BY SUB
TRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO STANDARDIZE PLEASE USE
SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE CALLING FIT ON AN ESTIMATOR
WITHNORMALIZEFALSE
MAXITER INTEGER OPTIONAL MAXIMUM NUMBERS OF ITERATIONS TO PERFORM THEREFORE MAXIMUM
FEATURES TO INCLUDE 10 OF NFEATURES BUT AT LEAST 5 IF AVAILABLE
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CPUS TO USE DURING THE CROSS VALIDA
TIONNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING
ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
VERBOSE BOOLEAN OR INTEGER OPTIONAL SETS THE VERBOSITY AMOUNT
ATTRIBUTES
INTERCEPT FLOAT OR ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION
COEF ARRAY SHAPE NFEATURES OR NTARGETS NFEATURES PARAMETER VECTOR W IN THE PROBLEM
FORMULATION
NNONZEROCOEFS INT ESTIMATED NUMBER OF NONZERO COEFFICIENTS GIVING THE BEST MEAN
SQUARED ERROR OVER THE CROSSVALIDATION FOLDS
NITER INT OR ARRAYLIKE NUMBER OF ACTIVE FEATURES ACROSS EVERY TARGET FOR THE MODEL REFIT WITH
THE BEST HYPERPARAMETERS GOT BY CROSSVALIDATING ACROSS ALL FOLDS
SEE ALSO
ORTHOGONALMP
ORTHOGONALMPGRAM
LARSPATH
LARS
LASSOLARS
ORTHOGONALMATCHINGPURSUIT
LARSCV
LASSOLARSCV

DECOMPOSITIONSPARSEENCODE
EXAMPLES
```
 FROM SKLEARNLINEARMODEL IMPORT ORTHOGONALMATCHINGPURSUITCV
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y  MAKEREGRESSIONNFEATURES100 NINFORMATIVE10
 NOISE4 RANDOMSTATE0
REG  ORTHOGONALMATCHINGPURSUITCVCV5FITX Y
REGSCOREX Y
09991
REGNNONZEROCOEFS
10
REGPREDICTX1
ARRAY783854
```
METHODS
FITSELF X Y FIT THE MODEL USING X Y AS TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFCOPYTRUE FITINTERCEPTTRUE NORMALIZETRUE MAXITERNONE CV'WARN'
NJOBSNONE VERBOSEFALSE
FITSELFXY
FIT THE MODEL USING X Y AS TRAINING DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES WILL BE CAST TO X'S DTYPE IF NECESSARY
RETURNS
SELF OBJECT RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS

XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELORTHOGONALMATCHINGPURSUITCV
•ORTHOGONAL MATCHING PURSUIT
SKLEARNLINEARMODEL RIDGECV
CLASSSKLEARNLINEARMODEL RIDGECVALPHAS01 10100 FITINTERCEPTTRUE NORMAL
IZEFALSE SCORINGNONE CVNONE GCVMODENONE
STORECVVALUESFALSE
RIDGE REGRESSION WITH BUILTIN CROSSVALIDATION

SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
BY DEFAULT IT PERFORMS GENERALIZED CROSSVALIDATION WHICH IS A FORM OF EFFICIENT LEAVEONEOUT CROSS VALIDATION
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHAS NUMPY ARRAY OF SHAPE NALPHAS ARRAY OF ALPHA VALUES TO TRY REGULARIZATION STRENGTH MUST BE A POSITIVE FLOAT REGULARIZATION IMPROVES THE CONDITIONING OF THE PROBLEM AND RE DUCES THE VARIANCE OF THE ESTIMATES LARGER VALUES SPECIFY STRONGER REGULARIZATION ALPHA CORRESPONDS TO C1 IN OTHER LINEAR MODELS SUCH AS LOGISTICREGRESSION OR LINEARSVC IF USING GENERALIZED CROSSVALIDATION ALPHAS MUST BE POSITIVE
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
SCORING STRING CALLABLE OR NONE OPTIONAL DEFAULT NONE A STRING SEE MODEL EVALUATION DOC UMENTATION OR A SCORER CALLABLE OBJECT FUNCTION WITH SIGNATURE SCORERESTIMATOR X Y IF NONE THE NEGATIVE MEAN SQUARED ERROR IF CV IS ‘AUTO’ OR NONE IE WHEN USING GENERALIZED CROSSVALIDATION AND R2 SCORE OTHERWISE
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE EFFICIENT LEAVEONEOUT CROSSVALIDATION ALSO KNOWN AS GENERALIZED CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF YIS BINARY OR MULTICLASS SKLEARNMODELSELECTION STRATIFIEDKFOLD IS USED ELSE SKLEARNMODELSELECTIONKFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
GCVMODE NONE ‘AUTO’ ‘SVD’ EIGEN’ OPTIONAL FLAG INDICATING WHICH STRATEGY TO USE WHEN PERFORMING GENERALIZED CROSSVALIDATION OPTIONS ARE
AUTO USE SVD IFNSAMPLES NFEATURES OTHERWISE USE EIGEN
SVD FORCE USE OF SINGULAR VALUE DECOMPOSITION OF X WHEN X IS DENSE EIGENVALUE DECOMPOSITION OF XTX WHEN X ISSPARSE
EIGEN FORCE COMPUTATION VIA EIGENDECOMPOSITION OF XXT
THE ‘AUTO’ MODE IS THE DEFAULT AND IS INTENDED TO PICK THE CHEAPER OPTION OF THE TWO DEPEND ING ON THE SHAPE OF THE TRAINING DATA
STORECVVALUES BOOLEAN DEFAULTFALSE FLAG INDICATING IF THE CROSSVALIDATION VALUES CORRE SPONDING TO EACH ALPHA SHOULD BE STORED IN THE CVVALUES ATTRIBUTE SEE BELOW THIS FLAG IS ONLY COMPATIBLE WITH CVNONE IE USING GENERALIZED CROSSVALIDATION
ATTRIBUTES

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CVVALUES ARRAY SHAPE NSAMPLES NALPHAS OR SHAPE NSAMPLES NTARGETS NALPHAS
OPTIONAL CROSSVALIDATION VALUES FOR EACH ALPHA IF STORECVVALUESTRUE AND
CVNONE AFTERFIT HAS BEEN CALLED THIS ATTRIBUTE WILL CONTAIN THE MEAN SQUARED
ERRORS BY DEFAULT OR THE VALUES OF THE LOSSSCOREFUNC FUNCTION IF PROVIDED IN THE
CONSTRUCTOR
COEF ARRAY SHAPE NFEATURES OR NTARGETS NFEATURES WEIGHT VECTORS
INTERCEPT FLOAT ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION SET TO 00
IFFITINTERCEPT FALSE
ALPHA FLOAT ESTIMATED REGULARIZATION PARAMETER
SEE ALSO
RIDGE RIDGE REGRESSION
RIDGECLASSIFIER RIDGE CLASSIFIER
RIDGECLASSIFIERCV RIDGE CLASSIFIER WITH BUILTIN CROSS VALIDATION
EXAMPLES
 FROM SKLEARNDATASETS IMPORT LOADDIABETES
 FROM SKLEARNLINEARMODEL IMPORT RIDGECV
X Y LOADDIABETESRETURNXY TRUE
CLF RIDGECVALPHAS1E3 1E2 1E1 1FITX Y
CLFSCOREX Y
05166
METHODS
FITSELF X Y SAMPLEWEIGHT FIT RIDGE REGRESSION MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHAS01 10100 FITINTERCEPTTRUE NORMALIZEFALSE SCORINGNONE CVNONE
GCVMODENONE STORECVVALUESFALSE
FITSELFXYSAMPLEWEIGHTNONE
FIT RIDGE REGRESSION MODEL
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA IF USING GCV WILL BE CAST TO
FLOAT64 IF NECESSARY
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES WILL BE CAST TO
X’S DTYPE IF NECESSARY
SAMPLEWEIGHT FLOAT OR ARRAYLIKE OF SHAPE NSAMPLES SAMPLE WEIGHT
RETURNS

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SELF OBJECT
NOTES
WHEN SAMPLEWEIGHT IS PROVIDED THE SELECTED HYPERPARAMETER MAY DEPEND ON WHETHER WE USE GENERALIZED
CROSSVALIDATION CVNONE OR CV'AUTO' OR ANOTHER FORM OF CROSSVALIDATION BECAUSE ONLY GENERALIZED
CROSSVALIDATION TAKES THE SAMPLE WEIGHTS INTO ACCOUNT WHEN COMPUTING THE VALIDATION SCORE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
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TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE

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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELRIDGECV
•FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS
•EFFECT OF TRANSFORMING THE TARGETS IN REGRESSION MODEL
SKLEARNLINEARMODEL RIDGECLASSIFIERCV
CLASSSKLEARNLINEARMODEL RIDGECLASSIFIERCV ALPHAS01 10100 FITINTERCEPTTRUE
NORMALIZEFALSE SCORINGNONE CVNONE
CLASSWEIGHTNONE STORECVVALUESFALSE
RIDGE CLASSIFIER WITH BUILTIN CROSSVALIDATION
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
BY DEFAULT IT PERFORMS GENERALIZED CROSSVALIDATION WHICH IS A FORM OF EFFICIENT LEAVEONEOUT CROSS
VALIDATION CURRENTLY ONLY THE NFEATURES NSAMPLES CASE IS HANDLED EFFICIENTLY
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHAS NUMPY ARRAY OF SHAPE NALPHAS ARRAY OF ALPHA VALUES TO TRY REGULARIZATION STRENGTH
MUST BE A POSITIVE FLOAT REGULARIZATION IMPROVES THE CONDITIONING OF THE PROBLEM AND RE
DUCES THE VARIANCE OF THE ESTIMATES LARGER VALUES SPECIFY STRONGER REGULARIZATION ALPHA
CORRESPONDS TO C1 IN OTHER LINEAR MODELS SUCH AS LOGISTICREGRESSION OR LINEARSVC
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
SCORING STRING CALLABLE OR NONE OPTIONAL DEFAULT NONE A STRING SEE MODEL EVALUATION DOC
UMENTATION OR A SCORER CALLABLE OBJECT FUNCTION WITH SIGNATURE SCORERESTIMATOR
X Y
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE EFFICIENT LEAVEONEOUT CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES

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REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CLASSWEIGHT DICT OR ‘BALANCED’ OPTIONAL WEIGHTS ASSOCIATED WITH CLASSES IN THE FORM
CLASSLABEL WEIGHT IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT ONE
THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP
BINCOUNTY
STORECVVALUES BOOLEAN DEFAULTFALSE FLAG INDICATING IF THE CROSSVALIDATION VALUES CORRE
SPONDING TO EACH ALPHA SHOULD BE STORED IN THE CVVALUES ATTRIBUTE SEE BELOW THIS
FLAG IS ONLY COMPATIBLE WITH CVNONE IE USING GENERALIZED CROSSVALIDATION
ATTRIBUTES
CVVALUES ARRAY SHAPE NSAMPLES NTARGETS NALPHAS OPTIONAL CROSSVALIDATION VALUES
FOR EACH ALPHA IF STORECVVALUESTRUE ANDCVNONE AFTERFIT HAS BEEN
CALLED THIS ATTRIBUTE WILL CONTAIN THE MEAN SQUARED ERRORS BY DEFAULT OR THE VALUES OF THE
LOSSSCOREFUNC FUNCTION IF PROVIDED IN THE CONSTRUCTOR
COEF ARRAY SHAPE 1 NFEATURES OR NTARGETS NFEATURES COEFFICIENT OF THE FEATURES IN THE
DECISION FUNCTION
COEF IS OF SHAPE 1 NFEATURES WHEN THE GIVEN PROBLEM IS BINARY
INTERCEPT FLOAT ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION SET TO 00
IFFITINTERCEPT FALSE
ALPHA FLOAT ESTIMATED REGULARIZATION PARAMETER
SEE ALSO
RIDGE RIDGE REGRESSION
RIDGECLASSIFIER RIDGE CLASSIFIER
RIDGECV RIDGE REGRESSION WITH BUILTIN CROSS VALIDATION
NOTES
FOR MULTICLASS CLASSIFICATION NCLASS CLASSIFIERS ARE TRAINED IN A ONEVERSUSALL APPROACH CONCRETELY THIS IS
IMPLEMENTED BY TAKING ADVANTAGE OF THE MULTIVARIATE RESPONSE SUPPORT IN RIDGE
EXAMPLES
 FROM SKLEARNDATASETS IMPORT LOADBREASTCANCER
 FROM SKLEARNLINEARMODEL IMPORT RIDGECLASSIFIERCV
X Y LOADBREASTCANCERRETURNXY TRUE
CLF RIDGECLASSIFIERCVALPHAS1E3 1E2 1E1 1FITX Y
CLFSCOREX Y
09630
METHODS

DECISIONFUNCTION SELF X PREDICT CONFIDENCE SCORES FOR SAMPLES
FITSELF X Y SAMPLEWEIGHT FIT THE RIDGE CLASSIFIER
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASS LABELS FOR SAMPLES IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHAS01 10100 FITINTERCEPTTRUE NORMALIZEFALSE SCORINGNONE CVNONE
CLASSWEIGHTNONE STORECVVALUESFALSE
DECISIONFUNCTION SELFX
PREDICT CONFIDENCE SCORES FOR SAMPLES
THE CONFIDENCE SCORE FOR A SAMPLE IS THE SIGNED DISTANCE OF THAT SAMPLE TO THE HYPERPLANE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
ARRAY SHAPENSAMPLES IF NCLASSES 2 ELSE NSAMPLES NCLASSES CONFIDENCE
SCORES PER SAMPLE CLASS COMBINATION IN THE BINARY CASE CONFIDENCE SCORE FOR
SELFCLASSES1 WHERE 0 MEANS THIS CLASS WOULD BE PREDICTED
FITSELFXYSAMPLEWEIGHTNONE
FIT THE RIDGE CLASSIFIER
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES WHEN USING GCV WILL BE CAST TO
FLOAT64 IF NECESSARY
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES WILL BE CAST TO X'S DTYPE IF NECESSARY
SAMPLEWEIGHT FLOAT OR NUMPY ARRAY OF SHAPE NSAMPLES SAMPLE WEIGHT
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT CLASS LABELS FOR SAMPLES IN X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS

CARRAY SHAPE NSAMPLES PREDICTED CLASS LABEL PER SAMPLE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
INFORMATION CRITERION
SOME MODELS CAN OFFER AN INFORMATIONTHEORETIC CLOSEDFORM FORMULA OF THE OPTIMAL ESTIMATE OF THE REGULARIZATION
PARAMETER BY COMPUTING A SINGLE REGULARIZATION PATH INSTEAD OF SEVERAL WHEN USING CROSSVALIDATION
HERE IS THE LIST OF MODELS BENEFITING FROM THE AKAIKE INFORMATION CRITERION AIC OR THE BAYESIAN INFORMATION CRITERION
BIC FOR AUTOMATED MODEL SELECTION
LINEARMODELLASSOLARSIC CRITERION LASSO MODEL FIT WITH LARS USING BIC OR AIC FOR MODEL SE
LECTION
SKLEARNLINEARMODEL LASSOLARSIC
CLASSSKLEARNLINEARMODEL LASSOLARSIC CRITERION’AIC’ FITINTERCEPTTRUE VERBOSEFALSE
NORMALIZETRUE PRECOMPUTE’AUTO’ MAXITER500
EPS2220446049250313E16 COPYXTRUE POSI
TIVEFALSE
LASSO MODEL FIT WITH LARS USING BIC OR AIC FOR MODEL SELECTION
THE OPTIMIZATION OBJECTIVE FOR LASSO IS
1 2 NSAMPLES Y XW22 ALPHA W1
AIC IS THE AKAIKE INFORMATION CRITERION AND BIC IS THE BAYES INFORMATION CRITERION SUCH CRITERIA ARE USEFUL
TO SELECT THE VALUE OF THE REGULARIZATION PARAMETER BY MAKING A TRADEOFF BETWEEN THE GOODNESS OF FIT AND THE
COMPLEXITY OF THE MODEL A GOOD MODEL SHOULD EXPLAIN WELL THE DATA WHILE BEING SIMPLE
READ MORE IN THE USER GUIDE

PARAMETERS
CRITERION ‘BIC’ ‘AIC’ THE TYPE OF CRITERION TO USE
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
VERBOSE BOOLEAN OR INTEGER OPTIONAL SETS THE VERBOSITY AMOUNT
NORMALIZE BOOLEAN OPTIONAL DEFAULT TRUE THIS PARAMETER IS IGNORED WHEN FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BEFORE REGRESSION BY SUB TRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE CALLING FIT ON AN ESTIMATOR WITHNORMALIZEFALSE
PRECOMPUTE TRUE FALSE ‘AUTO’ ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE PASSED AS ARGUMENT
MAXITER INTEGER OPTIONAL MAXIMUM NUMBER OF ITERATIONS TO PERFORM CAN BE USED FOR EARLY STOPPING
EPS FLOAT OPTIONAL THE MACHINEPRECISION REGULARIZATION IN THE COMPUTATION OF THE CHOLESKY DIAGONAL FACTORS INCREASE THIS FOR VERY ILLCONDITIONED SYSTEMS UNLIKE THE TOL PARAMETER IN SOME ITERATIVE OPTIMIZATIONBASED ALGORITHMS THIS PARAMETER DOES NOT CONTROL THE TOLERANCE OF THE OPTIMIZATION
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
POSITIVE BOOLEAN DEFAULTFALSE RESTRICT COEFFICIENTS TO BE 0 BE AWARE THAT YOU MIGHT WANT TO REMOVE FITINTERCEPT WHICH IS SET TRUE BY DEFAULT UNDER THE POSITIVE RESTRICTION THE MODEL COEFFICIENTS DO NOT CONVERGE TO THE ORDINARYLEASTSQUARES SOLUTION FOR SMALL VALUES OF ALPHA ONLY COEFFICIENTS UP TO THE SMALLEST ALPHA VALUE ALPHASALPHAS 0 MIN WHEN FITPATHTRUE REACHED BY THE STEPWISE LARSLASSO ALGORITHM ARE TYPICALLY IN CONGRUENCE WITH THE SOLUTION OF THE COORDINATE DESCENT LASSO ESTIMATOR AS A CONSEQUENCE USING LASSOLARSIC ONLY MAKES SENSE FOR PROBLEMS WHERE A SPARSE SOLUTION IS EXPECTED ANDOR REACHED
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES PARAMETER VECTOR W IN THE FORMULATION FORMULA
INTERCEPT FLOAT INDEPENDENT TERM IN DECISION FUNCTION
ALPHA FLOAT THE ALPHA PARAMETER CHOSEN BY THE INFORMATION CRITERION
NITER INT NUMBER OF ITERATIONS RUN BY LARSPATH TO FIND THE GRID OF ALPHAS
CRITERION ARRAY SHAPE NALPHAS THE VALUE OF THE INFORMATION CRITERIA ‘AIC’ ‘BIC’ ACROSS ALL ALPHAS THE ALPHA WHICH HAS THE SMALLEST INFORMATION CRITERION IS CHOSEN THIS VALUE IS LARGER BY A FACTOR OF NSAMPLES COMPARED TO EQNS 215 AND 216 IN ZOU ET AL 2007
SEE ALSO
LARSPATH LASSOLARS LASSOLARSCV
NOTES
THE ESTIMATION OF THE NUMBER OF DEGREES OF FREEDOM IS GIVEN BY

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“ON THE DEGREES OF FREEDOM OF THE LASSO” HUI ZOU TREVOR HASTIE AND ROBERT TIBSHIRANI ANN STATIST V OLUME
35 NUMBER 5 2007 21732192
HTTPSENWIKIPEDIAORGWIKIAKAIKEINFORMATIONCRITERION HTTPSENWIKIPEDIAORGWIKIBAYESIAN
INFORMATIONCRITERION
EXAMPLES
```
 FROM SKLEARN IMPORT LINEARMODEL
REG  LINEARMODELLASSOLARSICCRITERIONBIC
REGFIT1 1 0 0 1 1 11111 0 11111

LASSOLARSICCOPYXTRUE CRITERIONBIC EPS FITINTERCEPTTRUE
MAXITER500 NORMALIZETRUE POSITIVEFALSE PRECOMPUTEAUTO
VERBOSEFALSE
PRINTREGCOEF
 0 111
```
METHODS
FITSELF X Y COPYX FIT THE MODEL USING X Y AS TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFCRITERION’AIC’ FITINTERCEPTTRUE VERBOSEFALSE NORMALIZETRUE PRECOM
PUTE’AUTO’ MAXITER500 EPS2220446049250313E16 COPYXTRUE POSITIVEFALSE
FITSELFXYCOPYXNONE
FIT THE MODEL USING X Y AS TRAINING DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES WILL BE CAST TO X’S DTYPE IF NECESSARY
COPYX BOOLEAN OPTIONAL DEFAULT NONE IF PROVIDED THIS PARAMETER WILL OVERRIDE THE
CHOICE OF COPYX MADE AT INSTANCE CREATION IF TRUE X WILL BE COPIED ELSE IT MAY
BE OVERWRITTEN
RETURNS
SELF OBJECT RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS

PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
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PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
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NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
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SCORE FLOAT R2 OF SELFPREDICTX WRT Y
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THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
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PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELLASSOLARSIC
•LASSO MODEL SELECTION CROSSVALIDATION AIC BIC

OUT OF BAG ESTIMATES
WHEN USING ENSEMBLE METHODS BASE UPON BAGGING IE GENERATING NEW TRAINING SETS USING SAMPLING WITH REPLACEMENT PART OF THE TRAINING SET REMAINS UNUSED FOR EACH CLASSIFIER IN THE ENSEMBLE A DIFFERENT PART OF THE TRAINING SET IS LEFT OUT
THIS LEFT OUT PORTION CAN BE USED TO ESTIMATE THE GENERALIZATION ERROR WITHOUT HAVING TO RELY ON A SEPARATE VALIDATION SET THIS ESTIMATE COMES “FOR FREE” AS NO ADDITIONAL DATA IS NEEDED AND CAN BE USED FOR MODEL SELECTION
THIS IS CURRENTLY IMPLEMENTED IN THE FOLLOWING CLASSES
ENSEMBLERANDOMFORESTCLASSIFIER A RANDOM FOREST CLASSIFIER
ENSEMBLERANDOMFORESTREGRESSOR A RANDOM FOREST REGRESSOR
ENSEMBLEEXTRATREESCLASSIFIER AN EXTRATREES CLASSIFIER
ENSEMBLEEXTRATREESREGRESSOR NESTIMATORS
AN EXTRATREES REGRESSOR
ENSEMBLEGRADIENTBOOSTINGCLASSIFIER LOSS
GRADIENT BOOSTING FOR CLASSIFICATION
ENSEMBLEGRADIENTBOOSTINGREGRESSOR LOSS
GRADIENT BOOSTING FOR REGRESSION
SKLEARNENSEMBLE RANDOMFORESTCLASSIFIER
CLASSSKLEARNENSEMBLE RANDOMFORESTCLASSIFIER NESTIMATORS’WARN’ CRITE
RION’GINI’ MAXDEPTHNONE
MINSAMPLESSPLIT2 MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00
MAXFEATURES’AUTO’
MAXLEAFNODESNONE
MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE BOOTSTRAPTRUE
OOBSCOREFALSE NJOBSNONE
RANDOMSTATENONE VERBOSE0
WARMSTARTFALSE CLASSWEIGHTNONE
A RANDOM FOREST CLASSIFIER
A RANDOM FOREST IS A META ESTIMATOR THAT FITS A NUMBER OF DECISION TREE CLASSIFIERS ON VARIOUS SUBSAMPLES OF THE DATASET AND USES AVERAGING TO IMPROVE THE PREDICTIVE ACCURACY AND CONTROL OVERFITTING THE SUBSAMPLE SIZE IS ALWAYS THE SAME AS THE ORIGINAL INPUT SAMPLE SIZE BUT THE SAMPLES ARE DRAWN WITH REPLACEMENT IF BOOTSTRAPTRUE DEFAULT
READ MORE IN THE USER GUIDE
PARAMETERS
NESTIMATORS INTEGER OPTIONAL DEFAULT10 THE NUMBER OF TREES IN THE FOREST
CHANGED IN VERSION 020 THE DEFAULT VALUE OF NESTIMATORS WILL CHANGE FROM 10 IN VERSION 020 TO 100 IN VERSION 022
CRITERION STRING OPTIONAL DEFAULT”GINI” THE FUNCTION TO MEASURE THE QUALITY OF A SPLIT SUPPORTED CRITERIA ARE “GINI” FOR THE GINI IMPURITY AND “ENTROPY” FOR THE INFORMATION GAIN NOTE THIS PARAMETER IS TREESPECIFIC
MAXDEPTH INTEGER OR NONE OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF THE TREE IF NONE THEN NODES ARE EXPANDED UNTIL ALL LEAVES ARE PURE OR UNTIL ALL LEAVES CONTAIN LESS THAN

MINSAMPLESSPLIT SAMPLES
MINSAMPLESSPLIT INT FLOAT OPTIONAL DEFAULT2 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST
MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY
HAVE THE EFFECT OF SMOOTHING THE MODEL ESPECIALLY IN REGRESSION
• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE
SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE
EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED
MAXFEATURES INT FLOAT STRING OR NONE OPTIONAL DEFAULT”AUTO” THE NUMBER OF FEATURES TO
CONSIDER WHEN LOOKING FOR THE BEST SPLIT
• IF INT THEN CONSIDER MAXFEATURES FEATURES AT EACH SPLIT
• IF FLOAT THEN MAXFEATURES IS A FRACTION AND INTMAXFEATURES
NFEATURES FEATURES ARE CONSIDERED AT EACH SPLIT
• IF “AUTO” THEN MAXFEATURESSQRTNFEATURES
• IF “SQRT” THEN MAXFEATURESSQRTNFEATURES SAME AS “AUTO”
• IF “LOG2” THEN MAXFEATURESLOG2NFEATURES
• IF NONE THEN MAXFEATURESNFEATURES
NOTE THE SEARCH FOR A SPLIT DOES NOT STOP UNTIL AT LEAST ONE VALID PARTITION OF THE NODE SAMPLES
IS FOUND EVEN IF IT REQUIRES TO EFFECTIVELY INSPECT MORE THAN MAXFEATURES FEATURES
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULTNONE GROW TREES WITH MAXLEAFNODES
IN BESTFIRST FASHION BEST NODES ARE DEFINED AS RELATIVE REDUCTION IN IMPURITY IF NONE THEN
UNLIMITED NUMBER OF LEAF NODES
MINIMPURITYDECREASE FLOAT OPTIONAL DEFAULT0 A NODE WILL BE SPLIT IF THIS SPLIT INDUCES
A DECREASE OF THE IMPURITY GREATER THAN OR EQUAL TO THIS VALUE
THE WEIGHTED IMPURITY DECREASE EQUATION IS THE FOLLOWING
NT N IMPURITY NTR NT RIGHTIMPURITY
 NTL NT LEFTIMPURITY
WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE
NTL IS THE NUMBER OF SAMPLES IN THE LEFT CHILD AND NTR IS THE NUMBER OF SAMPLES IN
THE RIGHT CHILD
NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED

NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE
WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
DEPRECATED SINCE VERSION 019 MINIMPURITYSPLIT HAS BEEN DEPRECATED IN FAVOR OF
MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT
WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE
MINIMPURITYDECREASE INSTEAD
BOOTSTRAP BOOLEAN OPTIONAL DEFAULTTRUE WHETHER BOOTSTRAP SAMPLES ARE USED WHEN BUILD
ING TREES IF FALSE THE WHOLE DATSET IS USED TO BUILD EACH TREE
OOBSCORE BOOL DEFAULTFALSE WHETHER TO USE OUTOFBAG SAMPLES TO ESTIMATE THE GENERAL
IZATION ACCURACY
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR BOTH
FIT ANDPREDICT NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT
1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
VERBOSE INT OPTIONAL DEFAULT0 CONTROLS THE VERBOSITY WHEN FITTING AND PREDICTING
WARMSTART BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PRE
VIOUS CALL TO FIT AND ADD MORE ESTIMATORS TO THE ENSEMBLE OTHERWISE JUST FIT A WHOLE NEW
FOREST SEE THE GLOSSARY
CLASSWEIGHT DICT LIST OF DICTS “BALANCED” “BALANCEDSUBSAMPLE” OR NONE OPTIONAL DE
FAULTNONE WEIGHTS ASSOCIATED WITH CLASSES IN THE FORM CLASSLABEL WEIGHT
IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT ONE FOR MULTIOUTPUT PROBLEMS A LIST
OF DICTS CAN BE PROVIDED IN THE SAME ORDER AS THE COLUMNS OF Y
NOTE THAT FOR MULTIOUTPUT INCLUDING MULTILABEL WEIGHTS SHOULD BE DEFINED FOR EACH CLASS OF
EVERY COLUMN IN ITS OWN DICT FOR EXAMPLE FOR FOURCLASS MULTILABEL CLASSIFICATION WEIGHTS
SHOULD BE 0 1 1 1 0 1 1 5 0 1 1 1 0 1 1 1 INSTEAD OF 11 25
31 41
THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP
BINCOUNTY
THE “BALANCEDSUBSAMPLE” MODE IS THE SAME AS “BALANCED” EXCEPT THAT WEIGHTS ARE COM
PUTED BASED ON THE BOOTSTRAP SAMPLE FOR EVERY TREE GROWN
FOR MULTIOUTPUT THE WEIGHTS OF EACH COLUMN OF Y WILL BE MULTIPLIED
NOTE THAT THESE WEIGHTS WILL BE MULTIPLIED WITH SAMPLEWEIGHT PASSED THROUGH THE FIT
METHOD IF SAMPLEWEIGHT IS SPECIFIED
ATTRIBUTES
ESTIMATORS LIST OF DECISIONTREECLASSIFIER THE COLLECTION OF FITTED SUBESTIMATORS
CLASSES ARRAY OF SHAPE NCLASSES OR A LIST OF SUCH ARRAYS THE CLASSES LABELS SINGLE OUTPUT
PROBLEM OR A LIST OF ARRAYS OF CLASS LABELS MULTIOUTPUT PROBLEM
NCLASSES INT OR LIST THE NUMBER OF CLASSES SINGLE OUTPUT PROBLEM OR A LIST CONTAINING THE
NUMBER OF CLASSES FOR EACH OUTPUT MULTIOUTPUT PROBLEM

NFEATURES INT THE NUMBER OF FEATURES WHEN FIT IS PERFORMED
NOUTPUTS INT THE NUMBER OF OUTPUTS WHEN FIT IS PERFORMED
FEATUREIMPORTANCES ARRAY OF SHAPE NFEATURES RETURN THE FEATURE IMPORTANCES
THE HIGHER THE MORE IMPORTANT THE FEATURE
OOBSCORE FLOAT SCORE OF THE TRAINING DATASET OBTAINED USING AN OUTOFBAG ESTIMATE
OOBDECISIONFUNCTION ARRAY OF SHAPE NSAMPLES NCLASSES DECISION FUNCTION COM
PUTED WITH OUTOFBAG ESTIMATE ON THE TRAINING SET IF NESTIMATORS IS SMALL IT MIGHT
BE POSSIBLE THAT A DATA POINT WAS NEVER LEFT OUT DURING THE BOOTSTRAP IN THIS CASE
OOBDECISIONFUNCTION MIGHT CONTAIN NAN
SEE ALSO
DECISIONTREECLASSIFIER EXTRATREESCLASSIFIER
NOTES
THE DEFAULT VALUES FOR THE PARAMETERS CONTROLLING THE SIZE OF THE TREES EG MAXDEPTH
MINSAMPLESLEAF ETC LEAD TO FULLY GROWN AND UNPRUNED TREES WHICH CAN POTENTIALLY BE VERY LARGE ON
SOME DATA SETS TO REDUCE MEMORY CONSUMPTION THE COMPLEXITY AND SIZE OF THE TREES SHOULD BE CONTROLLED BY
SETTING THOSE PARAMETER VALUES
THE FEATURES ARE ALWAYS RANDOMLY PERMUTED AT EACH SPLIT THEREFORE THE BEST FOUND SPLIT MAY VARY EVEN WITH
THE SAME TRAINING DATA MAXFEATURESNFEATURES ANDBOOTSTRAPFALSE IF THE IMPROVEMENT OF THE
CRITERION IS IDENTICAL FOR SEVERAL SPLITS ENUMERATED DURING THE SEARCH OF THE BEST SPLIT TO OBTAIN A DETERMINISTIC
BEHAVIOUR DURING FITTING RANDOMSTATE HAS TO BE FIXED
REFERENCES
R45F14345C0001
EXAMPLES
 FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
 FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
X Y MAKECLASSIFICATIONNSAMPLES1000 NFEATURES4
 NINFORMATIVE2 NREDUNDANT0
 RANDOMSTATE0 SHUFFLE FALSE
CLF RANDOMFORESTCLASSIFIERNESTIMATORS100 MAXDEPTH2
 RANDOMSTATE0
CLFFITX Y
RANDOMFORESTCLASSIFIERBOOTSTRAPTRUE CLASSWEIGHTNONE CRITERIONGINI
MAXDEPTH2 MAXFEATURESAUTO MAXLEAFNODESNONE
MINIMPURITYDECREASE00 MINIMPURITYSPLITNONE
MINSAMPLESLEAF1 MINSAMPLESSPLIT2
MINWEIGHTFRACTIONLEAF00 NESTIMATORS100 NJOBSNONE
OOBSCOREFALSE RANDOMSTATE0 VERBOSE0 WARMSTARTFALSE
PRINTCLFFEATUREIMPORTANCES
014205973 076664038 00282433 006305659
PRINTCLFPREDICT0 0 0 0
1

METHODS
APPLY SELF X APPLY TREES IN THE FOREST TO X RETURN LEAF INDICES
DECISIONPATH SELF X RETURN THE DECISION PATH IN THE FOREST
FITSELF X Y SAMPLEWEIGHT BUILD A FOREST OF TREES FROM THE TRAINING SET X Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASS FOR X
PREDICTLOGPROBA SELF X PREDICT CLASS LOGPROBABILITIES FOR X
PREDICTPROBA SELF X PREDICT CLASS PROBABILITIES FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNESTIMATORS'WARN' CRITERION'GINI' MAXDEPTHNONE MINSAMPLESSPLIT2 MINSAMPLESLEAF1 MINWEIGHTFRACTIONLEAF00 MAXFEATURES'AUTO' MAXLEAFNODESNONE MINIMPURITYDECREASE00 MINIMPURITYSPLITNONE BOOTSTRAPTRUE OOBSCOREFALSE NJOBSNONE RANDOMSTATENONE VERBOSE0 WARMSTARTFALSE CLASSWEIGHTNONE
APPLYSELFX
APPLY TREES IN THE FOREST TO X RETURN LEAF INDICES
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES NESTIMATORS FOR EACH DATAPOINT X IN X AND FOR EACH TREE IN THE FOREST RETURN THE INDEX OF THE LEAF X ENDS UP IN
DECISIONPATH SELFX
RETURN THE DECISION PATH IN THE FOREST
NEW IN VERSION 018
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
INDICATOR SPARSE CSR ARRAY SHAPE NSAMPLES NNODES RETURN A NODE INDICATOR MATRIX WHERE NON ZERO ELEMENTS INDICATES THAT THE SAMPLES GOES THROUGH THE NODES
NNODESPTR ARRAY OF SIZE NESTIMATORS 1 THE COLUMNS FROM INDICA TORNNODESPTRINNODESPTRI1 GIVES THE INDICATOR VALUE FOR THE ITH ESTIMATOR
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES THE HIGHER THE MORE IMPORTANT THE FEATURE
RETURNS

FEATUREIMPORTANCES ARRAY SHAPE NFEATURES THE VALUES OF THIS ARRAY SUM TO 1 UNLESS
ALL TREES ARE SINGLE NODE TREES CONSISTING OF ONLY THE ROOT NODE IN WHICH CASE IT WILL BE AN
ARRAY OF ZEROS
FITSELFXYSAMPLEWEIGHTNONE
BUILD A FOREST OF TREES FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES INTERNALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX
IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSCMATRIX
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE TARGET VALUES CLASS LABELS
IN CLASSIFICATION REAL NUMBERS IN REGRESSION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEG
ATIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE IN THE CASE OF CLASSIFI
CATION SPLITS ARE ALSO IGNORED IF THEY WOULD RESULT IN ANY SINGLE CLASS CARRYING A NEGATIVE
WEIGHT IN EITHER CHILD NODE
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT CLASS FOR X
THE PREDICTED CLASS OF AN INPUT SAMPLE IS A VOTE BY THE TREES IN THE FOREST WEIGHTED BY THEIR PROBABILITY
ESTIMATES THAT IS THE PREDICTED CLASS IS THE ONE WITH HIGHEST MEAN PROBABILITY ESTIMATE ACROSS THE TREES
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
YARRAY OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE PREDICTED CLASSES
PREDICTLOGPROBA SELFX
PREDICT CLASS LOGPROBABILITIES FOR X
THE PREDICTED CLASS LOGPROBABILITIES OF AN INPUT SAMPLE IS COMPUTED AS THE LOG OF THE MEAN PREDICTED CLASS
PROBABILITIES OF THE TREES IN THE FOREST
PARAMETERS

XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES OR A LIST OF NOUTPUTS SUCH ARRAYS IF NOUTPUTS
 1 THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS TO
THAT IN THE ATTRIBUTE CLASSES
PREDICTPROBA SELFX
PREDICT CLASS PROBABILITIES FOR X
THE PREDICTED CLASS PROBABILITIES OF AN INPUT SAMPLE ARE COMPUTED AS THE MEAN PREDICTED CLASS PROBABILITIES
OF THE TREES IN THE FOREST THE CLASS PROBABILITY OF A SINGLE TREE IS THE FRACTION OF SAMPLES OF THE SAME CLASS
IN A LEAF
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
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RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES OR A LIST OF NOUTPUTS SUCH ARRAYS IF NOUTPUTS
 1 THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS TO
THAT IN THE ATTRIBUTE CLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNENSEMBLERANDOMFORESTCLASSIFIER
•COMPARISON OF CALIBRATION OF CLASSIFIERS
•PROBABILITY CALIBRATION FOR 3CLASS CLASSIFICATION

SCIKITLEARN USER GUIDE RELEASE 0213
•CLASSIFIER COMPARISON
•INDUCTIVE CLUSTERING
•PLOT CLASS PROBABILITIES CALCULATED BY THE VOTINGCLASSIFIER
•OOB ERRORS FOR RANDOM FORESTS
•FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES
•PLOT THE DECISION SURFACES OF ENSEMBLES OF TREES ON THE IRIS DATASET
•COMPARING RANDOMIZED SEARCH AND GRID SEARCH FOR HYPERPARAMETER ESTIMATION
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
SKLEARNENSEMBLE RANDOMFORESTREGRESSOR
CLASSSKLEARNENSEMBLE RANDOMFORESTREGRESSOR NESTIMATORS'WARN' CRITE
RION'MSE' MAXDEPTHNONE
MINSAMPLESSPLIT2 MINSAMPLESLEAF1
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PORTED CRITERIA ARE "MSE" FOR THE MEAN SQUARED ERROR WHICH IS EQUAL TO VARIANCE REDUCTION AS
FEATURE SELECTION CRITERION AND "MAE" FOR THE MEAN ABSOLUTE ERROR
NEW IN VERSION 018 MEAN ABSOLUTE ERROR MAE CRITERION
MAXDEPTH INTEGER OR NONE OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF THE TREE IF
NONE THEN NODES ARE EXPANDED UNTIL ALL LEAVES ARE PURE OR UNTIL ALL LEAVES CONTAIN LESS THAN
MINSAMPLESSPLIT SAMPLES
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TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS

MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST
MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY
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• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE
SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE
EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED
MAXFEATURES INT FLOAT STRING OR NONE OPTIONAL DEFAULT”AUTO” THE NUMBER OF FEATURES TO
CONSIDER WHEN LOOKING FOR THE BEST SPLIT
• IF INT THEN CONSIDER MAXFEATURES FEATURES AT EACH SPLIT
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• IF “AUTO” THEN MAXFEATURESNFEATURES
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UNLIMITED NUMBER OF LEAF NODES
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WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE
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NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED
NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE
WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
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MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT
WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE
MINIMPURITYDECREASE INSTEAD

BOOTSTRAP BOOLEAN OPTIONAL DEFAULTTRUE WHETHER BOOTSTRAP SAMPLES ARE USED WHEN BUILD
ING TREES IF FALSE THE WHOLE DATSET IS USED TO BUILD EACH TREE
OOBSCORE BOOL OPTIONAL DEFAULTFALSE WHETHER TO USE OUTOFBAG SAMPLES TO ESTIMATE THE
R2 ON UNSEEN DATA
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR BOTH
FIT ANDPREDICT NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT
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RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
VERBOSE INT OPTIONAL DEFAULT0 CONTROLS THE VERBOSITY WHEN FITTING AND PREDICTING
WARMSTART BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PRE
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NOUTPUTS INT THE NUMBER OF OUTPUTS WHEN FIT IS PERFORMED
OOBSCORE FLOAT SCORE OF THE TRAINING DATASET OBTAINED USING AN OUTOFBAG ESTIMATE
OOBPREDICTION ARRAY OF SHAPE NSAMPLES PREDICTION COMPUTED WITH OUTOFBAG ESTIMATE
ON THE TRAINING SET
SEE ALSO
DECISIONTREEREGRESSOR EXTRATREESREGRESSOR
NOTES
THE DEFAULT VALUES FOR THE PARAMETERS CONTROLLING THE SIZE OF THE TREES EG MAXDEPTH
MINSAMPLESLEAF ETC LEAD TO FULLY GROWN AND UNPRUNED TREES WHICH CAN POTENTIALLY BE VERY LARGE ON
SOME DATA SETS TO REDUCE MEMORY CONSUMPTION THE COMPLEXITY AND SIZE OF THE TREES SHOULD BE CONTROLLED BY
SETTING THOSE PARAMETER VALUES
THE FEATURES ARE ALWAYS RANDOMLY PERMUTED AT EACH SPLIT THEREFORE THE BEST FOUND SPLIT MAY VARY EVEN WITH
THE SAME TRAINING DATA MAXFEATURESNFEATURES ANDBOOTSTRAPFALSE IF THE IMPROVEMENT OF THE
CRITERION IS IDENTICAL FOR SEVERAL SPLITS ENUMERATED DURING THE SEARCH OF THE BEST SPLIT TO OBTAIN A DETERMINISTIC
BEHAVIOUR DURING FITTING RANDOMSTATE HAS TO BE FIXED
THE DEFAULT VALUE MAXFEATURESAUTO USESNFEATURES RATHER THAN NFEATURES 3 THE LATTER
WAS ORIGINALLY SUGGESTED IN 1 WHEREAS THE FORMER WAS MORE RECENTLY JUSTIFIED EMPIRICALLY IN 2
REFERENCES
RF91CAB2DC4271 RF91CAB2DC4272

EXAMPLES
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 FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTREGRESSOR
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y  MAKEREGRESSIONNFEATURES4 NINFORMATIVE2
 RANDOMSTATE0 SHUFFLE FALSE
REGR  RANDOMFORESTREGRESSORMAXDEPTH2 RANDOMSTATE0
 NESTIMATORS100
REGRFITX Y
RANDOMFORESTREGRESSORBOOTSTRAPTRUE CRITERIONMSE MAXDEPTH2
MAXFEATURESAUTO MAXLEAFNODESNONE
MINIMPURITYDECREASE00 MINIMPURITYSPLITNONE
MINSAMPLESLEAF1 MINSAMPLESSPLIT2
MINWEIGHTFRACTIONLEAF00 NESTIMATORS100 NJOBSNONE
OOBSCOREFALSE RANDOMSTATE0 VERBOSE0 WARMSTARTFALSE
PRINTREGRFEATUREIMPORTANCES
018146984 081473937 000145312 000233767
PRINTREGRPREDICT0 0 0 0
832987858
```
METHODS
APPLY SELF X APPLY TREES IN THE FOREST TO X RETURN LEAF INDICES
DECISIONPATH SELF X RETURN THE DECISION PATH IN THE FOREST
FITSELF X Y SAMPLEWEIGHT BUILD A FOREST OF TREES FROM THE TRAINING SET X Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT REGRESSION TARGET FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNESTIMATORS'WARN' CRITERION'MSE' MAXDEPTHNONE MINSAMPLESSPLIT2
MINSAMPLESLEAF1 MINWEIGHTFRACTIONLEAF00 MAXFEATURES'AUTO'
MAXLEAFNODESNONE MINIMPURITYDECREASE00 MINIMPURITYSPLITNONE
BOOTSTRAPTRUE OOBSCOREFALSE NJOBSNONE RANDOMSTATENONE VERBOSE0
WARMSTARTFALSE
APPLYSELFX
APPLY TREES IN THE FOREST TO X RETURN LEAF INDICES
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES NESTIMATORS FOR EACH DATAPOINT X IN X AND FOR
EACH TREE IN THE FOREST RETURN THE INDEX OF THE LEAF X ENDS UP IN
DECISIONPATH SELFX
RETURN THE DECISION PATH IN THE FOREST

SCIKITLEARN USER GUIDE RELEASE 0213
NEW IN VERSION 018
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
INDICATOR SPARSE CSR ARRAY SHAPE NSAMPLES NNODES RETURN A NODE INDICATOR MATRIX
WHERE NON ZERO ELEMENTS INDICATES THAT THE SAMPLES GOES THROUGH THE NODES
NNODESPTR ARRAY OF SIZE NESTIMATORS 1 THE COLUMNS FROM INDICA
TORNNODESPTRINNODESPTRI1 GIVES THE INDICATOR VALUE FOR THE ITH ESTIMATOR
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES THE HIGHER THE MORE IMPORTANT THE FEATURE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES THE VALUES OF THIS ARRAY SUM TO 1 UNLESS
ALL TREES ARE SINGLE NODE TREES CONSISTING OF ONLY THE ROOT NODE IN WHICH CASE IT WILL BE AN
ARRAY OF ZEROS
FITSELFXYSAMPLEWEIGHTNONE
BUILD A FOREST OF TREES FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES INTERNALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX
IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSCMATRIX
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE TARGET VALUES CLASS LABELS
IN CLASSIFICATION REAL NUMBERS IN REGRESSION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEG
ATIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE IN THE CASE OF CLASSIFI
CATION SPLITS ARE ALSO IGNORED IF THEY WOULD RESULT IN ANY SINGLE CLASS CARRYING A NEGATIVE
WEIGHT IN EITHER CHILD NODE
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT REGRESSION TARGET FOR X

THE PREDICTED REGRESSION TARGET OF AN INPUT SAMPLE IS COMPUTED AS THE MEAN PREDICTED REGRESSION TARGETS OF THE TREES IN THE FOREST
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
YARRAY OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED 2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNENSEMBLERANDOMFORESTREGRESSOR
•PREDICTION LATENCY
•PLOT INDIVIDUAL AND VOTING REGRESSION PREDICTIONS

•COMPARING RANDOM FORESTS AND THE MULTIOUTPUT META ESTIMATOR
•IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR
SKLEARNENSEMBLE EXTRATREESCLASSIFIER
CLASSSKLEARNENSEMBLE EXTRATREESCLASSIFIER NESTIMATORS'WARN' CRITE
RION'GINI' MAXDEPTHNONE
MINSAMPLESSPLIT2 MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00
MAXFEATURES'AUTO' MAXLEAFNODESNONE
MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE BOOTSTRAPFALSE
OOBSCOREFALSE NJOBSNONE
RANDOMSTATENONE VERBOSE0
WARMSTARTFALSE CLASSWEIGHTNONE
AN EXTRATREES CLASSIFIER
THIS CLASS IMPLEMENTS A META ESTIMATOR THAT FITS A NUMBER OF RANDOMIZED DECISION TREES AKA EXTRATREES ON
VARIOUS SUBSAMPLES OF THE DATASET AND USES AVERAGING TO IMPROVE THE PREDICTIVE ACCURACY AND CONTROL OVERFITTING
READ MORE IN THE USER GUIDE
PARAMETERS
NESTIMATORS INTEGER OPTIONAL DEFAULT10 THE NUMBER OF TREES IN THE FOREST
CHANGED IN VERSION 020 THE DEFAULT VALUE OF NESTIMATORS WILL CHANGE FROM 10 IN
VERSION 020 TO 100 IN VERSION 022
CRITERION STRING OPTIONAL DEFAULT"GINI" THE FUNCTION TO MEASURE THE QUALITY OF A SPLIT SUP
PORTED CRITERIA ARE "GINI" FOR THE GINI IMPURITY AND "ENTROPY" FOR THE INFORMATION GAIN
MAXDEPTH INTEGER OR NONE OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF THE TREE IF
NONE THEN NODES ARE EXPANDED UNTIL ALL LEAVES ARE PURE OR UNTIL ALL LEAVES CONTAIN LESS THAN
MINSAMPLESSPLIT SAMPLES
MINSAMPLESSPLIT INT FLOAT OPTIONAL DEFAULT2 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST
MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY
HAVE THE EFFECT OF SMOOTHING THE MODEL ESPECIALLY IN REGRESSION
• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE
SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE
EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED

MAXFEATURES INT FLOAT STRING OR NONE OPTIONAL DEFAULT”AUTO” THE NUMBER OF FEATURES TO
CONSIDER WHEN LOOKING FOR THE BEST SPLIT
• IF INT THEN CONSIDER MAXFEATURES FEATURES AT EACH SPLIT
• IF FLOAT THEN MAXFEATURES IS A FRACTION AND INTMAXFEATURES
NFEATURES FEATURES ARE CONSIDERED AT EACH SPLIT
• IF “AUTO” THEN MAXFEATURESSQRTNFEATURES
• IF “SQRT” THEN MAXFEATURESSQRTNFEATURES
• IF “LOG2” THEN MAXFEATURESLOG2NFEATURES
• IF NONE THEN MAXFEATURESNFEATURES
NOTE THE SEARCH FOR A SPLIT DOES NOT STOP UNTIL AT LEAST ONE VALID PARTITION OF THE NODE SAMPLES
IS FOUND EVEN IF IT REQUIRES TO EFFECTIVELY INSPECT MORE THAN MAXFEATURES FEATURES
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULTNONE GROW TREES WITH MAXLEAFNODES
IN BESTFIRST FASHION BEST NODES ARE DEFINED AS RELATIVE REDUCTION IN IMPURITY IF NONE THEN
UNLIMITED NUMBER OF LEAF NODES
MINIMPURITYDECREASE FLOAT OPTIONAL DEFAULT0 A NODE WILL BE SPLIT IF THIS SPLIT INDUCES
A DECREASE OF THE IMPURITY GREATER THAN OR EQUAL TO THIS VALUE
THE WEIGHTED IMPURITY DECREASE EQUATION IS THE FOLLOWING
NT N IMPURITY NTR NT RIGHTIMPURITY
 NTL NT LEFTIMPURITY
WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE
NTL IS THE NUMBER OF SAMPLES IN THE LEFT CHILD AND NTR IS THE NUMBER OF SAMPLES IN
THE RIGHT CHILD
NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED
NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE
WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
DEPRECATED SINCE VERSION 019 MINIMPURITYSPLIT HAS BEEN DEPRECATED IN FAVOR OF
MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT
WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE
MINIMPURITYDECREASE INSTEAD
BOOTSTRAP BOOLEAN OPTIONAL DEFAULTFALSE WHETHER BOOTSTRAP SAMPLES ARE USED WHEN BUILD
ING TREES IF FALSE THE WHOLE DATSET IS USED TO BUILD EACH TREE
OOBSCORE BOOL OPTIONAL DEFAULTFALSE WHETHER TO USE OUTOFBAG SAMPLES TO ESTIMATE THE
GENERALIZATION ACCURACY
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR BOTH
FIT ANDPREDICT NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT
1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
VERBOSE INT OPTIONAL DEFAULT0 CONTROLS THE VERBOSITY WHEN FITTING AND PREDICTING

WARMSTART BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PRE
VIOUS CALL TO FIT AND ADD MORE ESTIMATORS TO THE ENSEMBLE OTHERWISE JUST FIT A WHOLE NEW
FOREST SEE THE GLOSSARY
CLASSWEIGHT DICT LIST OF DICTS “BALANCED” “BALANCEDSUBSAMPLE” OR NONE OPTIONAL DE
FAULTNONE WEIGHTS ASSOCIATED WITH CLASSES IN THE FORM CLASSLABEL WEIGHT
IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT ONE FOR MULTIOUTPUT PROBLEMS A LIST
OF DICTS CAN BE PROVIDED IN THE SAME ORDER AS THE COLUMNS OF Y
NOTE THAT FOR MULTIOUTPUT INCLUDING MULTILABEL WEIGHTS SHOULD BE DEFINED FOR EACH CLASS OF
EVERY COLUMN IN ITS OWN DICT FOR EXAMPLE FOR FOURCLASS MULTILABEL CLASSIFICATION WEIGHTS
SHOULD BE 0 1 1 1 0 1 1 5 0 1 1 1 0 1 1 1 INSTEAD OF 11 25
31 41
THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP
BINCOUNTY
THE “BALANCEDSUBSAMPLE” MODE IS THE SAME AS “BALANCED” EXCEPT THAT WEIGHTS ARE COM
PUTED BASED ON THE BOOTSTRAP SAMPLE FOR EVERY TREE GROWN
FOR MULTIOUTPUT THE WEIGHTS OF EACH COLUMN OF Y WILL BE MULTIPLIED
NOTE THAT THESE WEIGHTS WILL BE MULTIPLIED WITH SAMPLEWEIGHT PASSED THROUGH THE FIT
METHOD IF SAMPLEWEIGHT IS SPECIFIED
ATTRIBUTES
ESTIMATORS LIST OF DECISIONTREECLASSIFIER THE COLLECTION OF FITTED SUBESTIMATORS
CLASSES ARRAY OF SHAPE NCLASSES OR A LIST OF SUCH ARRAYS THE CLASSES LABELS SINGLE OUTPUT
PROBLEM OR A LIST OF ARRAYS OF CLASS LABELS MULTIOUTPUT PROBLEM
NCLASSES INT OR LIST THE NUMBER OF CLASSES SINGLE OUTPUT PROBLEM OR A LIST CONTAINING THE
NUMBER OF CLASSES FOR EACH OUTPUT MULTIOUTPUT PROBLEM
FEATUREIMPORTANCES ARRAY OF SHAPE NFEATURES RETURN THE FEATURE IMPORTANCES
THE HIGHER THE MORE IMPORTANT THE FEATURE
NFEATURES INT THE NUMBER OF FEATURES WHEN FIT IS PERFORMED
NOUTPUTS INT THE NUMBER OF OUTPUTS WHEN FIT IS PERFORMED
OOBSCORE FLOAT SCORE OF THE TRAINING DATASET OBTAINED USING AN OUTOFBAG ESTIMATE
OOBDECISIONFUNCTION ARRAY OF SHAPE NSAMPLES NCLASSES DECISION FUNCTION COM
PUTED WITH OUTOFBAG ESTIMATE ON THE TRAINING SET IF NESTIMATORS IS SMALL IT MIGHT
BE POSSIBLE THAT A DATA POINT WAS NEVER LEFT OUT DURING THE BOOTSTRAP IN THIS CASE
OOBDECISIONFUNCTION MIGHT CONTAIN NAN
SEE ALSO
SKLEARNTREEEXTRATREECLASSIFIER BASE CLASSIFIER FOR THIS ENSEMBLE
RANDOMFORESTCLASSIFIER ENSEMBLE CLASSIFIER BASED ON TREES WITH OPTIMAL SPLITS
NOTES
THE DEFAULT VALUES FOR THE PARAMETERS CONTROLLING THE SIZE OF THE TREES EG MAXDEPTH
MINSAMPLESLEAF ETC LEAD TO FULLY GROWN AND UNPRUNED TREES WHICH CAN POTENTIALLY BE VERY LARGE ON

SOME DATA SETS TO REDUCE MEMORY CONSUMPTION THE COMPLEXITY AND SIZE OF THE TREES SHOULD BE CONTROLLED BY SETTING THOSE PARAMETER VALUES
REFERENCES
RC8F28BFAD63F1
METHODS
APPLY SELF X APPLY TREES IN THE FOREST TO X RETURN LEAF INDICES
DECISIONPATH SELF X RETURN THE DECISION PATH IN THE FOREST
FITSELF X Y SAMPLEWEIGHT BUILD A FOREST OF TREES FROM THE TRAINING SET X Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASS FOR X
PREDICTLOGPROBA SELF X PREDICT CLASS LOGPROBABILITIES FOR X
PREDICTPROBA SELF X PREDICT CLASS PROBABILITIES FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNESTIMATORS'WARN' CRITERION'GINI' MAXDEPTHNONE MINSAMPLESSPLIT2 MINSAMPLESLEAF1 MINWEIGHTFRACTIONLEAF00 MAXFEATURES'AUTO' MAXLEAFNODESNONE MINIMPURITYDECREASE00 MINIMPURITYSPLITNONE BOOTSTRAPFALSE OOBSCOREFALSE NJOBSNONE RANDOMSTATENONE VERBOSE0 WARMSTARTFALSE CLASSWEIGHTNONE
APPLYSELFX
APPLY TREES IN THE FOREST TO X RETURN LEAF INDICES
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTERNALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES NESTIMATORS FOR EACH DATAPOINT X IN X AND FOR EACH TREE IN THE FOREST RETURN THE INDEX OF THE LEAF X ENDS UP IN
DECISIONPATH SELFX
RETURN THE DECISION PATH IN THE FOREST
NEW IN VERSION 018
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTERNALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
INDICATOR SPARSE CSR ARRAY SHAPE NSAMPLES NNODES RETURN A NODE INDICATOR MATRIX WHERE NON ZERO ELEMENTS INDICATES THAT THE SAMPLES GOES THROUGH THE NODES

NNODESPTR ARRAY OF SIZE NESTIMATORS 1 THE COLUMNS FROM INDICA
TORNNODESPTRINNODESPTRI1 GIVES THE INDICATOR VALUE FOR THE ITH ESTIMATOR
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES THE HIGHER THE MORE IMPORTANT THE FEATURE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES THE VALUES OF THIS ARRAY SUM TO 1 UNLESS
ALL TREES ARE SINGLE NODE TREES CONSISTING OF ONLY THE ROOT NODE IN WHICH CASE IT WILL BE AN
ARRAY OF ZEROS
FITSELFXYSAMPLEWEIGHTNONE
BUILD A FOREST OF TREES FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES INTERNALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX
IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSCMATRIX
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE TARGET VALUES CLASS LABELS
IN CLASSIFICATION REAL NUMBERS IN REGRESSION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEG
ATIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE IN THE CASE OF CLASSIFI
CATION SPLITS ARE ALSO IGNORED IF THEY WOULD RESULT IN ANY SINGLE CLASS CARRYING A NEGATIVE
WEIGHT IN EITHER CHILD NODE
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT CLASS FOR X
THE PREDICTED CLASS OF AN INPUT SAMPLE IS A VOTE BY THE TREES IN THE FOREST WEIGHTED BY THEIR PROBABILITY
ESTIMATES THAT IS THE PREDICTED CLASS IS THE ONE WITH HIGHEST MEAN PROBABILITY ESTIMATE ACROSS THE TREES
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
YARRAY OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE PREDICTED CLASSES

PREDICTLOGPROBA SELFX
PREDICT CLASS LOGPROBABILITIES FOR X
THE PREDICTED CLASS LOGPROBABILITIES OF AN INPUT SAMPLE IS COMPUTED AS THE LOG OF THE MEAN PREDICTED CLASS PROBABILITIES OF THE TREES IN THE FOREST
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES OR A LIST OF NOUTPUTS SUCH ARRAYS IF NOUTPUTS 1 THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES
PREDICTPROBA SELFX
PREDICT CLASS PROBABILITIES FOR X
THE PREDICTED CLASS PROBABILITIES OF AN INPUT SAMPLE ARE COMPUTED AS THE MEAN PREDICTED CLASS PROBABILITIES OF THE TREES IN THE FOREST THE CLASS PROBABILITY OF A SINGLE TREE IS THE FRACTION OF SAMPLES OF THE SAME CLASS IN A LEAF
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES OR A LIST OF NOUTPUTS SUCH ARRAYS IF NOUTPUTS 1 THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF

EXAMPLES USING SKLEARNENSEMBLEEXTRATREESCLASSIFIER
•PIXEL IMPORTANCES WITH A PARALLEL FOREST OF TREES
•FEATURE IMPORTANCES WITH FORESTS OF TREES
•HASHING FEATURE TRANSFORMATION USING TOTALLY RANDOM TREES
•PLOT THE DECISION SURFACES OF ENSEMBLES OF TREES ON THE IRIS DATASET
SKLEARNENSEMBLE EXTRATREESREGRESSOR
CLASSSKLEARNENSEMBLE EXTRATREESREGRESSOR NESTIMATORS'WARN' CRITE
RION'MSE' MAXDEPTHNONE
MINSAMPLESSPLIT2 MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00
MAXFEATURES'AUTO' MAXLEAFNODESNONE
MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE BOOTSTRAPFALSE
OOBSCOREFALSE NJOBSNONE
RANDOMSTATENONE VERBOSE0
WARMSTARTFALSE
AN EXTRATREES REGRESSOR
THIS CLASS IMPLEMENTS A META ESTIMATOR THAT FITS A NUMBER OF RANDOMIZED DECISION TREES AKA EXTRATREES ON
VARIOUS SUBSAMPLES OF THE DATASET AND USES AVERAGING TO IMPROVE THE PREDICTIVE ACCURACY AND CONTROL OVERFITTING
READ MORE IN THE USER GUIDE
PARAMETERS
NESTIMATORS INTEGER OPTIONAL DEFAULT10 THE NUMBER OF TREES IN THE FOREST
CHANGED IN VERSION 020 THE DEFAULT VALUE OF NESTIMATORS WILL CHANGE FROM 10 IN
VERSION 020 TO 100 IN VERSION 022
CRITERION STRING OPTIONAL DEFAULT"MSE" THE FUNCTION TO MEASURE THE QUALITY OF A SPLIT SUP
PORTED CRITERIA ARE "MSE" FOR THE MEAN SQUARED ERROR WHICH IS EQUAL TO VARIANCE REDUCTION AS
FEATURE SELECTION CRITERION AND "MAE" FOR THE MEAN ABSOLUTE ERROR
NEW IN VERSION 018 MEAN ABSOLUTE ERROR MAE CRITERION
MAXDEPTH INTEGER OR NONE OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF THE TREE IF
NONE THEN NODES ARE EXPANDED UNTIL ALL LEAVES ARE PURE OR UNTIL ALL LEAVES CONTAIN LESS THAN
MINSAMPLESSPLIT SAMPLES
MINSAMPLESSPLIT INT FLOAT OPTIONAL DEFAULT2 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST
MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY
HAVE THE EFFECT OF SMOOTHING THE MODEL ESPECIALLY IN REGRESSION

• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE
SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE
EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED
MAXFEATURES INT FLOAT STRING OR NONE OPTIONAL DEFAULT”AUTO” THE NUMBER OF FEATURES TO
CONSIDER WHEN LOOKING FOR THE BEST SPLIT
• IF INT THEN CONSIDER MAXFEATURES FEATURES AT EACH SPLIT
• IF FLOAT THEN MAXFEATURES IS A FRACTION AND INTMAXFEATURES
NFEATURES FEATURES ARE CONSIDERED AT EACH SPLIT
• IF “AUTO” THEN MAXFEATURESNFEATURES
• IF “SQRT” THEN MAXFEATURESSQRTNFEATURES
• IF “LOG2” THEN MAXFEATURESLOG2NFEATURES
• IF NONE THEN MAXFEATURESNFEATURES
NOTE THE SEARCH FOR A SPLIT DOES NOT STOP UNTIL AT LEAST ONE VALID PARTITION OF THE NODE SAMPLES
IS FOUND EVEN IF IT REQUIRES TO EFFECTIVELY INSPECT MORE THAN MAXFEATURES FEATURES
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULTNONE GROW TREES WITH MAXLEAFNODES
IN BESTFIRST FASHION BEST NODES ARE DEFINED AS RELATIVE REDUCTION IN IMPURITY IF NONE THEN
UNLIMITED NUMBER OF LEAF NODES
MINIMPURITYDECREASE FLOAT OPTIONAL DEFAULT0 A NODE WILL BE SPLIT IF THIS SPLIT INDUCES
A DECREASE OF THE IMPURITY GREATER THAN OR EQUAL TO THIS VALUE
THE WEIGHTED IMPURITY DECREASE EQUATION IS THE FOLLOWING
NT N IMPURITY NTR NT RIGHTIMPURITY
 NTL NT LEFTIMPURITY
WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE
NTL IS THE NUMBER OF SAMPLES IN THE LEFT CHILD AND NTR IS THE NUMBER OF SAMPLES IN
THE RIGHT CHILD
NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED
NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE
WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
DEPRECATED SINCE VERSION 019 MINIMPURITYSPLIT HAS BEEN DEPRECATED IN FAVOR OF
MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT
WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE
MINIMPURITYDECREASE INSTEAD
BOOTSTRAP BOOLEAN OPTIONAL DEFAULTFALSE WHETHER BOOTSTRAP SAMPLES ARE USED WHEN BUILD
ING TREES IF FALSE THE WHOLE DATSET IS USED TO BUILD EACH TREE
OOBSCORE BOOL OPTIONAL DEFAULTFALSE WHETHER TO USE OUTOFBAG SAMPLES TO ESTIMATE THE
R2 ON UNSEEN DATA

NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR BOTH
FIT ANDPREDICT NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT
1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
VERBOSE INT OPTIONAL DEFAULT0 CONTROLS THE VERBOSITY WHEN FITTING AND PREDICTING
WARMSTART BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PRE
VIOUS CALL TO FIT AND ADD MORE ESTIMATORS TO THE ENSEMBLE OTHERWISE JUST FIT A WHOLE NEW
FOREST SEE THE GLOSSARY
ATTRIBUTES
ESTIMATORS LIST OF DECISIONTREEREGRESSOR THE COLLECTION OF FITTED SUBESTIMATORS
FEATUREIMPORTANCES ARRAY OF SHAPE NFEATURES RETURN THE FEATURE IMPORTANCES
THE HIGHER THE MORE IMPORTANT THE FEATURE
NFEATURES INT THE NUMBER OF FEATURES
NOUTPUTS INT THE NUMBER OF OUTPUTS
OOBSCORE FLOAT SCORE OF THE TRAINING DATASET OBTAINED USING AN OUTOFBAG ESTIMATE
OOBPREDICTION ARRAY OF SHAPE NSAMPLES PREDICTION COMPUTED WITH OUTOFBAG ESTIMATE
ON THE TRAINING SET
SEE ALSO
SKLEARNTREEEXTRATREEREGRESSOR BASE ESTIMATOR FOR THIS ENSEMBLE
RANDOMFORESTREGRESSOR ENSEMBLE REGRESSOR USING TREES WITH OPTIMAL SPLITS
NOTES
THE DEFAULT VALUES FOR THE PARAMETERS CONTROLLING THE SIZE OF THE TREES EG MAXDEPTH
MINSAMPLESLEAF ETC LEAD TO FULLY GROWN AND UNPRUNED TREES WHICH CAN POTENTIALLY BE VERY LARGE ON
SOME DATA SETS TO REDUCE MEMORY CONSUMPTION THE COMPLEXITY AND SIZE OF THE TREES SHOULD BE CONTROLLED BY
SETTING THOSE PARAMETER VALUES
REFERENCES
RA7D0C8995FBC1
METHODS
APPLY SELF X APPLY TREES IN THE FOREST TO X RETURN LEAF INDICES
DECISIONPATH SELF X RETURN THE DECISION PATH IN THE FOREST
FITSELF X Y SAMPLEWEIGHT BUILD A FOREST OF TREES FROM THE TRAINING SET X Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT REGRESSION TARGET FOR X
CONTINUED ON NEXT PAGE

TABLE 318 – CONTINUED FROM PREVIOUS PAGE
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNESTIMATORS'WARN' CRITERION'MSE' MAXDEPTHNONE MINSAMPLESSPLIT2
MINSAMPLESLEAF1 MINWEIGHTFRACTIONLEAF00 MAXFEATURES'AUTO'
MAXLEAFNODESNONE MINIMPURITYDECREASE00 MINIMPURITYSPLITNONE BOOT
STRAPFALSE OOBSCOREFALSE NJOBSNONE RANDOMSTATENONE VERBOSE0
WARMSTARTFALSE
APPLYSELFX
APPLY TREES IN THE FOREST TO X RETURN LEAF INDICES
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES NESTIMATORS FOR EACH DATAPOINT X IN X AND FOR
EACH TREE IN THE FOREST RETURN THE INDEX OF THE LEAF X ENDS UP IN
DECISIONPATH SELFX
RETURN THE DECISION PATH IN THE FOREST
NEW IN VERSION 018
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
INDICATOR SPARSE CSR ARRAY SHAPE NSAMPLES NNODES RETURN A NODE INDICATOR MATRIX
WHERE NON ZERO ELEMENTS INDICATES THAT THE SAMPLES GOES THROUGH THE NODES
NNODESPTR ARRAY OF SIZE NESTIMATORS 1 THE COLUMNS FROM INDICA
TORNNODESPTRINNODESPTRI1 GIVES THE INDICATOR VALUE FOR THE ITH ESTIMATOR
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES THE HIGHER THE MORE IMPORTANT THE FEATURE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES THE VALUES OF THIS ARRAY SUM TO 1 UNLESS
ALL TREES ARE SINGLE NODE TREES CONSISTING OF ONLY THE ROOT NODE IN WHICH CASE IT WILL BE AN
ARRAY OF ZEROS
FITSELFXYSAMPLEWEIGHTNONE
BUILD A FOREST OF TREES FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES INTERNALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX
IS PROVIDED IT WILL BE CONVERTED INTO A SPARSE CSCMATRIX

YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE TARGET VALUES CLASS LABELS
IN CLASSIFICATION REAL NUMBERS IN REGRESSION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEG
ATIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE IN THE CASE OF CLASSIFI
CATION SPLITS ARE ALSO IGNORED IF THEY WOULD RESULT IN ANY SINGLE CLASS CARRYING A NEGATIVE
WEIGHT IN EITHER CHILD NODE
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT REGRESSION TARGET FOR X
THE PREDICTED REGRESSION TARGET OF AN INPUT SAMPLE IS COMPUTED AS THE MEAN PREDICTED REGRESSION TARGETS OF
THE TREES IN THE FOREST
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
YARRAY OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y

NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNENSEMBLEEXTRATREESREGRESSOR
•FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS
•IMPUTING MISSING VALUES WITH VARIANTS OF ITERATIVEIMPUTER
SKLEARNENSEMBLE GRADIENTBOOSTINGCLASSIFIER
CLASSSKLEARNENSEMBLE GRADIENTBOOSTINGCLASSIFIER LOSS'DEVIANCE' LEARNINGRATE01
NESTIMATORS100 SUBSAM
PLE10 CRITERION'FRIEDMANMSE'
MINSAMPLESSPLIT2
MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00
MAXDEPTH3
MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE
INITNONE RANDOMSTATENONE
MAXFEATURESNONE VER
BOSE0 MAXLEAFNODESNONE
WARMSTARTFALSE PRE
SORT'AUTO' VALIDATIONFRACTION01
NITERNOCHANGENONE TOL00001
GRADIENT BOOSTING FOR CLASSIFICATION
GB BUILDS AN ADDITIVE MODEL IN A FORWARD STAGEWISE FASHION IT ALLOWS FOR THE OPTIMIZATION OF ARBITRARY DIFFEREN
TIABLE LOSS FUNCTIONS IN EACH STAGE NCLASSES REGRESSION TREES ARE FIT ON THE NEGATIVE GRADIENT OF THE BINOMIAL
OR MULTINOMIAL DEVIANCE LOSS FUNCTION BINARY CLASSIFICATION IS A SPECIAL CASE WHERE ONLY A SINGLE REGRESSION TREE
IS INDUCED
READ MORE IN THE USER GUIDE
PARAMETERS

SCIKITLEARN USER GUIDE RELEASE 0213
LOSS ‘DEVIANCE’ ‘EXPONENTIAL’ OPTIONAL DEFAULT’DEVIANCE’ LOSS FUNCTION TO BE OPTIMIZED
‘DEVIANCE’ REFERS TO DEVIANCE LOGISTIC REGRESSION FOR CLASSIFICATION WITH PROBABILISTIC OUT
PUTS FOR LOSS ‘EXPONENTIAL’ GRADIENT BOOSTING RECOVERS THE ADABOOST ALGORITHM
LEARNINGRATE FLOAT OPTIONAL DEFAULT01 LEARNING RATE SHRINKS THE CONTRIBUTION OF EACH TREE
BYLEARNINGRATE THERE IS A TRADEOFF BETWEEN LEARNINGRATE AND NESTIMATORS
NESTIMATORS INT DEFAULT100 THE NUMBER OF BOOSTING STAGES TO PERFORM GRADIENT BOOSTING
IS FAIRLY ROBUST TO OVERFITTING SO A LARGE NUMBER USUALLY RESULTS IN BETTER PERFORMANCE
SUBSAMPLE FLOAT OPTIONAL DEFAULT10 THE FRACTION OF SAMPLES TO BE USED FOR FITTING THE IN
DIVIDUAL BASE LEARNERS IF SMALLER THAN 10 THIS RESULTS IN STOCHASTIC GRADIENT BOOSTING
SUBSAMPLE INTERACTS WITH THE PARAMETER NESTIMATORS CHOOSING SUBSAMPLE
10 LEADS TO A REDUCTION OF VARIANCE AND AN INCREASE IN BIAS
CRITERION STRING OPTIONAL DEFAULT”FRIEDMANMSE” THE FUNCTION TO MEASURE THE QUALITY OF
A SPLIT SUPPORTED CRITERIA ARE “FRIEDMANMSE” FOR THE MEAN SQUARED ERROR WITH IMPROVE
MENT SCORE BY FRIEDMAN “MSE” FOR MEAN SQUARED ERROR AND “MAE” FOR THE MEAN ABSOLUTE
ERROR THE DEFAULT VALUE OF “FRIEDMANMSE” IS GENERALLY THE BEST AS IT CAN PROVIDE A BETTER
APPROXIMATION IN SOME CASES
NEW IN VERSION 018
MINSAMPLESSPLIT INT FLOAT OPTIONAL DEFAULT2 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST
MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY
HAVE THE EFFECT OF SMOOTHING THE MODEL ESPECIALLY IN REGRESSION
• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE
SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE
EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED
MAXDEPTH INTEGER OPTIONAL DEFAULT3 MAXIMUM DEPTH OF THE INDIVIDUAL REGRESSION ESTIMA
TORS THE MAXIMUM DEPTH LIMITS THE NUMBER OF NODES IN THE TREE TUNE THIS PARAMETER FOR
BEST PERFORMANCE THE BEST VALUE DEPENDS ON THE INTERACTION OF THE INPUT VARIABLES
MINIMPURITYDECREASE FLOAT OPTIONAL DEFAULT0 A NODE WILL BE SPLIT IF THIS SPLIT INDUCES
A DECREASE OF THE IMPURITY GREATER THAN OR EQUAL TO THIS VALUE
THE WEIGHTED IMPURITY DECREASE EQUATION IS THE FOLLOWING
NT N IMPURITY NTR NT RIGHTIMPURITY
 NTL NT LEFTIMPURITY

WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE
NTL IS THE NUMBER OF SAMPLES IN THE LEFT CHILD AND NTR IS THE NUMBER OF SAMPLES IN
THE RIGHT CHILD
NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED
NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE
WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
DEPRECATED SINCE VERSION 019 MINIMPURITYSPLIT HAS BEEN DEPRECATED IN FAVOR OF
MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT
WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE
MINIMPURITYDECREASE INSTEAD
INIT ESTIMATOR OR ‘ZERO’ OPTIONAL DEFAULTNONE AN ESTIMATOR OBJECT THAT IS USED TO COMPUTE
THE INITIAL PREDICTIONS INIT HAS TO PROVIDE FIT ANDPREDICTPROBA IF ‘ZERO’ THE
INITIAL RAW PREDICTIONS ARE SET TO ZERO BY DEFAULT A DUMMYESTIMATOR PREDICTING THE
CLASSES PRIORS IS USED
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
MAXFEATURES INT FLOAT STRING OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF FEATURES TO
CONSIDER WHEN LOOKING FOR THE BEST SPLIT
• IF INT THEN CONSIDER MAXFEATURES FEATURES AT EACH SPLIT
• IF FLOAT THEN MAXFEATURES IS A FRACTION AND INTMAXFEATURES
NFEATURES FEATURES ARE CONSIDERED AT EACH SPLIT
• IF “AUTO” THEN MAXFEATURESSQRTNFEATURES
• IF “SQRT” THEN MAXFEATURESSQRTNFEATURES
• IF “LOG2” THEN MAXFEATURESLOG2NFEATURES
• IF NONE THEN MAXFEATURESNFEATURES
CHOOSINGMAXFEATURES NFEATURES LEADS TO A REDUCTION OF VARIANCE AND AN IN
CREASE IN BIAS
NOTE THE SEARCH FOR A SPLIT DOES NOT STOP UNTIL AT LEAST ONE VALID PARTITION OF THE NODE SAMPLES
IS FOUND EVEN IF IT REQUIRES TO EFFECTIVELY INSPECT MORE THAN MAXFEATURES FEATURES
VERBOSE INT DEFAULT 0 ENABLE VERBOSE OUTPUT IF 1 THEN IT PRINTS PROGRESS AND PERFORMANCE
ONCE IN A WHILE THE MORE TREES THE LOWER THE FREQUENCY IF GREATER THAN 1 THEN IT PRINTS
PROGRESS AND PERFORMANCE FOR EVERY TREE
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULTNONE GROW TREES WITH MAXLEAFNODES
IN BESTFIRST FASHION BEST NODES ARE DEFINED AS RELATIVE REDUCTION IN IMPURITY IF NONE THEN
UNLIMITED NUMBER OF LEAF NODES
WARMSTART BOOL DEFAULT FALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO
FIT AND ADD MORE ESTIMATORS TO THE ENSEMBLE OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE
THE GLOSSARY
PRESORT BOOL OR ‘AUTO’ OPTIONAL DEFAULT’AUTO’ WHETHER TO PRESORT THE DATA TO SPEED UP THE
FINDING OF BEST SPLITS IN FITTING AUTO MODE BY DEFAULT WILL USE PRESORTING ON DENSE DATA AND

DEFAULT TO NORMAL SORTING ON SPARSE DATA SETTING PRESORT TO TRUE ON SPARSE DATA WILL RAISE AN ERROR
NEW IN VERSION 017 PRESORT PARAMETER
VALIDATIONFRACTION FLOAT OPTIONAL DEFAULT 01 THE PROPORTION OF TRAINING DATA TO SET ASIDE AS VALIDATION SET FOR EARLY STOPPING MUST BE BETWEEN 0 AND 1 ONLY USED IF NITERNOCHANGE IS SET TO AN INTEGER
NEW IN VERSION 020
NITERNOCHANGE INT DEFAULT NONE NITERNOCHANGE IS USED TO DECIDE IF EARLY STOP PING WILL BE USED TO TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT IMPROVING BY DE FAULT IT IS SET TO NONE TO DISABLE EARLY STOPPING IF SET TO A NUMBER IT WILL SET ASIDE VALIDATIONFRACTION SIZE OF THE TRAINING DATA AS VALIDATION AND TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT IMPROVING IN ALL OF THE PREVIOUS NITERNOCHANGE NUM BERS OF ITERATIONS THE SPLIT IS STRATIFIED
NEW IN VERSION 020
TOLFLOAT OPTIONAL DEFAULT 1E4 TOLERANCE FOR THE EARLY STOPPING WHEN THE LOSS IS NOT IMPROV ING BY AT LEAST TOL FOR NITERNOCHANGE ITERATIONS IF SET TO A NUMBER THE TRAINING STOPS
NEW IN VERSION 020
ATTRIBUTES
NESTIMATORS INT THE NUMBER OF ESTIMATORS AS SELECTED BY EARLY STOPPING IF NITERNOCHANGE IS SPECIFIED OTHERWISE IT IS SET TO NESTIMATORS
NEW IN VERSION 020
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES RETURN THE FEATURE IMPORTANCES THE HIGHER THE MORE IMPORTANT THE FEATURE
OOBIMPROVEMENT ARRAY SHAPE NESTIMATORS THE IMPROVEMENT IN LOSS DEVIANCE ON THE OUTOFBAG SAMPLES RELATIVE TO THE PREVIOUS ITERATION OOBIMPROVEMENT0 IS THE IMPROVEMENT IN LOSS OF THE FIRST STAGE OVER THE INIT ESTIMATOR
TRAINSCORE ARRAY SHAPE NESTIMATORS THE ITH SCORE TRAINSCOREI IS THE DE VIANCE LOSS OF THE MODEL AT ITERATION ION THE INBAG SAMPLE IF SUBSAMPLE 1 THIS IS THE DEVIANCE ON THE TRAINING DATA
LOSS LOSSFUNCTION THE CONCRETE LOSSFUNCTION OBJECT
INIT ESTIMATOR THE ESTIMATOR THAT PROVIDES THE INITIAL PREDICTIONS SET VIA THE INIT ARGUMENT ORLOSSINITESTIMATOR
ESTIMATORS NDARRAY OF DECISIONTREEREGRESSORSHAPE NESTIMATORS LOSSK THE COLLEC TION OF FITTED SUBESTIMATORS LOSSK IS 1 FOR BINARY CLASSIFICATION OTHERWISE NCLASSES
SEE ALSO
SKLEARNENSEMBLEHISTGRADIENTBOOSTINGCLASSIFIER
SKLEARNTREEDECISIONTREECLASSIFIER RANDOMFORESTCLASSIFIER
ADABOOSTCLASSIFIER

NOTES
THE FEATURES ARE ALWAYS RANDOMLY PERMUTED AT EACH SPLIT THEREFORE THE BEST FOUND SPLIT MAY VARY EVEN WITH THE SAME TRAINING DATA AND MAXFEATURESNFEATURES IF THE IMPROVEMENT OF THE CRITERION IS IDENTICAL FOR SEVERAL SPLITS ENUMERATED DURING THE SEARCH OF THE BEST SPLIT TO OBTAIN A DETERMINISTIC BEHAVIOUR DURING FITTING RANDOMSTATE HAS TO BE FIXED
REFERENCES
J FRIEDMAN GREEDY FUNCTION APPROXIMATION A GRADIENT BOOSTING MACHINE THE ANNALS OF STATISTICS V OL 29 NO 5 2001
10 FRIEDMAN STOCHASTIC GRADIENT BOOSTING 1999
T HASTIE R TIBSHIRANI AND J FRIEDMAN ELEMENTS OF STATISTICAL LEARNING ED 2 SPRINGER 2009
METHODS
APPLY SELF X APPLY TREES IN THE ENSEMBLE TO X RETURN LEAF INDICES
DECISIONFUNCTION SELF X COMPUTE THE DECISION FUNCTION OF X
FITSELF X Y SAMPLEWEIGHT MONITOR FIT THE GRADIENT BOOSTING MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASS FOR X
PREDICTLOGPROBA SELF X PREDICT CLASS LOGPROBABILITIES FOR X
PREDICTPROBA SELF X PREDICT CLASS PROBABILITIES FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
STAGEDDECISIONFUNCTION SELF X COMPUTE DECISION FUNCTION OF XFOR EACH ITERATION
STAGEDPREDICT SELF X PREDICT CLASS AT EACH STAGE FOR X
STAGEDPREDICTPROBA SELF X PREDICT CLASS PROBABILITIES AT EACH STAGE FOR X
INIT SELF LOSS’DEVIANCE’ LEARNINGRATE01 NESTIMATORS100 SUBSAM PLE10 CRITERION’FRIEDMANMSE’ MINSAMPLESSPLIT2 MINSAMPLESLEAF1 MINWEIGHTFRACTIONLEAF00 MAXDEPTH3 MINIMPURITYDECREASE00 MINIMPURITYSPLITNONE INITNONE RANDOMSTATENONE MAXFEATURESNONE VERBOSE0 MAXLEAFNODESNONE WARMSTARTFALSE PRESORT’AUTO’ VALIDA TIONFRACTION01 NITERNOCHANGENONE TOL00001
APPLYSELFX
APPLY TREES IN THE ENSEMBLE TO X RETURN LEAF INDICES
NEW IN VERSION 017
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED TO A SPARSE CSRMATRIX
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES NESTIMATORS NCLASSES FOR EACH DATAPOINT X IN X AND FOR EACH TREE IN THE ENSEMBLE RETURN THE INDEX OF THE LEAF X ENDS UP IN EACH ESTIMATOR

IN THE CASE OF BINARY CLASSIFICATION NCLASSES IS 1
DECISIONFUNCTION SELFX
COMPUTE THE DECISION FUNCTION OF X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
SCORE ARRAY SHAPE NSAMPLES NCLASSES OR NSAMPLES THE DECISION FUNCTION OF THE IN
PUT SAMPLES WHICH CORRESPONDS TO THE RAW VALUES PREDICTED FROM THE TREES OF THE ENSEMBLE
THE ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES REGRESSION AND
BINARY CLASSIFICATION PRODUCE AN ARRAY OF SHAPE NSAMPLES
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES THE HIGHER THE MORE IMPORTANT THE FEATURE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES THE VALUES OF THIS ARRAY SUM TO 1 UNLESS
ALL TREES ARE SINGLE NODE TREES CONSISTING OF ONLY THE ROOT NODE IN WHICH CASE IT WILL BE AN
ARRAY OF ZEROS
FITSELFXYSAMPLEWEIGHTNONE MONITORNONE
FIT THE GRADIENT BOOSTING MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES STRINGS OR INTEGERS IN CLASSIFICATION REAL
NUMBERS IN REGRESSION FOR CLASSIFICATION LABELS MUST CORRESPOND TO CLASSES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEG
ATIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE IN THE CASE OF CLASSIFI
CATION SPLITS ARE ALSO IGNORED IF THEY WOULD RESULT IN ANY SINGLE CLASS CARRYING A NEGATIVE
WEIGHT IN EITHER CHILD NODE
MONITOR CALLABLE OPTIONAL THE MONITOR IS CALLED AFTER EACH ITERATION WITH THE CURRENT ITER
ATION A REFERENCE TO THE ESTIMATOR AND THE LOCAL VARIABLES OF FITSTAGES AS KEYWORD
ARGUMENTSCALLABLEI SELF LOCALS IF THE CALLABLE RETURNS TRUE THE FIT
TING PROCEDURE IS STOPPED THE MONITOR CAN BE USED FOR VARIOUS THINGS SUCH AS COMPUTING
HELDOUT ESTIMATES EARLY STOPPING MODEL INTROSPECT AND SNAPSHOTING
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS

RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT CLASS FOR X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
YARRAY SHAPE NSAMPLES THE PREDICTED VALUES
PREDICTLOGPROBA SELFX
PREDICT CLASS LOGPROBABILITIES FOR X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
PARRAY SHAPE NSAMPLES NCLASSES THE CLASS LOGPROBABILITIES OF THE INPUT SAMPLES THE
ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES
RAISES
ATTRIBUTEERROR IF THELOSS DOES NOT SUPPORT PROBABILITIES
PREDICTPROBA SELFX
PREDICT CLASS PROBABILITIES FOR X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
PARRAY SHAPE NSAMPLES NCLASSES THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE
ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES
RAISES
ATTRIBUTEERROR IF THELOSS DOES NOT SUPPORT PROBABILITIES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS

RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
STAGEDDECISIONFUNCTION SELFX
COMPUTE DECISION FUNCTION OF XFOR EACH ITERATION
THIS METHOD ALLOWS MONITORING IE DETERMINE ERROR ON TESTING SET AFTER EACH STAGE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
SCORE GENERATOR OF ARRAY SHAPE NSAMPLES K THE DECISION FUNCTION OF THE INPUT SAM
PLES WHICH CORRESPONDS TO THE RAW VALUES PREDICTED FROM THE TREES OF THE ENSEMBLE THE
CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES REGRESSION AND BINARY CLASSIFICATION
ARE SPECIAL CASES WITH K 1 OTHERWISE KNCLASSES
STAGEDPREDICT SELFX
PREDICT CLASS AT EACH STAGE FOR X
THIS METHOD ALLOWS MONITORING IE DETERMINE ERROR ON TESTING SET AFTER EACH STAGE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
YGENERATOR OF ARRAY OF SHAPE NSAMPLES THE PREDICTED VALUE OF THE INPUT SAMPLES
STAGEDPREDICTPROBA SELFX
PREDICT CLASS PROBABILITIES AT EACH STAGE FOR X
THIS METHOD ALLOWS MONITORING IE DETERMINE ERROR ON TESTING SET AFTER EACH STAGE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
YGENERATOR OF ARRAY OF SHAPE NSAMPLES THE PREDICTED VALUE OF THE INPUT SAMPLES

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EXAMPLES USING SKLEARNENSEMBLEGRADIENTBOOSTINGCLASSIFIER
•GRADIENT BOOSTING REGULARIZATION
•EARLY STOPPING OF GRADIENT BOOSTING
•FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES
•GRADIENT BOOSTING OUTOFBAG ESTIMATES
•FEATURE DISCRETIZATION
SKLEARNENSEMBLE GRADIENTBOOSTINGREGRESSOR
CLASSSKLEARNENSEMBLE GRADIENTBOOSTINGREGRESSOR LOSS'LS' LEARNINGRATE01
NESTIMATORS100 SUBSAM
PLE10 CRITERION'FRIEDMANMSE'
MINSAMPLESSPLIT2
MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00
MAXDEPTH3
MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE
INITNONE RANDOMSTATENONE
MAXFEATURESNONE ALPHA09
VERBOSE0 MAXLEAFNODESNONE
WARMSTARTFALSE PRE
SORT'AUTO' VALIDATIONFRACTION01
NITERNOCHANGENONE TOL00001
GRADIENT BOOSTING FOR REGRESSION
GB BUILDS AN ADDITIVE MODEL IN A FORWARD STAGEWISE FASHION IT ALLOWS FOR THE OPTIMIZATION OF ARBITRARY DIFFER
ENTIABLE LOSS FUNCTIONS IN EACH STAGE A REGRESSION TREE IS FIT ON THE NEGATIVE GRADIENT OF THE GIVEN LOSS FUNCTION
READ MORE IN THE USER GUIDE
PARAMETERS
LOSS 'LS' 'LAD' 'HUBER' 'QUANTILE' OPTIONAL DEFAULT'LS' LOSS FUNCTION TO BE OPTIMIZED 'LS'
REFERS TO LEAST SQUARES REGRESSION 'LAD' LEAST ABSOLUTE DEVIATION IS A HIGHLY ROBUST LOSS
FUNCTION SOLELY BASED ON ORDER INFORMATION OF THE INPUT VARIABLES 'HUBER' IS A COMBINATION
OF THE TWO 'QUANTILE' ALLOWS QUANTILE REGRESSION USE ALPHA TO SPECIFY THE QUANTILE
LEARNINGRATE FLOAT OPTIONAL DEFAULT01 LEARNING RATE SHRINKS THE CONTRIBUTION OF EACH TREE
BYLEARNINGRATE THERE IS A TRADEOFF BETWEEN LEARNINGRATE AND NESTIMATORS
NESTIMATORS INT DEFAULT100 THE NUMBER OF BOOSTING STAGES TO PERFORM GRADIENT BOOSTING
IS FAIRLY ROBUST TO OVERFITTING SO A LARGE NUMBER USUALLY RESULTS IN BETTER PERFORMANCE
SUBSAMPLE FLOAT OPTIONAL DEFAULT10 THE FRACTION OF SAMPLES TO BE USED FOR FITTING THE IN
DIVIDUAL BASE LEARNERS IF SMALLER THAN 10 THIS RESULTS IN STOCHASTIC GRADIENT BOOSTING
SUBSAMPLE INTERACTS WITH THE PARAMETER NESTIMATORS CHOOSING SUBSAMPLE
10 LEADS TO A REDUCTION OF VARIANCE AND AN INCREASE IN BIAS
CRITERION STRING OPTIONAL DEFAULT"FRIEDMANMSE" THE FUNCTION TO MEASURE THE QUALITY OF
A SPLIT SUPPORTED CRITERIA ARE "FRIEDMANMSE" FOR THE MEAN SQUARED ERROR WITH IMPROVE
MENT SCORE BY FRIEDMAN "MSE" FOR MEAN SQUARED ERROR AND "MAE" FOR THE MEAN ABSOLUTE
ERROR THE DEFAULT VALUE OF "FRIEDMANMSE" IS GENERALLY THE BEST AS IT CAN PROVIDE A BETTER
APPROXIMATION IN SOME CASES

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NEW IN VERSION 018
MINSAMPLESSPLIT INT FLOAT OPTIONAL DEFAULT2 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST
MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY
HAVE THE EFFECT OF SMOOTHING THE MODEL ESPECIALLY IN REGRESSION
• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE
SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE
EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED
MAXDEPTH INTEGER OPTIONAL DEFAULT3 MAXIMUM DEPTH OF THE INDIVIDUAL REGRESSION ESTIMA
TORS THE MAXIMUM DEPTH LIMITS THE NUMBER OF NODES IN THE TREE TUNE THIS PARAMETER FOR
BEST PERFORMANCE THE BEST VALUE DEPENDS ON THE INTERACTION OF THE INPUT VARIABLES
MINIMPURITYDECREASE FLOAT OPTIONAL DEFAULT0 A NODE WILL BE SPLIT IF THIS SPLIT INDUCES
A DECREASE OF THE IMPURITY GREATER THAN OR EQUAL TO THIS VALUE
THE WEIGHTED IMPURITY DECREASE EQUATION IS THE FOLLOWING
NT N IMPURITY NTR NT RIGHTIMPURITY
 NTL NT LEFTIMPURITY
WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE
NTL IS THE NUMBER OF SAMPLES IN THE LEFT CHILD AND NTR IS THE NUMBER OF SAMPLES IN
THE RIGHT CHILD
NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED
NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE
WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
DEPRECATED SINCE VERSION 019 MINIMPURITYSPLIT HAS BEEN DEPRECATED IN FAVOR OF
MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT
WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE
MINIMPURITYDECREASE INSTEAD
INIT ESTIMATOR OR ‘ZERO’ OPTIONAL DEFAULTNONE AN ESTIMATOR OBJECT THAT IS USED TO COMPUTE
THE INITIAL PREDICTIONS INIT HAS TO PROVIDE FIT ANDPREDICT IF ‘ZERO’ THE INITIAL RAW
PREDICTIONS ARE SET TO ZERO BY DEFAULT A DUMMYESTIMATOR IS USED PREDICTING EITHER THE
AVERAGE TARGET VALUE FOR LOSS’LS’ OR A QUANTILE FOR THE OTHER LOSSES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE

RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
MAXFEATURES INT FLOAT STRING OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF FEATURES TO CONSIDER WHEN LOOKING FOR THE BEST SPLIT
• IF INT THEN CONSIDER MAXFEATURES FEATURES AT EACH SPLIT
• IF FLOAT THEN MAXFEATURES IS A FRACTION AND INTMAXFEATURES NFEATURES FEATURES ARE CONSIDERED AT EACH SPLIT
• IF “AUTO” THEN MAXFEATURESNFEATURES
• IF “SQRT” THEN MAXFEATURESSQRTNFEATURES
• IF “LOG2” THEN MAXFEATURESLOG2NFEATURES
• IF NONE THEN MAXFEATURESNFEATURES
CHOOSINGMAXFEATURES NFEATURES LEADS TO A REDUCTION OF VARIANCE AND AN IN CREASE IN BIAS
NOTE THE SEARCH FOR A SPLIT DOES NOT STOP UNTIL AT LEAST ONE VALID PARTITION OF THE NODE SAMPLES IS FOUND EVEN IF IT REQUIRES TO EFFECTIVELY INSPECT MORE THAN MAXFEATURES FEATURES
ALPHA FLOAT DEFAULT09 THE ALPHAQUANTILE OF THE HUBER LOSS FUNCTION AND THE QUANTILE LOSS FUNCTION ONLY IF LOSSHUBER ORLOSSQUANTILE
VERBOSE INT DEFAULT 0 ENABLE VERBOSE OUTPUT IF 1 THEN IT PRINTS PROGRESS AND PERFORMANCE ONCE IN A WHILE THE MORE TREES THE LOWER THE FREQUENCY IF GREATER THAN 1 THEN IT PRINTS PROGRESS AND PERFORMANCE FOR EVERY TREE
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULTNONE GROW TREES WITH MAXLEAFNODES IN BESTFIRST FASHION BEST NODES ARE DEFINED AS RELATIVE REDUCTION IN IMPURITY IF NONE THEN UNLIMITED NUMBER OF LEAF NODES
WARMSTART BOOL DEFAULT FALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AND ADD MORE ESTIMATORS TO THE ENSEMBLE OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
PRESORT BOOL OR ‘AUTO’ OPTIONAL DEFAULT’AUTO’ WHETHER TO PRESORT THE DATA TO SPEED UP THE FINDING OF BEST SPLITS IN FITTING AUTO MODE BY DEFAULT WILL USE PRESORTING ON DENSE DATA AND DEFAULT TO NORMAL SORTING ON SPARSE DATA SETTING PRESORT TO TRUE ON SPARSE DATA WILL RAISE AN ERROR
NEW IN VERSION 017 OPTIONAL PARAMETER PRESORT
VALIDATIONFRACTION FLOAT OPTIONAL DEFAULT 01 THE PROPORTION OF TRAINING DATA TO SET ASIDE AS VALIDATION SET FOR EARLY STOPPING MUST BE BETWEEN 0 AND 1 ONLY USED IF NITERNOCHANGE IS SET TO AN INTEGER
NEW IN VERSION 020
NITERNOCHANGE INT DEFAULT NONE NITERNOCHANGE IS USED TO DECIDE IF EARLY STOP PING WILL BE USED TO TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT IMPROVING BY DE FAULT IT IS SET TO NONE TO DISABLE EARLY STOPPING IF SET TO A NUMBER IT WILL SET ASIDE VALIDATIONFRACTION SIZE OF THE TRAINING DATA AS VALIDATION AND TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT IMPROVING IN ALL OF THE PREVIOUS NITERNOCHANGE NUM BERS OF ITERATIONS
NEW IN VERSION 020

TOLFLOAT OPTIONAL DEFAULT 1E4 TOLERANCE FOR THE EARLY STOPPING WHEN THE LOSS IS NOT IMPROV
ING BY AT LEAST TOL FOR NITERNOCHANGE ITERATIONS IF SET TO A NUMBER THE TRAINING
STOPS
NEW IN VERSION 020
ATTRIBUTES
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES RETURN THE FEATURE IMPORTANCES THE
HIGHER THE MORE IMPORTANT THE FEATURE
OOBIMPROVEMENT ARRAY SHAPE NESTIMATORS THE IMPROVEMENT IN LOSS DEVIANCE ON
THE OUTOFBAG SAMPLES RELATIVE TO THE PREVIOUS ITERATION OOBIMPROVEMENT0 IS THE
IMPROVEMENT IN LOSS OF THE FIRST STAGE OVER THE INIT ESTIMATOR
TRAINSCORE ARRAY SHAPE NESTIMATORS THE ITH SCORE TRAINSCOREI IS THE DE
VIANCE LOSS OF THE MODEL AT ITERATION ION THE INBAG SAMPLE IF SUBSAMPLE 1
THIS IS THE DEVIANCE ON THE TRAINING DATA
LOSS LOSSFUNCTION THE CONCRETE LOSSFUNCTION OBJECT
INIT ESTIMATOR THE ESTIMATOR THAT PROVIDES THE INITIAL PREDICTIONS SET VIA THE INIT ARGUMENT
ORLOSSINITESTIMATOR
ESTIMATORS ARRAY OF DECISIONTREEREGRESSOR SHAPE NESTIMATORS 1 THE COLLECTION OF FITTED
SUBESTIMATORS
SEE ALSO
SKLEARNENSEMBLEHISTGRADIENTBOOSTINGREGRESSOR
SKLEARNTREEDECISIONTREEREGRESSOR RANDOMFORESTREGRESSOR
NOTES
THE FEATURES ARE ALWAYS RANDOMLY PERMUTED AT EACH SPLIT THEREFORE THE BEST FOUND SPLIT MAY VARY EVEN WITH
THE SAME TRAINING DATA AND MAXFEATURESNFEATURES IF THE IMPROVEMENT OF THE CRITERION IS IDENTICAL FOR
SEVERAL SPLITS ENUMERATED DURING THE SEARCH OF THE BEST SPLIT TO OBTAIN A DETERMINISTIC BEHAVIOUR DURING FITTING
RANDOMSTATE HAS TO BE FIXED
REFERENCES
J FRIEDMAN GREEDY FUNCTION APPROXIMATION A GRADIENT BOOSTING MACHINE THE ANNALS OF STATISTICS V OL 29
NO 5 2001
10 FRIEDMAN STOCHASTIC GRADIENT BOOSTING 1999
T HASTIE R TIBSHIRANI AND J FRIEDMAN ELEMENTS OF STATISTICAL LEARNING ED 2 SPRINGER 2009
METHODS
APPLY SELF X APPLY TREES IN THE ENSEMBLE TO X RETURN LEAF INDICES
FITSELF X Y SAMPLEWEIGHT MONITOR FIT THE GRADIENT BOOSTING MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT REGRESSION TARGET FOR X
CONTINUED ON NEXT PAGE

TABLE 320 – CONTINUED FROM PREVIOUS PAGE
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
STAGEDPREDICT SELF X PREDICT REGRESSION TARGET AT EACH STAGE FOR X
INIT SELF LOSS'LS' LEARNINGRATE01 NESTIMATORS100 SUBSAMPLE10
CRITERION'FRIEDMANMSE' MINSAMPLESSPLIT2 MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00 MAXDEPTH3 MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE INITNONE RANDOMSTATENONE MAXFEATURESNONE AL
PHA09 VERBOSE0 MAXLEAFNODESNONE WARMSTARTFALSE PRESORT'AUTO' VALIDA
TIONFRACTION01 NITERNOCHANGENONE TOL00001
APPLYSELFX
APPLY TREES IN THE ENSEMBLE TO X RETURN LEAF INDICES
NEW IN VERSION 017
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED TO A SPARSE CSRMATRIX
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES NESTIMATORS FOR EACH DATAPOINT X IN X AND FOR
EACH TREE IN THE ENSEMBLE RETURN THE INDEX OF THE LEAF X ENDS UP IN EACH ESTIMATOR
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES THE HIGHER THE MORE IMPORTANT THE FEATURE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES THE VALUES OF THIS ARRAY SUM TO 1 UNLESS
ALL TREES ARE SINGLE NODE TREES CONSISTING OF ONLY THE ROOT NODE IN WHICH CASE IT WILL BE AN
ARRAY OF ZEROS
FITSELFXYSAMPLEWEIGHTNONE MONITORNONE
FIT THE GRADIENT BOOSTING MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES STRINGS OR INTEGERS IN CLASSIFICATION REAL
NUMBERS IN REGRESSION FOR CLASSIFICATION LABELS MUST CORRESPOND TO CLASSES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEG
ATIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE IN THE CASE OF CLASSIFI
CATION SPLITS ARE ALSO IGNORED IF THEY WOULD RESULT IN ANY SINGLE CLASS CARRYING A NEGATIVE
WEIGHT IN EITHER CHILD NODE
MONITOR CALLABLE OPTIONAL THE MONITOR IS CALLED AFTER EACH ITERATION WITH THE CURRENT ITER
ATION A REFERENCE TO THE ESTIMATOR AND THE LOCAL VARIABLES OF FITSTAGES AS KEYWORD

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ARGUMENTSCALLABLEI SELF LOCALS IF THE CALLABLE RETURNS TRUE THE FIT
TING PROCEDURE IS STOPPED THE MONITOR CAN BE USED FOR VARIOUS THINGS SUCH AS COMPUTING
HELDOUT ESTIMATES EARLY STOPPING MODEL INTROSPECT AND SNAPSHOTING
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT REGRESSION TARGET FOR X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
YARRAY SHAPE NSAMPLES THE PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE

SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
STAGEDPREDICT SELFX
PREDICT REGRESSION TARGET AT EACH STAGE FOR X
THIS METHOD ALLOWS MONITORING IE DETERMINE ERROR ON TESTING SET AFTER EACH STAGE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
YGENERATOR OF ARRAY OF SHAPE NSAMPLES THE PREDICTED VALUE OF THE INPUT SAMPLES
EXAMPLES USING SKLEARNENSEMBLEGRADIENTBOOSTINGREGRESSOR
•MODEL COMPLEXITY INFLUENCE
•PLOT INDIVIDUAL AND VOTING REGRESSION PREDICTIONS
•PREDICTION INTERVALS FOR GRADIENT BOOSTING REGRESSION
•GRADIENT BOOSTING REGRESSION
•PARTIAL DEPENDENCE PLOTS
333 MODEL EVALUATION QUANTIFYING THE QUALITY OF PREDICTIONS
THERE ARE 3 DIFFERENT APIS FOR EVALUATING THE QUALITY OF A MODEL'S PREDICTIONS
•ESTIMATOR SCORE METHOD ESTIMATORS HAVE A SCORE METHOD PROVIDING A DEFAULT EVALUATION CRITERION FOR THE
PROBLEM THEY ARE DESIGNED TO SOLVE THIS IS NOT DISCUSSED ON THIS PAGE BUT IN EACH ESTIMATOR'S DOCUMENTATION
•SCORING PARAMETER MODELEVALUATION TOOLS USING CROSSVALIDATION SUCH ASMODELSELECTION
CROSSVALSCORE ANDMODELSELECTIONGRIDSEARCHCV RELY ON AN INTERNAL SCORING STRATEGY THIS
IS DISCUSSED IN THE SECTION THE SCORING PARAMETER DEFINING MODEL EVALUATION RULES
•METRIC FUNCTIONS THEMETRICS MODULE IMPLEMENTS FUNCTIONS ASSESSING PREDICTION ERROR FOR SPECIFIC PURPOSES
THESE METRICS ARE DETAILED IN SECTIONS ON CLASSIFICATION METRICS MULTILABEL RANKING METRICS REGRESSION METRICS
ANDCLUSTERING METRICS
FINALLY DUMMY ESTIMATORS ARE USEFUL TO GET A BASELINE VALUE OF THOSE METRICS FOR RANDOM PREDICTIONS
SEE ALSO
FOR "PAIRWISE" METRICS BETWEEN SAMPLES AND NOT ESTIMATORS OR PREDICTIONS SEE THE PAIRWISE METRICS AFFINITIES AND
KERNELS SECTION

THESCORING PARAMETER DEFINING MODEL EVALUATION RULES
MODEL SELECTION AND EVALUATION USING TOOLS SUCH AS MODELSELECTIONGRIDSEARCHCV AND MODELSELECTIONCROSSVALSCORE TAKE ASCORING PARAMETER THAT CONTROLS WHAT METRIC THEY AP PLY TO THE ESTIMATORS EVALUATED
COMMON CASES PREDEFINED VALUES
FOR THE MOST COMMON USE CASES YOU CAN DESIGNATE A SCORER OBJECT WITH THE SCORING PARAMETER THE TABLE BELOW SHOWS ALL POSSIBLE VALUES ALL SCORER OBJECTS FOLLOW THE CONVENTION THAT HIGHER RETURN VALUES ARE BETTER THAN LOWER RETURN VALUES THUS METRICS WHICH MEASURE THE DISTANCE BETWEEN THE MODEL AND THE DATA LIKE METRICS MEANSQUAREDERROR ARE AVAILABLE AS NEGMEANSQUAREDERROR WHICH RETURN THE NEGATED VALUE OF THE METRIC
SCORING FUNCTION COMMENT
CLASSIFICATION
‘ACCURACY’ METRICSACCURACYSCORE
‘BALANCEDACCURACY’ METRICSBALANCEDACCURACYSCORE
‘AVERAGEPRECISION’ METRICSAVERAGEPRECISIONSCORE
‘BRIERSCORELOSS’ METRICSBRIERSCORELOSS
‘F1’ METRICSF1SCORE FOR BINARY TARGETS
‘F1MICRO’ METRICSF1SCORE MICROAVERAGED
‘F1MACRO’ METRICSF1SCORE MACROAVERAGED
‘F1WEIGHTED’ METRICSF1SCORE WEIGHTED AVERAGE
‘F1SAMPLES’ METRICSF1SCORE BY MULTILABEL SAMPLE
‘NEGLOGLOSS’ METRICSLOGLOSS REQUIRESPREDICTPROBA SUPPORT
‘PRECISION’ ETC METRICSPRECISIONSCORE SUFFIXES APPLY AS WITH ‘F1’
‘RECALL’ ETC METRICSRECALLSCORE SUFFIXES APPLY AS WITH ‘F1’
‘JACCARD’ ETC METRICSJACCARDSCORE SUFFIXES APPLY AS WITH ‘F1’
‘ROCAUC’ METRICSROCAUCSCORE
CLUSTERING
‘ADJUSTEDMUTUALINFOSCORE’ METRICSADJUSTEDMUTUALINFOSCORE
‘ADJUSTEDRANDSCORE’ METRICSADJUSTEDRANDSCORE
‘COMPLETENESSSCORE’ METRICSCOMPLETENESSSCORE
‘FOWLKESMALLOWSSCORE’ METRICSFOWLKESMALLOWSSCORE
‘HOMOGENEITYSCORE’ METRICSHOMOGENEITYSCORE
‘MUTUALINFOSCORE’ METRICSMUTUALINFOSCORE
‘NORMALIZEDMUTUALINFOSCORE’ METRICSNORMALIZEDMUTUALINFOSCORE
‘VMEASURESCORE’ METRICSVMEASURESCORE
REGRESSION
‘EXPLAINEDVARIANCE’ METRICSEXPLAINEDVARIANCESCORE
‘MAXERROR’ METRICSMAXERROR
‘NEGMEANABSOLUTEERROR’ METRICSMEANABSOLUTEERROR
‘NEGMEANSQUAREDERROR’ METRICSMEANSQUAREDERROR
‘NEGMEANSQUAREDLOGERROR’ METRICSMEANSQUAREDLOGERROR
‘NEGMEDIANABSOLUTEERROR’ METRICSMEDIANABSOLUTEERROR
‘R2’ METRICSR2SCORE
USAGE EXAMPLES
```
 FROM SKLEARN IMPORT SVM DATASETS
 FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
IRIS  DATASETSLOADIRIS
```

```
X Y  IRISDATA IRISTARGET
CLF  SVMSVCGAMMASCALE RANDOMSTATE0
CROSSVALSCORECLF X Y SCORINGRECALLMACRO
 CV5
ARRAY096 096 096 093 1
MODEL  SVMSVC
CROSSVALSCOREMODEL X Y CV5 SCORINGWRONGCHOICE
TRACEBACK MOST RECENT CALL LAST
VALUEERROR WRONGCHOICE IS NOT A VALID SCORING VALUE USE SORTEDSKLEARNMETRICS
‘→SCORERSKEYS TO GET VALID OPTIONS
```
NOTE THE VALUES LISTED BY THE VALUEERROR EXCEPTION CORRESPOND TO THE FUNCTIONS MEASURING PREDICTION ACCURACY DESCRIBED IN THE FOLLOWING SECTIONS THE SCORER OBJECTS FOR THOSE FUNCTIONS ARE STORED IN THE DICTIONARY SKLEARN METRICSSCORERS

DEFINING YOUR SCORING STRATEGY FROM METRIC FUNCTIONS

THE MODULE SKLEARNMETRICS ALSO EXPOSES A SET OF SIMPLE FUNCTIONS MEASURING A PREDICTION ERROR GIVEN GROUND TRUTH AND PREDICTION

- FUNCTIONS ENDING WITH SCORE RETURN A VALUE TO MAXIMIZE THE HIGHER THE BETTER
- FUNCTIONS ENDING WITH ERROR ORLOSS RETURN A VALUE TO MINIMIZE THE LOWER THE BETTER WHEN CONVERTING INTO A SCORER OBJECT USING MAKESCORER SET THEGREATERISBETTER PARAMETER TO FALSE TRUE BY DEFAULT SEE THE PARAMETER DESCRIPTION BELOW

METRICS AVAILABLE FOR VARIOUS MACHINE LEARNING TASKS ARE DETAILED IN SECTIONS BELOW

MANY METRICS ARE NOT GIVEN NAMES TO BE USED AS SCORING VALUES SOMETIMES BECAUSE THEY REQUIRE ADDITIONAL PARAM ETERS SUCH AS FBETASCORE IN SUCH CASES YOU NEED TO GENERATE AN APPROPRIATE SCORING OBJECT THE SIMPLEST WAY TO GENERATE A CALLABLE OBJECT FOR SCORING IS BY USING MAKESCORER THAT FUNCTION CONVERTS METRICS INTO CALLABLES THAT CAN BE USED FOR MODEL EVALUATION

ONE TYPICAL USE CASE IS TO WRAP AN EXISTING METRIC FUNCTION FROM THE LIBRARY WITH NONDEFAULT VALUES FOR ITS PARAMETERS SUCH AS THE BETA PARAMETER FOR THE FBETASCORE FUNCTION

```
 FROM SKLEARNMETRICS IMPORT FBETASCORE MAKESCORER
FTWOSCORER  MAKESCORERFBETASCORE BETA2
 FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
 FROM SKLEARNSVM IMPORT LINEARSVC
GRID  GRIDSEARCHCVLINEARSVC PARAMGRIDC 1 10
 SCORINGFTWOSCORER CV5
```

THE SECOND USE CASE IS TO BUILD A COMPLETELY CUSTOM SCORER OBJECT FROM A SIMPLE PYTHON FUNCTION USING MAKESCORER WHICH CAN TAKE SEVERAL PARAMETERS

- THE PYTHON FUNCTION YOU WANT TO USE MYCUSTOMLOSSFUNC IN THE EXAMPLE BELOW
- WHETHER THE PYTHON FUNCTION RETURNS A SCORE GREATERISBETTERTRUE THE DEFAULT OR A LOSS GREATERISBETTERFALSE IF A LOSS THE OUTPUT OF THE PYTHON FUNCTION IS NEGATED BY THE SCORER OB JECT CONFORMING TO THE CROSS VALIDATION CONVENTION THAT SCORERS RETURN HIGHER VALUES FOR BETTER MODELS
- FOR CLASSIFICATION METRICS ONLY WHETHER THE PYTHON FUNCTION YOU PROVIDED REQUIRES CONTINUOUS DECISION CERTAIN TIES NEEDSTHRESHOLDTRUE THE DEFAULT VALUE IS FALSE
- ANY ADDITIONAL PARAMETERS SUCH AS BETA ORLABELS INF1SCORE

HERE IS AN EXAMPLE OF BUILDING CUSTOM SCORERS AND OF USING THE GREATERISBETTER PARAMETER

```
 IMPORT NUMPY AS NP
 DEF MYCUSTOMLOSSFUNCYTRUE YPRED
 DIFF  NPABSYTRUE  YPREDMAX
 RETURN NPLOG1PDIFF

 SCORE WILL NEGATE THE RETURN VALUE OF MYCUSTOMLOSSFUNC
 WHICH WILL BE NPLOG2 0693 GIVEN THE VALUES FOR X
 AND Y DEFINED BELOW
SCORE  MAKESCORERMYCUSTOMLOSSFUNC GREATERISBETTER FALSE
X  1 1
Y  0 1
 FROM SKLEARNDUMMY IMPORT DUMMYCLASSIFIER
CLF  DUMMYCLASSIFIERSTRATEGYMOSTFREQUENT RANDOMSTATE0
CLF  CLFFITX Y
MYCUSTOMLOSSFUNCCLFPREDICTX Y
069
SCORECLF X Y
069
```

IMPLEMENTING YOUR OWN SCORING OBJECT

YOU CAN GENERATE EVEN MORE FLEXIBLE MODEL SCORERS BY CONSTRUCTING YOUR OWN SCORING OBJECT FROM SCRATCH WITHOUT USING THEMAKESCORER FACTORY FOR A CALLABLE TO BE A SCORER IT NEEDS TO MEET THE PROTOCOL SPECIFIED BY THE FOLLOWING TWO RULES

• IT CAN BE CALLED WITH PARAMETERS ESTIMATOR X Y WHEREESTIMATOR IS THE MODEL THAT SHOULD BE EVALUATEDXIS VALIDATION DATA AND YIS THE GROUND TRUTH TARGET FOR XIN THE SUPERVISED CASE OR NONE IN THE UNSUPERVISED CASE

• IT RETURNS A FLOATING POINT NUMBER THAT QUANTIFIES THE ESTIMATOR PREDICTION QUALITY ON X WITH REFERENCE TO Y AGAIN BY CONVENTION HIGHER NUMBERS ARE BETTER SO IF YOUR SCORER RETURNS LOSS THAT VALUE SHOULD BE NEGATED

NOTE USING CUSTOM SCORERS IN FUNCTIONS WHERE NJOBS 1

WHILE DEFINING THE CUSTOM SCORING FUNCTION ALONGSIDE THE CALLING FUNCTION SHOULD WORK OUT OF THE BOX WITH THE DEFAULT JOBLIB BACKEND LOKY IMPORTING IT FROM ANOTHER MODULE WILL BE A MORE ROBUST APPROACH AND WORK INDEPENDENTLY OF THE JOBLIB BACKEND

FOR EXAMPLE TO USE NJOBS GREATER THAN 1 IN THE EXAMPLE BELOW CUSTOMSCORINGFUNCTION FUNCTION IS SAVED IN A USERCREATED MODULE CUSTOMSCORERMODULEPY AND IMPORTED

```
 FROM CUSTOMSCORERMODULE IMPORT CUSTOMSCORINGFUNCTION
CROSSVALSCOREMODEL
XTRAIN
YTRAIN
SCORINGMAKESCORERCUSTOMSCORINGFUNCTION GREATERISBETTER FALSE
CV5
NJOBS1
```

USING MULTIPLE METRIC EVALUATION
SCIKITLEARN ALSO PERMITS EVALUATION OF MULTIPLE METRICS IN GRIDSEARCHCV RANDOMIZEDSEARCHCV AND CROSSVALIDATE
THERE ARE TWO WAYS TO SPECIFY MULTIPLE SCORING METRICS FOR THE SCORING PARAMETER
•AS AN ITERABLE OF STRING METRICS
SCORING ACCURACY PRECISION
•AS ADICT MAPPING THE SCORER NAME TO THE SCORING FUNCTION
 FROM SKLEARNMETRICS IMPORT ACCURACYSCORE
 FROM SKLEARNMETRICS IMPORT MAKESCORER
SCORING ACCURACY MAKESCORERACCURACYSCORE
 PREC PRECISION
NOTE THAT THE DICT VALUES CAN EITHER BE SCORER FUNCTIONS OR ONE OF THE PREDEFINED METRIC STRINGS
CURRENTLY ONLY THOSE SCORER FUNCTIONS THAT RETURN A SINGLE SCORE CAN BE PASSED INSIDE THE DICT SCORER FUNCTIONS THAT RETURN MULTIPLE VALUES ARE NOT PERMITTED AND WILL REQUIRE A WRAPPER TO RETURN A SINGLE METRIC
 FROM SKLEARNMODELSELECTION IMPORT CROSSVALIDATE
 FROM SKLEARNMETRICS IMPORT CONFUSIONMATRIX
 A SAMPLE TOY BINARY CLASSIFICATION DATASET
X Y DATASETSMAKECLASSIFICATIONNCLASSES2 RANDOMSTATE0
SVM LINEARSVCRANDOMSTATE0
 DEF TNYTRUE YPRED RETURNCONFUSIONMATRIXYTRUE YPRED0 0
 DEF FPYTRUE YPRED RETURNCONFUSIONMATRIXYTRUE YPRED0 1
 DEF FNYTRUE YPRED RETURNCONFUSIONMATRIXYTRUE YPRED1 0
 DEF TPYTRUE YPRED RETURNCONFUSIONMATRIXYTRUE YPRED1 1
SCORING TP MAKESCORERTP TN MAKESCORERTN
 FP MAKESCORERFP FN MAKESCORERFN
CVRESULTS CROSSVALIDATESVMFITX Y X Y
 SCORINGSCORING CV5
 GETTING THE TEST SET TRUE POSITIVE SCORES
PRINTCVRESULTSTESTTP
10 9 8 7 8
 GETTING THE TEST SET FALSE NEGATIVE SCORES
PRINTCVRESULTSTESTFN
0 1 2 3 2
CLASSIFICATION METRICS
THESKLEARNMETRICS MODULE IMPLEMENTS SEVERAL LOSS SCORE AND UTILITY FUNCTIONS TO MEASURE CLASSIFICATION PERFORMANCE SOME METRICS MIGHT REQUIRE PROBABILITY ESTIMATES OF THE POSITIVE CLASS CONFIDENCE VALUES OR BINARY DECISIONS VALUES MOST IMPLEMENTATIONS ALLOW EACH SAMPLE TO PROVIDE A WEIGHTED CONTRIBUTION TO THE OVERALL SCORE THROUGH THESAMPLEWEIGHT PARAMETER
SOME OF THESE ARE RESTRICTED TO THE BINARY CLASSIFICATION CASE
PRECISIONRECALLCURVE YTRUE PROBASPRED COMPUTE PRECISIONRECALL PAIRS FOR DIFFERENT PROBABILITY THRESHOLDS
ROCCURVE YTRUE YSCORE POSLABEL COMPUTE RECEIVER OPERATING CHARACTERISTIC ROC
BALANCEDACCURACYSCORE YTRUE YPRED COMPUTE THE BALANCED ACCURACY

OTHERS ALSO WORK IN THE MULTICLASS CASE
COHENKAPPASCORE Y1 Y2 LABELS WEIGHTS COHEN'S KAPPA A STATISTIC THAT MEASURES INTERANNOTATOR AGREEMENT
CONFUSIONMATRIX YTRUE YPRED LABELS COMPUTE CONFUSION MATRIX TO EVALUATE THE ACCURACY OF A CLASSIFICATION
HINGELOSS YTRUE PREDDECISION LABELS AVERAGE HINGE LOSS NONREGULARIZED
MATTHEWSCORRCOEF YTRUE YPRED COMPUTE THE MATTHEWS CORRELATION COEFFICIENT MCC
SOME ALSO WORK IN THE MULTILABEL CASE
ACCURACYSCORE YTRUE YPRED NORMALIZE ACCURACY CLASSIFICATION SCORE
CLASSIFICATIONREPORT YTRUE YPRED BUILD A TEXT REPORT SHOWING THE MAIN CLASSIFICATION METRICS
F1SCORE YTRUE YPRED LABELS COMPUTE THE F1 SCORE ALSO KNOWN AS BALANCED FSCORE OR FMEASURE
FBETASCORE YTRUE YPRED BETA LABELS COMPUTE THE FBETA SCORE
HAMMINGLOSS YTRUE YPRED LABELS COMPUTE THE AVERAGE HAMMING LOSS
JACCARDSCORE YTRUE YPRED LABELS JACCARD SIMILARITY COEFFICIENT SCORE
LOGLOSS YTRUE YPRED EPS NORMALIZE LOG LOSS AKA LOGISTIC LOSS OR CROSSENTROPY LOSS
MULTILABELCONFUSIONMATRIX YTRUE YPRED COMPUTE A CONFUSION MATRIX FOR EACH CLASS OR SAMPLE
PRECISIONRECALLFSCORESUPPORT YTRUE YPREDCOMPUTE PRECISION RECALL FMEASURE AND SUPPORT FOR EACH CLASS
PRECISIONSCORE YTRUE YPRED LABELS COMPUTE THE PRECISION
RECALLSCORE YTRUE YPRED LABELS COMPUTE THE RECALL
ZEROONELOSS YTRUE YPRED NORMALIZE ZEROONE CLASSIFICATION LOSS
AND SOME WORK WITH BINARY AND MULTILABEL BUT NOT MULTICLASS PROBLEMS
AVERAGEPRECISIONSCORE YTRUE YSCORE COMPUTE AVERAGE PRECISION AP FROM PREDICTION SCORES
ROCAUCSCORE YTRUE YSCORE AVERAGE COMPUTE AREA UNDER THE RECEIVER OPERATING CHARACTERIS TIC CURVE ROC AUC FROM PREDICTION SCORES
IN THE FOLLOWING SUBSECTIONS WE WILL DESCRIBE EACH OF THOSE FUNCTIONS PRECEDED BY SOME NOTES ON COMMON API AND METRIC DEFINITION
FROM BINARY TO MULTICLASS AND MULTILABEL
SOME METRICS ARE ESSENTIALLY DEFINED FOR BINARY CLASSIFICATION TASKS EG F1SCORE ROCAUCSCORE IN THESE CASES BY DEFAULT ONLY THE POSITIVE LABEL IS EVALUATED ASSUMING BY DEFAULT THAT THE POSITIVE CLASS IS LABELLED 1THOUGH THIS MAY BE CONFIGURABLE THROUGH THE POSLABEL PARAMETER
IN EXTENDING A BINARY METRIC TO MULTICLASS OR MULTILABEL PROBLEMS THE DATA IS TREATED AS A COLLECTION OF BINARY PROBLEMS ONE FOR EACH CLASS THERE ARE THEN A NUMBER OF WAYS TO AVERAGE BINARY METRIC CALCULATIONS ACROSS THE SET OF CLASSES EACH OF WHICH MAY BE USEFUL IN SOME SCENARIO WHERE AVAILABLE YOU SHOULD SELECT AMONG THESE USING THE AVERAGE PARAMETER
•MACRO SIMPLY CALCULATES THE MEAN OF THE BINARY METRICS GIVING EQUAL WEIGHT TO EACH CLASS IN PROBLEMS WHERE INFREQUENT CLASSES ARE NONETHELESS IMPORTANT MACROAVERAGING MAY BE A MEANS OF HIGHLIGHTING THEIR PERFORMANCE ON THE OTHER HAND THE ASSUMPTION THAT ALL CLASSES ARE EQUALLY IMPORTANT IS OFTEN UNTRUE SUCH THAT MACROAVERAGING WILL OVEREMPHASIZE THE TYPICALLY LOW PERFORMANCE ON AN INFREQUENT CLASS

•WEIGHTED ACCOUNTS FOR CLASS IMBALANCE BY COMPUTING THE AVERAGE OF BINARY METRICS IN WHICH EACH CLASS'S SCORE IS WEIGHTED BY ITS PRESENCE IN THE TRUE DATA SAMPLE
•MICRO GIVES EACH SAMPLECLASS PAIR AN EQUAL CONTRIBUTION TO THE OVERALL METRIC EXCEPT AS A RESULT OF SAMPLE WEIGHT RATHER THAN SUMMING THE METRIC PER CLASS THIS SUMS THE DIVIDENDS AND DIVISORS THAT MAKE UP THE PERCLASS METRICS TO CALCULATE AN OVERALL QUOTIENT MICROAVERAGING MAY BE PREFERRED IN MULTILABEL SETTINGS INCLUDING MULTICLASS CLASSIFICATION WHERE A MAJORITY CLASS IS TO BE IGNORED
•SAMPLES APPLIES ONLY TO MULTILABEL PROBLEMS IT DOES NOT CALCULATE A PERCLASS MEASURE INSTEAD CALCULATING THE METRIC OVER THE TRUE AND PREDICTED CLASSES FOR EACH SAMPLE IN THE EVALUATION DATA AND RETURNING THEIR SAMPLEWEIGHT WEIGHTED AVERAGE
• SELECTING AVERAGENONE WILL RETURN AN ARRAY WITH THE SCORE FOR EACH CLASS
WHILE MULTICLASS DATA IS PROVIDED TO THE METRIC LIKE BINARY TARGETS AS AN ARRAY OF CLASS LABELS MULTILABEL DATA IS SPECIFIED AS AN INDICATOR MATRIX IN WHICH CELL I J HAS VALUE 1 IF SAMPLE IHAS LABELJAND VALUE 0 OTHERWISE
ACCURACY SCORE
THEACCURACYSCORE FUNCTION COMPUTES THE ACCURACY EITHER THE FRACTION DEFAULT OR THE COUNT NORMALIZEFALSE OF CORRECT PREDICTIONS
IN MULTILABEL CLASSIFICATION THE FUNCTION RETURNS THE SUBSET ACCURACY IF THE ENTIRE SET OF PREDICTED LABELS FOR A SAMPLE STRICTLY MATCH WITH THE TRUE SET OF LABELS THEN THE SUBSET ACCURACY IS 10 OTHERWISE IT IS 00
IF□□IS THE PREDICTED VALUE OF THE □TH SAMPLE AND □□IS THE CORRESPONDING TRUE VALUE THEN THE FRACTION OF CORRECT PREDICTIONS OVER □SAMPLES IS DEFINED AS
ACCURACY □□ 1
□SAMPLES□SAMPLES−1∑
□01□□□□
WHERE 1□IS THE INDICATOR FUNCTION

```
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT ACCURACYSCORE
YPRED  0 2 1 3
YTRUE  0 1 2 3
ACCURACYSCOREYTRUE YPRED
05
ACCURACYSCOREYTRUE YPRED NORMALIZE FALSE
2
```

IN THE MULTILABEL CASE WITH BINARY LABEL INDICATORS

```
ACCURACYSCORENPARRAY0 1 1 1 NPONES2 2
05
```

EXAMPLE
• SEE TEST WITH PERMUTATIONS THE SIGNIFICANCE OF A CLASSIFICATION SCORE FOR AN EXAMPLE OF ACCURACY SCORE USAGE USING PERMUTATIONS OF THE DATASET

BALANCED ACCURACY SCORE
THEBALANCEDACCURACYSCORE FUNCTION COMPUTES THE BALANCED ACCURACY WHICH AVOIDS INFLATED PERFORMANCE ESTIMATES ON IMBALANCED DATASETS IT IS THE MACROAVERAGE OF RECALL SCORES PER CLASS OR EQUIVALENTLY RAW ACCURACY WHERE EACH SAMPLE IS WEIGHTED ACCORDING TO THE INVERSE PREVALENCE OF ITS TRUE CLASS THUS FOR BALANCED DATASETS THE SCORE IS EQUAL TO ACCURACY
IN THE BINARY CASE BALANCED ACCURACY IS EQUAL TO THE ARITHMETIC MEAN OF SENSITIVITY TRUE POSITIVE RATE AND SPECIFICITY TRUE NEGATIVE RATE OR THE AREA UNDER THE ROC CURVE WITH BINARY PREDICTIONS RATHER THAN SCORES
IF THE CLASSIFIER PERFORMS EQUALLY WELL ON EITHER CLASS THIS TERM REDUCES TO THE CONVENTIONAL ACCURACY IE THE NUMBER OF CORRECT PREDICTIONS DIVIDED BY THE TOTAL NUMBER OF PREDICTIONS
IN CONTRAST IF THE CONVENTIONAL ACCURACY IS ABOVE CHANCE ONLY BECAUSE THE CLASSIFIER TAKES ADVANTAGE OF AN IMBALANCED TEST SET THEN THE BALANCED ACCURACY AS APPROPRIATE WILL DROP TO1
□□□□□□□□
THE SCORE RANGES FROM 0 TO 1 OR WHEN ADJUSTEDTRUE IS USED IT RESCALED TO THE RANGE1
1−□□□□□□□□TO 1 INCLUSIVE
WITH PERFORMANCE AT RANDOM SCORING 0
IF□□IS THE TRUE VALUE OF THE □TH SAMPLE AND □□IS THE CORRESPONDING SAMPLE WEIGHT THEN WE ADJUST THE SAMPLE WEIGHT TO
□□□□Σ
□1□□□□□□
WHERE 1□IS THE INDICATOR FUNCTION GIVEN PREDICTED □□FOR SAMPLE □ BALANCED ACCURACY IS DEFINED AS
BALANCEDACCURACY □□ □ 1Σ□□Σ
□1□□□□ □□
WITHADJUSTEDTRUE BALANCED ACCURACY REPORTS THE RELATIVE INCREASE FROM BALANCEDACCURACY □0 □ 1
□□□□□□□□ IN THE BINARY CASE THIS IS ALSO KNOWN AS YOUDEN’S J STATISTIC OR INFORMEDNESS
NOTE THE MULTICLASS DEFINITION HERE SEEMS THE MOST REASONABLE EXTENSION OF THE METRIC USED IN BINARY CLASSIFICATION THOUGH THERE IS NO CERTAIN CONSENSUS IN THE LITERATURE
• OUR DEFINITION MOSLEY2013 KELLEHER2015 ANDGUYON2015 WHERE GUYON2015 ADOPT THE ADJUSTED VER SION TO ENSURE THAT RANDOM PREDICTIONS HAVE A SCORE OF 0AND PERFECT PREDICTIONS HAVE A SCORE OF 1
• CLASS BALANCED ACCURACY AS DESCRIBED IN MOSLEY2013 THE MINIMUM BETWEEN THE PRECISION AND THE RECALL FOR EACH CLASS IS COMPUTED THOSE VALUES ARE THEN AVERAGED OVER THE TOTAL NUMBER OF CLASSES TO GET THE BALANCED ACCURACY
• BALANCED ACCURACY AS DESCRIBED IN URBANOWICZ2015 THE AVERAGE OF SENSITIVITY AND SPECIFICITY IS COMPUTED FOR EACH CLASS AND THEN AVERAGED OVER TOTAL NUMBER OF CLASSES
REFERENCES
COHEN’S KAPPA
THE FUNCTION COHENKAPPASCORE COMPUTES COHEN’S KAPPA STATISTIC THIS MEASURE IS INTENDED TO COMPARE LABEL INGS BY DIFFERENT HUMAN ANNOTATORS NOT A CLASSIFIER VERSUS A GROUND TRUTH
THE KAPPA SCORE SEE DOCSTRING IS A NUMBER BETWEEN 1 AND 1 SCORES ABOVE 8 ARE GENERALLY CONSIDERED GOOD AGREE MENT ZERO OR LOWER MEANS NO AGREEMENT PRACTICALLY RANDOM LABELS

KAPPA SCORES CAN BE COMPUTED FOR BINARY OR MULTICLASS PROBLEMS BUT NOT FOR MULTILABEL PROBLEMS EXCEPT BY MANUALLY COMPUTING A PERLABEL SCORE AND NOT FOR MORE THAN TWO ANNOTATORS

```
 FROM SKLEARNMETRICS IMPORT COHENKAPPASCORE
YTRUE  2 0 2 2 0 1
YPRED  0 0 2 2 0 2
COHENKAPPASCOREYTRUE YPRED
04285714285714286
```

CONFUSION MATRIX

THECONFUSIONMATRIX FUNCTION EVALUATES CLASSIFICATION ACCURACY BY COMPUTING THE CONFUSION MATRIX WITH EACH ROW CORRESPONDING TO THE TRUE CLASS HTTPSENWIKIPEDIAORGWIKICONFUSIONMATRIX‘ WIKIPEDIA AND OTHER REFERENCES MAY USE DIFFERENT CONVENTION FOR AXES

BY DEFINITION ENTRY □ □IN A CONFUSION MATRIX IS THE NUMBER OF OBSERVATIONS ACTUALLY IN GROUP □ BUT PREDICTED TO BE IN GROUP □ HERE IS AN EXAMPLE

```
 FROM SKLEARNMETRICS IMPORT CONFUSIONMATRIX
YTRUE  2 0 2 2 0 1
YPRED  0 0 2 2 0 2
CONFUSIONMATRIXYTRUE YPRED
ARRAY2 0 0
0 0 1
1 0 2
```

HERE IS A VISUAL REPRESENTATION OF SUCH A CONFUSION MATRIX THIS FIGURE COMES FROM THE CONFUSION MATRIX EXAMPLE

FOR BINARY PROBLEMS WE CAN GET COUNTS OF TRUE NEGATIVES FALSE POSITIVES FALSE NEGATIVES AND TRUE POSITIVES AS FOLLOWS

```
YTRUE  0 0 0 1 1 1 1 1
YPRED  0 1 0 1 0 1 0 1
TN FP FN TP  CONFUSIONMATRIXYTRUE YPREDRAVEL
```

TN FP FN TP
2 1 2 3
EXAMPLE
• SEE CONFUSION MATRIX FOR AN EXAMPLE OF USING A CONFUSION MATRIX TO EVALUATE CLASSIFIER OUTPUT QUALITY
• SEE RECOGNIZING HANDWRITTEN DIGITS FOR AN EXAMPLE OF USING A CONFUSION MATRIX TO CLASSIFY HANDWRITTEN DIGITS
• SEE CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES FOR AN EXAMPLE OF USING A CONFUSION MATRIX TO CLASSIFY TEXT DOCUMENTS
CLASSIFICATION REPORT
THECLASSIFICATIONREPORT FUNCTION BUILDS A TEXT REPORT SHOWING THE MAIN CLASSIFICATION METRICS HERE IS A SMALL EXAMPLE WITH CUSTOM TARGETNAMES AND INFERRED LABELS
FROM SKLEARNMETRICS IMPORT CLASSIFICATIONREPORT
YTRUE 0 1 2 2 0
YPRED 0 0 2 1 0
TARGETNAMES CLASS 0 CLASS 1 CLASS 2
PRINTCLASSIFICATIONREPORTYTRUE YPRED TARGETNAMESTARGETNAMES
PRECISION RECALL F1SCORE SUPPORT
CLASS 0 067 100 080 2
CLASS 1 000 000 000 1
CLASS 2 100 050 067 2
ACCURACY 060 5
MACRO AVG 056 050 049 5
WEIGHTED AVG 067 060 059 5
EXAMPLE
• SEE RECOGNIZING HANDWRITTEN DIGITS FOR AN EXAMPLE OF CLASSIFICATION REPORT USAGE FOR HANDWRITTEN DIGITS
• SEE CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES FOR AN EXAMPLE OF CLASSIFICATION REPORT USAGE FOR TEXT DOCUMENTS
• SEE PARAMETER ESTIMATION USING GRID SEARCH WITH CROSSVALIDATION FOR AN EXAMPLE OF CLASSIFICATION REPORT USAGE FOR GRID SEARCH WITH NESTED CROSSVALIDATION
HAMMING LOSS
THEHAMMINGLOSS COMPUTES THE AVERAGE HAMMING LOSS OR HAMMING DISTANCE BETWEEN TWO SETS OF SAMPLES
IF□□IS THE PREDICTED VALUE FOR THE □TH LABEL OF A GIVEN SAMPLE □□IS THE CORRESPONDING TRUE VALUE AND □LABELS IS THE NUMBER OF CLASSES OR LABELS THEN THE HAMMING LOSS □□□□□□□□ BETWEEN TWO SAMPLES IS DEFINED AS
□□□□□□□□ □□ 1
□LABELS□LABELS−1∑
□01□□□□

WHERE 1□IS THE INDICATOR FUNCTION
```
 FROM SKLEARNMETRICS IMPORT HAMMINGLOSS
YPRED  1 2 3 4
YTRUE  2 2 3 4
HAMMINGLOSSYTRUE YPRED
```
025
IN THE MULTILABEL CASE WITH BINARY LABEL INDICATORS
```
HAMMINGLOSSNPARRAY0 1 1 1 NPZEROS2 2
```
075
NOTE IN MULTICLASS CLASSIFICATION THE HAMMING LOSS CORRESPONDS TO THE HAMMING DISTANCE BETWEEN YTRUE AND YPRED WHICH IS SIMILAR TO THE ZERO ONE LOSS FUNCTION HOWEVER WHILE ZEROONE LOSS PENALIZES PREDICTION SETS THAT DO NOT STRICTLY MATCH TRUE SETS THE HAMMING LOSS PENALIZES INDIVIDUAL LABELS THUS THE HAMMING LOSS UPPER BOUNDED BY THE ZEROONE LOSS IS ALWAYS BETWEEN ZERO AND ONE INCLUSIVE AND PREDICTING A PROPER SUBSET OR SUPERSET OF THE TRUE LABELS WILL GIVE A HAMMING LOSS BETWEEN ZERO AND ONE EXCLUSIVE

PRECISION RECALL AND FMEASURES

INTUITIVELY PRECISION IS THE ABILITY OF THE CLASSIFIER NOT TO LABEL AS POSITIVE A SAMPLE THAT IS NEGATIVE AND RECALL IS THE ABILITY OF THE CLASSIFIER TO FIND ALL THE POSITIVE SAMPLES

THE FMEASURE □□AND□1MEASURES CAN BE INTERPRETED AS A WEIGHTED HARMONIC MEAN OF THE PRECISION AND RECALL A □□MEASURE REACHES ITS BEST VALUE AT 1 AND ITS WORST SCORE AT 0 WITH □ 1□□AND□1ARE EQUIVALENT AND THE RECALL AND THE PRECISION ARE EQUALLY IMPORTANT

THEPRECISIONRECALLCURVE COMPUTES A PRECISIONRECALL CURVE FROM THE GROUND TRUTH LABEL AND A SCORE GIVEN BY THE CLASSIFIER BY VARYING A DECISION THRESHOLD

THEAVERAGEPRECISIONSCORE FUNCTION COMPUTES THE AVERAGE PRECISION AP FROM PREDICTION SCORES THE VALUE IS BETWEEN 0 AND 1 AND HIGHER IS BETTER AP IS DEFINED AS

AP∑
□□□−□□−1□□

WHERE □□AND□□ARE THE PRECISION AND RECALL AT THE NTH THRESHOLD WITH RANDOM PREDICTIONS THE AP IS THE FRACTION OF POSITIVE SAMPLES

REFERENCES MANNING2008 ANDEVERINGHAM2010 PRESENT ALTERNATIVE VARIANTS OF AP THAT INTERPOLATE THE PRECISION RECALL CURVE CURRENTLY AVERAGEPRECISIONSCORE DOES NOT IMPLEMENT ANY INTERPOLATED VARIANT REFERENCES DAVIS2006 ANDFLACH2015 DESCRIBE WHY A LINEAR INTERPOLATION OF POINTS ON THE PRECISIONRECALL CURVE PROVIDES AN OVERLYOPTIMISTIC MEASURE OF CLASSIFIER PERFORMANCE THIS LINEAR INTERPOLATION IS USED WHEN COMPUTING AREA UNDER THE CURVE WITH THE TRAPEZOIDAL RULE IN AUC

SEVERAL FUNCTIONS ALLOW YOU TO ANALYZE THE PRECISION RECALL AND FMEASURES SCORE

AVERAGEPRECISIONSCORE YTRUE YSCORE COMPUTE AVERAGE PRECISION AP FROM PREDICTION SCORES

F1SCORE YTRUE YPRED LABELS COMPUTE THE F1 SCORE ALSO KNOWN AS BALANCED FSCORE OR FMEASURE

FBETASCORE YTRUE YPRED BETA LABELS COMPUTE THE FBETA SCORE

PRECISIONRECALLCURVE YTRUE PROBASPRED COMPUTE PRECISIONRECALL PAIRS FOR DIFFERENT PROBABILITY THRESHOLDS

CONTINUED ON NEXT PAGE

TABLE 326 – CONTINUED FROM PREVIOUS PAGE
PRECISIONRECALLFSCORESUPPORT YTRUE
YPREDCOMPUTE PRECISION RECALL FMEASURE AND SUPPORT FOR EACH
CLASS
PRECISIONSCORE YTRUE YPRED LABELS COMPUTE THE PRECISION
RECALLSCORE YTRUE YPRED LABELS COMPUTE THE RECALL
NOTE THAT THE PRECISIONRECALLCURVE FUNCTION IS RESTRICTED TO THE BINARY CASE THE
AVERAGEPRECISIONSCORE FUNCTION WORKS ONLY IN BINARY CLASSIFICATION AND MULTILABEL INDICATOR FORMAT
EXAMPLES
• SEE CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES FOR AN EXAMPLE OF F1SCORE USAGE TO CLASSIFY
TEXT DOCUMENTS
• SEE PARAMETER ESTIMATION USING GRID SEARCH WITH CROSSVALIDATION FOR AN EXAMPLE OF PRECISIONSCORE
ANDRECALLSCORE USAGE TO ESTIMATE PARAMETERS USING GRID SEARCH WITH NESTED CROSSVALIDATION
• SEE PRECISIONRECALL FOR AN EXAMPLE OF PRECISIONRECALLCURVE USAGE TO EVALUATE CLASSIFIER OUTPUT
QUALITY
REFERENCES
BINARY CLASSIFICATION
IN A BINARY CLASSIFICATION TASK THE TERMS ‘’POSITIVE” AND ‘’NEGATIVE” REFER TO THE CLASSIFIER’S PREDICTION AND THE TERMS
‘’TRUE” AND ‘’FALSE” REFER TO WHETHER THAT PREDICTION CORRESPONDS TO THE EXTERNAL JUDGMENT SOMETIMES KNOWN AS THE
‘’OBSERVATION‘‘ GIVEN THESE DEFINITIONS WE CAN FORMULATE THE FOLLOWING TABLE
ACTUAL CLASS OBSERVATION
PREDICTED CLASS EXPECTATION TP TRUE POSITIVE CORRECT RESULT FP FALSE POSITIVE UNEXPECTED RESULT
FN FALSE NEGATIVE MISSING RESULT TN TRUE NEGATIVE CORRECT ABSENCE OF RESULT
IN THIS CONTEXT WE CAN DEFINE THE NOTIONS OF PRECISION RECALL AND FMEASURE
PRECISION □□
□□□□
RECALL □□
□□□□
□□ 1 □2PRECISION×RECALL
□2PRECISION RECALL
HERE ARE SOME SMALL EXAMPLES IN BINARY CLASSIFICATION
FROM SKLEARN IMPORT METRICS
YPRED 0 1 0 0
YTRUE 0 1 0 1
METRICSPRECISIONSCOREYTRUE YPRED
10
METRICSRECALLSCOREYTRUE YPRED
05

METRICSF1SCOREYTRUE YPRED
066
METRICSFBETASCOREYTRUE YPRED BETA05
083
METRICSFBETASCOREYTRUE YPRED BETA1
066
METRICSFBETASCOREYTRUE YPRED BETA2
055
METRICSPRECISIONRECALLFSCORESUPPORTYTRUE YPRED BETA05
ARRAY066 1 ARRAY1 05 ARRAY071 083 ARRAY2
‘→2
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT PRECISIONRECALLCURVE
 FROM SKLEARNMETRICS IMPORT AVERAGEPRECISIONSCORE
YTRUE NPARRAY0 0 1 1
YSCORES NPARRAY01 04 035 08
PRECISION RECALL THRESHOLD PRECISIONRECALLCURVEYTRUE YSCORES
PRECISION
ARRAY066 05 1 1
RECALL
ARRAY1 05 05 0
THRESHOLD
ARRAY035 04 08
AVERAGEPRECISIONSCOREYTRUE YSCORES
083
MULTICLASS AND MULTILABEL CLASSIFICATION
IN MULTICLASS AND MULTILABEL CLASSIFICATION TASK THE NOTIONS OF PRECISION RECALL AND FMEASURES CAN BE AP
PLIED TO EACH LABEL INDEPENDENTLY THERE ARE A FEW WAYS TO COMBINE RESULTS ACROSS LABELS SPECIFIED BY THE
AVERAGE ARGUMENT TO THE AVERAGEPRECISIONSCORE MULTILABEL ONLY F1SCORE FBETASCORE
PRECISIONRECALLFSCORESUPPORT PRECISIONSCORE ANDRECALLSCORE FUNCTIONS AS DESCRIBED
ABOVE NOTE THAT IF ALL LABELS ARE INCLUDED “MICRO”AVERAGING IN A MULTICLASS SETTING WILL PRODUCE PRECISION RECALL AND
□THAT ARE ALL IDENTICAL TO ACCURACY ALSO NOTE THAT “WEIGHTED” AVERAGING MAY PRODUCE AN FSCORE THAT IS NOT BETWEEN
PRECISION AND RECALL
TO MAKE THIS MORE EXPLICIT CONSIDER THE FOLLOWING NOTATION
•□THE SET OF PREDICTED □□□□□□ □□□□□ PAIRS
•□THE SET OF TRUE□□□□□□ □□□□□ PAIRS
•□THE SET OF LABELS
•□THE SET OF SAMPLES
•□□THE SUBSET OF □WITH SAMPLE □ IE□□□′ □∈□□′□
•□□THE SUBSET OF □WITH LABEL □
• SIMILARLY □□AND□□ARE SUBSETS OF □
•□□ □ □∩□
□FOR SOME SETS □AND□
•□□ □ □∩□
□CONVENTIONS VARY ON HANDLING □∅ THIS IMPLEMENTATION USES □□ □ 0 AND SIMILAR
FOR□

•□□□ □
1 □2□□□×□□□
□2□□□□□□
THEN THE METRICS ARE DEFINED AS
AVERAGE PRECISION RECALL FBETA
MICRO □□□ □□□ □□□□
SAMPLES1
□∑
□∈□□□□□□□1
□∑
□∈□□□□□□□1
□∑
□∈□□□□□□□□
MACRO1
□∑
□∈□□□□□□□1
□∑
□∈□□□□□□□1
□∑
□∈□□□□□□□□
WEIGHTED1∑
□∈□□□□∑
□∈□□□□□□□□□1∑
□∈□□□□∑
□∈□□□□□□□□□1∑
□∈□□□□∑
□∈□□□□□□□□□□
NONE⟨□□□□□□□∈□⟩⟨□□□□□□□∈□⟩⟨□□□□□□□∈□⟩
FROM SKLEARN IMPORT METRICS
YTRUE 0 1 2 0 1 2
YPRED 0 2 1 0 0 1
METRICSPRECISIONSCOREYTRUE YPRED AVERAGEMACRO
022
METRICSRECALLSCOREYTRUE YPRED AVERAGEMICRO

033
METRICSF1SCOREYTRUE YPRED AVERAGEWEIGHTED
026
METRICSFBETASCOREYTRUE YPRED AVERAGEMACRO BETA05
023
METRICSPRECISIONRECALLFSCORESUPPORTYTRUE YPRED BETA05 AVERAGE NONE

ARRAY066 0 0 ARRAY1 0 0 ARRAY071 0
‹→ 0 ARRAY2 2 2
FOR MULTICLASS CLASSIFICATION WITH A “NEGATIVE CLASS” IT IS POSSIBLE TO EXCLUDE SOME LABELS
METRICSRECALLSCOREYTRUE YPRED LABELS1 2 AVERAGEMICRO
EXCLUDING 0 NO LABELS WERE CORRECTLY RECALLED
00
SIMILARLY LABELS NOT PRESENT IN THE DATA SAMPLE MAY BE ACCOUNTED FOR IN MACROAVERAGING
METRICSPRECISIONSCOREYTRUE YPRED LABELS0 1 2 3 AVERAGEMACRO

0166
JACCARD SIMILARITY COEFFICIENT SCORE
THEJACCARDSCORE FUNCTION COMPUTES THE AVERAGE OF JACCARD SIMILARITY COEFFICIENTS ALSO CALLED THE JACCARD INDEX BETWEEN PAIRS OF LABEL SETS
THE JACCARD SIMILARITY COEFFICIENT OF THE □TH SAMPLES WITH A GROUND TRUTH LABEL SET □□AND PREDICTED LABEL SET □□ IS DEFINED AS
□□□□□ □□∩□□
□□∪□□
JACCARDSCORE WORKS LIKEPRECISIONRECALLFSCORESUPPORT AS A NAIVELY SETWISE MEASURE APPLYING NATIVELY TO BINARY TARGETS AND EXTENDED TO APPLY TO MULTILABEL AND MULTICLASS THROUGH THE USE OF FROM BINARY TO MULTICLASS AND MULTILABEL SEEABOVE
IN THE BINARY CASE

```
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT JACCARDSCORE
YTRUE  NPARRAY0 1 1
 1 1 0
YPRED  NPARRAY1 1 1
 1 0 0
JACCARDSCOREYTRUE0 YPRED0
06666
```

IN THE MULTILABEL CASE WITH BINARY LABEL INDICATORS

```
JACCARDSCOREYTRUE YPRED AVERAGESAMPLES
05833
JACCARDSCOREYTRUE YPRED AVERAGEMACRO
06666
JACCARDSCOREYTRUE YPRED AVERAGE NONE
ARRAY05 05 1
```

MULTICLASS PROBLEMS ARE BINARIZED AND TREATED LIKE THE CORRESPONDING MULTILABEL PROBLEM

```
YPRED  0 2 1 2
YTRUE  0 1 2 2
JACCARDSCOREYTRUE YPRED AVERAGE NONE

ARRAY1  0  033
JACCARDSCOREYTRUE YPRED AVERAGEMACRO
044
JACCARDSCOREYTRUE YPRED AVERAGEMICRO
033
```

HINGE LOSS

THEHINGELOSS FUNCTION COMPUTES THE AVERAGE DISTANCE BETWEEN THE MODEL AND THE DATA USING HINGE LOSS A ONE SIDED METRIC THAT CONSIDERS ONLY PREDICTION ERRORS HINGE LOSS IS USED IN MAXIMAL MARGIN CLASSIFIERS SUCH AS SUPPORT VECTOR MACHINES

IF THE LABELS ARE ENCODED WITH 1 AND 1 □ IS THE TRUE VALUE AND □IS THE PREDICTED DECISIONS AS OUTPUT BY DECISIONFUNCTION THEN THE HINGE LOSS IS DEFINED AS

□HINGE□ □ MAX1−□□01−□□

IF THERE ARE MORE THAN TWO LABELS HINGELOSS USES A MULTICLASS VARIANT DUE TO CRAMMER SINGER HERE IS THE PAPER DESCRIBING IT

IF□□IS THE PREDICTED DECISION FOR TRUE LABEL AND □□IS THE MAXIMUM OF THE PREDICTED DECISIONS FOR ALL OTHER LABELS WHERE PREDICTED DECISIONS ARE OUTPUT BY DECISION FUNCTION THEN MULTICLASS HINGE LOSS IS DEFINED BY

□HINGE□□ □□ MAX1 □□−□□0

HERE A SMALL EXAMPLE DEMONSTRATING THE USE OF THE HINGELOSS FUNCTION WITH A SVM CLASSIFIER IN A BINARY CLASS PROBLEM

```
 FROM SKLEARN IMPORT SVM
 FROM SKLEARNMETRICS IMPORT HINGELOSS
X  0 1
Y  1 1
```

SCIKITLEARN USER GUIDE RELEASE 0213
EST SVMLINEARSVCRANDOMSTATE0
ESTFITX Y
LINEARSVCC10 CLASSWEIGHTNONE DUALTRUE FITINTERCEPTTRUE
INTERCEPTSCALING1 LOSSSQUAREDHINGE MAXITER1000
MULTICLASSOVR PENALTYL2 RANDOMSTATE0 TOL00001
VERBOSE0
PREDDECISION ESTDECISIONFUNCTION2 3 05
PREDDECISION
ARRAY218 236 009
HINGELOSS1 1 1 PREDDECISION
03
HERE IS AN EXAMPLE DEMONSTRATING THE USE OF THE HINGELOSS FUNCTION WITH A SVM CLASSIFIER IN A MULTICLASS PROBLEM
X NPARRAY0 1 2 3
Y NPARRAY0 1 2 3
LABELS NPARRAY0 1 2 3
EST SVMLINEARSVC
ESTFITX Y
LINEARSVCC10 CLASSWEIGHTNONE DUALTRUE FITINTERCEPTTRUE
INTERCEPTSCALING1 LOSSSQUAREDHINGE MAXITER1000
MULTICLASSOVR PENALTYL2 RANDOMSTATENONE TOL00001
VERBOSE0
PREDDECISION ESTDECISIONFUNCTION1 2 3
YTRUE 0 2 3
HINGELOSSYTRUE PREDDECISION LABELS
056
LOG LOSS
LOG LOSS ALSO CALLED LOGISTIC REGRESSION LOSS OR CROSSENTROPY LOSS IS DEFINED ON PROBABILITY ESTIMATES IT IS COMMONLY USED IN MULTINOMIAL LOGISTIC REGRESSION AND NEURAL NETWORKS AS WELL AS IN SOME VARIANTS OF EXPECTATIONMAXIMIZATION AND CAN BE USED TO EVALUATE THE PROBABILITY OUTPUTS PREDICTPROBA OF A CLASSIFIER INSTEAD OF ITS DISCRETE PREDIC TIONS
FOR BINARY CLASSIFICATION WITH A TRUE LABEL □∈01AND A PROBABILITY ESTIMATE □ PR □ 1 THE LOG LOSS PER SAMPLE IS THE NEGATIVE LOGLIKELIHOOD OF THE CLASSIFIER GIVEN THE TRUE LABEL
□LOG□ □ −LOG PR □□ −□LOG□ 1−□ LOG1−□
THIS EXTENDS TO THE MULTICLASS CASE AS FOLLOWS LET THE TRUE LABELS FOR A SET OF SAMPLES BE ENCODED AS A 1OFK BINARY INDICATOR MATRIX □ IE □□□ 1IF SAMPLE □HAS LABEL □TAKEN FROM A SET OF □LABELS LET □BE A MATRIX OF PROBABILITY ESTIMATES WITH □□□ PR □□□ 1 THEN THE LOG LOSS OF THE WHOLE SET IS
□LOG□ □ −LOG PR □□ −1
□□−1∑
□0□−1∑
□0□□□LOG□□□
TO SEE HOW THIS GENERALIZES THE BINARY LOG LOSS GIVEN ABOVE NOTE THAT IN THE BINARY CASE □□0 1−□□1AND□□0 1−□□1 SO EXPANDING THE INNER SUM OVER □□□∈01GIVES THE BINARY LOG LOSS
THELOGLOSS FUNCTION COMPUTES LOG LOSS GIVEN A LIST OF GROUNDTRUTH LABELS AND A PROBABILITY MATRIX AS RETURNED BY AN ESTIMATOR'S PREDICTPROBA METHOD
 FROM SKLEARNMETRICS IMPORT LOGLOSS
YTRUE 0 0 1 1

YPRED 9 1 8 2 3 7 01 99
LOGLOSSYTRUE YPRED
01738
THE FIRST9 1 INYPRED DENOTES 90 PROBABILITY THAT THE FIRST SAMPLE HAS LABEL 0 THE LOG LOSS IS NONNEGATIVE
MATTHEWS CORRELATION COEFFICIENT
THEMATTHEWSCORRCOEF FUNCTION COMPUTES THE MATTHEW'S CORRELATION COEFFICIENT MCC FOR BINARY CLASSES
QUOTING WIKIPEDIA
"THE MATTHEWS CORRELATION COEFFICIENT IS USED IN MACHINE LEARNING AS A MEASURE OF THE QUALITY OF BINARY
TWOCLASS CLASSIFICATIONS IT TAKES INTO ACCOUNT TRUE AND FALSE POSITIVES AND NEGATIVES AND IS GENERALLY
REGARDED AS A BALANCED MEASURE WHICH CAN BE USED EVEN IF THE CLASSES ARE OF VERY DIFFERENT SIZES THE
MCC IS IN ESSENCE A CORRELATION COEFFICIENT VALUE BETWEEN 1 AND 1 A COEFFICIENT OF 1 REPRESENTS
A PERFECT PREDICTION 0 AN AVERAGE RANDOM PREDICTION AND 1 AN INVERSE PREDICTION THE STATISTIC IS ALSO
KNOWN AS THE PHI COEFFICIENT"
IN THE BINARY TWOCLASS CASE □□□□□□AND□□ARE RESPECTIVELY THE NUMBER OF TRUE POSITIVES TRUE NEGATIVES FALSE
POSITIVES AND FALSE NEGATIVES THE MCC IS DEFINED AS
□□□ □□×□□−□□×□□√
□□□□□□□□□□□□□□□□□□□□
IN THE MULTICLASS CASE THE MATTHEWS CORRELATION COEFFICIENT CAN BE DEFINED IN TERMS OF A CONFUSIONMATRIX □FOR
□CLASSES TO SIMPLIFY THE DEFINITION CONSIDER THE FOLLOWING INTERMEDIATE VARIABLES
•□□∑□
□□□□THE NUMBER OF TIMES CLASS □TRULY OCCURRED
•□□∑□
□□□□THE NUMBER OF TIMES CLASS □WAS PREDICTED
•□∑□
□□□□THE TOTAL NUMBER OF SAMPLES CORRECTLY PREDICTED
•□∑□
□∑□
□□□□THE TOTAL NUMBER OF SAMPLES
THEN THE MULTICLASS MCC IS DEFINED AS
□□□ □×□−∑□
□□□×□□√
□2−∑□
□□2
□×□2−∑□
□□2
□
WHEN THERE ARE MORE THAN TWO LABELS THE VALUE OF THE MCC WILL NO LONGER RANGE BETWEEN 1 AND 1 INSTEAD THE
MINIMUM VALUE WILL BE SOMEWHERE BETWEEN 1 AND 0 DEPENDING ON THE NUMBER AND DISTRIBUTION OF GROUND TRUE LABELS
THE MAXIMUM VALUE IS ALWAYS 1
HERE IS A SMALL EXAMPLE ILLUSTRATING THE USAGE OF THE MATTHEWSCORRCOEF FUNCTION
 FROM SKLEARNMETRICS IMPORT MATTHEWSCORRCOEF
YTRUE 1 1 1 1
YPRED 1 1 1 1
MATTHEWSCORRCOEFYTRUE YPRED
033
MULTILABEL CONFUSION MATRIX
THEMULTILABELCONFUSIONMATRIX FUNCTION COMPUTES CLASSWISE DEFAULT OR SAMPLEWISE SAMPLE
WISETRUE MULTILABEL CONFUSION MATRIX TO EVALUATE THE ACCURACY OF A CLASSIFICATION MULTILABELCONFUSIONMATRIX

ALSO TREATS MULTICLASS DATA AS IF IT WERE MULTILABEL AS THIS IS A TRANSFORMATION COMMONLY APPLIED TO EVALUATE MULTICLASS PROBLEMS WITH BINARY CLASSIFICATION METRICS SUCH AS PRECISION RECALL ETC
WHEN CALCULATING CLASSWISE MULTILABEL CONFUSION MATRIX THE COUNT OF TRUE NEGATIVES FOR CLASS IS00 FALSE NEGATIVES IS 10 TRUE POSITIVES IS 11AND FALSE POSITIVES IS 01
HERE IS AN EXAMPLE DEMONSTRATING THE USE OF THE MULTILABELCONFUSIONMATRIX FUNCTION WITH MULTILABEL INDICATOR MATRIX INPUT

```
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT MULTILABELCONFUSIONMATRIX
YTRUE  NPARRAY1 0 1
 0 1 0
YPRED  NPARRAY1 0 0
 0 1 1
MULTILABELCONFUSIONMATRIXYTRUE YPRED
ARRAY1 0
0 1
1 0
0 1
0 1
1 0
```

OR A CONFUSION MATRIX CAN BE CONSTRUCTED FOR EACH SAMPLE'S LABELS

```
MULTILABELCONFUSIONMATRIXYTRUE YPRED SAMPLEWISE TRUE
ARRAY1 0
1 1
1 1
0 1
```

HERE IS AN EXAMPLE DEMONSTRATING THE USE OF THE MULTILABELCONFUSIONMATRIX FUNCTION WITH MULTICLASS INPUT

```
YTRUE  CAT ANT CAT CAT ANT BIRD
YPRED  ANT ANT CAT CAT ANT CAT
MULTILABELCONFUSIONMATRIXYTRUE YPRED
 LABELSANT BIRD CAT
ARRAY3 1
0 2
5 0
1 0
2 1
1 2
```

HERE ARE SOME EXAMPLES DEMONSTRATING THE USE OF THE MULTILABELCONFUSIONMATRIX FUNCTION TO CALCULATE RECALL OR SENSITIVITY SPECIFICITY FALL OUT AND MISS RATE FOR EACH CLASS IN A PROBLEM WITH MULTILABEL INDICATOR MATRIX INPUT
CALCULATING RECALL ALSO CALLED THE TRUE POSITIVE RATE OR THE SENSITIVITY FOR EACH CLASS

```
YTRUE  NPARRAY0 0 1
 0 1 0
 1 1 0
```

YPRED NPARRAY0 1 0
 0 0 1
 1 1 0
MCM MULTILABELCONFUSIONMATRIXYTRUE YPRED
TN MCM 0 0
TP MCM 1 1
FN MCM 1 0
FP MCM 0 1
TP TP FN
ARRAY1 05 0
CALCULATING SPECIFICITY ALSO CALLED THE TRUE NEGATIVE RATE FOR EACH CLASS
TN TN FP
ARRAY1 0 05
CALCULATING FALL OUT ALSO CALLED THE FALSE POSITIVE RATE FOR EACH CLASS
FP FP TN
ARRAY0 1 05
CALCULATING MISS RATE ALSO CALLED THE FALSE NEGATIVE RATE FOR EACH CLASS
FN FN TP
ARRAY0 05 1
RECEIVER OPERATING CHARACTERISTIC ROC
THE FUNCTION ROCCURVE COMPUTES THE RECEIVER OPERATING CHARACTERISTIC CURVE OR ROC CURVE QUOTING WIKIPEDIA
“A RECEIVER OPERATING CHARACTERISTIC ROC OR SIMPLY ROC CURVE IS A GRAPHICAL PLOT WHICH ILLUSTRATES
THE PERFORMANCE OF A BINARY CLASSIFIER SYSTEM AS ITS DISCRIMINATION THRESHOLD IS VARIED IT IS CREATED BY
PLOTTING THE FRACTION OF TRUE POSITIVES OUT OF THE POSITIVES TPR TRUE POSITIVE RATE VS THE FRACTION OF FALSE
POSITIVES OUT OF THE NEGATIVES FPR FALSE POSITIVE RATE AT VARIOUS THRESHOLD SETTINGS TPR IS ALSO KNOWN
AS SENSITIVITY AND FPR IS ONE MINUS THE SPECIFICITY OR TRUE NEGATIVE RATE”
THIS FUNCTION REQUIRES THE TRUE BINARY VALUE AND THE TARGET SCORES WHICH CAN EITHER BE PROBABILITY ESTIMATES OF THE
POSITIVE CLASS CONFIDENCE VALUES OR BINARY DECISIONS HERE IS A SMALL EXAMPLE OF HOW TO USE THE ROCCURVE FUNCTION
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT ROCCURVE
Y NPARRAY1 1 2 2
SCORES NPARRAY01 04 035 08
FPR TPR THRESHOLDS ROCCURVEY SCORES POSLABEL2
FPR
ARRAY0 0 05 05 1
TPR
ARRAY0 05 05 1 1
THRESHOLDS
ARRAY18 08 04 035 01

THIS FIGURE SHOWS AN EXAMPLE OF SUCH AN ROC CURVE
THEROCAUCSCORE FUNCTION COMPUTES THE AREA UNDER THE RECEIVER OPERATING CHARACTERISTIC ROC CURVE WHICH IS ALSO DENOTED BY AUC OR AUROC BY COMPUTING THE AREA UNDER THE ROC CURVE THE CURVE INFORMATION IS SUMMARIZED IN ONE NUMBER FOR MORE INFORMATION SEE THE WIKIPEDIA ARTICLE ON AUC

```
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT ROCAUCSCORE
YTRUE  NPARRAY0 0 1 1
YSCORES  NPARRAY01 04 035 08
ROCAUCSCOREYTRUE YSCORES
075
```

IN MULTILABEL CLASSIFICATION THE ROCAUCSCORE FUNCTION IS EXTENDED BY AVERAGING OVER THE LABELS AS ABOVE
COMPARED TO METRICS SUCH AS THE SUBSET ACCURACY THE HAMMING LOSS OR THE F1 SCORE ROC DOESN'T REQUIRE OPTIMIZING A THRESHOLD FOR EACH LABEL THE ROCAUCSCORE FUNCTION CAN ALSO BE USED IN MULTICLASS CLASSIFICATION IF THE PREDICTED OUTPUTS HAVE BEEN BINARIZED
IN APPLICATIONS WHERE A HIGH FALSE POSITIVE RATE IS NOT TOLERABLE THE PARAMETER MAXFPR OFROCAUCSCORE CAN BE USED TO SUMMARIZE THE ROC CURVE UP TO THE GIVEN LIMIT

EXAMPLES
• SEE RECEIVER OPERATING CHARACTERISTIC ROC FOR AN EXAMPLE OF USING ROC TO EVALUATE THE QUALITY OF THE OUTPUT OF A CLASSIFIER
• SEE RECEIVER OPERATING CHARACTERISTIC ROC WITH CROSS VALIDATION FOR AN EXAMPLE OF USING ROC TO EVALUATE CLASSIFIER OUTPUT QUALITY USING CROSSVALIDATION
• SEE SPECIES DISTRIBUTION MODELING FOR AN EXAMPLE OF USING ROC TO MODEL SPECIES DISTRIBUTION
ZERO ONE LOSS
THEZEROONELOSS FUNCTION COMPUTES THE SUM OR THE AVERAGE OF THE 01 CLASSIFICATION LOSS □0−1 OVER □SAMPLES
BY DEFAULT THE FUNCTION NORMALIZES OVER THE SAMPLE TO GET THE SUM OF THE □0−1 SETNORMALIZE TOFALSE
IN MULTILABEL CLASSIFICATION THE ZEROONELOSS SCORES A SUBSET AS ONE IF ITS LABELS STRICTLY MATCH THE PREDICTIONS AND AS A ZERO IF THERE ARE ANY ERRORS BY DEFAULT THE FUNCTION RETURNS THE PERCENTAGE OF IMPERFECTLY PREDICTED SUBSETS TO GET THE COUNT OF SUCH SUBSETS INSTEAD SET NORMALIZE TOFALSE
IF□□IS THE PREDICTED VALUE OF THE □TH SAMPLE AND □□IS THE CORRESPONDING TRUE VALUE THEN THE 01 LOSS □0−1IS DEFINED AS
□0−1□□□□ 1 □□□□
WHERE 1□IS THE INDICATOR FUNCTION
```
 FROM SKLEARNMETRICS IMPORT ZEROONELOSS
YPRED  1 2 3 4
YTRUE  2 2 3 4
ZEROONELOSSYTRUE YPRED
```
025

ZEROONELOSSYTRUE YPRED NORMALIZE FALSE
1
IN THE MULTILABEL CASE WITH BINARY LABEL INDICATORS WHERE THE FIRST LABEL SET 01 HAS AN ERROR
ZEROONELOSSNPARRAY0 1 1 1 NPONES2 2
05
ZEROONELOSSNPARRAY0 1 1 1 NPONES2 2 NORMALIZE FALSE
1
EXAMPLE
• SEE RECURSIVE FEATURE ELIMINATION WITH CROSSVALIDATION FOR AN EXAMPLE OF ZERO ONE LOSS USAGE TO PERFORM RECURSIVE FEATURE ELIMINATION WITH CROSSVALIDATION
BRIER SCORE LOSS
THEBRIERSCORELOSS FUNCTION COMPUTES THE BRIER SCORE FOR BINARY CLASSES QUOTING WIKIPEDIA
“THE BRIER SCORE IS A PROPER SCORE FUNCTION THAT MEASURES THE ACCURACY OF PROBABILISTIC PREDICTIONS IT IS APPLICABLE TO TASKS IN WHICH PREDICTIONS MUST ASSIGN PROBABILITIES TO A SET OF MUTUALLY EXCLUSIVE DISCRETE OUTCOMES”
THIS FUNCTION RETURNS A SCORE OF THE MEAN SQUARE DIFFERENCE BETWEEN THE ACTUAL OUTCOME AND THE PREDICTED PROBABILITY OF THE POSSIBLE OUTCOME THE ACTUAL OUTCOME HAS TO BE 1 OR 0 TRUE OR FALSE WHILE THE PREDICTED PROBABILITY OF THE ACTUAL OUTCOME CAN BE A VALUE BETWEEN 0 AND 1
THE BRIER SCORE LOSS IS ALSO BETWEEN 0 TO 1 AND THE LOWER THE SCORE THE MEAN SQUARE DIFFERENCE IS SMALLER THE MORE ACCURATE THE PREDICTION IS IT CAN BE THOUGHT OF AS A MEASURE OF THE “CALIBRATION” OF A SET OF PROBABILISTIC PREDICTIONS
□□1
□□∑
□1□□−□□2
WHERE □IS THE TOTAL NUMBER OF PREDICTIONS □□IS THE PREDICTED PROBABILITY OF THE ACTUAL OUTCOME □□
HERE IS A SMALL EXAMPLE OF USAGE OF THIS FUNCTION
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT BRIERSCORELOSS
YTRUE  NPARRAY0 1 1 0
YTRUECATEGORICAL  NPARRAYSPAM HAM HAM SPAM
YPROB  NPARRAY01 09 08 04
YPRED  NPARRAY0 1 1 0
BRIERSCORELOSSYTRUE YPROB
0055
BRIERSCORELOSSYTRUE 1  YPROB POSLABEL0
0055
BRIERSCORELOSSYTRUECATEGORICAL YPROB POSLABELHAM
0055
BRIERSCORELOSSYTRUE YPROB  05
00
```

EXAMPLE
• SEE PROBABILITY CALIBRATION OF CLASSIFIERS FOR AN EXAMPLE OF BRIER SCORE LOSS USAGE TO PERFORM PROBABILITY CALIBRATION OF CLASSIFIERS
REFERENCES
• G BRIER VERIFICATION OF FORECASTS EXPRESSED IN TERMS OF PROBABILITY MONTHLY WEATHER REVIEW 781 1950
MULTILABEL RANKING METRICS
IN MULTILABEL LEARNING EACH SAMPLE CAN HAVE ANY NUMBER OF GROUND TRUTH LABELS ASSOCIATED WITH IT THE GOAL IS TO GIVE HIGH SCORES AND BETTER RANK TO THE GROUND TRUTH LABELS
COVERAGE ERROR
THECOVERAGEERROR FUNCTION COMPUTES THE AVERAGE NUMBER OF LABELS THAT HAVE TO BE INCLUDED IN THE FINAL PREDIC TION SUCH THAT ALL TRUE LABELS ARE PREDICTED THIS IS USEFUL IF YOU WANT TO KNOW HOW MANY TOPSCOREDLABELS YOU HAVE TO PREDICT IN AVERAGE WITHOUT MISSING ANY TRUE ONE THE BEST VALUE OF THIS METRICS IS THUS THE AVERAGE NUMBER OF TRUE LABELS
NOTE OUR IMPLEMENTATION’S SCORE IS 1 GREATER THAN THE ONE GIVEN IN TSOUMAKAS ET AL 2010 THIS EXTENDS IT TO HANDLE THE DEGENERATE CASE IN WHICH AN INSTANCE HAS 0 TRUE LABELS
FORMALLY GIVEN A BINARY INDICATOR MATRIX OF THE GROUND TRUTH LABELS ∈01SAMPLES×LABELSAND THE SCORE ASSOCIATED WITH EACH LABEL ∈RSAMPLES×LABELS THE COVERAGE IS DEFINED AS
 1
SAMPLESSAMPLES−1∑
0MAX
1RANK
WITH RANK
≥ GIVEN THE RANK DEFINITION TIES IN YSCORES ARE BROKEN BY GIVING THE MAXIMAL RANK THAT WOULD HAVE BEEN ASSIGNED TO ALL TIED VALUES
HERE IS A SMALL EXAMPLE OF USAGE OF THIS FUNCTION
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT COVERAGEERROR
YTRUE  NPARRAY1 0 0 0 0 1
YSCORE  NPARRAY075 05 1 1 02 01
COVERAGEERRORYTRUE YSCORE
25
```
LABEL RANKING AVERAGE PRECISION
THELABELRANKINGAVERAGEPRECISIONSCORE FUNCTION IMPLEMENTS LABEL RANKING AVERAGE PRECISION LRAP THIS METRIC IS LINKED TO THE AVERAGEPRECISIONSCORE FUNCTION BUT IS BASED ON THE NOTION OF LA BEL RANKING INSTEAD OF PRECISION AND RECALL

LABEL RANKING AVERAGE PRECISION LRAP AVERAGES OVER THE SAMPLES THE ANSWER TO THE FOLLOWING QUESTION FOR EACH GROUND TRUTH LABEL WHAT FRACTION OF HIGHERRANKED LABELS WERE TRUE LABELS THIS PERFORMANCE MEASURE WILL BE HIGHER IF YOU ARE ABLE TO GIVE BETTER RANK TO THE LABELS ASSOCIATED WITH EACH SAMPLE THE OBTAINED SCORE IS ALWAYS STRICTLY GREATER THAN 0 AND THE BEST VALUE IS 1 IF THERE IS EXACTLY ONE RELEVANT LABEL PER SAMPLE LABEL RANKING AVERAGE PRECISION IS EQUIVALENT TO THE MEAN RECIPROCAL RANK

FORMALLY GIVEN A BINARY INDICATOR MATRIX OF THE GROUND TRUTH LABELS ∈01SAMPLES×LABELSAND THE SCORE ASSOCIATED WITH EACH LABEL ∈RSAMPLES×LABELS THE AVERAGE PRECISION IS DEFINED AS

□□□□ □□ 1
□SAMPLES□SAMPLES−1∑
□01
□□0∑
□□□□1ℒ□□
RANK □□
WHEREℒ□□
□□□□ 1□□□≥□□□
RANK □□□□□
□□□□≥□□□□□□·COMPUTES THE CARDINALITY OF THE SET IE THE NUMBER OF ELEMENTS IN THE SET AND · 0IS THE ℓ0“NORM” WHICH COMPUTES THE NUMBER OF NONZERO ELEMENTS IN A VECTOR

HERE IS A SMALL EXAMPLE OF USAGE OF THIS FUNCTION

```
IMPORT NUMPY AS NP
FROM SKLEARNMETRICS IMPORT LABELRANKINGAVERAGEPRECISIONSCORE
YTRUE  NPARRAY1 0 0 0 0 1
YSCORE  NPARRAY075 05 1 1 02 01
LABELRANKINGAVERAGEPRECISIONSCOREYTRUE YSCORE
0416
```

RANKING LOSS

THELABELRANKINGLOSS FUNCTION COMPUTES THE RANKING LOSS WHICH AVERAGES OVER THE SAMPLES THE NUMBER OF LABEL PAIRS THAT ARE INCORRECTLY ORDERED IE TRUE LABELS HAVE A LOWER SCORE THAN FALSE LABELS WEIGHTED BY THE INVERSE OF THE NUMBER OF ORDERED PAIRS OF FALSE AND TRUE LABELS THE LOWEST ACHIEVABLE RANKING LOSS IS ZERO

FORMALLY GIVEN A BINARY INDICATOR MATRIX OF THE GROUND TRUTH LABELS ∈01SAMPLES×LABELSAND THE SCORE ASSOCIATED WITH EACH LABEL ∈RSAMPLES×LABELS THE RANKING LOSS IS DEFINED AS

□□□□□□□ □□□□□□ 1
□SAMPLES□SAMPLES−1∑
□01
□□0□LABELS−□□0□□□
□ □ □□□≤□□□ □□□ 1 □□□ 0□□□
WHERE·COMPUTES THE CARDINALITY OF THE SET IE THE NUMBER OF ELEMENTS IN THE SET AND ·0IS THE ℓ0“NORM” WHICH COMPUTES THE NUMBER OF NONZERO ELEMENTS IN A VECTOR

HERE IS A SMALL EXAMPLE OF USAGE OF THIS FUNCTION

```
IMPORT NUMPY AS NP
FROM SKLEARNMETRICS IMPORT LABELRANKINGLOSS
YTRUE  NPARRAY1 0 0 0 0 1
YSCORE  NPARRAY075 05 1 1 02 01
LABELRANKINGLOSSYTRUE YSCORE
075
```

WITH THE FOLLOWING PREDICTION WE HAVE PERFECT AND MINIMAL LOSS

```
YSCORE  NPARRAY10 01 02 01 02 09
LABELRANKINGLOSSYTRUE YSCORE
00
```

REFERENCES
• TSOUMAKAS G KATAKIS I VLAHAVAS I 2010 MINING MULTILABEL DATA IN DATA MINING AND KNOWLEDGE DISCOVERY HANDBOOK PP 667685 SPRINGER US
REGRESSION METRICS
THESKLEARNMETRICS MODULE IMPLEMENTS SEVERAL LOSS SCORE AND UTILITY FUNCTIONS TO MEASURE REGRESSION PERFORMANCE SOME OF THOSE HAVE BEEN ENHANCED TO HANDLE THE MULTIOUTPUT CASE MEANSQUAREDERROR MEANABSOLUTEERROR EXPLAINEDVARIANCESCORE ANDR2SCORE
THESE FUNCTIONS HAVE AN MULTIOUTPUT KEYWORD ARGUMENT WHICH SPECIFIES THE WAY THE SCORES OR LOSSES FOR EACH INDIVIDUAL TARGET SHOULD BE AVERAGED THE DEFAULT IS UNIFORMAVERAGE WHICH SPECIFIES A UNIFORMLY WEIGHTED MEAN OVER OUTPUTS IF AN NDARRAY OF SHAPENOUTPUTS IS PASSED THEN ITS ENTRIES ARE INTERPRETED AS WEIGHTS AND AN ACCORDING WEIGHTED AVERAGE IS RETURNED IF MULTIOUTPUT ISRAWVALUES IS SPECIFIED THEN ALL UNALTERED INDIVIDUAL SCORES OR LOSSES WILL BE RETURNED IN AN ARRAY OF SHAPE NOUTPUTS
THER2SCORE ANDEXPLAINEDVARIANCESCORE ACCEPT AN ADDITIONAL VALUE VARIANCEWEIGHTED FOR THEMULTIOUTPUT PARAMETER THIS OPTION LEADS TO A WEIGHTING OF EACH INDIVIDUAL SCORE BY THE VARIANCE OF THE CORRESPONDING TARGET VARIABLE THIS SETTING QUANTIFIES THE GLOBALLY CAPTURED UNSCALED VARIANCE IF THE TARGET VARIABLES ARE OF DIFFERENT SCALE THEN THIS SCORE PUTS MORE IMPORTANCE ON WELL EXPLAINING THE HIGHER VARIANCE VARIABLES MULTIOUTPUTVARIANCEWEIGHTED IS THE DEFAULT VALUE FOR R2SCORE FOR BACKWARD COMPATIBILITY THIS WILL BE CHANGED TO UNIFORMAVERAGE IN THE FUTURE
EXPLAINED VARIANCE SCORE
THEEXPLAINEDVARIANCESCORE COMPUTES THE EXPLAINED VARIANCE REGRESSION SCORE
IF□IS THE ESTIMATED TARGET OUTPUT □THE CORRESPONDING CORRECT TARGET OUTPUT AND □ □□ IS VARIANCE THE SQUARE OF THE STANDARD DEVIATION THEN THE EXPLAINED VARIANCE IS ESTIMATED AS FOLLOW
□□□□□□□□□ □□□□□□□□□ □□ 1−□ □□□−□
□ □□□
THE BEST POSSIBLE SCORE IS 10 LOWER VALUES ARE WORSE
HERE IS A SMALL EXAMPLE OF USAGE OF THE EXPLAINEDVARIANCESCORE FUNCTION
```
 FROM SKLEARNMETRICS IMPORT EXPLAINEDVARIANCESCORE
YTRUE  3 05 2 7
YPRED  25 00 2 8
EXPLAINEDVARIANCESCOREYTRUE YPRED
0957
YTRUE  05 1 1 1 7 6
YPRED  0 2 1 2 8 5
EXPLAINEDVARIANCESCOREYTRUE YPRED MULTIOUTPUTRAWVALUES

ARRAY0967 1
EXPLAINEDVARIANCESCOREYTRUE YPRED MULTIOUTPUT03 07
```

MAX ERROR
THEMAXERROR FUNCTION COMPUTES THE MAXIMUM RESIDUAL ERROR A METRIC THAT CAPTURES THE WORST CASE ERROR BETWEEN
THE PREDICTED VALUE AND THE TRUE VALUE IN A PERFECTLY FITTED SINGLE OUTPUT REGRESSION MODEL MAXERROR WOULD BE0
ON THE TRAINING SET AND THOUGH THIS WOULD BE HIGHLY UNLIKELY IN THE REAL WORLD THIS METRIC SHOWS THE EXTENT OF ERROR THAT
THE MODEL HAD WHEN IT WAS FITTED
IF□□IS THE PREDICTED VALUE OF THE □TH SAMPLE AND □□IS THE CORRESPONDING TRUE VALUE THEN THE MAX ERROR IS DEFINED AS
MAX ERROR □□ □□□□□−□□
HERE IS A SMALL EXAMPLE OF USAGE OF THE MAXERROR FUNCTION
 FROM SKLEARNMETRICS IMPORT MAXERROR
YTRUE 3 2 7 1
YPRED 9 2 7 1
MAXERRORYTRUE YPRED
6
THEMAXERROR DOES NOT SUPPORT MULTIOUTPUT
MEAN ABSOLUTE ERROR
THEMEANABSOLUTEERROR FUNCTION COMPUTES MEAN ABSOLUTE ERROR A RISK METRIC CORRESPONDING TO THE EXPECTED
VALUE OF THE ABSOLUTE ERROR LOSS OR □1NORM LOSS
IF□□IS THE PREDICTED VALUE OF THE □TH SAMPLE AND □□IS THE CORRESPONDING TRUE VALUE THEN THE MEAN ABSOLUTE ERROR
MAE ESTIMATED OVER □SAMPLES IS DEFINED AS
MAE □□ 1
□SAMPLES□SAMPLES−1∑
□0□□−□□
HERE IS A SMALL EXAMPLE OF USAGE OF THE MEANABSOLUTEERROR FUNCTION
 FROM SKLEARNMETRICS IMPORT MEANABSOLUTEERROR
YTRUE 3 05 2 7
YPRED 25 00 2 8
MEANABSOLUTEERRORYTRUE YPRED
05
YTRUE 05 1 1 1 7 6
YPRED 0 2 1 2 8 5
MEANABSOLUTEERRORYTRUE YPRED
075
MEANABSOLUTEERRORYTRUE YPRED MULTIOUTPUTRAWVALUES
ARRAY05 1
MEANABSOLUTEERRORYTRUE YPRED MULTIOUTPUT03 07

085
MEAN SQUARED ERROR
THEMEANSQUAREDERROR FUNCTION COMPUTES MEAN SQUARE ERROR A RISK METRIC CORRESPONDING TO THE EXPECTED
VALUE OF THE SQUARED QUADRATIC ERROR OR LOSS

IF□□IS THE PREDICTED VALUE OF THE □TH SAMPLE AND □□IS THE CORRESPONDING TRUE VALUE THEN THE MEAN SQUARED ERROR MSE ESTIMATED OVER □SAMPLES IS DEFINED AS

MSE□□ 1
□SAMPLES□SAMPLES−1∑
□0□□−□□2

HERE IS A SMALL EXAMPLE OF USAGE OF THE MEANSQUAREDERROR FUNCTION

```
 FROM SKLEARNMETRICS IMPORT MEANSQUAREDERROR
YTRUE  3 05 2 7
YPRED  25 00 2 8
MEANSQUAREDERRORYTRUE YPRED
0375
YTRUE  05 1 1 1 7 6
YPRED  0 2 1 2 8 5
MEANSQUAREDERRORYTRUE YPRED
07083
```

EXAMPLES

• SEE GRADIENT BOOSTING REGRESSION FOR AN EXAMPLE OF MEAN SQUARED ERROR USAGE TO EVALUATE GRADIENT BOOSTING REGRESSION

MEAN SQUARED LOGARITHMIC ERROR

THEMEANSQUAREDLOGERROR FUNCTION COMPUTES A RISK METRIC CORRESPONDING TO THE EXPECTED VALUE OF THE SQUARED LOGARITHMIC QUADRATIC ERROR OR LOSS

IF□□IS THE PREDICTED VALUE OF THE □TH SAMPLE AND □□IS THE CORRESPONDING TRUE VALUE THEN THE MEAN SQUARED LOGARITHMIC ERROR MSLE ESTIMATED OVER □SAMPLES IS DEFINED AS

MSLE □□ 1
□SAMPLES□SAMPLES−1∑
□0LOG□1 □□−LOG□1 □□2

WHERE LOG□□MEANS THE NATURAL LOGARITHM OF □ THIS METRIC IS BEST TO USE WHEN TARGETS HAVING EXPONENTIAL GROWTH SUCH AS POPULATION COUNTS AVERAGE SALES OF A COMMODITY OVER A SPAN OF YEARS ETC NOTE THAT THIS METRIC PENALIZES AN UNDERPREDICTED ESTIMATE GREATER THAN AN OVERPREDICTED ESTIMATE

HERE IS A SMALL EXAMPLE OF USAGE OF THE MEANSQUAREDLOGERROR FUNCTION

```
 FROM SKLEARNMETRICS IMPORT MEANSQUAREDLOGERROR
YTRUE  3 5 25 7
YPRED  25 5 4 8
MEANSQUAREDLOGERRORYTRUE YPRED
0039
YTRUE  05 1 1 2 7 6
YPRED  05 2 1 25 8 8
MEANSQUAREDLOGERRORYTRUE YPRED
0044
```

MEDIAN ABSOLUTE ERROR

THEMEDIANABSOLUTEERROR IS PARTICULARLY INTERESTING BECAUSE IT IS ROBUST TO OUTLIERS THE LOSS IS CALCULATED BY TAKING THE MEDIAN OF ALL ABSOLUTE DIFFERENCES BETWEEN THE TARGET AND THE PREDICTION

IF□□IS THE PREDICTED VALUE OF THE □TH SAMPLE AND □□IS THE CORRESPONDING TRUE VALUE THEN THE MEDIAN ABSOLUTE ERROR MEDAE ESTIMATED OVER □SAMPLES IS DEFINED AS
MEDAE □□ MEDIAN □1−□1 □□−□□
THEMEDIANABSOLUTEERROR DOES NOT SUPPORT MULTIOUTPUT
HERE IS A SMALL EXAMPLE OF USAGE OF THE MEDIANABSOLUTEERROR FUNCTION
FROM SKLEARNMETRICS IMPORT MEDIANABSOLUTEERROR
YTRUE 3 05 2 7
YPRED 25 00 2 8
MEDIANABSOLUTEERRORYTRUE YPRED
05
R2SCORE THE COEFFICIENT OF DETERMINATION
THER2SCORE FUNCTION COMPUTES THE COEFFICIENT OF DETERMINATION USUALLY DENOTED AS R2
IT REPRESENTS THE PROPORTION OF VARIANCE OF Y THAT HAS BEEN EXPLAINED BY THE INDEPENDENT VARIABLES IN THE MODEL IT PROVIDES AN INDICATION OF GOODNESS OF FIT AND THEREFORE A MEASURE OF HOW WELL UNSEEN SAMPLES ARE LIKELY TO BE PREDICTED BY THE MODEL THROUGH THE PROPORTION OF EXPLAINED VARIANCE
AS SUCH VARIANCE IS DATASET DEPENDENT R2MAY NOT BE MEANINGFULLY COMPARABLE ACROSS DIFFERENT DATASETS BEST POSSIBLE SCORE IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2SCORE OF 00
IF□□IS THE PREDICTED VALUE OF THE □TH SAMPLE AND □□IS THE CORRESPONDING TRUE VALUE FOR TOTAL □SAMPLES THE ESTIMATED R2IS DEFINED AS
□2□□ 1−∑□
□1□□−□□2
∑□
□1□□−□□2
WHERE □□1
□∑□
□1□□AND∑□
□1□□−□□2∑□
□1□2
□
NOTE THATR2SCORE CALCULATES UNADJUSTED R2WITHOUT CORRECTING FOR BIAS IN SAMPLE VARIANCE OF Y
HERE IS A SMALL EXAMPLE OF USAGE OF THE R2SCORE FUNCTION
FROM SKLEARNMETRICS IMPORT R2SCORE
YTRUE 3 05 2 7
YPRED 25 00 2 8
R2SCOREYTRUE YPRED
0948
YTRUE 05 1 1 1 7 6
YPRED 0 2 1 2 8 5
R2SCOREYTRUE YPRED MULTIOUTPUTVARIANCEWEIGHTED

0938
YTRUE 05 1 1 1 7 6
YPRED 0 2 1 2 8 5
R2SCOREYTRUE YPRED MULTIOUTPUTUNIFORMAVERAGE

0936
R2SCOREYTRUE YPRED MULTIOUTPUTRAWVALUES

ARRAY0965 0908
R2SCOREYTRUE YPRED MULTIOUTPUT03 07

0925
EXAMPLE
• SEE LASSO AND ELASTIC NET FOR SPARSE SIGNALS FOR AN EXAMPLE OF R2SCORE USAGE TO EVALUATE LASSO AND ELASTIC NET ON SPARSE SIGNALS
CLUSTERING METRICS
THESKLEARNMETRICS MODULE IMPLEMENTS SEVERAL LOSS SCORE AND UTILITY FUNCTIONS FOR MORE INFORMATION SEE THE CLUSTERING PERFORMANCE EVALUATION SECTION FOR INSTANCE CLUSTERING AND BICLUSTERING EVALUATION FOR BICLUSTERING
DUMMY ESTIMATORS
WHEN DOING SUPERVISED LEARNING A SIMPLE SANITY CHECK CONSISTS OF COMPARING ONE'S ESTIMATOR AGAINST SIMPLE RULES OF THUMBDUMMYCLASSIFIER IMPLEMENTS SEVERAL SUCH SIMPLE STRATEGIES FOR CLASSIFICATION
•STRATIFIED GENERATES RANDOM PREDICTIONS BY RESPECTING THE TRAINING SET CLASS DISTRIBUTION
•MOSTFREQUENT ALWAYS PREDICTS THE MOST FREQUENT LABEL IN THE TRAINING SET
•PRIOR ALWAYS PREDICTS THE CLASS THAT MAXIMIZES THE CLASS PRIOR LIKE MOSTFREQUENT AND PREDICTPROBA RETURNS THE CLASS PRIOR
•UNIFORM GENERATES PREDICTIONS UNIFORMLY AT RANDOM
•CONSTANT ALWAYS PREDICTS A CONSTANT LABEL THAT IS PROVIDED BY THE USER A MAJOR MOTIVATION OF THIS METHOD IS F1SCORING WHEN THE POSITIVE CLASS IS IN THE MINORITY
NOTE THAT WITH ALL THESE STRATEGIES THE PREDICT METHOD COMPLETELY IGNORES THE INPUT DATA
TO ILLUSTRATE DUMMYCLASSIFIER FIRST LET'S CREATE AN IMBALANCED DATASET
FROM SKLEARNDATASETS IMPORT LOADIRIS
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
IRIS LOADIRIS
X Y IRISDATA IRISTARGET
YY 1 1
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y RANDOMSTATE0
NEXT LET'S COMPARE THE ACCURACY OF SVC ANDMOSTFREQUENT
FROM SKLEARNDUMMY IMPORT DUMMYCLASSIFIER
FROM SKLEARNSVM IMPORT SVC
CLF SVCKERNELLINEAR C1FITXTRAIN YTRAIN
CLFSCOREXTEST YTEST
063
CLF DUMMYCLASSIFIERSTRATEGYMOSTFREQUENT RANDOMSTATE0
CLFFITXTRAIN YTRAIN
DUMMYCLASSIFIERCONSTANTNONE RANDOMSTATE0 STRATEGYMOSTFREQUENT
CLFSCOREXTEST YTEST
057
WE SEE THAT SVC DOESN'T DO MUCH BETTER THAN A DUMMY CLASSIFIER NOW LET'S CHANGE THE KERNEL

SCIKITLEARN USER GUIDE RELEASE 0213
CLF SVCGAMMASCALE KERNELRBF C1FITXTRAIN YTRAIN
CLFSCOREXTEST YTEST
094
WE SEE THAT THE ACCURACY WAS BOOSTED TO ALMOST 100 A CROSS VALIDATION STRATEGY IS RECOMMENDED FOR A BETTER ESTIMATE OF THE ACCURACY IF IT IS NOT TOO CPU COSTLY FOR MORE INFORMATION SEE THE CROSSVALIDATION EVALUATING ESTIMATOR PERFORMANCE SECTION MOREOVER IF YOU WANT TO OPTIMIZE OVER THE PARAMETER SPACE IT IS HIGHLY RECOMMENDED TO USE AN APPROPRIATE METHODOLOGY SEE THE TUNING THE HYPERPARAMETERS OF AN ESTIMATOR SECTION FOR DETAILS
MORE GENERALLY WHEN THE ACCURACY OF A CLASSIFIER IS TOO CLOSE TO RANDOM IT PROBABLY MEANS THAT SOMETHING WENT WRONG FEATURES ARE NOT HELPFUL A HYPERPARAMETER IS NOT CORRECTLY TUNED THE CLASSIFIER IS SUFFERING FROM CLASS IMBALANCE ETC
DUMMYREGRESSOR ALSO IMPLEMENTS FOUR SIMPLE RULES OF THUMB FOR REGRESSION
•MEAN ALWAYS PREDICTS THE MEAN OF THE TRAINING TARGETS
•MEDIAN ALWAYS PREDICTS THE MEDIAN OF THE TRAINING TARGETS
•QUANTILE ALWAYS PREDICTS A USER PROVIDED QUANTILE OF THE TRAINING TARGETS
•CONSTANT ALWAYS PREDICTS A CONSTANT VALUE THAT IS PROVIDED BY THE USER
IN ALL THESE STRATEGIES THE PREDICT METHOD COMPLETELY IGNORES THE INPUT DATA
334 MODEL PERSISTENCE
AFTER TRAINING A SCIKITLEARN MODEL IT IS DESIRABLE TO HAVE A WAY TO PERSIST THE MODEL FOR FUTURE USE WITHOUT HAVING TO RETRAIN THE FOLLOWING SECTION GIVES YOU AN EXAMPLE OF HOW TO PERSIST A MODEL WITH PICKLE WE’LL ALSO REVIEW A FEW SECURITY AND MAINTAINABILITY ISSUES WHEN WORKING WITH PICKLE SERIALIZATION
AN ALTERNATIVE TO PICKLING IS TO EXPORT THE MODEL TO ANOTHER FORMAT USING ONE OF THE MODEL EXPORT TOOLS LISTED UNDER RELATED PROJECTS UNLIKE PICKLING ONCE EXPORTED YOU CANNOT RECOVER THE FULL SCIKITLEARN ESTIMATOR OBJECT BUT YOU CAN DEPLOY THE MODEL FOR PREDICTION USUALLY BY USING TOOLS SUPPORTING OPEN MODEL INTERCHANGE FORMATS SUCH AS ‘ONNX‘ OR‘PMML‘
PERSISTENCE EXAMPLE
IT IS POSSIBLE TO SAVE A MODEL IN SCIKITLEARN BY USING PYTHON’S BUILTIN PERSISTENCE MODEL NAMELY PICKLE
 FROM SKLEARN IMPORT SVM
 FROM SKLEARN IMPORT DATASETS
CLF SVMSVCGAMMASCALE
IRIS DATASETSLOADIRIS
X Y IRISDATA IRISTARGET
CLFFITX Y
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMASCALE KERNELRBF
MAXITER1 PROBABILITYFALSE RANDOMSTATENONE SHRINKINGTRUE
TOL0001 VERBOSEFALSE
 IMPORT PICKLE
S PICKLEDUMPSCLF
CLF2 PICKLELOADSS
CLF2PREDICTX01
ARRAY0
Y0
0
568 CHAPTER 3 USER GUIDE

IN THE SPECIFIC CASE OF SCIKITLEARN IT MAY BE BETTER TO USE JOBLIB'S REPLACEMENT OF PICKLE DUMP LOAD WHICH IS MORE EFFICIENT ON OBJECTS THAT CARRY LARGE NUMPY ARRAYS INTERNALLY AS IS OFTEN THE CASE FOR FITTED SCIKITLEARN ESTIMATORS BUT CAN ONLY PICKLE TO THE DISK AND NOT TO A STRING

```
FROM JOBLIB IMPORT DUMP LOAD
DUMPCLF FILENAMEJOBLIB
```

LATER YOU CAN LOAD BACK THE PICKLED MODEL POSSIBLY IN ANOTHER PYTHON PROCESS WITH

```
CLF LOADFILENAMEJOBLIB
```

NOTEDUMP ANDLOAD FUNCTIONS ALSO ACCEPT FILELIKE OBJECT INSTEAD OF FILENAMES MORE INFORMATION ON DATA PERSISTENCE WITH JOBLIB IS AVAILABLE HERE

SECURITY MAINTAINABILITY LIMITATIONS

PICKLE AND JOBLIB BY EXTENSION HAS SOME ISSUES REGARDING MAINTAINABILITY AND SECURITY BECAUSE OF THIS

- NEVER UNPICKLE UNTRUSTED DATA AS IT COULD LEAD TO MALICIOUS CODE BEING EXECUTED UPON LOADING
- WHILE MODELS SAVED USING ONE VERSION OF SCIKITLEARN MIGHT LOAD IN OTHER VERSIONS THIS IS ENTIRELY UNSUPPORTED AND INADVISABLE IT SHOULD ALSO BE KEPT IN MIND THAT OPERATIONS PERFORMED ON SUCH DATA COULD GIVE DIFFERENT AND UNEXPECTED RESULTS

IN ORDER TO REBUILD A SIMILAR MODEL WITH FUTURE VERSIONS OF SCIKITLEARN ADDITIONAL METADATA SHOULD BE SAVED ALONG THE PICKLED MODEL

- THE TRAINING DATA EG A REFERENCE TO AN IMMUTABLE SNAPSHOT
- THE PYTHON SOURCE CODE USED TO GENERATE THE MODEL
- THE VERSIONS OF SCIKITLEARN AND ITS DEPENDENCIES
- THE CROSS VALIDATION SCORE OBTAINED ON THE TRAINING DATA

THIS SHOULD MAKE IT POSSIBLE TO CHECK THAT THE CROSSVALIDATION SCORE IS IN THE SAME RANGE AS BEFORE

SINCE A MODEL INTERNAL REPRESENTATION MAY BE DIFFERENT ON TWO DIFFERENT ARCHITECTURES DUMPING A MODEL ON ONE ARCHITECTURE AND LOADING IT ON ANOTHER ARCHITECTURE IS NOT SUPPORTED

IF YOU WANT TO KNOW MORE ABOUT THESE ISSUES AND EXPLORE OTHER POSSIBLE SERIALIZATION METHODS PLEASE REFER TO THIS TALK BY ALEX GAYNOR

335 VALIDATION CURVES PLOTTING SCORES TO EVALUATE MODELS

EVERY ESTIMATOR HAS ITS ADVANTAGES AND DRAWBACKS ITS GENERALIZATION ERROR CAN BE DECOMPOSED IN TERMS OF BIAS VARIANCE AND NOISE THE BIAS OF AN ESTIMATOR IS ITS AVERAGE ERROR FOR DIFFERENT TRAINING SETS THE VARIANCE OF AN ESTIMATOR INDICATES HOW SENSITIVE IT IS TO VARYING TRAINING SETS NOISE IS A PROPERTY OF THE DATA

IN THE FOLLOWING PLOT WE SEE A FUNCTION □□ COS3 2□□AND SOME NOISY SAMPLES FROM THAT FUNCTION WE USE THREE DIFFERENT ESTIMATORS TO FIT THE FUNCTION LINEAR REGRESSION WITH POLYNOMIAL FEATURES OF DEGREE 1 4 AND 15 WE SEE THAT THE FIRST ESTIMATOR CAN AT BEST PROVIDE ONLY A POOR FIT TO THE SAMPLES AND THE TRUE FUNCTION BECAUSE IT IS TOO SIMPLE HIGH BIAS THE SECOND ESTIMATOR APPROXIMATES IT ALMOST PERFECTLY AND THE LAST ESTIMATOR APPROXIMATES THE TRAINING DATA PERFECTLY BUT DOES NOT FIT THE TRUE FUNCTION VERY WELL IE IT IS VERY SENSITIVE TO VARYING TRAINING DATA HIGH VARIANCE BIAS AND VARIANCE ARE INHERENT PROPERTIES OF ESTIMATORS AND WE USUALLY HAVE TO SELECT LEARNING ALGORITHMS AND HYPER PARAMETERS SO THAT BOTH BIAS AND VARIANCE ARE AS LOW AS POSSIBLE SEE BIASVARIANCE DILEMMA ANOTHER WAY TO REDUCE

THE VARIANCE OF A MODEL IS TO USE MORE TRAINING DATA HOWEVER YOU SHOULD ONLY COLLECT MORE TRAINING DATA IF THE TRUE FUNCTION IS TOO COMPLEX TO BE APPROXIMATED BY AN ESTIMATOR WITH A LOWER VARIANCE
IN THE SIMPLE ONEDIMENSIONAL PROBLEM THAT WE HAVE SEEN IN THE EXAMPLE IT IS EASY TO SEE WHETHER THE ESTIMATOR SUFFERS FROM BIAS OR VARIANCE HOWEVER IN HIGHDIMENSIONAL SPACES MODELS CAN BECOME VERY DIFFICULT TO VISUALIZE FOR THIS REASON IT IS OFTEN HELPFUL TO USE THE TOOLS DESCRIBED BELOW
EXAMPLES
•UNDERFITTING VS OVERFITTING
•PLOTTING VALIDATION CURVES
•PLOTTING LEARNING CURVES
VALIDATION CURVE
TO VALIDATE A MODEL WE NEED A SCORING FUNCTION SEE MODEL EVALUATION QUANTIFYING THE QUALITY OF PREDICTIONS FOR EXAMPLE ACCURACY FOR CLASSIFIERS THE PROPER WAY OF CHOOSING MULTIPLE HYPERPARAMETERS OF AN ESTIMATOR ARE OF COURSE GRID SEARCH OR SIMILAR METHODS SEE TUNING THE HYPERPARAMETERS OF AN ESTIMATOR THAT SELECT THE HYPERPARAMETER WITH THE MAXIMUM SCORE ON A VALIDATION SET OR MULTIPLE VALIDATION SETS NOTE THAT IF WE OPTIMIZED THE HYPERPARAMETERS BASED ON A VALIDATION SCORE THE VALIDATION SCORE IS BIASED AND NOT A GOOD ESTIMATE OF THE GENERALIZATION ANY LONGER TO GET A PROPER ESTIMATE OF THE GENERALIZATION WE HAVE TO COMPUTE THE SCORE ON ANOTHER TEST SET
HOWEVER IT IS SOMETIMES HELPFUL TO PLOT THE INFLUENCE OF A SINGLE HYPERPARAMETER ON THE TRAINING SCORE AND THE VALIDATION SCORE TO FIND OUT WHETHER THE ESTIMATOR IS OVERFITTING OR UNDERFITTING FOR SOME HYPERPARAMETER VALUES
THE FUNCTION VALIDATIONCURVE CAN HELP IN THIS CASE

```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT VALIDATIONCURVE
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNLINEARMODEL IMPORT RIDGE
NPRANDOMSEED0
IRIS  LOADIRIS
X Y  IRISDATA IRISTARGET
INDICES  NPARANGEYSHAPE0
NPRANDOMSHUFFLEINDICES
```

```
X Y  XINDICES YINDICES
TRAINSCORES VALIDSCORES  VALIDATIONCURVERIDGE X Y ALPHA
 NPLOGSPACE7 3 3
 CV5
TRAINSCORES
ARRAY093 094 092 091 092
093 094 092 091 092
051 052 049 047 049
VALIDSCORES
ARRAY090 084 094 096 093
090 084 094 096 093
046 025 050 049 052
```
IF THE TRAINING SCORE AND THE VALIDATION SCORE ARE BOTH LOW THE ESTIMATOR WILL BE UNDERFITTING IF THE TRAINING SCORE IS HIGH AND THE VALIDATION SCORE IS LOW THE ESTIMATOR IS OVERFITTING AND OTHERWISE IT IS WORKING VERY WELL A LOW TRAINING SCORE AND A HIGH VALIDATION SCORE IS USUALLY NOT POSSIBLE ALL THREE CASES CAN BE FOUND IN THE PLOT BELOW WHERE WE VARY THE PARAMETER □OF AN SVM ON THE DIGITS DATASET

LEARNING CURVE

A LEARNING CURVE SHOWS THE VALIDATION AND TRAINING SCORE OF AN ESTIMATOR FOR VARYING NUMBERS OF TRAINING SAMPLES IT IS A TOOL TO FIND OUT HOW MUCH WE BENEFIT FROM ADDING MORE TRAINING DATA AND WHETHER THE ESTIMATOR SUFFERS MORE FROM A VARIANCE ERROR OR A BIAS ERROR IF BOTH THE VALIDATION SCORE AND THE TRAINING SCORE CONVERGE TO A VALUE THAT IS TOO LOW WITH INCREASING SIZE OF THE TRAINING SET WE WILL NOT BENEFIT MUCH FROM MORE TRAINING DATA IN THE FOLLOWING PLOT YOU CAN SEE AN EXAMPLE NAIVE BAYES ROUGHLY CONVERGES TO A LOW SCORE

WE WILL PROBABLY HAVE TO USE AN ESTIMATOR OR A PARAMETRIZATION OF THE CURRENT ESTIMATOR THAT CAN LEARN MORE COMPLEX CONCEPTS IE HAS A LOWER BIAS IF THE TRAINING SCORE IS MUCH GREATER THAN THE VALIDATION SCORE FOR THE MAXIMUM NUMBER OF TRAINING SAMPLES ADDING MORE TRAINING SAMPLES WILL MOST LIKELY INCREASE GENERALIZATION IN THE FOLLOWING PLOT YOU CAN SEE THAT THE SVM COULD BENEFIT FROM MORE TRAINING EXAMPLES

WE CAN USE THE FUNCTION LEARNINGCURVE TO GENERATE THE VALUES THAT ARE REQUIRED TO PLOT SUCH A LEARNING CURVE NUMBER OF SAMPLES THAT HAVE BEEN USED THE AVERAGE SCORES ON THE TRAINING SETS AND THE AVERAGE SCORES ON THE VALIDATION SETS

```
 FROM SKLEARNMODELSELECTION IMPORT LEARNINGCURVE
 FROM SKLEARNSVM IMPORT SVC
```

```
TRAINSIZES TRAINSCORES VALIDSCORES  LEARNINGCURVE
 SVCKERNELLINEAR X Y TRAINSIZES50 80 110 CV5
TRAINSIZES
ARRAY 50 80 110
TRAINSCORES
ARRAY098 098  098 098 098
098 1  098 098 098
098 1  098 098 099
VALIDSCORES
ARRAY1  093 1  1  096
1  096 1  1  096
1  096 1  1  096
```

34 INSPECTION

341 PARTIAL DEPENDENCE PLOTS

PARTIAL DEPENDENCE PLOTS PDP SHOW THE DEPENDENCE BETWEEN THE TARGET RESPONSE1AND A SET OF ‘TARGET’ FEATURES MARGINALIZING OVER THE VALUES OF ALL OTHER FEATURES THE ‘COMPLEMENT’ FEATURES INTUITIVELY WE CAN INTERPRET THE PARTIAL DEPENDENCE AS THE EXPECTED TARGET RESPONSE AS A FUNCTION OF THE ‘TARGET’ FEATURES

DUE TO THE LIMITS OF HUMAN PERCEPTION THE SIZE OF THE TARGET FEATURE SET MUST BE SMALL USUALLY ONE OR TWO THUS THE TARGET FEATURES ARE USUALLY CHOSEN AMONG THE MOST IMPORTANT FEATURES

THE FIGURE BELOW SHOWS FOUR ONEWAY AND ONE TWOWAY PARTIAL DEPENDENCE PLOTS FOR THE CALIFORNIA HOUSING DATASET WITH AGRADIENTBOOSTINGREGRESSOR

ONEWAY PDPS TELL US ABOUT THE INTERACTION BETWEEN THE TARGET RESPONSE AND THE TARGET FEATURE EG LINEAR NONLINEAR THE UPPER LEFT PLOT IN THE ABOVE FIGURE SHOWS THE EFFECT OF THE MEDIAN INCOME IN A DISTRICT ON THE MEDIAN HOUSE PRICE

1FOR CLASSIFICATION THE TARGET RESPONSE MAY BE THE PROBABILITY OF A CLASS THE POSITIVE CLASS FOR BINARY CLASSIFICATION OR THE D

WE CAN CLEARLY SEE A LINEAR RELATIONSHIP AMONG THEM NOTE THAT PDPS ASSUME THAT THE TARGET FEATURES ARE INDEPENDENT FROM THE COMPLEMENT FEATURES AND THIS ASSUMPTION IS OFTEN VIOLATED IN PRACTICE
PDPS WITH TWO TARGET FEATURES SHOW THE INTERACTIONS AMONG THE TWO FEATURES FOR EXAMPLE THE TWOVARIABLE PDP IN THE ABOVE FIGURE SHOWS THE DEPENDENCE OF MEDIAN HOUSE PRICE ON JOINT VALUES OF HOUSE AGE AND AVERAGE OCCUPANTS PER HOUSEHOLD WE CAN CLEARLY SEE AN INTERACTION BETWEEN THE TWO FEATURES FOR AN AVERAGE OCCUPANCY GREATER THAN TWO THE HOUSE PRICE IS NEARLY INDEPENDENT OF THE HOUSE AGE WHEREAS FOR VALUES LESS THAN 2 THERE IS A STRONG DEPENDENCE ON AGE
THESKLEARNINSPECTION MODULE PROVIDES A CONVENIENCE FUNCTION PLOTPARTIALDEPENDENCE TO CRE
ATE ONEWAY AND TWOWAY PARTIAL DEPENDENCE PLOTS IN THE BELOW EXAMPLE WE SHOW HOW TO CREATE A GRID OF PARTIAL DEPENDENCE PLOTS TWO ONEWAY PDPS FOR THE FEATURES 0AND1AND A TWOWAY PDP BETWEEN THE TWO FEATURES
```
 FROM SKLEARNDATASETS IMPORT MAKEHASTIE102
 FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGCLASSIFIER
 FROM SKLEARNINSPECTION IMPORT PLOTPARTIALDEPENDENCE
X Y  MAKEHASTIE102RANDOMSTATE0
CLF  GRADIENTBOOSTINGCLASSIFIERNESTIMATORS100 LEARNINGRATE10
 MAXDEPTH1 RANDOMSTATE0FITX Y
FEATURES  0 1 0 1
PLOTPARTIALDEPENDENCECLF X FEATURES
```
YOU CAN ACCESS THE NEWLY CREATED FIGURE AND AXES OBJECTS USING PLTGCF ANDPLTGCA
FOR MULTICLASS CLASSIFICATION YOU NEED TO SET THE CLASS LABEL FOR WHICH THE PDPS SHOULD BE CREATED VIA THE TARGET ARGUMENT
```
 FROM SKLEARNDATASETS IMPORT LOADIRIS
IRIS  LOADIRIS
MCCLF  GRADIENTBOOSTINGCLASSIFIERNESTIMATORS10
 MAXDEPTH1FITIRISDATA IRISTARGET
FEATURES  3 2 3 2
PLOTPARTIALDEPENDENCEMCCLF X FEATURES TARGET0
```
THE SAME PARAMETER TARGET IS USED TO SPECIFY THE TARGET IN MULTIOUTPUT REGRESSION SETTINGS
IF YOU NEED THE RAW VALUES OF THE PARTIAL DEPENDENCE FUNCTION RATHER THAN THE PLOTS YOU CAN USE THE SKLEARN INSPECTIONPARTIALDEPENDENCE FUNCTION
```
 FROM SKLEARNINSPECTION IMPORT PARTIALDEPENDENCE
PDP AXES  PARTIALDEPENDENCECLF X 0
PDP
ARRAY 2466 2466
AXES
ARRAY1624 1592
```
THE VALUES AT WHICH THE PARTIAL DEPENDENCE SHOULD BE EVALUATED ARE DIRECTLY GENERATED FROM X FOR 2WAY PAR TIAL DEPENDENCE A 2DGRID OF VALUES IS GENERATED THE VALUES FIELD RETURNED BY SKLEARNINSPECTION PARTIALDEPENDENCE GIVES THE ACTUAL VALUES USED IN THE GRID FOR EACH TARGET FEATURE THEY ALSO CORRESPOND TO THE AXIS OF THE PLOTS
FOR EACH VALUE OF THE ‘TARGET’ FEATURES IN THE GRID THE PARTIAL DEPENDENCE FUNCTION NEEDS TO MARGINALIZE THE PREDICTIONS OF THE ESTIMATOR OVER ALL POSSIBLE VALUES OF THE ‘COMPLEMENT’ FEATURES WITH THE BRUTE METHOD THIS IS DONE BY REPLACING EVERY TARGET FEATURE VALUE OF XBY THOSE IN THE GRID AND COMPUTING THE AVERAGE PREDICTION
IN DECISION TREES THIS CAN BE EVALUATED EFFICIENTLY WITHOUT REFERENCE TO THE TRAINING DATA RECURSION METHOD FOR EACH GRID POINT A WEIGHTED TREE TRAVERSAL IS PERFORMED IF A SPLIT NODE INVOLVES A ‘TARGET’ FEATURE THE CORRESPONDING LEFT OR RIGHT BRANCH IS FOLLOWED OTHERWISE BOTH BRANCHES ARE FOLLOWED EACH BRANCH IS WEIGHTED BY THE FRACTION OF

TRAINING SAMPLES THAT ENTERED THAT BRANCH FINALLY THE PARTIAL DEPENDENCE IS GIVEN BY A WEIGHTED AVERAGE OF ALL VISITED LEAVES NOTE THAT WITH THE RECURSION METHODXIS ONLY USED TO GENERATE THE GRID NOT TO COMPUTE THE AVERAGED PREDICTIONS THE AVERAGED PREDICTIONS WILL ALWAYS BE COMPUTED ON THE DATA WITH WHICH THE TREES WERE TRAINED

EXAMPLES

•PARTIAL DEPENDENCE PLOTS

REFERENCES

35 DATASET TRANSFORMATIONS

SCIKITLEARN PROVIDES A LIBRARY OF TRANSFORMERS WHICH MAY CLEAN SEE PREPROCESSING DATA REDUCE SEE UNSUPERVISED DIMENSIONALITY REDUCTION EXPAND SEE KERNEL APPROXIMATION OR GENERATE SEE FEATURE EXTRACTION FEATURE REPRESENTATIONS

LIKE OTHER ESTIMATORS THESE ARE REPRESENTED BY CLASSES WITH A FIT METHOD WHICH LEARNS MODEL PARAMETERS EG MEAN AND STANDARD DEVIATION FOR NORMALIZATION FROM A TRAINING SET AND A TRANSFORM METHOD WHICH APPLIES THIS TRANSFORMATION MODEL TO UNSEEN DATA FITTRANSFORM MAY BE MORE CONVENIENT AND EFFICIENT FOR MODELLING AND TRANSFORMING THE TRAINING DATA SIMULTANEOUSLY

COMBINING SUCH TRANSFORMERS EITHER IN PARALLEL OR SERIES IS COVERED IN PIPELINES AND COMPOSITE ESTIMATORS PAIR WISE METRICS AFFINITIES AND KERNELS COVERS TRANSFORMING FEATURE SPACES INTO AFFINITY MATRICES WHILE TRANSFORMING THE PREDICTION TARGET Y CONSIDERS TRANSFORMATIONS OF THE TARGET SPACE EG CATEGORICAL LABELS FOR USE IN SCIKITLEARN

351 PIPELINES AND COMPOSITE ESTIMATORS

TRANSFORMERS ARE USUALLY COMBINED WITH CLASSIFIERS REGRESSORS OR OTHER ESTIMATORS TO BUILD A COMPOSITE ESTIMATOR THE MOST COMMON TOOL IS A PIPELINE PIPELINE IS OFTEN USED IN COMBINATION WITH FEATUREUNION WHICH CONCATENATES THE OUTPUT OF TRANSFORMERS INTO A COMPOSITE FEATURE SPACE TRANSFORMEDTARGETREGRESSOR DEALS WITH TRANSFORMING THE TARGET IE LOGTRANSFORM Y IN CONTRAST PIPELINES ONLY TRANSFORM THE OBSERVED DATA X

PIPELINE CHAINING ESTIMATORS

PIPELINE CAN BE USED TO CHAIN MULTIPLE ESTIMATORS INTO ONE THIS IS USEFUL AS THERE IS OFTEN A FIXED SEQUENCE OF STEPS IN PROCESSING THE DATA FOR EXAMPLE FEATURE SELECTION NORMALIZATION AND CLASSIFICATION PIPELINE SERVES MULTIPLE PURPOSES HERE

CONVENIENCE AND ENCAPSULATION YOU ONLY HAVE TO CALL FIT ANDPREDICT ONCE ON YOUR DATA TO FIT A WHOLE SEQUENCE OF ESTIMATORS

JOINT PARAMETER SELECTION YOU CAN GRID SEARCH OVER PARAMETERS OF ALL ESTIMATORS IN THE PIPELINE AT ONCE

SAFETY PIPELINES HELP AVOID LEAKING STATISTICS FROM YOUR TEST DATA INTO THE TRAINED MODEL IN CROSSVALIDATION BY ENSURING THAT THE SAME SAMPLES ARE USED TO TRAIN THE TRANSFORMERS AND PREDICTORS

ALL ESTIMATORS IN A PIPELINE EXCEPT THE LAST ONE MUST BE TRANSFORMERS IE MUST HAVE A TRANSFORM METHOD THE LAST ESTIMATOR MAY BE ANY TYPE TRANSFORMER CLASSIFIER ETC

USAGE
CONSTRUCTION
THEPIPELINE IS BUILT USING A LIST OF KEY VALUE PAIRS WHERE THE KEY IS A STRING CONTAINING THE NAME YOU WANT TO GIVE THIS STEP AND VALUE IS AN ESTIMATOR OBJECT

```
 FROM SKLEARNPIPELINE IMPORT PIPELINE
 FROM SKLEARNSVM IMPORT SVC
 FROM SKLEARNDECOMPOSITION IMPORT PCA
ESTIMATORS  REDUCEDIM PCA CLF SVC
PIPE  PIPELINEESTIMATORS
PIPE
PIPELINEMEMORYNONE
STEPSREDUCEDIM PCACOPYTRUE
CLF SVCC10 VERBOSEFALSE
```

THE UTILITY FUNCTION MAKEPIPELINE IS A SHORTHAND FOR CONSTRUCTING PIPELINES IT TAKES A VARIABLE NUMBER OF ESTIMATORS AND RETURNS A PIPELINE FILLING IN THE NAMES AUTOMATICALLY

```
 FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
 FROM SKLEARNNAIVEBAYES IMPORT MULTINOMIALNB
 FROM SKLEARNPREPROCESSING IMPORT BINARIZER
MAKEPIPELINEBINARIZER MULTINOMIALNB
PIPELINEMEMORYNONE
STEPSBINARIZER BINARIZERCOPYTRUE THRESHOLD00
MULTINOMIALNB MULTINOMIALNBALPHA10
CLASSPRIORNONE
FITPRIORTRUE
VERBOSEFALSE
```

ACCESSING STEPS

THE ESTIMATORS OF A PIPELINE ARE STORED AS A LIST IN THE STEPS ATTRIBUTE BUT CAN BE ACCESSED BY INDEX OR NAME BY INDEXING WITH IDX THE PIPELINE

```
PIPESTEPS0
REDUCEDIM PCACOPYTRUE ITERATEDPOWERAUTO NCOMPONENTSNONE
RANDOMSTATENONE SVDSOLVERAUTO TOL00
WHITENFALSE
PIPE0
PCACOPYTRUE ITERATEDPOWERAUTO NCOMPONENTSNONE RANDOMSTATENONE
SVDSOLVERAUTO TOL00 WHITENFALSE
PIPEREDUCEDIM
PCACOPYTRUE
```

PIPELINE’SNAMEDSTEPS ATTRIBUTE ALLOWS ACCESSING STEPS BY NAME WITH TAB COMPLETION IN INTERACTIVE ENVIRONMENTS

```
PIPENAMEDSTEPSREDUCEDIM ISPIPEREDUCEDIM
TRUE
```

A SUBPIPELINE CAN ALSO BE EXTRACTED USING THE SLICING NOTATION COMMONLY USED FOR PYTHON SEQUENCES SUCH AS LISTS OR STRINGS ALTHOUGH ONLY A STEP OF 1 IS PERMITTED THIS IS CONVENIENT FOR PERFORMING ONLY SOME OF THE TRANSFORMATIONS OR THEIR INVERSE

PIPE1
PIPELINEMEMORYNONE STEPSREDUCEDIM PCACOPYTRUE
PIPE1
PIPELINEMEMORYNONE STEPSCLF SVCC10
NESTED PARAMETERS
PARAMETERS OF THE ESTIMATORS IN THE PIPELINE CAN BE ACCESSED USING THE ESTIMATORPARAMETER SYNTAX
PIPESETPARAMSCLFC10
PIPELINEMEMORYNONE
STEPSREDUCEDIM PCACOPYTRUE ITERATEDPOWERAUTO
CLF SVCC10 CACHESIZE200 CLASSWEIGHTNONE
VERBOSEFALSE
THIS IS PARTICULARLY IMPORTANT FOR DOING GRID SEARCHES
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
PARAMGRID DICTREDUCEDIMNCOMPONENTS2 5 10
CLFC01 10 100
GRIDSEARCH GRIDSEARCHCVPIPE PARAMGRIDPARAMGRID
INDIVIDUAL STEPS MAY ALSO BE REPLACED AS PARAMETERS AND NONFINAL STEPS MAY BE IGNORED BY SETTING THEM TO
PASSTHROUGH
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
PARAMGRID DICTREDUCEDIMPASSTHROUGH PCA5 PCA10
CLFSVC LOGISTICREGRESSION
CLFC01 10 100
GRIDSEARCH GRIDSEARCHCVPIPE PARAMGRIDPARAMGRID
THE ESTIMATORS OF THE PIPELINE CAN BE RETRIEVED BY INDEX
PIPE0
PCACOPYTRUE
OR BY NAME
PIPEREDUCEDIM
PCACOPYTRUE
EXAMPLES
•PIPELINE ANOVA SVM
•SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
•PIPELINING CHAINING A PCA AND A LOGISTIC REGRESSION
•EXPLICIT FEATURE MAP APPROXIMATION FOR RBF KERNELS
•SVMANOVA SVM WITH UNIVARIATE FEATURE SELECTION
•SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV

SEE ALSO
•TUNING THE HYPERPARAMETERS OF AN ESTIMATOR
NOTES
CALLINGFIT ON THE PIPELINE IS THE SAME AS CALLING FIT ON EACH ESTIMATOR IN TURN TRANSFORM THE INPUT AND PASS IT ON TO THE NEXT STEP THE PIPELINE HAS ALL THE METHODS THAT THE LAST ESTIMATOR IN THE PIPELINE HAS IE IF THE LAST ESTIMATOR IS A CLASSIFIER THE PIPELINE CAN BE USED AS A CLASSIFIER IF THE LAST ESTIMATOR IS A TRANSFORMER AGAIN SO IS THE PIPELINE
CACHING TRANSFORMERS AVOID REPEATED COMPUTATION
FITTING TRANSFORMERS MAY BE COMPUTATIONALLY EXPENSIVE WITH ITS MEMORY PARAMETER SET PIPELINE WILL CACHE EACH TRANSFORMER AFTER CALLING FIT THIS FEATURE IS USED TO AVOID COMPUTING THE FIT TRANSFORMERS WITHIN A PIPELINE IF THE PARAMETERS AND INPUT DATA ARE IDENTICAL A TYPICAL EXAMPLE IS THE CASE OF A GRID SEARCH IN WHICH THE TRANSFORMERS CAN BE FITTED ONLY ONCE AND REUSED FOR EACH CONFIGURATION
THE PARAMETER MEMORY IS NEEDED IN ORDER TO CACHE THE TRANSFORMERS MEMORY CAN BE EITHER A STRING CONTAINING THE DIRECTORY WHERE TO CACHE THE TRANSFORMERS OR A JOBLIBMEMORY OBJECT
```
 FROM TEMPFILE IMPORT MKDTEMP
 FROM SHUTIL IMPORT RMTREE
 FROM SKLEARNDECOMPOSITION IMPORT PCA
 FROM SKLEARNSVM IMPORT SVC
 FROM SKLEARNPIPELINE IMPORT PIPELINE
ESTIMATORS  REDUCEDIM PCA CLF SVC
CACHEDIR  MKDTEMP
PIPE  PIPELINEESTIMATORS MEMORYCACHEDIR
PIPE
PIPELINE
STEPSREDUCEDIM PCACOPYTRUE
CLF SVCC10 VERBOSEFALSE
 CLEAR THE CACHE DIRECTORY WHEN YOU DONT NEED IT ANYMORE
RMTREECACHEDIR
```
WARNING SIDE EFFECT OF CACHING TRANSFORMERS
USING APIPELINE WITHOUT CACHE ENABLED IT IS POSSIBLE TO INSPECT THE ORIGINAL INSTANCE SUCH AS
```
 FROM SKLEARNDATASETS IMPORT LOADDIGITS
DIGITS  LOADDIGITS
PCA1  PCA
SVM1  SVCGAMMASCALE
PIPE  PIPELINEREDUCEDIM PCA1 CLF SVM1
PIPEFITDIGITSDATA DIGITSTARGET

PIPELINEMEMORYNONE
STEPSREDUCEDIM PCA CLF SVC
VERBOSEFALSE
 THE PCA INSTANCE CAN BE INSPECTED DIRECTLY
PRINTPCA1COMPONENTS
177484909E19  407058917E18
```

ENABLING CACHING TRIGGERS A CLONE OF THE TRANSFORMERS BEFORE FITTING THEREFORE THE TRANSFORMER INSTANCE GIVEN TO THE PIPELINE CANNOT BE INSPECTED DIRECTLY IN FOLLOWING EXAMPLE ACCESSING THE PCA INSTANCEPCA2 WILL RAISE AN ATTRIBUTEERROR SINCEPCA2 WILL BE AN UNFITTED TRANSFORMER INSTEAD USE THE ATTRIBUTE NAMEDSTEPS TO INSPECT ESTIMATORS WITHIN THE PIPELINE

```
CACHEDIR  MKDTEMP
PCA2  PCA
SVM2  SVCGAMMASCALE
CACHEDPIPE  PIPELINEREDUCEDIM PCA2 CLF SVM2
 MEMORYCACHEDIR
CACHEDPIPEFITDIGITSDATA DIGITSTARGET

PIPELINEMEMORY
STEPSREDUCEDIM PCA CLF SVC
VERBOSEFALSE
PRINTCACHEDPIPENAMEDSTEPSREDUCEDIMCOMPONENTS

177484909E19  407058917E18
 REMOVE THE CACHE DIRECTORY
RMTREECACHEDIR
```

EXAMPLES

•SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV

TRANSFORMING TARGET IN REGRESSION

TRANSFORMEDTARGETREGRESSOR TRANSFORMS THE TARGETS YBEFORE FITTING A REGRESSION MODEL THE PREDICTIONS ARE MAPPED BACK TO THE ORIGINAL SPACE VIA AN INVERSE TRANSFORM IT TAKES AS AN ARGUMENT THE REGRESSOR THAT WILL BE USED FOR PREDICTION AND THE TRANSFORMER THAT WILL BE APPLIED TO THE TARGET VARIABLE

```
 IMPORT NUMPY AS NP
 FROM SKLEARNDATASETS IMPORT LOADBOSTON
 FROM SKLEARNCOMPOSE IMPORT TRANSFORMEDTARGETREGRESSOR
 FROM SKLEARNPREPROCESSING IMPORT QUANTILETRANSFORMER
 FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION
 FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
BOSTON  LOADBOSTON
X  BOSTONDATA
Y  BOSTONTARGET
TRANSFORMER  QUANTILETRANSFORMEROUTPUTDISTRIBUTIONNORMAL
REGRESSOR  LINEARREGRESSION
REGR  TRANSFORMEDTARGETREGRESSORREGRESSORREGRESSOR
 TRANSFORMERTRANSFORMER
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLITX Y RANDOMSTATE0
REGRFITXTRAIN YTRAIN
TRANSFORMEDTARGETREGRESSOR
PRINTR2 SCORE 02FFORMATREGRSCOREXTEST YTEST
R2 SCORE 067
RAWTARGETREGR  LINEARREGRESSIONFITXTRAIN YTRAIN
PRINTR2 SCORE 02FFORMATRAWTARGETREGRSCOREXTEST YTEST
R2 SCORE 064
```

FOR SIMPLE TRANSFORMATIONS INSTEAD OF A TRANSFORMER OBJECT A PAIR OF FUNCTIONS CAN BE PASSED DEFINING THE TRANSFOR
MATION AND ITS INVERSE MAPPING

```
 DEF FUNCX
 RETURN NPLOGX
 DEF INVERSEFUNCX
 RETURN NPEXPX
```

SUBSEQUENTLY THE OBJECT IS CREATED AS

```
REGR  TRANSFORMEDTARGETREGRESSORREGRESSORREGRESSOR
 FUNCFUNC
 INVERSEFUNCINVERSEFUNC
REGRFITXTRAIN YTRAIN
TRANSFORMEDTARGETREGRESSOR
PRINTR2 SCORE 02FFORMATREGRSCOREXTEST YTEST
R2 SCORE 065
```

BY DEFAULT THE PROVIDED FUNCTIONS ARE CHECKED AT EACH FIT TO BE THE INVERSE OF EACH OTHER HOWEVER IT IS POSSIBLE TO
BYPASS THIS CHECKING BY SETTING CHECKINVERSE TOFALSE

```
 DEF INVERSEFUNCX
 RETURN X
REGR  TRANSFORMEDTARGETREGRESSORREGRESSORREGRESSOR
 FUNCFUNC
 INVERSEFUNCINVERSEFUNC
 CHECKINVERSE FALSE
REGRFITXTRAIN YTRAIN
TRANSFORMEDTARGETREGRESSOR
PRINTR2 SCORE 02FFORMATREGRSCOREXTEST YTEST
R2 SCORE 450
```

NOTE THE TRANSFORMATION CAN BE TRIGGERED BY SETTING EITHER TRANSFORMER OR THE PAIR OF FUNCTIONS FUNC AND
INVERSEFUNC HOWEVER SETTING BOTH OPTIONS WILL RAISE AN ERROR

EXAMPLES

•EFFECT OF TRANSFORMING THE TARGETS IN REGRESSION MODEL

FEATUREUNION COMPOSITE FEATURE SPACES

FEATUREUNION COMBINES SEVERAL TRANSFORMER OBJECTS INTO A NEW TRANSFORMER THAT COMBINES THEIR OUTPUT A
FEATUREUNION TAKES A LIST OF TRANSFORMER OBJECTS DURING FITTING EACH OF THESE IS FIT TO THE DATA INDEPENDENTLY
THE TRANSFORMERS ARE APPLIED IN PARALLEL AND THE FEATURE MATRICES THEY OUTPUT ARE CONCATENATED SIDEBYSIDE INTO A
LARGER MATRIX

WHEN YOU WANT TO APPLY DIFFERENT TRANSFORMATIONS TO EACH FIELD OF THE DATA SEE THE RELATED CLASS SKLEARNCOMPOSE
COLUMNTRANSFORMER SEEUSER GUIDE

FEATUREUNION SERVES THE SAME PURPOSES AS PIPELINE CONVENIENCE AND JOINT PARAMETER ESTIMATION AND VALIDA
TION

FEATUREUNION ANDPIPELINE CAN BE COMBINED TO CREATE COMPLEX MODELS

AFEATUREUNION HAS NO WAY OF CHECKING WHETHER TWO TRANSFORMERS MIGHT PRODUCE IDENTICAL FEATURES IT ONLY PRODUCES A UNION WHEN THE FEATURE SETS ARE DISJOINT AND MAKING SURE THEY ARE THE CALLER'S RESPONSIBILITY

USAGE

AFEATUREUNION IS BUILT USING A LIST OF KEY VALUE PAIRS WHERE THE KEY IS THE NAME YOU WANT TO GIVE TO A GIVEN TRANSFORMATION AN ARBITRARY STRING IT ONLY SERVES AS AN IDENTIFIER AND VALUE IS AN ESTIMATOR OBJECT

```
 FROM SKLEARNPIPELINE IMPORT FEATUREUNION
 FROM SKLEARNDECOMPOSITION IMPORT PCA
 FROM SKLEARNDECOMPOSITION IMPORT KERNELPCA
```

ESTIMATORS LINEARPCA PCA KERNELPCA KERNELPCA
COMBINED FEATUREUNIONESTIMATORS
COMBINED
FEATUREUNIONNJOBSNONE
TRANSFORMERLISTLINEARPCA PCACOPYTRUE
KERNELPCA KERNELPCAALPHA10
TRANSFORMERWEIGHTSNONE VERBOSEFALSE

LIKE PIPELINES FEATURE UNIONS HAVE A SHORTHAND CONSTRUCTOR CALLED MAKEUNION THAT DOES NOT REQUIRE EXPLICIT NAMING OF THE COMPONENTS

LIKEPIPELINE INDIVIDUAL STEPS MAY BE REPLACED USING SETPARAMS AND IGNORED BY SETTING TO DROP

COMBINEDSETPARAMSKERNELPCADROP

FEATUREUNIONNJOBSNONE
TRANSFORMERLISTLINEARPCA PCACOPYTRUE
KERNELPCA DROP
TRANSFORMERWEIGHTSNONE VERBOSEFALSE

EXAMPLES

•CONCATENATING MULTIPLE FEATURE EXTRACTION METHODS

COLUMNTRANSFORMER FOR HETEROGENEOUS DATA

WARNING THECOMPOSECOLUMNTRANSFORMER CLASS IS EXPERIMENTAL AND THE API IS SUBJECT TO CHANGE

MANY DATASETS CONTAIN FEATURES OF DIFFERENT TYPES SAY TEXT FLOATS AND DATES WHERE EACH TYPE OF FEATURE REQUIRES SEPARATE PREPROCESSING OR FEATURE EXTRACTION STEPS OFTEN IT IS EASIEST TO PREPROCESS DATA BEFORE APPLYING SCIKITLEARN METHODS FOR EXAMPLE USING PANDAS PROCESSING YOUR DATA BEFORE PASSING IT TO SCIKITLEARN MIGHT BE PROBLEMATIC FOR ONE OF THE FOLLOWING REASONS

1 INCORPORATING STATISTICS FROM TEST DATA INTO THE PREPROCESSORS MAKES CROSSVALIDATION SCORES UNRELIABLE KNOWN AS DATA LEAKAGE FOR EXAMPLE IN THE CASE OF SCALERS OR IMPUTING MISSING VALUES

2 YOU MAY WANT TO INCLUDE THE PARAMETERS OF THE PREPROCESSORS IN A PARAMETER SEARCH

THECOLUMNTRANSFORMER HELPS PERFORMING DIFFERENT TRANSFORMATIONS FOR DIFFERENT COLUMNS OF THE DATA WITHIN A PIPELINE THAT IS SAFE FROM DATA LEAKAGE AND THAT CAN BE PARAMETRIZED COLUMNTRANSFORMER WORKS ON ARRAYS SPARSE MATRICES AND PANDAS DATAFRAMES

TO EACH COLUMN A DIFFERENT TRANSFORMATION CAN BE APPLIED SUCH AS PREPROCESSING OR A SPECIFIC FEATURE EXTRACTION METHOD

```
 IMPORT PANDAS AS PD
X  PDDATAFRAME
 CITY LONDON LONDON PARIS SALLISAW
 TITLE HIS LAST BOW HOW WATSON LEARNED THE TRICK
 A MOVEABLE FEAST THE GRAPES OF WRATH
 EXPERTRATING 5 3 4 5
 USERRATING 4 5 4 3
```

FOR THIS DATA WE MIGHT WANT TO ENCODE THE CITY COLUMN AS A CATEGORICAL VARIABLE USING PREPROCESSING ONEHOTENCODER BUT APPLY A FEATUREEXTRACTIONTEXTCOUNTVECTORIZER TO THETITLE COLUMN
AS WE MIGHT USE MULTIPLE FEATURE EXTRACTION METHODS ON THE SAME COLUMN WE GIVE EACH TRANSFORMER A UNIQUE NAME SAY CITYCATEGORY ANDTITLEBOW BY DEFAULT THE REMAINING RATING COLUMNS ARE IGNORED REMAINDERDROP

```
 FROM SKLEARNCOMPOSE IMPORT COLUMNTRANSFORMER
 FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT COUNTVECTORIZER
 FROM SKLEARNPREPROCESSING IMPORT ONEHOTENCODER
COLUMNTRANS  COLUMNTRANSFORMER
 CITYCATEGORY ONEHOTENCODERDTYPEINTCITY
 TITLEBOW COUNTVECTORIZER TITLE
 REMAINDERDROP
COLUMNTRANSFITX
COLUMNTRANSFORMERNJOBSNONE REMAINDERDROP SPARSETHRESHOLD03
TRANSFORMERWEIGHTSNONE
TRANSFORMERS
COLUMNTRANSGETFEATURENAMES

CITYCATEGORYX0LONDON CITYCATEGORYX0PARIS CITYCATEGORYX0SALLISAW
TITLEBOWBOW TITLEBOWFEAST TITLEBOWGRAPES TITLEBOWHIS
TITLEBOWHOW TITLEBOWLAST TITLEBOWLEARNED TITLEBOWMOVEABLE
TITLEBOWOF TITLEBOWTHE TITLEBOWTRICK TITLEBOWWATSON
TITLEBOWWRATH
COLUMNTRANSTRANSFORMXTOARRAY

ARRAY1 0 0 1 0 0 1 0 1 0 0 0 0 0 0 0
1 0 0 0 0 0 0 1 0 1 0 0 1 1 1 0
0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0
0 0 1 0 0 1 0 0 0 0 0 1 1 0 0 1
```

IN THE ABOVE EXAMPLE THE COUNTVECTORIZER EXPECTS A 1D ARRAY AS INPUT AND THEREFORE THE COLUMNS WERE SPECIFIED AS A STRING TITLE HOWEVER PREPROCESSINGONEHOTENCODER AS MOST OF OTHER TRANSFORMERS EXPECTS 2D DATA THEREFORE IN THAT CASE YOU NEED TO SPECIFY THE COLUMN AS A LIST OF STRINGS CITY
APART FROM A SCALAR OR A SINGLE ITEM LIST THE COLUMN SELECTION CAN BE SPECIFIED AS A LIST OF MULTIPLE ITEMS AN INTEGER ARRAY A SLICE OR A BOOLEAN MASK STRINGS CAN REFERENCE COLUMNS IF THE INPUT IS A DATAFRAME INTEGERS ARE ALWAYS INTERPRETED AS THE POSITIONAL COLUMNS
WE CAN KEEP THE REMAINING RATING COLUMNS BY SETTING REMAINDERPASSTHROUGH THE VALUES ARE APPENDED TO THE END OF THE TRANSFORMATION

```
COLUMNTRANS  COLUMNTRANSFORMER
 CITYCATEGORY ONEHOTENCODERDTYPEINTCITY
```

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TITLEBOW COUNTVECTORIZER TITLE
REMAINDERPASSTHROUGH
COLUMNTRANSFITTRANSFORMX

ARRAY1 0 0 1 0 0 1 0 1 0 0 0 0 0 0 0 5 4
1 0 0 0 0 0 0 1 0 1 0 0 1 1 1 0 3 5
0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0 4 4
0 0 1 0 0 1 0 0 0 0 0 1 1 0 0 1 5 3
THEREMAINDER PARAMETER CAN BE SET TO AN ESTIMATOR TO TRANSFORM THE REMAINING RATING COLUMNS THE TRANSFORMED VALUES ARE APPENDED TO THE END OF THE TRANSFORMATION
FROM SKLEARNPREPROCESSING IMPORT MINMAXSCALER
COLUMNTRANS COLUMNTRANSFORMER
CITYCATEGORY ONEHOTENCODER CITY
TITLEBOW COUNTVECTORIZER TITLE
REMAINDERMINMAXSCALER
COLUMNTRANSFITTRANSFORMX 2

ARRAY1 05
0 1
05 05
1 0
THEMAKECOLUMNTRANSFORMER FUNCTION IS AVAILABLE TO MORE EASILY CREATE A COLUMNTRANSFORMER OBJECT SPECIFICALLY THE NAMES WILL BE GIVEN AUTOMATICALLY THE EQUIVALENT FOR THE ABOVE EXAMPLE WOULD BE
FROM SKLEARNCOMPOSE IMPORT MAKECOLUMNTRANSFORMER
COLUMNTRANS MAKECOLUMNTRANSFORMER
ONEHOTENCODER CITY
COUNTVECTORIZER TITLE
REMAINDERMINMAXSCALER
COLUMNTRANS
COLUMNTRANSFORMERNJOBSNONE REMAINDERMINMAXSCALERCOPYTRUE
SPARSETHRESHOLD03
TRANSFORMERWEIGHTSNONE
TRANSFORMERSONEHOTENCODER
EXAMPLES
•COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
•COLUMN TRANSFORMER WITH MIXED TYPES
352 FEATURE EXTRACTION
THESKLEARNFEATUREEXTRACTION MODULE CAN BE USED TO EXTRACT FEATURES IN A FORMAT SUPPORTED BY MACHINE LEARNING ALGORITHMS FROM DATASETS CONSISTING OF FORMATS SUCH AS TEXT AND IMAGE
NOTE FEATURE EXTRACTION IS VERY DIFFERENT FROM FEATURE SELECTION THE FORMER CONSISTS IN TRANSFORMING ARBITRARY DATA SUCH AS TEXT OR IMAGES INTO NUMERICAL FEATURES USABLE FOR MACHINE LEARNING THE LATTER IS A MACHINE LEARNING TECHNIQUE
35 DATASET TRANSFORMATIONS 583

APPLIED ON THESE FEATURES
LOADING FEATURES FROM DICTS
THE CLASSDICTVECTORIZER CAN BE USED TO CONVERT FEATURE ARRAYS REPRESENTED AS LISTS OF STANDARD PYTHON DICT OBJECTS TO THE NUMPYSCIPY REPRESENTATION USED BY SCIKITLEARN ESTIMATORS
WHILE NOT PARTICULARLY FAST TO PROCESS PYTHON'S DICT HAS THE ADVANTAGES OF BEING CONVENIENT TO USE BEING SPARSE ABSENT FEATURES NEED NOT BE STORED AND STORING FEATURE NAMES IN ADDITION TO VALUES
DICTVECTORIZER IMPLEMENTS WHAT IS CALLED ONEOFK OR "ONEHOT" CODING FOR CATEGORICAL AKA NOMINAL DISCRETE FEATURES CATEGORICAL FEATURES ARE "ATTRIBUTEVALUE" PAIRS WHERE THE VALUE IS RESTRICTED TO A LIST OF DISCRETE OF POSSIBILITIES WITHOUT ORDERING EG TOPIC IDENTIFIERS TYPES OF OBJECTS TAGS NAMES
IN THE FOLLOWING "CITY" IS A CATEGORICAL ATTRIBUTE WHILE "TEMPERATURE" IS A TRADITIONAL NUMERICAL FEATURE MEASUREMENTS
```
 CITY DUBAI TEMPERATURE 33
 CITY LONDON TEMPERATURE 12
 CITY SAN FRANCISCO TEMPERATURE 18

 FROM SKLEARNFEATUREEXTRACTION IMPORT DICTVECTORIZER
VEC  DICTVECTORIZER
VECFITTRANSFORMMEASUREMENTSTOARRAY
ARRAY 1 0 0 33
 0 1 0 12
 0 0 1 18
VECGETFEATURENAMES
CITYDUBAI CITYLONDON CITYSAN FRANCISCO TEMPERATURE
```
DICTVECTORIZER IS ALSO A USEFUL REPRESENTATION TRANSFORMATION FOR TRAINING SEQUENCE CLASSIFIERS IN NATURAL LAN GUAGE PROCESSING MODELS THAT TYPICALLY WORK BY EXTRACTING FEATURE WINDOWS AROUND A PARTICULAR WORD OF INTEREST FOR EXAMPLE SUPPOSE THAT WE HAVE A FIRST ALGORITHM THAT EXTRACTS PART OF SPEECH POS TAGS THAT WE WANT TO USE AS COMPLEMENTARY TAGS FOR TRAINING A SEQUENCE CLASSIFIER EG A CHUNKER THE FOLLOWING DICT COULD BE SUCH A WINDOW OF FEATURES EXTRACTED AROUND THE WORD 'SAT' IN THE SENTENCE 'THE CAT SAT ON THE MAT'
```
POSWINDOW

 WORD2 THE
 POS2 DT
 WORD1 CAT
 POS1 NN
 WORD1 ON
 POS1 PP
```

IN A REAL APPLICATION ONE WOULD EXTRACT MANY SUCH DICTIONARIES

THIS DESCRIPTION CAN BE VECTORIZED INTO A SPARSE TWODIMENSIONAL MATRIX SUITABLE FOR FEEDING INTO A CLASSIFIER MAYBE AFTER BEING PIPED INTO A TEXTTFIDFTRANSFORMER FOR NORMALIZATION
```
VEC  DICTVECTORIZER
POSVECTORIZED  VECFITTRANSFORMPOSWINDOW
```

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POSVECTORIZED
1X6 SPARSE MATRIX OF TYPE NUMPYFLOAT64
WITH 6 STORED ELEMENTS IN COMPRESSED SPARSE FORMAT
POSVECTORIZEDTOARRAY
ARRAY1 1 1 1 1 1
VECGETFEATURENAMES
POS1PP POS1NN POS2DT WORD1ON WORD1CAT WORD2THE
AS YOU CAN IMAGINE IF ONE EXTRACTS SUCH A CONTEXT AROUND EACH INDIVIDUAL WORD OF A CORPUS OF DOCUMENTS THE RESULTING MATRIX WILL BE VERY WIDE MANY ONEHOTFEATURES WITH MOST OF THEM BEING VALUED TO ZERO MOST OF THE TIME SO AS TO MAKE THE RESULTING DATA STRUCTURE ABLE TO FIT IN MEMORY THE DICTVECTORIZER CLASS USES A SCIPYSPARSE MATRIX BY DEFAULT INSTEAD OF A NUMPYNDARRAY

FEATURE HASHING

THE CLASSFEATUREHASHER IS A HIGHSPEED LOWMEMORY VECTORIZER THAT USES A TECHNIQUE KNOWN AS FEATURE HASHING OR THE “HASHING TRICK” INSTEAD OF BUILDING A HASH TABLE OF THE FEATURES ENCOUNTERED IN TRAINING AS THE VECTORIZERS DO INSTANCES OF FEATUREHASHER APPLY A HASH FUNCTION TO THE FEATURES TO DETERMINE THEIR COLUMN INDEX IN SAMPLE MATRICES DIRECTLY THE RESULT IS INCREASED SPEED AND REDUCED MEMORY USAGE AT THE EXPENSE OF INSPECTABILITY THE HASHER DOES NOT REMEMBER WHAT THE INPUT FEATURES LOOKED LIKE AND HAS NO INVERSETRANSFORM METHOD

SINCE THE HASH FUNCTION MIGHT CAUSE COLLISIONS BETWEEN UNRELATED FEATURES A SIGNED HASH FUNCTION IS USED AND THE SIGN OF THE HASH VALUE DETERMINES THE SIGN OF THE VALUE STORED IN THE OUTPUT MATRIX FOR A FEATURE THIS WAY COLLISIONS ARE LIKELY TO CANCEL OUT RATHER THAN ACCUMULATE ERROR AND THE EXPECTED MEAN OF ANY OUTPUT FEATURE’S VALUE IS ZERO THIS MECHANISM IS ENABLED BY DEFAULT WITH ALTERNATESIGNTRUE AND IS PARTICULARLY USEFUL FOR SMALL HASH TABLE SIZES NFEATURES 10000 FOR LARGE HASH TABLE SIZES IT CAN BE DISABLED TO ALLOW THE OUTPUT TO BE PASSED TO ESTIMATORS LIKE SKLEARNNAIVEBAYESMULTINOMIALNB ORSKLEARNFEATURESELECTIONCHI2 FEATURE SELECTORS THAT EXPECT NONNEGATIVE INPUTS

FEATUREHASHER ACCEPTS EITHER MAPPINGS LIKE PYTHON’S DICT AND ITS VARIANTS IN THE COLLECTIONS MODULE FEATURE VALUE PAIRS OR STRINGS DEPENDING ON THE CONSTRUCTOR PARAMETER INPUTTYPE MAPPING ARE TREATED AS LISTS OFFEATURE VALUE PAIRS WHILE SINGLE STRINGS HAVE AN IMPLICIT VALUE OF 1 SO FEAT1 FEAT2 FEAT3 IS INTERPRETED AS FEAT1 1 FEAT2 1 FEAT3 1 IF A SINGLE FEATURE OCCURS MULTIPLE TIMES IN A SAMPLE THE ASSOCIATED VALUES WILL BE SUMMED SO FEAT 2 ANDFEAT 35 BECOME FEAT 55 THE OUTPUT FROM FEATUREHASHER IS ALWAYS A SCIPYSPARSE MATRIX IN THE CSR FORMAT

FEATURE HASHING CAN BE EMPLOYED IN DOCUMENT CLASSIFICATION BUT UNLIKE TEXTCOUNTVECTORIZER FEATUREHASHER DOES NOT DO WORD SPLITTING OR ANY OTHER PREPROCESSING EXCEPT UNICODETOUTF8 ENCODING SEE VECTORIZING A LARGE TEXT CORPUS WITH THE HASHING TRICK BELOW FOR A COMBINED TOKENIZERHASHER

AS AN EXAMPLE CONSIDER A WORDLEVEL NATURAL LANGUAGE PROCESSING TASK THAT NEEDS FEATURES EXTRACTED FROM TOKEN PARTOFSPEECH PAIRS ONE COULD USE A PYTHON GENERATOR FUNCTION TO EXTRACT FEATURES

```
DEFTOKENFEATURESTOKEN PARTOFSPEECH
IFTOKENISDIGIT
YIELDNUMERIC
ELSE
YIELDTOKENFORMATTOKENLOWER
YIELDTOKENPOS FORMATTOKEN PARTOFSPEECH
IFTOKEN0ISUPPER
YIELDUPPERCASEINITIAL
IFTOKENISUPPER
YIELDALLUPPERCASE
YIELDPOSFORMATPARTOFSPEECH
```

THEN THERAWX TO BE FED TO FEATUREHASHERTRANSFORM CAN BE CONSTRUCTED USING

RAWX TOKENFEATURESTOK POSTAGGERTOK FORTOKINCORPUS
AND FED TO A HASHER WITH
HASHER FEATUREHASHERINPUTTYPESTRING
X HASHERTRANSFORMRAWX
TO GET ASCIPYSPARSE MATRIXX
NOTE THE USE OF A GENERATOR COMPREHENSION WHICH INTRODUCES LAZINESS INTO THE FEATURE EXTRACTION TOKENS ARE ONLY PROCESSED ON DEMAND FROM THE HASHER
IMPLEMENTATION DETAILS
FEATUREHASHER USES THE SIGNED 32BIT VARIANT OF MURMURHASH3 AS A RESULT AND BECAUSE OF LIMITATIONS IN SCIPY SPARSE THE MAXIMUM NUMBER OF FEATURES SUPPORTED IS CURRENTLY 231−1
THE ORIGINAL FORMULATION OF THE HASHING TRICK BY WEINBERGER ET AL USED TWO SEPARATE HASH FUNCTIONS *h*AND□TO DETER MINE THE COLUMN INDEX AND SIGN OF A FEATURE RESPECTIVELY THE PRESENT IMPLEMENTATION WORKS UNDER THE ASSUMPTION THAT THE SIGN BIT OF MURMURHASH3 IS INDEPENDENT OF ITS OTHER BITS
SINCE A SIMPLE MODULO IS USED TO TRANSFORM THE HASH FUNCTION TO A COLUMN INDEX IT IS ADVISABLE TO USE A POWER OF TWO AS THENFEATURES PARAMETER OTHERWISE THE FEATURES WILL NOT BE MAPPED EVENLY TO THE COLUMNS
REFERENCES
• KILIAN WEINBERGER ANIRBAN DASGUPTA JOHN LANGFORD ALEX SMOLA AND JOSH ATTENBERG 2009 FEATURE HASH ING FOR LARGE SCALE MULTITASK LEARNING PROC ICML
• MURMURHASH3
TEXT FEATURE EXTRACTION
THE BAG OF WORDS REPRESENTATION
TEXT ANALYSIS IS A MAJOR APPLICATION FIELD FOR MACHINE LEARNING ALGORITHMS HOWEVER THE RAW DATA A SEQUENCE OF SYMBOLS CANNOT BE FED DIRECTLY TO THE ALGORITHMS THEMSELVES AS MOST OF THEM EXPECT NUMERICAL FEATURE VECTORS WITH A FIXED SIZE RATHER THAN THE RAW TEXT DOCUMENTS WITH VARIABLE LENGTH
IN ORDER TO ADDRESS THIS SCIKITLEARN PROVIDES UTILITIES FOR THE MOST COMMON WAYS TO EXTRACT NUMERICAL FEATURES FROM TEXT CONTENT NAMELY
•TOKENIZING STRINGS AND GIVING AN INTEGER ID FOR EACH POSSIBLE TOKEN FOR INSTANCE BY USING WHITESPACES AND PUNCTUATION AS TOKEN SEPARATORS
•COUNTING THE OCCURRENCES OF TOKENS IN EACH DOCUMENT
•NORMALIZING AND WEIGHTING WITH DIMINISHING IMPORTANCE TOKENS THAT OCCUR IN THE MAJORITY OF SAMPLES DOCU MENTS
IN THIS SCHEME FEATURES AND SAMPLES ARE DEFINED AS FOLLOWS
• EACH INDIVIDUAL TOKEN OCCURRENCE FREQUENCY NORMALIZED OR NOT IS TREATED AS A FEATURE
• THE VECTOR OF ALL THE TOKEN FREQUENCIES FOR A GIVEN DOCUMENT IS CONSIDERED A MULTIVARIATE SAMPLE

A CORPUS OF DOCUMENTS CAN THUS BE REPRESENTED BY A MATRIX WITH ONE ROW PER DOCUMENT AND ONE COLUMN PER TOKEN
EG WORD OCCURRING IN THE CORPUS
WE CALL VECTORIZATION THE GENERAL PROCESS OF TURNING A COLLECTION OF TEXT DOCUMENTS INTO NUMERICAL FEATURE VECTORS THIS
SPECIFIC STRATEGY TOKENIZATION COUNTING AND NORMALIZATION IS CALLED THE BAG OF WORDS OR “BAG OF NGRAMS” REPRESEN
TATION DOCUMENTS ARE DESCRIBED BY WORD OCCURRENCES WHILE COMPLETELY IGNORING THE RELATIVE POSITION INFORMATION OF
THE WORDS IN THE DOCUMENT
SPARSITY
AS MOST DOCUMENTS WILL TYPICALLY USE A VERY SMALL SUBSET OF THE WORDS USED IN THE CORPUS THE RESULTING MATRIX WILL
HAVE MANY FEATURE VALUES THAT ARE ZEROS TYPICALLY MORE THAN 99 OF THEM
FOR INSTANCE A COLLECTION OF 10000 SHORT TEXT DOCUMENTS SUCH AS EMAILS WILL USE A VOCABULARY WITH A SIZE IN THE ORDER
OF 100000 UNIQUE WORDS IN TOTAL WHILE EACH DOCUMENT WILL USE 100 TO 1000 UNIQUE WORDS INDIVIDUALLY
IN ORDER TO BE ABLE TO STORE SUCH A MATRIX IN MEMORY BUT ALSO TO SPEED UP ALGEBRAIC OPERATIONS MATRIX VECTOR IMPLE
MENTATIONS WILL TYPICALLY USE A SPARSE REPRESENTATION SUCH AS THE IMPLEMENTATIONS AVAILABLE IN THE SCIPYSPARSE
PACKAGE
COMMON VECTORIZER USAGE
COUNTVECTORIZER IMPLEMENTS BOTH TOKENIZATION AND OCCURRENCE COUNTING IN A SINGLE CLASS
```
 FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT COUNTVECTORIZER
```
THIS MODEL HAS MANY PARAMETERS HOWEVER THE DEFAULT VALUES ARE QUITE REASONABLE PLEASE SEE THE REFERENCE DOCUMEN
TATION FOR THE DETAILS
```
VECTORIZER  COUNTVECTORIZER
VECTORIZER
COUNTVECTORIZERANALYZERWORD BINARYFALSE DECODEERRORSTRICT
DTYPE NUMPYINT64 ENCODINGUTF8 INPUTCONTENT
LOWERCASETRUE MAXDF10 MAXFEATURESNONE MINDF1
NGRAMRANGE1 1 PREPROCESSORNONE STOPWORDSNONE
STRIPACCENTSNONE TOKENPATTERNUBWWB
TOKENIZERNONE VOCABULARYNONE
```
LET’S USE IT TO TOKENIZE AND COUNT THE WORD OCCURRENCES OF A MINIMALISTIC CORPUS OF TEXT DOCUMENTS
```
CORPUS
 THIS IS THE FIRST DOCUMENT
 THIS IS THE SECOND SECOND DOCUMENT
 AND THE THIRD ONE
 IS THIS THE FIRST DOCUMENT

X  VECTORIZERFITTRANSFORMCORPUS
X
4X9 SPARSE MATRIX OF TYPE  NUMPYINT64
WITH 19 STORED ELEMENTS IN COMPRESSED SPARSE  FORMAT
```
THE DEFAULT CONFIGURATION TOKENIZES THE STRING BY EXTRACTING WORDS OF AT LEAST 2 LETTERS THE SPECIFIC FUNCTION THAT DOES
THIS STEP CAN BE REQUESTED EXPLICITLY

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ANALYZE VECTORIZERBUILDANALYZER
ANALYZETHIS IS A TEXT DOCUMENT TO ANALYZE
 THIS IS TEXT DOCUMENT TO ANALYZE
TRUE
EACH TERM FOUND BY THE ANALYZER DURING THE FIT IS ASSIGNED A UNIQUE INTEGER INDEX CORRESPONDING TO A COLUMN IN THE RESULTING MATRIX THIS INTERPRETATION OF THE COLUMNS CAN BE RETRIEVED AS FOLLOWS
VECTORIZERGETFEATURENAMES
 AND DOCUMENT FIRST IS ONE
 SECOND THE THIRD THIS
TRUE
XTOARRAY
ARRAY0 1 1 1 0 0 1 0 1
0 1 0 1 0 2 1 0 1
1 0 0 0 1 0 1 1 0
0 1 1 1 0 0 1 0 1
THE CONVERSE MAPPING FROM FEATURE NAME TO COLUMN INDEX IS STORED IN THE VOCABULARY ATTRIBUTE OF THE VECTORIZER
VECTORIZERVOCABULARYGETDOCUMENT
1
HENCE WORDS THAT WERE NOT SEEN IN THE TRAINING CORPUS WILL BE COMPLETELY IGNORED IN FUTURE CALLS TO THE TRANSFORM METHOD
VECTORIZERTRANSFORMSOMETHING COMPLETELY NEWTOARRAY

ARRAY0 0 0 0 0 0 0 0 0
NOTE THAT IN THE PREVIOUS CORPUS THE FIRST AND THE LAST DOCUMENTS HAVE EXACTLY THE SAME WORDS HENCE ARE ENCODED IN EQUAL VECTORS IN PARTICULAR WE LOSE THE INFORMATION THAT THE LAST DOCUMENT IS AN INTERROGATIVE FORM TO PRESERVE SOME OF THE LOCAL ORDERING INFORMATION WE CAN EXTRACT 2GRAMS OF WORDS IN ADDITION TO THE 1GRAMS INDIVIDUAL WORDS
BIGRAMVECTORIZER COUNTVECTORIZERNGRAMRANGE1 2
 TOKENPATTERNRBWB MINDF1
ANALYZE BIGRAMVECTORIZERBUILDANALYZER
ANALYZEBIGRAMS ARE COOL
 BI GRAMS ARE COOL BI GRAMS GRAMS ARE ARE COOL
TRUE
THE VOCABULARY EXTRACTED BY THIS VECTORIZER IS HENCE MUCH BIGGER AND CAN NOW RESOLVE AMBIGUITIES ENCODED IN LOCAL POSITIONING PATTERNS
X2 BIGRAMVECTORIZERFITTRANSFORMCORPUSTOARRAY
X2

ARRAY0 0 1 1 1 1 1 0 0 0 0 0 1 1 0 0 0 0 1 1 0
0 0 1 0 0 1 1 0 0 2 1 1 1 0 1 0 0 0 1 1 0
1 1 0 0 0 0 0 0 1 0 0 0 1 0 0 1 1 1 0 0 0
0 0 1 1 1 1 0 1 0 0 0 0 1 1 0 0 0 0 1 0 1
IN PARTICULAR THE INTERROGATIVE FORM “IS THIS” IS ONLY PRESENT IN THE LAST DOCUMENT
FEATUREINDEX BIGRAMVECTORIZERVOCABULARYGETIS THIS
X2 FEATUREINDEX

ARRAY0 0 0 1
USING STOP WORDS
STOP WORDS ARE WORDS LIKE “AND” “THE” “HIM” WHICH ARE PRESUMED TO BE UNINFORMATIVE IN REPRESENTING THE CONTENT OF A TEXT AND WHICH MAY BE REMOVED TO AVOID THEM BEING CONSTRUED AS SIGNAL FOR PREDICTION SOMETIMES HOWEVER SIMILAR WORDS ARE USEFUL FOR PREDICTION SUCH AS IN CLASSIFYING WRITING STYLE OR PERSONALITY
THERE ARE SEVERAL KNOWN ISSUES IN OUR PROVIDED ‘ENGLISH’ STOP WORD LIST SEE NQY18
PLEASE TAKE CARE IN CHOOSING A STOP WORD LIST POPULAR STOP WORD LISTS MAY INCLUDE WORDS THAT ARE HIGHLY INFORMATIVE TO SOME TASKS SUCH AS COMPUTER
YOU SHOULD ALSO MAKE SURE THAT THE STOP WORD LIST HAS HAD THE SAME PREPROCESSING AND TOKENIZATION APPLIED AS THE ONE USED IN THE VECTORIZER THE WORD WE’VE IS SPLIT INTO WEANDVEBY COUNTVECTORIZER’S DEFAULT TOKENIZER SO IF WE’VE IS IN STOPWORDS BUT VEIS NOT VEWILL BE RETAINED FROM WE’VE IN TRANSFORMED TEXT OUR VECTORIZERS WILL TRY TO IDENTIFY AND WARN ABOUT SOME KINDS OF INCONSISTENCIES
REFERENCES
TF–IDF TERM WEIGHTING
IN A LARGE TEXT CORPUS SOME WORDS WILL BE VERY PRESENT EG “THE” “A” “IS” IN ENGLISH HENCE CARRYING VERY LITTLE MEANINGFUL INFORMATION ABOUT THE ACTUAL CONTENTS OF THE DOCUMENT IF WE WERE TO FEED THE DIRECT COUNT DATA DIRECTLY TO A CLASSIFIER THOSE VERY FREQUENT TERMS WOULD SHADOW THE FREQUENCIES OF RARER YET MORE INTERESTING TERMS
IN ORDER TO REWEIGHT THE COUNT FEATURES INTO FLOATING POINT VALUES SUITABLE FOR USAGE BY A CLASSIFIER IT IS VERY COMMON TO USE THE TF–IDF TRANSFORM
TF MEANS TERMFREQUENCY WHILE TF–IDF MEANS TERMFREQUENCY TIMES INVERSE DOCUMENTFREQUENCY TFIDFTD TFTD×IDFT
USING THE TFIDFTRANSFORMER ’S DEFAULT SETTINGS TFIDFTRANSFORMERNORML2 USEIDFTRUE SMOOTHIDFTRUE SUBLINEARTFFALSE THE TERM FREQUENCY THE NUMBER OF TIMES A TERM OCCURS IN A GIVEN DOCUMENT IS MULTIPLIED WITH IDF COMPONENT WHICH IS COMPUTED AS
IDF□ LOG1□
1DF□ 1
WHERE □IS THE TOTAL NUMBER OF DOCUMENTS IN THE DOCUMENT SET AND DF □IS THE NUMBER OF DOCUMENTS IN THE DOCUMENT SET THAT CONTAIN TERM □ THE RESULTING TFIDF VECTORS ARE THEN NORMALIZED BY THE EUCLIDEAN NORM
□□□□□ □
□2□√
□12□22⋯□□2
THIS WAS ORIGINALLY A TERM WEIGHTING SCHEME DEVELOPED FOR INFORMATION RETRIEVAL AS A RANKING FUNCTION FOR SEARCH ENGINES RESULTS THAT HAS ALSO FOUND GOOD USE IN DOCUMENT CLASSIFICATION AND CLUSTERING
THE FOLLOWING SECTIONS CONTAIN FURTHER EXPLANATIONS AND EXAMPLES THAT ILLUSTRATE HOW THE TFIDFS ARE COMPUTED EXACTLY AND HOW THE TFIDFS COMPUTED IN SCIKITLEARN’S TFIDFTRANSFORMER ANDTFIDFVECTORIZER DIFFER SLIGHTLY FROM THE STANDARD TEXTBOOK NOTATION THAT DEFINES THE IDF AS
IDF□ LOG□
1DF□
IN THETFIDFTRANSFORMER ANDTFIDFVECTORIZER WITHSMOOTHIDFFALSE THE “1” COUNT IS ADDED TO THE IDF INSTEAD OF THE IDF’S DENOMINATOR
IDF□ LOG□
DF□ 1

THIS NORMALIZATION IS IMPLEMENTED BY THE TFIDFTRANSFORMER CLASS
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFTRANSFORMER
TRANSFORMER TFIDFTRANSFORMERSMOOTHIDF FALSE
TRANSFORMER
TFIDFTRANSFORMERNORML2 SMOOTHIDFFALSE SUBLINEARTFFALSE
USEIDFTRUE
AGAIN PLEASE SEE THE REFERENCE DOCUMENTATION FOR THE DETAILS ON ALL THE PARAMETERS
LET'S TAKE AN EXAMPLE WITH THE FOLLOWING COUNTS THE FIRST TERM IS PRESENT 100 OF THE TIME HENCE NOT VERY INTERESTING
THE TWO OTHER FEATURES ONLY IN LESS THAN 50 OF THE TIME HENCE PROBABLY MORE REPRESENTATIVE OF THE CONTENT OF THE
DOCUMENTS
COUNTS 3 0 1
2 0 0
3 0 0
4 0 0
3 2 0
3 0 2

TFIDF TRANSFORMERFITTRANSFORMCOUNTS
TFIDF
6X3 SPARSE MATRIX OF TYPE NUMPYFLOAT64
WITH 9 STORED ELEMENTS IN COMPRESSED SPARSE FORMAT
TFIDFTOARRAY
ARRAY081940995 0 057320793
1 0 0
1 0 0
1 0 0
047330339 088089948 0
058149261 0 081355169
EACH ROW IS NORMALIZED TO HAVE UNIT EUCLIDEAN NORM
□□□□□ □
□2□√
□12□22⋯□□2
FOR EXAMPLE WE CAN COMPUTE THE TFIDF OF THE FIRST TERM IN THE FIRST DOCUMENT IN THE COUNTS ARRAY AS FOLLOWS
□ 6
DF□TERM1 6
IDF□TERM1 LOG□
DF□ 1 LOG1 1 1
TFIDF TERM1TF×IDF 3×1 3
NOW IF WE REPEAT THIS COMPUTATION FOR THE REMAINING 2 TERMS IN THE DOCUMENT WE GET
TFIDF TERM2 0×LOG6 1 1 0
TFIDF TERM3 1×LOG6 2 1≈20986
AND THE VECTOR OF RAW TFIDFS
TFIDF RAW 3020986
THEN APPLYING THE EUCLIDEAN L2 NORM WE OBTAIN THE FOLLOWING TFIDFS FOR DOCUMENT 1
3020986√
3202209862 081900573

FURTHERMORE THE DEFAULT PARAMETER SMOOTHIDFTRUE ADDS “1” TO THE NUMERATOR AND DENOMINATOR AS IF AN EXTRA DOCUMENT WAS SEEN CONTAINING EVERY TERM IN THE COLLECTION EXACTLY ONCE WHICH PREVENTS ZERO DIVISIONS
IDF LOG1
1DF 1
USING THIS MODIFICATION THE TFIDF OF THE THIRD TERM IN DOCUMENT 1 CHANGES TO 18473
TFIDF TERM3 1×LOG73 1≈18473
AND THE L2NORMALIZED TFIDF CHANGES TO
3018473√
3202184732 08515005243
TRANSFORMER TFIDFTRANSFORMER
TRANSFORMERFITTRANSFORMCOUNTSTOARRAY
ARRAY085151335 0 052433293
1 0 0
1 0 0
1 0 0
055422893 083236428 0
063035731 0 077630514
THE WEIGHTS OF EACH FEATURE COMPUTED BY THE FIT METHOD CALL ARE STORED IN A MODEL ATTRIBUTE
TRANSFORMERIDF
ARRAY1 225 184
AS TF–IDF IS VERY OFTEN USED FOR TEXT FEATURES THERE IS ALSO ANOTHER CLASS CALLED TFIDFVECTORIZER THAT COMBINES ALL THE OPTIONS OF COUNTVECTORIZER ANDTFIDFTRANSFORMER IN A SINGLE MODEL
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFVECTORIZER
VECTORIZER TFIDFVECTORIZER
VECTORIZERFITTRANSFORMCORPUS

4X9 SPARSE MATRIX OF TYPE NUMPYFLOAT64
WITH 19 STORED ELEMENTS IN COMPRESSED SPARSE FORMAT
WHILE THE TF–IDF NORMALIZATION IS OFTEN VERY USEFUL THERE MIGHT BE CASES WHERE THE BINARY OCCURRENCE MARKERS MIGHT OFFER BETTER FEATURES THIS CAN BE ACHIEVED BY USING THE BINARY PARAMETER OF COUNTVECTORIZER IN PARTICULAR SOME ESTIMATORS SUCH AS BERNOULLI NAIVE BAYES EXPLICITLY MODEL DISCRETE BOOLEAN RANDOM VARIABLES ALSO VERY SHORT TEXTS ARE LIKELY TO HAVE NOISY TF–IDF VALUES WHILE THE BINARY OCCURRENCE INFO IS MORE STABLE
AS USUAL THE BEST WAY TO ADJUST THE FEATURE EXTRACTION PARAMETERS IS TO USE A CROSSVALIDATED GRID SEARCH FOR INSTANCE BY PIPELINING THE FEATURE EXTRACTOR WITH A CLASSIFIER
•SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
DECODING TEXT FILES
TEXT IS MADE OF CHARACTERS BUT FILES ARE MADE OF BYTES THESE BYTES REPRESENT CHARACTERS ACCORDING TO SOME ENCODING TO WORK WITH TEXT FILES IN PYTHON THEIR BYTES MUST BE DECODED TO A CHARACTER SET CALLED UNICODE COMMON ENCODINGS ARE ASCII LATIN1 WESTERN EUROPE KOI8R RUSSIAN AND THE UNIVERSAL ENCODINGS UTF8 AND UTF16 MANY OTHERS EXIST
NOTE AN ENCODING CAN ALSO BE CALLED A ‘CHARACTER SET’ BUT THIS TERM IS LESS ACCURATE SEVERAL ENCODINGS CAN EXIST FOR A SINGLE CHARACTER SET

THE TEXT FEATURE EXTRACTORS IN SCIKITLEARN KNOW HOW TO DECODE TEXT FILES BUT ONLY IF YOU TELL THEM WHAT ENCODING THE FILES ARE IN THE COUNTVECTORIZER TAKES ANENCODING PARAMETER FOR THIS PURPOSE FOR MODERN TEXT FILES THE CORRECT ENCODING IS PROBABLY UTF8 WHICH IS THEREFORE THE DEFAULT ENCODINGUTF8
IF THE TEXT YOU ARE LOADING IS NOT ACTUALLY ENCODED WITH UTF8 HOWEVER YOU WILL GET A UNICODEDECODEERROR
THE VECTORIZERS CAN BE TOLD TO BE SILENT ABOUT DECODING ERRORS BY SETTING THE DECODEERROR PARAMETER TO EITHER IGNORE ORREPLACE SEE THE DOCUMENTATION FOR THE PYTHON FUNCTION BYTESDECODE FOR MORE DETAILS TYPE HELPBYTESDECODE AT THE PYTHON PROMPT
IF YOU ARE HAVING TROUBLE DECODING TEXT HERE ARE SOME THINGS TO TRY
• FIND OUT WHAT THE ACTUAL ENCODING OF THE TEXT IS THE FILE MIGHT COME WITH A HEADER OR README THAT TELLS YOU THE ENCODING OR THERE MIGHT BE SOME STANDARD ENCODING YOU CAN ASSUME BASED ON WHERE THE TEXT COMES FROM
• YOU MAY BE ABLE TO FIND OUT WHAT KIND OF ENCODING IT IS IN GENERAL USING THE UNIX COMMAND FILE THE PYTHON CHARDET MODULE COMES WITH A SCRIPT CALLED CHARDETECTPY THAT WILL GUESS THE SPECIFIC ENCODING THOUGH YOU CANNOT RELY ON ITS GUESS BEING CORRECT
• YOU COULD TRY UTF8 AND DISREGARD THE ERRORS YOU CAN DECODE BYTE STRINGS WITH BYTES DECODEERRORSREPLACE TO REPLACE ALL DECODING ERRORS WITH A MEANINGLESS CHARACTER OR SET DECODEERRORREPLACE IN THE VECTORIZER THIS MAY DAMAGE THE USEFULNESS OF YOUR FEATURES
• REAL TEXT MAY COME FROM A VARIETY OF SOURCES THAT MAY HAVE USED DIFFERENT ENCODINGS OR EVEN BE SLOPPILY DECODED IN A DIFFERENT ENCODING THAN THE ONE IT WAS ENCODED WITH THIS IS COMMON IN TEXT RETRIEVED FROM THE WEB THE PYTHON PACKAGE FTFY CAN AUTOMATICALLY SORT OUT SOME CLASSES OF DECODING ERRORS SO YOU COULD TRY DECODING THE UNKNOWN TEXT AS LATIN1 AND THEN USING FTFY TO FIX ERRORS
• IF THE TEXT IS IN A MISHMASH OF ENCODINGS THAT IS SIMPLY TOO HARD TO SORT OUT WHICH IS THE CASE FOR THE 20 NEWSGROUPS DATASET YOU CAN FALL BACK ON A SIMPLE SINGLEBYTE ENCODING SUCH AS LATIN1 SOME TEXT MAY DISPLAY INCORRECTLY BUT AT LEAST THE SAME SEQUENCE OF BYTES WILL ALWAYS REPRESENT THE SAME FEATURE
FOR EXAMPLE THE FOLLOWING SNIPPET USES CHARDET NOT SHIPPED WITH SCIKITLEARN MUST BE INSTALLED SEPARATELY TO FIGURE OUT THE ENCODING OF THREE TEXTS IT THEN VECTORIZES THE TEXTS AND PRINTS THE LEARNED VOCABULARY THE OUTPUT IS NOT SHOWN HERE

```
 IMPORT CHARDET
TEXT1  BSEI MIR GEGR XC3XBCXC3X9F T MEIN SAUERKRAUT
TEXT2  BHOLDSELIG SIND DEINE GER XFCCHE
TEXT3  B XFFXFE AX00UX00FX00 X00 FX00LX00XFCX00 GX00EX00LX00NX00
‹→X00DX00EX00SX00 X00 GX00EX00SX00AX00NX00GX00EX00SX00X00
‹→X00HX00EX00RX00ZX00LX00IX00EX00BX00CX00HX00EX00NX00X00
‹→X00TX00RX00AX00GX00 X00 IX00CX00HX00 X00 DX00IX00CX00HX00
‹→X00FX00OX00RX00TX00
DECODED  XDECODECHARDETDETECTXENCODING
 FOR XINTEXT1 TEXT2 TEXT3
V  COUNTVECTORIZERFITDECODEDVOCABULARY
 FOR TERMINV PRINTV
```

DEPENDING ON THE VERSION OF CHARDET IT MIGHT GET THE FIRST ONE WRONG
FOR AN INTRODUCTION TO UNICODE AND CHARACTER ENCODINGS IN GENERAL SEE JOEL SPOLSKY'S ABSOLUTE MINIMUM EVERY SOFTWARE DEVELOPER MUST KNOW ABOUT UNICODE

APPLICATIONS AND EXAMPLES

THE BAG OF WORDS REPRESENTATION IS QUITE SIMPLISTIC BUT SURPRISINGLY USEFUL IN PRACTICE
IN PARTICULAR IN A SUPERVISED SETTING IT CAN BE SUCCESSFULLY COMBINED WITH FAST AND SCALABLE LINEAR MODELS TO TRAIN DOCUMENT CLASSIFIERS FOR INSTANCE

•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
IN AN UNSUPERVISED SETTING IT CAN BE USED TO GROUP SIMILAR DOCUMENTS TOGETHER BY APPLYING CLUSTERING ALGORITHMS SUCH ASKMEANS
•CLUSTERING TEXT DOCUMENTS USING KMEANS
FINALLY IT IS POSSIBLE TO DISCOVER THE MAIN TOPICS OF A CORPUS BY RELAXING THE HARD ASSIGNMENT CONSTRAINT OF CLUSTERING FOR INSTANCE BY USING NONNEGATIVE MATRIX FACTORIZATION NMF OR NNMF
•TOPIC EXTRACTION WITH NONNEGATIVE MATRIX FACTORIZATION AND LATENT DIRICHLET ALLOCATION
LIMITATIONS OF THE BAG OF WORDS REPRESENTATION
A COLLECTION OF UNIGRAMS WHAT BAG OF WORDS IS CANNOT CAPTURE PHRASES AND MULTIWORD EXPRESSIONS EFFECTIVELY DISRE GARDING ANY WORD ORDER DEPENDENCE ADDITIONALLY THE BAG OF WORDS MODEL DOESN'T ACCOUNT FOR POTENTIAL MISSPELLINGS OR WORD DERIVATIONS
NGRAMS TO THE RESCUE INSTEAD OF BUILDING A SIMPLE COLLECTION OF UNIGRAMS N1 ONE MIGHT PREFER A COLLECTION OF BIGRAMS N2 WHERE OCCURRENCES OF PAIRS OF CONSECUTIVE WORDS ARE COUNTED
ONE MIGHT ALTERNATIVELY CONSIDER A COLLECTION OF CHARACTER NGRAMS A REPRESENTATION RESILIENT AGAINST MISSPELLINGS AND DERIVATIONS
FOR EXAMPLE LET'S SAY WE'RE DEALING WITH A CORPUS OF TWO DOCUMENTS WORDS WPRDS THE SECOND DOCU MENT CONTAINS A MISSPELLING OF THE WORD 'WORDS' A SIMPLE BAG OF WORDS REPRESENTATION WOULD CONSIDER THESE TWO AS VERY DISTINCT DOCUMENTS DIFFERING IN BOTH OF THE TWO POSSIBLE FEATURES A CHARACTER 2GRAM REPRESENTATION HOWEVER WOULD FIND THE DOCUMENTS MATCHING IN 4 OUT OF 8 FEATURES WHICH MAY HELP THE PREFERRED CLASSIFIER DECIDE BETTER
NGRAMVECTORIZER COUNTVECTORIZERANALYZERCHARWB NGRAMRANGE2 2
COUNTS NGRAMVECTORIZERFITTRANSFORMWORDS WPRDS
NGRAMVECTORIZERGETFEATURENAMES
W DS OR PR RD S WO WP
TRUE
COUNTSTOARRAYASTYPEINT
ARRAY1 1 1 0 1 1 1 0
1 1 0 1 1 1 0 1
IN THE ABOVE EXAMPLE CHARWB ANALYZER IS USED WHICH CREATES NGRAMS ONLY FROM CHARACTERS INSIDE WORD BOUNDARIES PADDED WITH SPACE ON EACH SIDE THE CHAR ANALYZER ALTERNATIVELY CREATES NGRAMS THAT SPAN ACROSS WORDS
NGRAMVECTORIZER COUNTVECTORIZERANALYZERCHARWB NGRAMRANGE5 5
NGRAMVECTORIZERFITTRANSFORMJUMPY FOX

1X4 SPARSE MATRIX OF TYPE NUMPYINT64
WITH 4 STORED ELEMENTS IN COMPRESSED SPARSE FORMAT
NGRAMVECTORIZERGETFEATURENAMES
FOX JUMP JUMPY UMPY
TRUE
NGRAMVECTORIZER COUNTVECTORIZERANALYZERCHAR NGRAMRANGE5 5
NGRAMVECTORIZERFITTRANSFORMJUMPY FOX

1X5 SPARSE MATRIX OF TYPE NUMPYINT64
WITH 5 STORED ELEMENTS IN COMPRESSED SPARSE FORMAT
NGRAMVECTORIZERGETFEATURENAMES
JUMPY MPY F PY FO UMPY Y FOX
TRUE

THE WORD BOUNDARIESAWARE VARIANT CHARWB IS ESPECIALLY INTERESTING FOR LANGUAGES THAT USE WHITESPACES FOR WORD SEPARATION AS IT GENERATES SIGNIFICANTLY LESS NOISY FEATURES THAN THE RAW CHAR VARIANT IN THAT CASE FOR SUCH LANGUAGES IT CAN INCREASE BOTH THE PREDICTIVE ACCURACY AND CONVERGENCE SPEED OF CLASSIFIERS TRAINED USING SUCH FEATURES WHILE RETAINING THE ROBUSTNESS WITH REGARDS TO MISSPELLINGS AND WORD DERIVATIONS
WHILE SOME LOCAL POSITIONING INFORMATION CAN BE PRESERVED BY EXTRACTING NGRAMS INSTEAD OF INDIVIDUAL WORDS BAG OF WORDS AND BAG OF NGRAMS DESTROY MOST OF THE INNER STRUCTURE OF THE DOCUMENT AND HENCE MOST OF THE MEANING CARRIED BY THAT INTERNAL STRUCTURE
IN ORDER TO ADDRESS THE WIDER TASK OF NATURAL LANGUAGE UNDERSTANDING THE LOCAL STRUCTURE OF SENTENCES AND PARAGRAPHS SHOULD THUS BE TAKEN INTO ACCOUNT MANY SUCH MODELS WILL THUS BE CASTED AS “STRUCTURED OUTPUT” PROBLEMS WHICH ARE CURRENTLY OUTSIDE OF THE SCOPE OF SCIKITLEARN
VECTORIZING A LARGE TEXT CORPUS WITH THE HASHING TRICK
THE ABOVE VECTORIZATION SCHEME IS SIMPLE BUT THE FACT THAT IT HOLDS AN IN MEMORY MAPPING FROM THE STRING TOKENS TO THE INTEGER FEATURE INDICES THEVOCABULARY ATTRIBUTE CAUSES SEVERAL PROBLEMS WHEN DEALING WITH LARGE DATASETS
• THE LARGER THE CORPUS THE LARGER THE VOCABULARY WILL GROW AND HENCE THE MEMORY USE TOO
• FITTING REQUIRES THE ALLOCATION OF INTERMEDIATE DATA STRUCTURES OF SIZE PROPORTIONAL TO THAT OF THE ORIGINAL DATASET
• BUILDING THE WORDMAPPING REQUIRES A FULL PASS OVER THE DATASET HENCE IT IS NOT POSSIBLE TO FIT TEXT CLASSIFIERS IN A STRICTLY ONLINE MANNER
• PICKLING AND UNPICKLING VECTORIZERS WITH A LARGE VOCABULARY CAN BE VERY SLOW TYPICALLY MUCH SLOWER THAN PICKLING UNPICKLING FLAT DATA STRUCTURES SUCH AS A NUMPY ARRAY OF THE SAME SIZE
• IT IS NOT EASILY POSSIBLE TO SPLIT THE VECTORIZATION WORK INTO CONCURRENT SUB TASKS AS THE VOCABULARY ATTRIBUTE WOULD HAVE TO BE A SHARED STATE WITH A FINE GRAINED SYNCHRONIZATION BARRIER THE MAPPING FROM TOKEN STRING TO FEATURE INDEX IS DEPENDENT ON ORDERING OF THE FIRST OCCURRENCE OF EACH TOKEN HENCE WOULD HAVE TO BE SHARED POTENTIALLY HARMING THE CONCURRENT WORKERS’ PERFORMANCE TO THE POINT OF MAKING THEM SLOWER THAN THE SEQUENTIAL VARIANT
IT IS POSSIBLE TO OVERCOME THOSE LIMITATIONS BY COMBINING THE “HASHING TRICK” FEATURE HASHING IMPLEMENTED BY THE SKLEARNFEATUREEXTRACTIONFEATUREHASHER CLASS AND THE TEXT PREPROCESSING AND TOKENIZATION FEATURES OF THECOUNTVECTORIZER
THIS COMBINATION IS IMPLEMENTING IN HASHINGVECTORIZER A TRANSFORMER CLASS THAT IS MOSTLY API COMPATIBLE WITH COUNTVECTORIZER HASHINGVECTORIZER IS STATELESS MEANING THAT YOU DON’T HAVE TO CALL FIT ON IT
```
 FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT HASHINGVECTORIZER
HV  HASHINGVECTORIZERNFEATURES10
HVTRANSFORMCORPUS

4X10 SPARSE MATRIX OF TYPE  NUMPYFLOAT64
WITH 16 STORED ELEMENTS IN COMPRESSED SPARSE  FORMAT
```
YOU CAN SEE THAT 16 NONZERO FEATURE TOKENS WERE EXTRACTED IN THE VECTOR OUTPUT THIS IS LESS THAN THE 19 NONZEROS EXTRACTED PREVIOUSLY BY THE COUNTVECTORIZER ON THE SAME TOY CORPUS THE DISCREPANCY COMES FROM HASH FUNCTION COLLISIONS BECAUSE OF THE LOW VALUE OF THE NFEATURES PARAMETER
IN A REAL WORLD SETTING THE NFEATURES PARAMETER CAN BE LEFT TO ITS DEFAULT VALUE OF 220ROUGHLY ONE MILLION POSSIBLE FEATURES IF MEMORY OR DOWNSTREAM MODELS SIZE IS AN ISSUE SELECTING A LOWER VALUE SUCH AS 218MIGHT HELP WITHOUT INTRODUCING TOO MANY ADDITIONAL COLLISIONS ON TYPICAL TEXT CLASSIFICATION TASKS

NOTE THAT THE DIMENSIONALITY DOES NOT AFFECT THE CPU TRAINING TIME OF ALGORITHMS WHICH OPERATE ON CSR MATRICES LINEARSVCDUALTRUE PERCEPTRON SGDCLASSIFIER PASSIVEAGGRESSIVE BUT IT DOES FOR ALGO
RITHMS THAT WORK WITH CSC MATRICES LINEARSVCDUALFALSE LASSO ETC
LET'S TRY AGAIN WITH THE DEFAULT SETTING
HV HASHINGVECTORIZER
HVTRANSFORMCORPUS

4X1048576 SPARSE MATRIX OF TYPE NUMPYFLOAT64
WITH 19 STORED ELEMENTS IN COMPRESSED SPARSE FORMAT
WE NO LONGER GET THE COLLISIONS BUT THIS COMES AT THE EXPENSE OF A MUCH LARGER DIMENSIONALITY OF THE OUTPUT SPACE OF COURSE OTHER TERMS THAN THE 19 USED HERE MIGHT STILL COLLIDE WITH EACH OTHER
THEHASHINGVECTORIZER ALSO COMES WITH THE FOLLOWING LIMITATIONS
• IT IS NOT POSSIBLE TO INVERT THE MODEL NO INVERSETRANSFORM METHOD NOR TO ACCESS THE ORIGINAL STRING REPRESENTATION OF THE FEATURES BECAUSE OF THE ONEWAY NATURE OF THE HASH FUNCTION THAT PERFORMS THE MAPPING
• IT DOES NOT PROVIDE IDF WEIGHTING AS THAT WOULD INTRODUCE STATEFULNESS IN THE MODEL A TFIDFTRANSFORMER CAN BE APPENDED TO IT IN A PIPELINE IF REQUIRED
PERFORMING OUTOFCORE SCALING WITH HASHINGVECTORIZER
AN INTERESTING DEVELOPMENT OF USING A HASHINGVECTORIZER IS THE ABILITY TO PERFORM OUTOFCORE SCALING THIS MEANS THAT WE CAN LEARN FROM DATA THAT DOES NOT FIT INTO THE COMPUTER'S MAIN MEMORY
A STRATEGY TO IMPLEMENT OUTOFCORE SCALING IS TO STREAM DATA TO THE ESTIMATOR IN MINIBATCHES EACH MINIBATCH IS VECTORIZED USING HASHINGVECTORIZER SO AS TO GUARANTEE THAT THE INPUT SPACE OF THE ESTIMATOR HAS ALWAYS THE SAME DIMENSIONALITY THE AMOUNT OF MEMORY USED AT ANY TIME IS THUS BOUNDED BY THE SIZE OF A MINIBATCH ALTHOUGH THERE IS NO LIMIT TO THE AMOUNT OF DATA THAT CAN BE INGESTED USING SUCH AN APPROACH FROM A PRACTICAL POINT OF VIEW THE LEARNING TIME IS OFTEN LIMITED BY THE CPU TIME ONE WANTS TO SPEND ON THE TASK
FOR A FULLFLEDGED EXAMPLE OF OUTOFCORE SCALING IN A TEXT CLASSIFICATION TASK SEE OUTOFCORE CLASSIFICATION OF TEXT DOCUMENTS
CUSTOMIZING THE VECTORIZER CLASSES
IT IS POSSIBLE TO CUSTOMIZE THE BEHAVIOR BY PASSING A CALLABLE TO THE VECTORIZER CONSTRUCTOR
 DEF MYTOKENIZERS
 RETURN SSPLIT

VECTORIZER COUNTVECTORIZERTOKENIZERMYTOKENIZER
VECTORIZERBUILDANALYZERUSOME PUNCTUATION
 SOME PUNCTUATION
TRUE
IN PARTICULAR WE NAME
•PREPROCESSOR A CALLABLE THAT TAKES AN ENTIRE DOCUMENT AS INPUT AS A SINGLE STRING AND RETURNS A POSSIBLY TRANSFORMED VERSION OF THE DOCUMENT STILL AS AN ENTIRE STRING THIS CAN BE USED TO REMOVE HTML TAGS LOWERCASE THE ENTIRE DOCUMENT ETC
•TOKENIZER A CALLABLE THAT TAKES THE OUTPUT FROM THE PREPROCESSOR AND SPLITS IT INTO TOKENS THEN RETURNS A LIST OF THESE

•ANALYZER A CALLABLE THAT REPLACES THE PREPROCESSOR AND TOKENIZER THE DEFAULT ANALYZERS ALL CALL THE PREPRO
CESSOR AND TOKENIZER BUT CUSTOM ANALYZERS WILL SKIP THIS NGRAM EXTRACTION AND STOP WORD FILTERING TAKE PLACE
AT THE ANALYZER LEVEL SO A CUSTOM ANALYZER MAY HAVE TO REPRODUCE THESE STEPS
LUCENE USERS MIGHT RECOGNIZE THESE NAMES BUT BE AWARE THAT SCIKITLEARN CONCEPTS MAY NOT MAP ONETOONE ONTO
LUCENE CONCEPTS
TO MAKE THE PREPROCESSOR TOKENIZER AND ANALYZERS AWARE OF THE MODEL PARAMETERS IT IS POSSIBLE TO DERIVE FROM THE CLASS
AND OVERRIDE THE BUILDPREPROCESSOR BUILDTOKENIZER ANDBUILDANALYZER FACTORY METHODS INSTEAD
OF PASSING CUSTOM FUNCTIONS
SOME TIPS AND TRICKS
• IF DOCUMENTS ARE PRETOKENIZED BY AN EXTERNAL PACKAGE THEN STORE THEM IN FILES OR STRINGS WITH THE TOKENS
SEPARATED BY WHITESPACE AND PASS ANALYZERSTRSPLIT
• FANCY TOKENLEVEL ANALYSIS SUCH AS STEMMING LEMMATIZING COMPOUND SPLITTING FILTERING BASED ON PARTOF
SPEECH ETC ARE NOT INCLUDED IN THE SCIKITLEARN CODEBASE BUT CAN BE ADDED BY CUSTOMIZING EITHER THE TOKENIZER
OR THE ANALYZER HERE’S A COUNTVECTORIZER WITH A TOKENIZER AND LEMMATIZER USING NLTK

```
 FROM NLTK IMPORT WORDTOKENIZE
 FROM NLTKSTEM IMPORT WORDNETLEMMATIZER
 CLASS LEMMATOKENIZER OBJECT
 DEF INITSELF
 SELFWNL  WORDNETLEMMATIZER
 DEF CALLSELF DOC
 RETURN SELFWNLLEMMATIZET FORTINWORDTOKENIZEDOC

VECT  COUNTVECTORIZERTOKENIZERLEMMATOKENIZER
```

NOTE THAT THIS WILL NOT FILTER OUT PUNCTUATION
THE FOLLOWING EXAMPLE WILL FOR INSTANCE TRANSFORM SOME BRITISH SPELLING TO AMERICAN SPELLING

```
 IMPORT RE
 DEF TOBRITISHTOKENS
 FOR TINTOKENS
 T  RESUBROUR R1OR T
 T  RESUBRBTRE R1ER T
 T  RESUBRIYSEINGATION R1Z2 T
 T  RESUBROGUE OG T
 YIELD T

 CLASS CUSTOMVECTORIZER COUNTVECTORIZER
 DEF BUILDTOKENIZERSELF
 TOKENIZE  SUPERBUILDTOKENIZER
 RETURN LAMBDA DOC LISTTOBRITISHTOKENIZEDOC

PRINTCUSTOMVECTORIZERBUILDANALYZERUCOLOR COLOUR
```

COLOR COLOR
FOR OTHER STYLES OF PREPROCESSING EXAMPLES INCLUDE STEMMING LEMMATIZATION OR NORMALIZING NUMERICAL TOKENS
WITH THE LATTER ILLUSTRATED IN
–BICLUSTERING DOCUMENTS WITH THE SPECTRAL COCLUSTERING ALGORITHM
CUSTOMIZING THE VECTORIZER CAN ALSO BE USEFUL WHEN HANDLING ASIAN LANGUAGES THAT DO NOT USE AN EXPLICIT WORD SEPARATOR
SUCH AS WHITESPACE

IMAGE FEATURE EXTRACTION
PATCH EXTRACTION
THEEXTRACTPATCHES2D FUNCTION EXTRACTS PATCHES FROM AN IMAGE STORED AS A TWODIMENSIONAL ARRAY OR
THREEDIMENSIONAL WITH COLOR INFORMATION ALONG THE THIRD AXIS FOR REBUILDING AN IMAGE FROM ALL ITS PATCHES USE
RECONSTRUCTFROMPATCHES2D FOR EXAMPLE LET USE GENERATE A 4X4 PIXEL PICTURE WITH 3 COLOR CHANNELS EG
IN RGB FORMAT
```
 IMPORT NUMPY AS NP
 FROM SKLEARNFEATUREEXTRACTION IMPORT IMAGE
ONEIMAGE  NPARANGE4 43RESHAPE4 4 3
ONEIMAGE  0  R CHANNEL OF A FAKE RGB PICTURE
ARRAY 0 3 6 9
12 15 18 21
24 27 30 33
36 39 42 45
PATCHES  IMAGEEXTRACTPATCHES2DONEIMAGE 2 2 MAXPATCHES2
 RANDOMSTATE0
PATCHESSHAPE
2 2 2 3
PATCHES   0
ARRAY 0 3
12 15
15 18
27 30
PATCHES  IMAGEEXTRACTPATCHES2DONEIMAGE 2 2
PATCHESSHAPE
9 2 2 3
PATCHES4   0
ARRAY15 18
27 30
```
LET US NOW TRY TO RECONSTRUCT THE ORIGINAL IMAGE FROM THE PATCHES BY AVERAGING ON OVERLAPPING AREAS
```
RECONSTRUCTED  IMAGERECONSTRUCTFROMPATCHES2DPATCHES 4 4 3
NPTESTINGASSERTARRAYEQUALONEIMAGE RECONSTRUCTED
```
THEPATCHEXTRACTOR CLASS WORKS IN THE SAME WAY AS EXTRACTPATCHES2D ONLY IT SUPPORTS MULTIPLE IMAGES
AS INPUT IT IS IMPLEMENTED AS AN ESTIMATOR SO IT CAN BE USED IN PIPELINES SEE
```
FIVEIMAGES  NPARANGE5 443RESHAPE5 4 4 3
PATCHES  IMAGEPATCHEXTRACTOR2 2TRANSFORMFIVEIMAGES
PATCHESSHAPE
45 2 2 3
```
CONNECTIVITY GRAPH OF AN IMAGE
SEVERAL ESTIMATORS IN THE SCIKITLEARN CAN USE CONNECTIVITY INFORMATION BETWEEN FEATURES OR SAMPLES FOR INSTANCE WARD
CLUSTERING HIERARCHICAL CLUSTERING CAN CLUSTER TOGETHER ONLY NEIGHBORING PIXELS OF AN IMAGE THUS FORMING CONTIGUOUS
PATCHES
FOR THIS PURPOSE THE ESTIMATORS USE A ‘CONNECTIVITY’ MATRIX GIVING WHICH SAMPLES ARE CONNECTED

THE FUNCTION IMGTOGRAPH RETURNS SUCH A MATRIX FROM A 2D OR 3D IMAGE SIMILARLY GRIDTOGRAPH BUILD A CONNECTIVITY MATRIX FOR IMAGES GIVEN THE SHAPE OF THESE IMAGE

THESE MATRICES CAN BE USED TO IMPOSE CONNECTIVITY IN ESTIMATORS THAT USE CONNECTIVITY INFORMATION SUCH AS WARD CLUSTERING HIERARCHICAL CLUSTERING BUT ALSO TO BUILD PRECOMPUTED KERNELS OR SIMILARITY MATRICES

NOTE EXAMPLES

•A DEMO OF STRUCTURED WARD HIERARCHICAL CLUSTERING ON AN IMAGE OF COINS

•SPECTRAL CLUSTERING FOR IMAGE SEGMENTATION

•FEATURE AGGLOMERATION VS UNIVARIATE SELECTION

353 PREPROCESSING DATA

THESKLEARNPREPROCESSING PACKAGE PROVIDES SEVERAL COMMON UTILITY FUNCTIONS AND TRANSFORMER CLASSES TO CHANGE RAW FEATURE VECTORS INTO A REPRESENTATION THAT IS MORE SUITABLE FOR THE DOWNSTREAM ESTIMATORS

IN GENERAL LEARNING ALGORITHMS BENEFIT FROM STANDARDIZATION OF THE DATA SET IF SOME OUTLIERS ARE PRESENT IN THE SET ROBUST SCALERS OR TRANSFORMERS ARE MORE APPROPRIATE THE BEHAVIORS OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS ON A DATASET CONTAINING MARGINAL OUTLIERS IS HIGHLIGHTED IN COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS

STANDARDIZATION OR MEAN REMOVAL AND VARIANCE SCALING

STANDARDIZATION OF DATASETS IS A COMMON REQUIREMENT FOR MANY MACHINE LEARNING ESTIMATORS IMPLEMENTED IN SCIKITLEARN THEY MIGHT BEHAVE BADLY IF THE INDIVIDUAL FEATURES DO NOT MORE OR LESS LOOK LIKE STANDARD NORMALLY DIS TRIBUTED DATA GAUSSIAN WITH ZERO MEAN AND UNIT VARIANCE

IN PRACTICE WE OFTEN IGNORE THE SHAPE OF THE DISTRIBUTION AND JUST TRANSFORM THE DATA TO CENTER IT BY REMOVING THE MEAN VALUE OF EACH FEATURE THEN SCALE IT BY DIVIDING NONCONSTANT FEATURES BY THEIR STANDARD DEVIATION

FOR INSTANCE MANY ELEMENTS USED IN THE OBJECTIVE FUNCTION OF A LEARNING ALGORITHM SUCH AS THE RBF KERNEL OF SUPPORT VECTOR MACHINES OR THE L1 AND L2 REGULARIZERS OF LINEAR MODELS ASSUME THAT ALL FEATURES ARE CENTERED AROUND ZERO AND HAVE VARIANCE IN THE SAME ORDER IF A FEATURE HAS A VARIANCE THAT IS ORDERS OF MAGNITUDE LARGER THAN OTHERS IT MIGHT DOMINATE THE OBJECTIVE FUNCTION AND MAKE THE ESTIMATOR UNABLE TO LEARN FROM OTHER FEATURES CORRECTLY AS EXPECTED

THE FUNCTION SCALE PROVIDES A QUICK AND EASY WAY TO PERFORM THIS OPERATION ON A SINGLE ARRAYLIKE DATASET

```
 FROM SKLEARN IMPORT PREPROCESSING
 IMPORT NUMPY AS NP
```

SCIKITLEARN USER GUIDE RELEASE 0213
XTRAIN NPARRAY 1 1 2
  2 0 0
  0 1 1
XSCALED PREPROCESSINGSCALEXTRAIN
XSCALED
ARRAY 0 122 133
 122 0 026
122 122 106
SCALED DATA HAS ZERO MEAN AND UNIT VARIANCE
XSCALEDMEANAXIS0
ARRAY0 0 0
XSCALEDSTDAXIS0
ARRAY1 1 1
THEPREPROCESSING MODULE FURTHER PROVIDES A UTILITY CLASS STANDARDSCALER THAT IMPLEMENTS THE
TRANSFORMER API TO COMPUTE THE MEAN AND STANDARD DEVIATION ON A TRAINING SET SO AS TO BE ABLE TO LATER REAPPLY
THE SAME TRANSFORMATION ON THE TESTING SET THIS CLASS IS HENCE SUITABLE FOR USE IN THE EARLY STEPS OF A SKLEARN
PIPELINEPIPELINE
SCALER PREPROCESSINGSTANDARDSCALERFITXTRAIN
SCALER
STANDARDSCALERCOPYTRUE WITHMEANTRUE WITHSTDTRUE
SCALERMEAN
ARRAY1 0 033
SCALERSCALE
ARRAY081 081 124
SCALERTRANSFORMXTRAIN
ARRAY 0 122 133
 122 0 026
122 122 106
THE SCALER INSTANCE CAN THEN BE USED ON NEW DATA TO TRANSFORM IT THE SAME WAY IT DID ON THE TRAINING SET
XTEST 1 1 0
SCALERTRANSFORMXTEST
ARRAY244 122 026
IT IS POSSIBLE TO DISABLE EITHER CENTERING OR SCALING BY EITHER PASSING WITHMEANFALSE ORWITHSTDFALSE TO
THE CONSTRUCTOR OF STANDARDSCALER
SCALING FEATURES TO A RANGE
AN ALTERNATIVE STANDARDIZATION IS SCALING FEATURES TO LIE BETWEEN A GIVEN MINIMUM AND MAXIMUM VALUE OFTEN BETWEEN
ZERO AND ONE OR SO THAT THE MAXIMUM ABSOLUTE VALUE OF EACH FEATURE IS SCALED TO UNIT SIZE THIS CAN BE ACHIEVED USING
MINMAXSCALER ORMAXABSSCALER RESPECTIVELY
THE MOTIVATION TO USE THIS SCALING INCLUDE ROBUSTNESS TO VERY SMALL STANDARD DEVIATIONS OF FEATURES AND PRESERVING ZERO
ENTRIES IN SPARSE DATA
HERE IS AN EXAMPLE TO SCALE A TOY DATA MATRIX TO THE 0 1 RANGE

SCIKITLEARN USER GUIDE RELEASE 0213
XTRAIN NPARRAY 1 1 2
  2 0 0
  0 1 1

MINMAXSCALER PREPROCESSINGMINMAXSCALER
XTRAINMINMAX MINMAXSCALERFITTRANSFORMXTRAIN
XTRAINMINMAX
ARRAY05 0 1
1 05 033333333
0 1 0
THE SAME INSTANCE OF THE TRANSFORMER CAN THEN BE APPLIED TO SOME NEW TEST DATA UNSEEN DURING THE FIT CALL THE SAME SCALING AND SHIFTING OPERATIONS WILL BE APPLIED TO BE CONSISTENT WITH THE TRANSFORMATION PERFORMED ON THE TRAIN DATA
XTEST NPARRAY3 1 4
XTESTMINMAX MINMAXSCALERTRANSFORMXTEST
XTESTMINMAX
ARRAY15 0 166666667
IT IS POSSIBLE TO INTROSPECT THE SCALER ATTRIBUTES TO FIND ABOUT THE EXACT NATURE OF THE TRANSFORMATION LEARNED ON THE TRAINING DATA
MINMAXSCALERSCALE
ARRAY05 05 033
MINMAXSCALERMIN
ARRAY0 05 033
IFMINMAXSCALER IS GIVEN AN EXPLICIT FEATURERANGEMIN MAX THE FULL FORMULA IS
XSTD X XMINAXIS0 XMAXAXIS0 XMINAXIS0
XSCALED XSTD MAX MIN MIN
MAXABSSCALER WORKS IN A VERY SIMILAR FASHION BUT SCALES IN A WAY THAT THE TRAINING DATA LIES WITHIN THE RANGE 1 1BY DIVIDING THROUGH THE LARGEST MAXIMUM VALUE IN EACH FEATURE IT IS MEANT FOR DATA THAT IS ALREADY CENTERED AT ZERO OR SPARSE DATA
HERE IS HOW TO USE THE TOY DATA FROM THE PREVIOUS EXAMPLE WITH THIS SCALER
XTRAIN NPARRAY 1 1 2
  2 0 0
  0 1 1

MAXABSSCALER PREPROCESSINGMAXABSSCALER
XTRAINMAXABS MAXABSSCALERFITTRANSFORMXTRAIN
XTRAINMAXABS DOCTEST NORMALIZEWHITESPACE
ARRAY 05 1 1
 1 0 0
 0 1 05
XTEST NPARRAY 3 1 4
XTESTMAXABS MAXABSSCALERTRANSFORMXTEST
XTESTMAXABS
ARRAY15 1 2
MAXABSSCALERSCALE
ARRAY2 1 2

AS WITHSCALE THE MODULE FURTHER PROVIDES CONVENIENCE FUNCTIONS MINMAXSCALE ANDMAXABSSCALE IF YOU DON’T WANT TO CREATE AN OBJECT

SCALING SPARSE DATA

CENTERING SPARSE DATA WOULD DESTROY THE SPARSENESS STRUCTURE IN THE DATA AND THUS RARELY IS A SENSIBLE THING TO DO HOWEVER IT CAN MAKE SENSE TO SCALE SPARSE INPUTS ESPECIALLY IF FEATURES ARE ON DIFFERENT SCALES MAXABSSCALER ANDMAXABSSCALE WERE SPECIFICALLY DESIGNED FOR SCALING SPARSE DATA AND ARE THE RECOMMENDED WAY TO GO ABOUT THIS HOWEVER SCALE ANDSTANDARDSCALER CAN ACCEPT SCIPYSPARSE MATRICES AS INPUT AS LONG ASWITHMEANFALSE IS EXPLICITLY PASSED TO THE CONSTRUCTOR OTHERWISE A VALUEERROR WILL BE RAISED AS SILENTLY CENTERING WOULD BREAK THE SPARSITY AND WOULD OFTEN CRASH THE EXECUTION BY ALLOCATING EXCESSIVE AMOUNTS OF MEMORY UNINTENTIONALLY ROBUSTSCALER CANNOT BE FITTED TO SPARSE INPUTS BUT YOU CAN USE THE TRANSFORM METHOD ON SPARSE INPUTS

NOTE THAT THE SCALERS ACCEPT BOTH COMPRESSED SPARSE ROWS AND COMPRESSED SPARSE COLUMNS FORMAT SEE SCIPY SPARSECSRMATRIX ANDSCIPYSPARSECSCMATRIX ANY OTHER SPARSE INPUT WILL BE CONVERTED TO THE COMPRESSED SPARSE ROWS REPRESENTATION TO AVOID UNNECESSARY MEMORY COPIES IT IS RECOMMENDED TO CHOOSE THE CSR OR CSC REPRESENTATION UPSTREAM

FINALLY IF THE CENTERED DATA IS EXPECTED TO BE SMALL ENOUGH EXPLICITLY CONVERTING THE INPUT TO AN ARRAY USING THE TOARRAY METHOD OF SPARSE MATRICES IS ANOTHER OPTION

SCALING DATA WITH OUTLIERS

IF YOUR DATA CONTAINS MANY OUTLIERS SCALING USING THE MEAN AND VARIANCE OF THE DATA IS LIKELY TO NOT WORK VERY WELL IN THESE CASES YOU CAN USE ROBUSTSCALE ANDROBUSTSCALER AS DROPIN REPLACEMENTS INSTEAD THEY USE MORE ROBUST ESTIMATES FOR THE CENTER AND RANGE OF YOUR DATA

REFERENCES

FURTHER DISCUSSION ON THE IMPORTANCE OF CENTERING AND SCALING DATA IS AVAILABLE ON THIS FAQ SHOULD I NORMAL IZESTANDARDIZERESCALE THE DATA

SCALING VS WHITENING

IT IS SOMETIMES NOT ENOUGH TO CENTER AND SCALE THE FEATURES INDEPENDENTLY SINCE A DOWNSTREAM MODEL CAN FURTHER MAKE SOME ASSUMPTION ON THE LINEAR INDEPENDENCE OF THE FEATURES

TO ADDRESS THIS ISSUE YOU CAN USE SKLEARNDECOMPOSITIONPCA WITHWHITENTRUE TO FURTHER REMOVE THE LINEAR CORRELATION ACROSS FEATURES

SCALING A 1D ARRAY

ALL ABOVE FUNCTIONS IE SCALE MINMAXSCALE MAXABSSCALE ANDROBUSTSCALE ACCEPT 1D ARRAY WHICH CAN BE USEFUL IN SOME SPECIFIC CASE

CENTERING KERNEL MATRICES
IF YOU HAVE A KERNEL MATRIX OF A KERNEL □THAT COMPUTES A DOT PRODUCT IN A FEATURE SPACE DEFINED BY FUNCTION □*h*□ A KERNELCENTERER CAN TRANSFORM THE KERNEL MATRIX SO THAT IT CONTAINS INNER PRODUCTS IN THE FEATURE SPACE DEFINED BY □*h*□FOLLOWED BY REMOVAL OF THE MEAN IN THAT SPACE
NONLINEAR TRANSFORMATION
TWO TYPES OF TRANSFORMATIONS ARE AVAILABLE QUANTILE TRANSFORMS AND POWER TRANSFORMS BOTH QUANTILE AND POWER TRANSFORMS ARE BASED ON MONOTONIC TRANSFORMATIONS OF THE FEATURES AND THUS PRESERVE THE RANK OF THE VALUES ALONG EACH FEATURE
QUANTILE TRANSFORMS PUT ALL FEATURES INTO THE SAME DESIRED DISTRIBUTION BASED ON THE FORMULA □−1□□WHERE □IS THE CUMULATIVE DISTRIBUTION FUNCTION OF THE FEATURE AND □−1THE QUANTILE FUNCTION OF THE DESIRED OUTPUT DISTRIBUTION □ THIS FORMULA IS USING THE TWO FOLLOWING FACTS I IF □IS A RANDOM VARIABLE WITH A CONTINUOUS CUMULATIVE DISTRIBUTION FUNCTION □THEN□□IS UNIFORMLY DISTRIBUTED ON 01 II IF □IS A RANDOM VARIABLE WITH UNIFORM DISTRIBUTION ON 01THEN□−1□HAS DISTRIBUTION □ BY PERFORMING A RANK TRANSFORMATION A QUANTILE TRANSFORM SMOOTHS OUT UNUSUAL DISTRIBUTIONS AND IS LESS INFLUENCED BY OUTLIERS THAN SCALING METHODS IT DOES HOWEVER DISTORT CORRELATIONS AND DISTANCES WITHIN AND ACROSS FEATURES
POWER TRANSFORMS ARE A FAMILY OF PARAMETRIC TRANSFORMATIONS THAT AIM TO MAP DATA FROM ANY DISTRIBUTION TO AS CLOSE TO A GAUSSIAN DISTRIBUTION
MAPPING TO A UNIFORM DISTRIBUTION
QUANTILETRANSFORMER ANDQUANTILETRANSFORM PROVIDE A NONPARAMETRIC TRANSFORMATION TO MAP THE DATA TO A UNIFORM DISTRIBUTION WITH VALUES BETWEEN 0 AND 1

```
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
IRIS  LOADIRIS
X Y  IRISDATA IRISTARGET
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLITX Y RANDOMSTATE0
QUANTILETRANSFORMER  PREPROCESSINGQUANTILETRANSFORMERRANDOMSTATE0
XTRAINTRANS  QUANTILETRANSFORMERFITTRANSFORMXTRAIN
XTESTTRANS  QUANTILETRANSFORMERTRANSFORMXTEST
NPPERCENTILEXTRAIN 0 0 25 50 75 100
ARRAY 43 51 58 65 79
```

THIS FEATURE CORRESPONDS TO THE SEPAL LENGTH IN CM ONCE THE QUANTILE TRANSFORMATION APPLIED THOSE LANDMARKS APPROACH CLOSELY THE PERCENTILES PREVIOUSLY DEFINED

```
NPPERCENTILEXTRAINTRANS 0 0 25 50 75 100

ARRAY 000  024 049 073 099
```

THIS CAN BE CONFIRMED ON A INDEPENDENT TESTING SET WITH SIMILAR REMARKS

```
NPPERCENTILEXTEST 0 0 25 50 75 100

ARRAY 44  5125 575  6175 73
NPPERCENTILEXTESTTRANS 0 0 25 50 75 100

ARRAY 001 025 046 060  094
```

MAPPING TO A GAUSSIAN DISTRIBUTION
IN MANY MODELING SCENARIOS NORMALITY OF THE FEATURES IN A DATASET IS DESIRABLE POWER TRANSFORMS ARE A FAMILY OF PARAMETRIC MONOTONIC TRANSFORMATIONS THAT AIM TO MAP DATA FROM ANY DISTRIBUTION TO AS CLOSE TO A GAUSSIAN DISTRIBUTION AS POSSIBLE IN ORDER TO STABILIZE VARIANCE AND MINIMIZE SKEWNESS
POWERTRANSFORMER CURRENTLY PROVIDES TWO SUCH POWER TRANSFORMATIONS THE YEOJOHNSON TRANSFORM AND THE BOX COX TRANSFORM
THE YEOJOHNSON TRANSFORM IS GIVEN BY
□□
□ ⎧
⎪⎪⎪⎪⎪⎪⎪⎨
⎪⎪⎪⎪⎪⎪⎪⎩□□ 1□−1□ IF□ 0 □□≥0
LN □□ 1 IF□ 0 □□≥0
−−□□ 12−□−12−□IF□ 2 □□0
−LN−□□ 1 IF□ 2 □□0
WHILE THE BOXCOX TRANSFORM IS GIVEN BY
□□
□ ⎧
⎪⎨
⎪⎩□□
□−1
□IF□ 0
LN □□IF□ 0
BOXCOX CAN ONLY BE APPLIED TO STRICTLY POSITIVE DATA IN BOTH METHODS THE TRANSFORMATION IS PARAMETERIZED BY □ WHICH IS DETERMINED THROUGH MAXIMUM LIKELIHOOD ESTIMATION HERE IS AN EXAMPLE OF USING BOXCOX TO MAP SAMPLES DRAWN FROM A LOGNORMAL DISTRIBUTION TO A NORMAL DISTRIBUTION

```
PT  PREPROCESSINGPOWERTRANSFORMERMETHODBOXCOX STANDARDIZE FALSE
XLOGNORMAL  NPRANDOMRANDOMSTATE616LOGNORMALSIZE3 3
XLOGNORMAL
ARRAY128 118 084
094 160 038
135 021 109
PTFITTRANSFORMXLOGNORMAL
ARRAY 049 017 015
005 058 057
 069 084 010
```

WHILE THE ABOVE EXAMPLE SETS THE STANDARDIZE OPTION TOFALSE POWERTRANSFORMER WILL APPLY ZEROMEAN UNITVARIANCE NORMALIZATION TO THE TRANSFORMED OUTPUT BY DEFAULT
BELOW ARE EXAMPLES OF BOXCOX AND YEOJOHNSON APPLIED TO VARIOUS PROBABILITY DISTRIBUTIONS NOTE THAT WHEN APPLIED TO CERTAIN DISTRIBUTIONS THE POWER TRANSFORMS ACHIEVE VERY GAUSSIANLIKE RESULTS BUT WITH OTHERS THEY ARE INEFFECTIVE THIS HIGHLIGHTS THE IMPORTANCE OF VISUALIZING THE DATA BEFORE AND AFTER TRANSFORMATION
IT IS ALSO POSSIBLE TO MAP DATA TO A NORMAL DISTRIBUTION USING QUANTILETRANSFORMER BY SETTING OUTPUTDISTRIBUTIONNORMAL USING THE EARLIER EXAMPLE WITH THE IRIS DATASET

```
QUANTILETRANSFORMER  PREPROCESSINGQUANTILETRANSFORMER
 OUTPUTDISTRIBUTIONNORMAL RANDOMSTATE0
XTRANS  QUANTILETRANSFORMERFITTRANSFORMX
QUANTILETRANSFORMERQUANTILES
ARRAY43 2  1  01
44 22 11 01
44 22 12 01
```

77 41 67 25
77 42 67 25
79 44 69 25
THUS THE MEDIAN OF THE INPUT BECOMES THE MEAN OF THE OUTPUT CENTERED AT 0 THE NORMAL OUTPUT IS CLIPPED SO THAT THE INPUT'S MINIMUM AND MAXIMUM — CORRESPONDING TO THE 1E7 AND 1 1E7 QUANTILES RESPECTIVELY — DO NOT BECOME INFINITE UNDER THE TRANSFORMATION

NORMALIZATION

NORMALIZATION IS THE PROCESS OF SCALING INDIVIDUAL SAMPLES TO HAVE UNIT NORM THIS PROCESS CAN BE USEFUL IF YOU PLAN TO USE A QUADRATIC FORM SUCH AS THE DOTPRODUCT OR ANY OTHER KERNEL TO QUANTIFY THE SIMILARITY OF ANY PAIR OF SAMPLES THIS ASSUMPTION IS THE BASE OF THE VECTOR SPACE MODEL OFTEN USED IN TEXT CLASSIFICATION AND CLUSTERING CONTEXTS THE FUNCTION NORMALIZE PROVIDES A QUICK AND EASY WAY TO PERFORM THIS OPERATION ON A SINGLE ARRAYLIKE DATASET EITHER USING THE L1ORL2NORMS

X   1 1 2
  2 0 0
  0 1 1
XNORMALIZED PREPROCESSINGNORMALIZEX NORML2
XNORMALIZED
ARRAY 040 040 081
 1 0 0
 0 070 070

THEPREPROCESSING MODULE FURTHER PROVIDES A UTILITY CLASS NORMALIZER THAT IMPLEMENTS THE SAME OPERATION USING THETRANSFORMER API EVEN THOUGH THE FIT METHOD IS USELESS IN THIS CASE THE CLASS IS STATELESS AS THIS OPERATION TREATS SAMPLES INDEPENDENTLY

THIS CLASS IS HENCE SUITABLE FOR USE IN THE EARLY STEPS OF A SKLEARNPIPELINEPIPELINE

NORMALIZER PREPROCESSINGNORMALIZERFITX FIT DOES NOTHING
NORMALIZER
NORMALIZERCOPYTRUE NORML2

THE NORMALIZER INSTANCE CAN THEN BE USED ON SAMPLE VECTORS AS ANY TRANSFORMER

NORMALIZERTRANSFORMX
ARRAY 040 040 081
 1 0 0
 0 070 070
NORMALIZERTRANSFORM1 1 0
ARRAY070 070 0

SPARSE INPUT

NORMALIZE ANDNORMALIZER ACCEPT BOTH DENSE ARRAYLIKE AND SPARSE MATRICES FROM SCIPYSPARSE AS INPUT

FOR SPARSE INPUT THE DATA IS CONVERTED TO THE COMPRESSED SPARSE ROWS REPRESENTATION SEESCIPYSPARSE CSRMATRIX BEFORE BEING FED TO EFFICIENT CYTHON ROUTINES TO AVOID UNNECESSARY MEMORY COPIES IT IS RECOM MENDED TO CHOOSE THE CSR REPRESENTATION UPSTREAM

ENCODING CATEGORICAL FEATURES
OFTEN FEATURES ARE NOT GIVEN AS CONTINUOUS VALUES BUT CATEGORICAL FOR EXAMPLE A PERSON COULD HAVE FEA
TURESMALE FEMALE FROM EUROPE FROM US FROM ASIA USES FIREFOX
USES CHROME USES SAFARI USES INTERNET EXPLORER SUCH FEATURES CAN BE EFFICIENTLY
CODED AS INTEGERS FOR INSTANCE MALE FROM US USES INTERNET EXPLORER COULD BE EXPRESSED
AS0 1 3 WHILEFEMALE FROM ASIA USES CHROME WOULD BE1 2 1
TO CONVERT CATEGORICAL FEATURES TO SUCH INTEGER CODES WE CAN USE THE ORDINALENCODER THIS ESTIMATOR TRANSFORMS
EACH CATEGORICAL FEATURE TO ONE NEW FEATURE OF INTEGERS 0 TO NCATEGORIES 1
ENC PREPROCESSINGORDINALENCODER
X MALE FROM US USES SAFARI FEMALE FROM EUROPE USES FIREFOX
‘→
ENCFITX
ORDINALENCODERCATEGORIESAUTO DTYPE NUMPYFLOAT64
ENCTRANSFORMFEMALE FROM US USES SAFARI
ARRAY0 1 1
SUCH INTEGER REPRESENTATION CAN HOWEVER NOT BE USED DIRECTLY WITH ALL SCIKITLEARN ESTIMATORS AS THESE EXPECT CONTINU
OUS INPUT AND WOULD INTERPRET THE CATEGORIES AS BEING ORDERED WHICH IS OFTEN NOT DESIRED IE THE SET OF BROWSERS WAS
ORDERED ARBITRARILY
ANOTHER POSSIBILITY TO CONVERT CATEGORICAL FEATURES TO FEATURES THAT CAN BE USED WITH SCIKITLEARN ESTIMATORS IS
TO USE A ONEOFK ALSO KNOWN AS ONEHOT OR DUMMY ENCODING THIS TYPE OF ENCODING CAN BE OBTAINED WITH
THEONEHOTENCODER WHICH TRANSFORMS EACH CATEGORICAL FEATURE WITH NCATEGORIES POSSIBLE VALUES INTO
NCATEGORIES BINARY FEATURES WITH ONE OF THEM 1 AND ALL OTHERS 0
CONTINUING THE EXAMPLE ABOVE
ENC PREPROCESSINGONEHOTENCODER
X MALE FROM US USES SAFARI FEMALE FROM EUROPE USES FIREFOX
‘→
ENCFITX
ONEHOTENCODERCATEGORICALFEATURESNONE CATEGORIESNONE DROPNONE
DTYPE NUMPYFLOAT64 HANDLEUNKNOWNERROR
NVALUESNONE SPARSETRUE
ENCTRANSFORMFEMALE FROM US USES SAFARI
 MALE FROM EUROPE USES SAFARITOARRAY
ARRAY1 0 0 1 0 1
0 1 1 0 0 1
BY DEFAULT THE VALUES EACH FEATURE CAN TAKE IS INFERRED AUTOMATICALLY FROM THE DATASET AND CAN BE FOUND IN THE
CATEGORIES ATTRIBUTE
ENCCATEGORIES
ARRAYFEMALE MALE DTYPEOBJECT ARRAYFROM EUROPE FROM US
‘→DTYPEOBJECT ARRAYUSES FIREFOX USES SAFARI DTYPEOBJECT
IT IS POSSIBLE TO SPECIFY THIS EXPLICITLY USING THE PARAMETER CATEGORIES THERE ARE TWO GENDERS FOUR POSSIBLE
CONTINENTS AND FOUR WEB BROWSERS IN OUR DATASET
GENDERS FEMALE MALE
LOCATIONS FROM AFRICA FROM ASIA FROM EUROPE FROM US
BROWSERS USES CHROME USES FIREFOX USES IE USES SAFARI
ENC PREPROCESSINGONEHOTENCODERCATEGORIESGENDERS LOCATIONS BROWSERS
 NOTE THAT FOR THERE ARE MISSING CATEGORICAL VALUES FOR THE 2ND AND 3RD
 FEATURE

X MALE FROM US USES SAFARI FEMALE FROM EUROPE USES FIREFOX
‘→
ENCFITX
ONEHOTENCODERCATEGORICALFEATURESNONE
CATEGORIES DROPNONE
DTYPE NUMPYFLOAT64 HANDLEUNKNOWNERROR
NVALUESNONE SPARSETRUE
ENCTRANSFORMFEMALE FROM ASIA USES CHROMETOARRAY
ARRAY1 0 0 1 0 0 1 0 0 0
IF THERE IS A POSSIBILITY THAT THE TRAINING DATA MIGHT HAVE MISSING CATEGORICAL FEATURES IT CAN OFTEN BE
BETTER TO SPECIFY HANDLEUNKNOWNIGNORE INSTEAD OF SETTING THE CATEGORIES MANUALLY AS ABOVE
WHENHANDLEUNKNOWNIGNORE IS SPECIFIED AND UNKNOWN CATEGORIES ARE ENCOUNTERED DURING TRANS
FORM NO ERROR WILL BE RAISED BUT THE RESULTING ONEHOT ENCODED COLUMNS FOR THIS FEATURE WILL BE ALL ZEROS
HANDLEUNKNOWNIGNORE IS ONLY SUPPORTED FOR ONEHOT ENCODING
ENC PREPROCESSINGONEHOTENCODERHANDLEUNKNOWNIGNORE
X MALE FROM US USES SAFARI FEMALE FROM EUROPE USES FIREFOX
‘→
ENCFITX
ONEHOTENCODERCATEGORICALFEATURESNONE CATEGORIESNONE DROPNONE
DTYPE NUMPYFLOAT64 HANDLEUNKNOWNIGNORE
NVALUESNONE SPARSETRUE
ENCTRANSFORMFEMALE FROM ASIA USES CHROMETOARRAY
ARRAY1 0 0 0 0 0
IT IS ALSO POSSIBLE TO ENCODE EACH COLUMN INTO NCATEGORIES 1 COLUMNS INSTEAD OF NCATEGORIES COLUMNS
BY USING THE DROP PARAMETER THIS PARAMETER ALLOWS THE USER TO SPECIFY A CATEGORY FOR EACH FEATURE TO BE DROPPED THIS
IS USEFUL TO AVOID COLINEARITY IN THE INPUT MATRIX IN SOME CLASSIFIERS SUCH FUNCTIONALITY IS USEFUL FOR EXAMPLE WHEN
USING NONREGULARIZED REGRESSION LINEARREGRESSION SINCE COLINEARITY WOULD CAUSE THE COVARIANCE MATRIX TO BE
NONINVERTIBLE WHEN THIS PARAMENTER IS NOT NONE HANDLEUNKNOWN MUST BE SET TO ERROR
X MALE FROM US USES SAFARI FEMALE FROM EUROPE USES FIREFOX
‘→
DROPENC PREPROCESSINGONEHOTENCODERDROPFIRSTFITX
DROPENCCATEGORIES
ARRAYFEMALE MALE DTYPEOBJECT ARRAYFROM EUROPE FROM US
‘→DTYPEOBJECT ARRAYUSES FIREFOX USES SAFARI DTYPEOBJECT
DROPENCTRANSFORMXTOARRAY
ARRAY1 1 1
0 0 0
SEELOADING FEATURES FROM DICTS FOR CATEGORICAL FEATURES THAT ARE REPRESENTED AS A DICT NOT AS SCALARS
DISCRETIZATION
DISCRETIZATION OTHERWISE KNOWN AS QUANTIZATION OR BINNING PROVIDES A WAY TO PARTITION CONTINUOUS FEATURES INTO DIS
CRETE VALUES CERTAIN DATASETS WITH CONTINUOUS FEATURES MAY BENEFIT FROM DISCRETIZATION BECAUSE DISCRETIZATION CAN
TRANSFORM THE DATASET OF CONTINUOUS ATTRIBUTES TO ONE WITH ONLY NOMINAL ATTRIBUTES
ONEHOT ENCODED DISCRETIZED FEATURES CAN MAKE A MODEL MORE EXPRESSIVE WHILE MAINTAINING INTERPRETABILITY FOR
INSTANCE PREPROCESSING WITH A DISCRETIZER CAN INTRODUCE NONLINEARITY TO LINEAR MODELS

KBINS DISCRETIZATION
KBINSDISCRETIZER DISCRETIZES FEATURES INTO KBINS
X NPARRAY 3 5 15
  0 6 14
  6 3 11
EST PREPROCESSINGKBINSDISCRETIZERNBINS3 2 2 ENCODEORDINALFITX
BY DEFAULT THE OUTPUT IS ONEHOT ENCODED INTO A SPARSE MATRIX SEE ENCODING CATEGORICAL FEATURES AND THIS CAN BE CONFIGURED WITH THE ENCODE PARAMETER FOR EACH FEATURE THE BIN EDGES ARE COMPUTED DURING FIT AND TOGETHER WITH THE NUMBER OF BINS THEY WILL DEFINE THE INTERVALS THEREFORE FOR THE CURRENT EXAMPLE THESE INTERVALS ARE DEFINED AS
• FEATURE 1 −∞−1−122∞
• FEATURE 2 −∞55∞
• FEATURE 3 −∞1414∞
BASED ON THESE BIN INTERVALS XIS TRANSFORMED AS FOLLOWS
ESTTRANSFORMX
ARRAY 0 1 1
 1 1 1
 2 0 0
THE RESULTING DATASET CONTAINS ORDINAL ATTRIBUTES WHICH CAN BE FURTHER USED IN A SKLEARNPIPELINEPIPELINE
DISCRETIZATION IS SIMILAR TO CONSTRUCTING HISTOGRAMS FOR CONTINUOUS DATA HOWEVER HISTOGRAMS FOCUS ON COUNTING FEATURES WHICH FALL INTO PARTICULAR BINS WHEREAS DISCRETIZATION FOCUSES ON ASSIGNING FEATURE VALUES TO THESE BINS
KBINSDISCRETIZER IMPLEMENTS DIFFERENT BINNING STRATEGIES WHICH CAN BE SELECTED WITH THE STRATEGY PARAME
TER THE ‘UNIFORM’ STRATEGY USES CONSTANTWIDTH BINS THE ‘QUANTILE’ STRATEGY USES THE QUANTILES VALUES TO HAVE EQUALLY POPULATED BINS IN EACH FEATURE THE ‘KMEANS’ STRATEGY DEFINES BINS BASED ON A KMEANS CLUSTERING PROCEDURE PERFORMED ON EACH FEATURE INDEPENDENTLY
EXAMPLES
•USING KBINSDISCRETIZER TO DISCRETIZE CONTINUOUS FEATURES
•FEATURE DISCRETIZATION
•DEMONSTRATING THE DIFFERENT STRATEGIES OF KBINSDISCRETIZER
FEATURE BINARIZATION
FEATURE BINARIZATION IS THE PROCESS OF THRESHOLDING NUMERICAL FEATURES TO GET BOOLEAN VALUES THIS CAN BE USEFUL FOR DOWNSTREAM PROBABILISTIC ESTIMATORS THAT MAKE ASSUMPTION THAT THE INPUT DATA IS DISTRIBUTED ACCORDING TO A MULTIVARIATE BERNOULLI DISTRIBUTION FOR INSTANCE THIS IS THE CASE FOR THE SKLEARNNEURALNETWORKBERNOULLIRBM
IT IS ALSO COMMON AMONG THE TEXT PROCESSING COMMUNITY TO USE BINARY FEATURE VALUES PROBABLY TO SIMPLIFY THE PROBA BILISTIC REASONING EVEN IF NORMALIZED COUNTS AKA TERM FREQUENCIES OR TFIDF VALUED FEATURES OFTEN PERFORM SLIGHTLY BETTER IN PRACTICE
AS FOR THE NORMALIZER THE UTILITY CLASS BINARIZER IS MEANT TO BE USED IN THE EARLY STAGES OF SKLEARN PIPELINEPIPELINE THEFIT METHOD DOES NOTHING AS EACH SAMPLE IS TREATED INDEPENDENTLY OF OTHERS

X 1 1 2
 2 0 0
 0 1 1
BINARIZER PREPROCESSINGBINARIZERFITX FIT DOES NOTHING
BINARIZER
BINARIZERCOPYTRUE THRESHOLD00
BINARIZERTRANSFORMX
ARRAY1 0 1
1 0 0
0 1 0
IT IS POSSIBLE TO ADJUST THE THRESHOLD OF THE BINARIZER
BINARIZER PREPROCESSINGBINARIZERTHRESHOLD11
BINARIZERTRANSFORMX
ARRAY0 0 1
1 0 0
0 0 0
AS FOR THESTANDARDSCALER ANDNORMALIZER CLASSES THE PREPROCESSING MODULE PROVIDES A COMPANION FUNCTION
BINARIZE TO BE USED WHEN THE TRANSFORMER API IS NOT NECESSARY
NOTE THAT THE BINARIZER IS SIMILAR TO THE KBINSDISCRETIZER WHENK 2 AND WHEN THE BIN EDGE IS AT THE
VALUETHRESHOLD
SPARSE INPUT
BINARIZE ANDBINARIZER ACCEPT BOTH DENSE ARRAYLIKE AND SPARSE MATRICES FROM SCIPYSPARSE AS INPUT
FOR SPARSE INPUT THE DATA IS CONVERTED TO THE COMPRESSED SPARSE ROWS REPRESENTATION SEESCIPYSPARSE
CSRMATRIX TO AVOID UNNECESSARY MEMORY COPIES IT IS RECOMMENDED TO CHOOSE THE CSR REPRESENTATION UP
STREAM
IMPUTATION OF MISSING VALUES
TOOLS FOR IMPUTING MISSING VALUES ARE DISCUSSED AT IMPUTATION OF MISSING VALUES
GENERATING POLYNOMIAL FEATURES
OFTEN IT’S USEFUL TO ADD COMPLEXITY TO THE MODEL BY CONSIDERING NONLINEAR FEATURES OF THE INPUT DATA A SIMPLE AND COM
MON METHOD TO USE IS POLYNOMIAL FEATURES WHICH CAN GET FEATURES’ HIGHORDER AND INTERACTION TERMS IT IS IMPLEMENTED
INPOLYNOMIALFEATURES
 IMPORT NUMPY AS NP
 FROM SKLEARNPREPROCESSING IMPORT POLYNOMIALFEATURES
X NPARANGE6RESHAPE3 2
X
ARRAY0 1
2 3
4 5
POLY POLYNOMIALFEATURES2
POLYFITTRANSFORMX

ARRAY 1 0 1 0 0 1
 1 2 3 4 6 9
 1 4 5 16 20 25
THE FEATURES OF X HAVE BEEN TRANSFORMED FROM □1 □2TO1 □1 □2 □2
1 □1□2 □2
2
IN SOME CASES ONLY INTERACTION TERMS AMONG FEATURES ARE REQUIRED AND IT CAN BE GOTTEN WITH THE SETTING
INTERACTIONONLYTRUE
X NPARANGE9RESHAPE3 3
X
ARRAY0 1 2
3 4 5
6 7 8
POLY POLYNOMIALFEATURESDEGREE3 INTERACTIONONLY TRUE
POLYFITTRANSFORMX
ARRAY 1 0 1 2 0 0 2 0
 1 3 4 5 12 15 20 60
 1 6 7 8 42 48 56 336
THE FEATURES OF X HAVE BEEN TRANSFORMED FROM □1 □2 □3TO1 □1 □2 □3 □1□2 □1□3 □2□3 □1□2□3
NOTE THAT POLYNOMIAL FEATURES ARE USED IMPLICITLY IN KERNEL METHODS EG SKLEARNSVMSVC SKLEARN
DECOMPOSITIONKERNELPCA WHEN USING POLYNOMIAL KERNEL FUNCTIONS
SEEPOLYNOMIAL INTERPOLATION FOR RIDGE REGRESSION USING CREATED POLYNOMIAL FEATURES
CUSTOM TRANSFORMERS
OFTEN YOU WILL WANT TO CONVERT AN EXISTING PYTHON FUNCTION INTO A TRANSFORMER TO ASSIST IN DATA CLEANING OR PROCESSING
YOU CAN IMPLEMENT A TRANSFORMER FROM AN ARBITRARY FUNCTION WITH FUNCTIONTRANSFORMER FOR EXAMPLE TO BUILD
A TRANSFORMER THAT APPLIES A LOG TRANSFORMATION IN A PIPELINE DO
 IMPORT NUMPY AS NP
 FROM SKLEARNPREPROCESSING IMPORT FUNCTIONTRANSFORMER
TRANSFORMER FUNCTIONTRANSFORMERNPLOG1P VALIDATE TRUE
X NPARRAY0 1 2 3
TRANSFORMERTRANSFORMX
ARRAY0 069314718
109861229 138629436
YOU CAN ENSURE THAT FUNC ANDINVERSEFUNC ARE THE INVERSE OF EACH OTHER BY SETTING CHECKINVERSETRUE
AND CALLING FIT BEFORETRANSFORM PLEASE NOTE THAT A WARNING IS RAISED AND CAN BE TURNED INTO AN ERROR WITH A
FILTERWARNINGS
 IMPORT WARNINGS
WARNINGSFILTERWARNINGSERROR MESSAGE CHECKINVERSE
 CATEGORYUSERWARNING APPEND FALSE
FOR A FULL CODE EXAMPLE THAT DEMONSTRATES USING A FUNCTIONTRANSFORMER TO DO CUSTOM FEATURE SELECTION SEE
USING FUNCTIONTRANSFORMER TO SELECT COLUMNS
354 IMPUTATION OF MISSING VALUES
FOR VARIOUS REASONS MANY REAL WORLD DATASETS CONTAIN MISSING VALUES OFTEN ENCODED AS BLANKS NANS OR OTHER PLACE
HOLDERS SUCH DATASETS HOWEVER ARE INCOMPATIBLE WITH SCIKITLEARN ESTIMATORS WHICH ASSUME THAT ALL VALUES IN AN ARRAY

ARE NUMERICAL AND THAT ALL HAVE AND HOLD MEANING A BASIC STRATEGY TO USE INCOMPLETE DATASETS IS TO DISCARD ENTIRE ROWS ANDOR COLUMNS CONTAINING MISSING VALUES HOWEVER THIS COMES AT THE PRICE OF LOSING DATA WHICH MAY BE VALUABLE EVEN THOUGH INCOMPLETE A BETTER STRATEGY IS TO IMPUTE THE MISSING VALUES IE TO INFER THEM FROM THE KNOWN PART OF THE DATA SEE THE GLOSSARY OF COMMON TERMS AND API ELEMENTS ENTRY ON IMPUTATION

UNIVARIATE VS MULTIVARIATE IMPUTATION

ONE TYPE OF IMPUTATION ALGORITHM IS UNIVARIATE WHICH IMPUTES VALUES IN THE ITH FEATURE DIMENSION USING ONLY NON MISSING VALUES IN THAT FEATURE DIMENSION EG IMPUTESIMPLEIMPUTER BY CONTRAST MULTIVARIATE IMPUTA TION ALGORITHMS USE THE ENTIRE SET OF AVAILABLE FEATURE DIMENSIONS TO ESTIMATE THE MISSING VALUES EG IMPUTE ITERATIVEIMPUTER

UNIVARIATE FEATURE IMPUTATION

THESIMPLEIMPUTER CLASS PROVIDES BASIC STRATEGIES FOR IMPUTING MISSING VALUES MISSING VALUES CAN BE IMPUTED WITH A PROVIDED CONSTANT VALUE OR USING THE STATISTICS MEAN MEDIAN OR MOST FREQUENT OF EACH COLUMN IN WHICH THE MISSING VALUES ARE LOCATED THIS CLASS ALSO ALLOWS FOR DIFFERENT MISSING VALUES ENCODINGS

THE FOLLOWING SNIPPET DEMONSTRATES HOW TO REPLACE MISSING VALUES ENCODED AS NPNAN USING THE MEAN VALUE OF THE COLUMNS AXIS 0 THAT CONTAIN THE MISSING VALUES

```
 IMPORT NUMPY AS NP
 FROM SKLEARNIMPUTE IMPORT SIMPLEIMPUTER
IMP  SIMPLEIMPUTERMISSINGVALUESNPNAN STRATEGYMEAN
IMPFIT1 2 NPNAN 3 7 6
SIMPLEIMPUTERADDINDICATORFALSE COPYTRUE FILLVALUENONE
MISSINGVALUESNAN STRATEGYMEAN VERBOSE0
X  NPNAN 2 6 NPNAN 7 6
PRINTIMPTRANSFORMX
4 2
6 3666
7 6
```

THESIMPLEIMPUTER CLASS ALSO SUPPORTS SPARSE MATRICES

```
 IMPORT SCIPYSPARSE AS SP
X  SPCSCMATRIX1 2 0 1 8 4
IMP  SIMPLEIMPUTERMISSINGVALUES1 STRATEGYMEAN
IMPFITX
SIMPLEIMPUTERADDINDICATORFALSE COPYTRUE FILLVALUENONE
MISSINGVALUES1 STRATEGYMEAN VERBOSE0
XTEST  SPCSCMATRIX1 2 6 1 7 6
PRINTIMPTRANSFORMXTESTTOARRAY
3 2
6 3
7 6
```

NOTE THAT THIS FORMAT IS NOT MEANT TO BE USED TO IMPLICITLY STORE MISSING VALUES IN THE MATRIX BECAUSE IT WOULD DENSIFY IT AT TRANSFORM TIME MISSING VALUES ENCODED BY 0 MUST BE USED WITH DENSE INPUT

THESIMPLEIMPUTER CLASS ALSO SUPPORTS CATEGORICAL DATA REPRESENTED AS STRING VALUES OR PANDAS CATEGORICALS WHEN USING THEMOSTFREQUENT ORCONSTANT STRATEGY

```
 IMPORT PANDAS AS PD
DF  PDDATAFRAMEA X
 NPNAN Y
```

```
 A NPNAN
 B Y DTYPECATEGORY

IMP  SIMPLEIMPUTERSTRATEGYMOSTFREQUENT
PRINTIMPFITTRANSFORMDF
A X
A Y
A Y
B Y
```
MULTIVARIATE FEATURE IMPUTATION

A MORE SOPHISTICATED APPROACH IS TO USE THE ITERATIVEIMPUTER CLASS WHICH MODELS EACH FEATURE WITH MISSING VALUES AS A FUNCTION OF OTHER FEATURES AND USES THAT ESTIMATE FOR IMPUTATION IT DOES SO IN AN ITERATED ROUNDROBIN FASHION AT EACH STEP A FEATURE COLUMN IS DESIGNATED AS OUTPUT YAND THE OTHER FEATURE COLUMNS ARE TREATED AS INPUTS X A REGRESSOR IS FIT ON X Y FOR KNOWNY THEN THE REGRESSOR IS USED TO PREDICT THE MISSING VALUES OF Y THIS IS DONE FOR EACH FEATURE IN AN ITERATIVE FASHION AND THEN IS REPEATED FOR MAXITER IMPUTATION ROUNDS THE RESULTS OF THE FINAL IMPUTATION ROUND ARE RETURNED

NOTE THIS ESTIMATOR IS STILL EXPERIMENTAL FOR NOW THE PREDICTIONS AND THE API MIGHT CHANGE WITHOUT ANY DEPRECATION CYCLE TO USE IT YOU NEED TO EXPLICITLY IMPORT ENABLEITERATIVEIMPUTER

```
 IMPORT NUMPY AS NP
 FROM SKLEARNEXPERIMENTAL IMPORT ENABLEITERATIVEIMPUTER
 FROM SKLEARNIMPUTE IMPORT ITERATIVEIMPUTER
IMP  ITERATIVEIMPUTERMAXITER10 RANDOMSTATE0
IMPFIT1 2 3 6 4 8 NPNAN 3 7 NPNAN
ITERATIVEIMPUTERADDINDICATORFALSE ESTIMATORNONE
IMPUTATIONORDERASCENDING INITIALSTRATEGYMEAN
MAXITER10 MAXVALUENONE MINVALUENONE
MISSINGVALUESNAN NNEARESTFEATURESNONE
RANDOMSTATE0 SAMPLEPOSTERIORFALSE TOL0001
VERBOSE0
XTEST  NPNAN 2 6 NPNAN NPNAN 6
 THE MODEL LEARNS THAT THE SECOND FEATURE IS DOUBLE THE FIRST
PRINTNPROUNDIMPTRANSFORMXTEST
 1 2
 6 12
 3 6
```
BOTHSIMPLEIMPUTER ANDITERATIVEIMPUTER CAN BE USED IN A PIPELINE AS A WAY TO BUILD A COMPOSITE ESTIMATOR THAT SUPPORTS IMPUTATION SEE IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR

FLEXIBILITY OF ITERATIVEIMPUTER

THERE ARE MANY WELLESTABLISHED IMPUTATION PACKAGES IN THE R DATA SCIENCE ECOSYSTEM AMELIA MI MICE MISS FOREST ETC MISSFOREST IS POPULAR AND TURNS OUT TO BE A PARTICULAR INSTANCE OF DIFFERENT SEQUENTIAL IMPUTA TION ALGORITHMS THAT CAN ALL BE IMPLEMENTED WITH ITERATIVEIMPUTER BY PASSING IN DIFFERENT REGRESSORS TO BE USED FOR PREDICTING MISSING FEATURE VALUES IN THE CASE OF MISSFOREST THIS REGRESSOR IS A RANDOM FOREST SEE SPHXGLRAUTOEXAMPLESPLOTITERATIVEIMPUTERVARIANTSCOMPARISONPY

MULTIPLE VS SINGLE IMPUTATION

IN THE STATISTICS COMMUNITY IT IS COMMON PRACTICE TO PERFORM MULTIPLE IMPUTATIONS GENERATING FOR EXAMPLE MSEPARATE IMPUTATIONS FOR A SINGLE FEATURE MATRIX EACH OF THESE MIMPUTATIONS IS THEN PUT THROUGH THE SUBSEQUENT ANALYSIS PIPELINE EG FEATURE ENGINEERING CLUSTERING REGRESSION CLASSIFICATION THE MFINAL ANALYSIS RESULTS EG HELDOUT VALIDATION ERRORS ALLOW THE DATA SCIENTIST TO OBTAIN UNDERSTANDING OF HOW ANALYTIC RESULTS MAY DIFFER AS A CONSEQUENCE OF THE INHERENT UNCERTAINTY CAUSED BY THE MISSING VALUES THE ABOVE PRACTICE IS CALLED MULTIPLE IMPUTATION

OUR IMPLEMENTATION OF ITERATIVEIMPUTER WAS INSPIRED BY THE R MICE PACKAGE MULTIVARIATE IMPUTATION BY CHAINED EQUATIONS1 BUT DIFFERS FROM IT BY RETURNING A SINGLE IMPUTATION INSTEAD OF MULTIPLE IMPUTATIONS HOWEVER ITERATIVEIMPUTER CAN ALSO BE USED FOR MULTIPLE IMPUTATIONS BY APPLYING IT REPEATEDLY TO THE SAME DATASET WITH DIFFERENT RANDOM SEEDS WHEN SAMPLEPOSTERIORTRUE SEE2 CHAPTER 4 FOR MORE DISCUSSION ON MULTIPLE VS SINGLE IMPUTATIONS

IT IS STILL AN OPEN PROBLEM AS TO HOW USEFUL SINGLE VS MULTIPLE IMPUTATION IS IN THE CONTEXT OF PREDICTION AND CLASSIFICATION WHEN THE USER IS NOT INTERESTED IN MEASURING UNCERTAINTY DUE TO MISSING VALUES

NOTE THAT A CALL TO THE TRANSFORM METHOD OFITERATIVEIMPUTER IS NOT ALLOWED TO CHANGE THE NUMBER OF SAMPLES THEREFORE MULTIPLE IMPUTATIONS CANNOT BE ACHIEVED BY A SINGLE CALL TO TRANSFORM

REFERENCES

MARKING IMPUTED VALUES

THEMISSINGINDICATOR TRANSFORMER IS USEFUL TO TRANSFORM A DATASET INTO CORRESPONDING BINARY MATRIX INDICATING THE PRESENCE OF MISSING VALUES IN THE DATASET THIS TRANSFORMATION IS USEFUL IN CONJUNCTION WITH IMPUTATION WHEN USING IMPUTATION PRESERVING THE INFORMATION ABOUT WHICH VALUES HAD BEEN MISSING CAN BE INFORMATIVE

NAN IS USUALLY USED AS THE PLACEHOLDER FOR MISSING VALUES HOWEVER IT ENFORCES THE DATA TYPE TO BE FLOAT THE PARAMETER MISSINGVALUES ALLOWS TO SPECIFY OTHER PLACEHOLDER SUCH AS INTEGER IN THE FOLLOWING EXAMPLE WE WILL USE 1AS MISSING VALUES

```
 FROM SKLEARNIMPUTE IMPORT MISSINGINDICATOR
X  NPARRAY1 1 1 3
 4 1 0 1
 8 1 1 0
INDICATOR  MISSINGINDICATORMISSINGVALUES1
MASKMISSINGVALUESONLY  INDICATORFITTRANSFORMX
MASKMISSINGVALUESONLY
ARRAY TRUE TRUE FALSE
FALSE TRUE TRUE
FALSE TRUE FALSE
```

THEFEATURES PARAMETER IS USED TO CHOOSE THE FEATURES FOR WHICH THE MASK IS CONSTRUCTED BY DEFAULT IT IS MISSINGONLY WHICH RETURNS THE IMPUTER MASK OF THE FEATURES CONTAINING MISSING VALUES AT FIT TIME

```
INDICATORFEATURES
ARRAY0 1 3
```

THEFEATURES PARAMETER CAN BE SET TO ALL TO RETURNED ALL FEATURES WHETHER OR NOT THEY CONTAIN MISSING VALUES

```
INDICATOR  MISSINGINDICATORMISSINGVALUES1 FEATURESALL
MASKALL  INDICATORFITTRANSFORMX
```

1STEF VAN BUUREN KARIN GROOTHUISOUDSHOORN 2011 “MICE MULTIVARIATE IMPUTATION BY CHAINED EQUATIONS IN R” JOURNAL OF STATISTI SOFTWARE 45 167

2RODERICK J A LITTLE AND DONALD B RUBIN 1986 “STATISTICAL ANALYSIS WITH MISSING DATA” JOHN WILEY SONS INC NEW YORK NY USA

SCIKITLEARN USER GUIDE RELEASE 0213
MASKALL
ARRAY TRUE TRUE FALSE FALSE
FALSE TRUE FALSE TRUE
FALSE TRUE FALSE FALSE
INDICATORFEATURES
ARRAY0 1 2 3
WHEN USING THE MISSINGINDICATOR IN APIPELINE BE SURE TO USE THE FEATUREUNION OR
COLUMNTRANSFORMER TO ADD THE INDICATOR FEATURES TO THE REGULAR FEATURES FIRST WE OBTAIN THE IRIS DATASET
AND ADD SOME MISSING VALUES TO IT
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNIMPUTE IMPORT SIMPLEIMPUTER MISSINGINDICATOR
 FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
 FROM SKLEARNPIPELINE IMPORT FEATUREUNION MAKEPIPELINE
 FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
X Y LOADIRISRETURNXY TRUE
MASK NPRANDOMRANDINT0 2 SIZEXSHAPEASTYPENPBOOL
XMASK NPNAN
XTRAIN XTEST YTRAIN   TRAINTESTSPLITX Y TESTSIZE100
 RANDOMSTATE0
NOW WE CREATE A FEATUREUNION ALL FEATURES WILL BE IMPUTED USING SIMPLEIMPUTER IN ORDER TO ENABLE CLASSI
FIERS TO WORK WITH THIS DATA ADDITIONALLY IT ADDS THE THE INDICATOR VARIABLES FROM MISSINGINDICATOR
TRANSFORMER FEATUREUNION
 TRANSFORMERLIST
 FEATURES SIMPLEIMPUTERSTRATEGYMEAN
 INDICATORS MISSINGINDICATOR
TRANSFORMER TRANSFORMERFITXTRAIN YTRAIN
RESULTS TRANSFORMERTRANSFORMXTEST
RESULTSSHAPE
100 8
OF COURSE WE CANNOT USE THE TRANSFORMER TO MAKE ANY PREDICTIONS WE SHOULD WRAP THIS IN A PIPELINE WITH A
CLASSIFIER EG A DECISIONTREECLASSIFIER TO BE ABLE TO MAKE PREDICTIONS
CLF MAKEPIPELINETRANSFORMER DECISIONTREECLASSIFIER
CLF CLFFITXTRAIN YTRAIN
RESULTS CLFPREDICTXTEST
RESULTSSHAPE
100
355 UNSUPERVISED DIMENSIONALITY REDUCTION
IF YOUR NUMBER OF FEATURES IS HIGH IT MAY BE USEFUL TO REDUCE IT WITH AN UNSUPERVISED STEP PRIOR TO SUPERVISED STEPS
MANY OF THE UNSUPERVISED LEARNING METHODS IMPLEMENT A TRANSFORM METHOD THAT CAN BE USED TO REDUCE THE DIMEN
SIONALITY BELOW WE DISCUSS TWO SPECIFIC EXAMPLE OF THIS PATTERN THAT ARE HEAVILY USED
PIPELINING
THE UNSUPERVISED DATA REDUCTION AND THE SUPERVISED ESTIMATOR CAN BE CHAINED IN ONE STEP SEE PIPELINE CHAINING
ESTIMATORS

PCA PRINCIPAL COMPONENT ANALYSIS
DECOMPOSITIONPCA LOOKS FOR A COMBINATION OF FEATURES THAT CAPTURE WELL THE VARIANCE OF THE ORIGINAL FEATURES
SEEDECOMPOSING SIGNALS IN COMPONENTS MATRIX FACTORIZATION PROBLEMS
EXAMPLES
•FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
RANDOM PROJECTIONS
THE MODULE RANDOMPROJECTION PROVIDES SEVERAL TOOLS FOR DATA REDUCTION BY RANDOM PROJECTIONS SEE THE
RELEVANT SECTION OF THE DOCUMENTATION RANDOM PROJECTION
EXAMPLES
•THE JOHNSONLINDENSTRAUSS BOUND FOR EMBEDDING WITH RANDOM PROJECTIONS
FEATURE AGGLOMERATION
CLUSTERFEATUREAGGLOMERATION APPLIES HIERARCHICAL CLUSTERING TO GROUP TOGETHER FEATURES THAT BEHAVE SIM
ILARLY
EXAMPLES
•FEATURE AGGLOMERATION VS UNIVARIATE SELECTION
•FEATURE AGGLOMERATION
FEATURE SCALING
NOTE THAT IF FEATURES HAVE VERY DIFFERENT SCALING OR STATISTICAL PROPERTIES CLUSTERFEATUREAGGLOMERATION
MAY NOT BE ABLE TO CAPTURE THE LINKS BETWEEN RELATED FEATURES USING A PREPROCESSINGSTANDARDSCALER
CAN BE USEFUL IN THESE SETTINGS
356 RANDOM PROJECTION
THESKLEARNRANDOMPROJECTION MODULE IMPLEMENTS A SIMPLE AND COMPUTATIONALLY EFFICIENT WAY TO REDUCE
THE DIMENSIONALITY OF THE DATA BY TRADING A CONTROLLED AMOUNT OF ACCURACY AS ADDITIONAL VARIANCE FOR FASTER PROCESSING
TIMES AND SMALLER MODEL SIZES THIS MODULE IMPLEMENTS TWO TYPES OF UNSTRUCTURED RANDOM MATRIX GAUSSIAN RANDOM
MATRIX ANDSPARSE RANDOM MATRIX
THE DIMENSIONS AND DISTRIBUTION OF RANDOM PROJECTIONS MATRICES ARE CONTROLLED SO AS TO PRESERVE THE PAIRWISE DISTANCES
BETWEEN ANY TWO SAMPLES OF THE DATASET THUS RANDOM PROJECTION IS A SUITABLE APPROXIMATION TECHNIQUE FOR DISTANCE
BASED METHOD

REFERENCES
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• ELLA BINGHAM AND HEIKKI MANNILA 2001 RANDOM PROJECTION IN DIMENSIONALITY REDUCTION APPLICATIONS TO IMAGE AND TEXT DATA IN PROCEEDINGS OF THE SEVENTH ACM SIGKDD INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING KDD '01 ACM NEW YORK NY USA 245250
THE JOHNSONLINDENSTRAUSS LEMMA
THE MAIN THEORETICAL RESULT BEHIND THE EFFICIENCY OF RANDOM PROJECTION IS THE JOHNSONLINDENSTRAUSS LEMMA QUOTING WIKIPEDIA
IN MATHEMATICS THE JOHNSONLINDENSTRAUSS LEMMA IS A RESULT CONCERNING LOWDISTORTION EMBEDDINGS OF POINTS FROM HIGHDIMENSIONAL INTO LOWDIMENSIONAL EUCLIDEAN SPACE THE LEMMA STATES THAT A SMALL SET OF POINTS IN A HIGHDIMENSIONAL SPACE CAN BE EMBEDDED INTO A SPACE OF MUCH LOWER DIMENSION IN SUCH A WAY THAT DISTANCES BETWEEN THE POINTS ARE NEARLY PRESERVED THE MAP USED FOR THE EMBEDDING IS AT LEAST LIPSCHITZ AND CAN EVEN BE TAKEN TO BE AN ORTHOGONAL PROJECTION
KNOWING ONLY THE NUMBER OF SAMPLES THE SKLEARNRANDOMPROJECTION JOHNSONLINDENSTRAUSSMINDIM ESTIMATES CONSERVATIVELY THE MINIMAL SIZE OF THE RANDOM SUBSPACE TO GUARANTEE A BOUNDED DISTORTION INTRODUCED BY THE RANDOM PROJECTION
FROM SKLEARNRANDOMPROJECTION IMPORT JOHNSONLINDENSTRAUSSMINDIM
JOHNSONLINDENSTRAUSSMINDIMNSAMPLES1E6 EPS05
663
JOHNSONLINDENSTRAUSSMINDIMNSAMPLES1E6 EPS05 01 001
ARRAY 663 11841 1112658
JOHNSONLINDENSTRAUSSMINDIMNSAMPLES1E4 1E5 1E6 EPS01
ARRAY 7894 9868 11841
EXAMPLE
• SEE THE JOHNSONLINDENSTRAUSS BOUND FOR EMBEDDING WITH RANDOM PROJECTIONS FOR A THEORETICAL EXPLICATION ON THE JOHNSONLINDENSTRAUSS LEMMA AND AN EMPIRICAL VALIDATION USING SPARSE RANDOM MATRICES
REFERENCES
• SANJOY DASGUPTA AND ANUPAM GUPTA 1999 AN ELEMENTARY PROOF OF THE JOHNSONLINDENSTRAUSS LEMMA
GAUSSIAN RANDOM PROJECTION
THESKLEARNRANDOMPROJECTIONGAUSSIANRANDOMPROJECTION REDUCES THE DIMENSIONALITY BY PRO JECTING THE ORIGINAL INPUT SPACE ON A RANDOMLY GENERATED MATRIX WHERE COMPONENTS ARE DRAWN FROM THE FOLLOWING DISTRIBUTION □01
□□□□□□□□□□□□
HERE A SMALL EXCERPT WHICH ILLUSTRATES HOW TO USE THE GAUSSIAN RANDOM PROJECTION TRANSFORMER

```
 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT RANDOMPROJECTION
X  NPRANDOMRAND100 10000
TRANSFORMER  RANDOMPROJECTIONGAUSSIANRANDOMPROJECTION
XNEW  TRANSFORMERFITTRANSFORMX
XNEWSHAPE
100 3947
```
SPARSE RANDOM PROJECTION

THESKLEARNRANDOMPROJECTIONSPARSERANDOMPROJECTION REDUCES THE DIMENSIONALITY BY PROJECTING THE ORIGINAL INPUT SPACE USING A SPARSE RANDOM MATRIX

SPARSE RANDOM MATRICES ARE AN ALTERNATIVE TO DENSE GAUSSIAN RANDOM PROJECTION MATRIX THAT GUARANTEES SIMILAR EMBEDDING QUALITY WHILE BEING MUCH MORE MEMORY EFFICIENT AND ALLOWING FASTER COMPUTATION OF THE PROJECTED DATA

IF WE DEFINE S 1 DENSITY THE ELEMENTS OF THE RANDOM MATRIX ARE DRAWN FROM

$$\begin{cases} -\sqrt{} \\ \\ \end{cases}$$

□

□COMPONENTS12□

0 WITH PROBABILITY 1−1□

√

□

□COMPONENTS12□

WHERE □COMPONENTS IS THE SIZE OF THE PROJECTED SUBSPACE BY DEFAULT THE DENSITY OF NON ZERO ELEMENTS IS SET TO THE MINIMUM DENSITY AS RECOMMENDED BY PING LI ET AL 1√□FEATURES

HERE A SMALL EXCERPT WHICH ILLUSTRATES HOW TO USE THE SPARSE RANDOM PROJECTION TRANSFORMER

```
 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT RANDOMPROJECTION
X  NPRANDOMRAND100 10000
TRANSFORMER  RANDOMPROJECTIONSPARSERANDOMPROJECTION
XNEW  TRANSFORMERFITTRANSFORMX
XNEWSHAPE
100 3947
```

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• PING LI TREVOR J HASTIE AND KENNETH W CHURCH 2006 VERY SPARSE RANDOM PROJECTIONS IN PROCEEDINGS OF THE 12TH ACM SIGKDD INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING KDD ‘06 ACM NEW YORK NY USA 287296

357 KERNEL APPROXIMATION

THIS SUBMODULE CONTAINS FUNCTIONS THAT APPROXIMATE THE FEATURE MAPPINGS THAT CORRESPOND TO CERTAIN KERNELS AS THEY ARE USED FOR EXAMPLE IN SUPPORT VECTOR MACHINES SEE SUPPORT VECTOR MACHINES THE FOLLOWING FEATURE FUNCTIONS PERFORM NONLINEAR TRANSFORMATIONS OF THE INPUT WHICH CAN SERVE AS A BASIS FOR LINEAR CLASSIFICATION OR OTHER ALGORITHMS THE ADVANTAGE OF USING APPROXIMATE EXPLICIT FEATURE MAPS COMPARED TO THE KERNEL TRICK WHICH MAKES USE OF FEATURE MAPS IMPLICITLY IS THAT EXPLICIT MAPPINGS CAN BE BETTER SUITED FOR ONLINE LEARNING AND CAN SIGNIFICANTLY REDUCE THE COST OF LEARNING WITH VERY LARGE DATASETS STANDARD KERNELIZED SVMS DO NOT SCALE WELL TO LARGE DATASETS BUT USING AN

APPROXIMATE KERNEL MAP IT IS POSSIBLE TO USE MUCH MORE EFFICIENT LINEAR SVMS IN PARTICULAR THE COMBINATION OF KERNEL MAP APPROXIMATIONS WITH SGDCLASSIFIER CAN MAKE NONLINEAR LEARNING ON LARGE DATASETS POSSIBLE
SINCE THERE HAS NOT BEEN MUCH EMPIRICAL WORK USING APPROXIMATE EMBEDDINGS IT IS ADVISABLE TO COMPARE RESULTS AGAINST EXACT KERNEL METHODS WHEN POSSIBLE
SEE ALSO
POLYNOMIAL REGRESSION EXTENDING LINEAR MODELS WITH BASIS FUNCTIONS FOR AN EXACT POLYNOMIAL TRANSFORMATION
NYSTROEM METHOD FOR KERNEL APPROXIMATION
THE NYSTROEM METHOD AS IMPLEMENTED IN NYSTROEM IS A GENERAL METHOD FOR LOWRANK APPROXIMATIONS OF KERNELS IT ACHIEVES THIS BY ESSENTIALLY SUBSAMPLING THE DATA ON WHICH THE KERNEL IS EVALUATED BY DEFAULT NYSTROEM USES THE RBF KERNEL BUT IT CAN USE ANY KERNEL FUNCTION OR A PRECOMPUTED KERNEL MATRIX THE NUMBER OF SAMPLES USED WHICH IS ALSO THE DIMENSIONALITY OF THE FEATURES COMPUTED IS GIVEN BY THE PARAMETER NCOMPONENTS
RADIAL BASIS FUNCTION KERNEL
THERBFSAMPLER CONSTRUCTS AN APPROXIMATE MAPPING FOR THE RADIAL BASIS FUNCTION KERNEL ALSO KNOWN AS RANDOM KITCHEN SINKS RR2007 THIS TRANSFORMATION CAN BE USED TO EXPLICITLY MODEL A KERNEL MAP PRIOR TO APPLYING A LINEAR ALGORITHM FOR EXAMPLE A LINEAR SVM
```
 FROM SKLEARNKERNELAPPROXIMATION IMPORT RBFSAMPLER
 FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
X  0 0 1 1 1 0 0 1
Y  0 0 1 1
RBFFEATURE  RBFSAMPLERGAMMA1 RANDOMSTATE1
XFEATURES  RBFFEATUREFITTRANSFORMX
CLF  SGDCLASSIFIERMAXITER5
CLFFITXFEATURES Y
SGDCLASSIFIERALPHA00001 AVERAGEFALSE CLASSWEIGHTNONE
EARLYSTOPPINGFALSE EPSILON01 ETA000 FITINTERCEPTTRUE
L1RATIO015 LEARNINGRATEOPTIMAL LOSSHINGE MAXITER5
NITERNOCHANGE5 NJOBSNONE PENALTYL2 POWERT05
RANDOMSTATENONE SHUFFLETRUE TOL0001 VALIDATIONFRACTION01
VERBOSE0 WARMSTARTFALSE
CLFSCOREXFEATURES Y
10
```
THE MAPPING RELIES ON A MONTE CARLO APPROXIMATION TO THE KERNEL VALUES THE FIT FUNCTION PERFORMS THE MONTE CARLO SAMPLING WHEREAS THE TRANSFORM METHOD PERFORMS THE MAPPING OF THE DATA BECAUSE OF THE INHERENT RANDOMNESS OF THE PROCESS RESULTS MAY VARY BETWEEN DIFFERENT CALLS TO THE FIT FUNCTION
THEFIT FUNCTION TAKES TWO ARGUMENTS NCOMPONENTS WHICH IS THE TARGET DIMENSIONALITY OF THE FEATURE TRANSFORM ANDGAMMA THE PARAMETER OF THE RBFKERNEL A HIGHER NCOMPONENTS WILL RESULT IN A BETTER APPROXIMATION OF THE KERNEL AND WILL YIELD RESULTS MORE SIMILAR TO THOSE PRODUCED BY A KERNEL SVM NOTE THAT “FITTING” THE FEATURE FUNCTION DOES NOT ACTUALLY DEPEND ON THE DATA GIVEN TO THE FIT FUNCTION ONLY THE DIMENSIONALITY OF THE DATA IS USED DETAILS ON THE METHOD CAN BE FOUND IN RR2007
FOR A GIVEN VALUE OF NCOMPONENTS RBFSAMPLER IS OFTEN LESS ACCURATE AS NYSTROEM RBFSAMPLER IS CHEAPER TO COMPUTE THOUGH MAKING USE OF LARGER FEATURE SPACES MORE EFFICIENT
EXAMPLES

FIG 39 COMPARING AN EXACT RBF KERNEL LEFT WITH THE APPROXIMATION RIGHT
•EXPLICIT FEATURE MAP APPROXIMATION FOR RBF KERNELS
ADDITIVE CHI SQUARED KERNEL
THE ADDITIVE CHI SQUARED KERNEL IS A KERNEL ON HISTOGRAMS OFTEN USED IN COMPUTER VISION
THE ADDITIVE CHI SQUARED KERNEL AS USED HERE IS GIVEN BY
□□ □ Σ
□2□□□□
□□□□
THIS IS NOT EXACTLY THE SAME AS SKLEARNMETRICSADDITIVECHI2KERNEL THE AUTHORS OF VZ2010 PREFER
THE VERSION ABOVE AS IT IS ALWAYS POSITIVE DEFINITE SINCE THE KERNEL IS ADDITIVE IT IS POSSIBLE TO TREAT ALL COMPONENTS
□□SEPARATELY FOR EMBEDDING THIS MAKES IT POSSIBLE TO SAMPLE THE FOURIER TRANSFORM IN REGULAR INTERVALS INSTEAD OF
APPROXIMATING USING MONTE CARLO SAMPLING
THE CLASSADDITIVECHI2SAMPLER IMPLEMENTS THIS COMPONENT WISE DETERMINISTIC SAMPLING EACH COMPONENT
IS SAMPLED □TIMES YIELDING 2□ 1 DIMENSIONS PER INPUT DIMENSION THE MULTIPLE OF TWO STEMS FROM THE REAL AND
COMPLEX PART OF THE FOURIER TRANSFORM IN THE LITERATURE □IS USUALLY CHOSEN TO BE 1 OR 2 TRANSFORMING THE DATASET TO
SIZENSAMPLES 5NFEATURES IN THE CASE OF □ 2
THE APPROXIMATE FEATURE MAP PROVIDED BY ADDITIVECHI2SAMPLER CAN BE COMBINED WITH THE APPROXIMATE FEATURE
MAP PROVIDED BY RBFSAMPLER TO YIELD AN APPROXIMATE FEATURE MAP FOR THE EXPONENTIATED CHI SQUARED KERNEL SEE
THEVZ2010 FOR DETAILS AND VVZ2010 FOR COMBINATION WITH THE RBFSAMPLER
SKEWED CHI SQUARED KERNEL
THE SKEWED CHI SQUARED KERNEL IS GIVEN BY
□□ □ Π
□2√□□□√□□□
□□□□ 2□
IT HAS PROPERTIES THAT ARE SIMILAR TO THE EXPONENTIATED CHI SQUARED KERNEL OFTEN USED IN COMPUTER VISION BUT ALLOWS FOR
A SIMPLE MONTE CARLO APPROXIMATION OF THE FEATURE MAP

THE USAGE OF THE SKEWEDCHI2SAMPLER IS THE SAME AS THE USAGE DESCRIBED ABOVE FOR THE RBFSAMPLER THE ONLY DIFFERENCE IS IN THE FREE PARAMETER THAT IS CALLED FOR A MOTIVATION FOR THIS MAPPING AND THE MATHEMATICAL DETAILS SEE LS2010

MATHEMATICAL DETAILS

KERNEL METHODS LIKE SUPPORT VECTOR MACHINES OR KERNELIZED PCA RELY ON A PROPERTY OF REPRODUCING KERNEL HILBERT SPACES FOR ANY POSITIVE DEFINITE KERNEL FUNCTION A SO CALLED MERCER KERNEL IT IS GUARANTEED THAT THERE EXISTS A MAPPING INTO A HILBERT SPACE $\mathcal{H}$ SUCH THAT

□□ □ ⟨□□ □□⟩

WHERE⟨··⟩DENOTES THE INNER PRODUCT IN THE HILBERT SPACE

IF AN ALGORITHM SUCH AS A LINEAR SUPPORT VECTOR MACHINE OR PCA RELIES ONLY ON THE SCALAR PRODUCT OF DATA POINTS □□ ONE MAY USE THE VALUE OF □□□ □□ WHICH CORRESPONDS TO APPLYING THE ALGORITHM TO THE MAPPED DATA POINTS □□□ THE ADVANTAGE OF USING IS THAT THE MAPPING NEVER HAS TO BE CALCULATED EXPLICITLY ALLOWING FOR ARBITRARY LARGE FEATURES EVEN INFINITE

ONE DRAWBACK OF KERNEL METHODS IS THAT IT MIGHT BE NECESSARY TO STORE MANY KERNEL VALUES □□□ □□DURING OPTIMIZA TION IF A KERNELIZED CLASSIFIER IS APPLIED TO NEW DATA □□□□□ □□NEEDS TO BE COMPUTED TO MAKE PREDICTIONS POSSIBLY FOR MANY DIFFERENT □□IN THE TRAINING SET

THE CLASSES IN THIS SUBMODULE ALLOW TO APPROXIMATE THE EMBEDDING THEREBY WORKING EXPLICITLY WITH THE REPRESENTA TIONS □□□ WHICH OBVIATES THE NEED TO APPLY THE KERNEL OR STORE TRAINING EXAMPLES

REFERENCES

358 PAIRWISE METRICS AFFINITIES AND KERNELS

THESKLEARNMETRICSPAIRWISE SUBMODULE IMPLEMENTS UTILITIES TO EVALUATE PAIRWISE DISTANCES OR AFFINITY OF SETS OF SAMPLES

THIS MODULE CONTAINS BOTH DISTANCE METRICS AND KERNELS A BRIEF SUMMARY IS GIVEN ON THE TWO HERE

DISTANCE METRICS ARE FUNCTIONS DA B SUCH THATDA B DA C IF OBJECTSAANDBARE CONSIDERED “MORE SIMILAR” THAN OBJECTS AANDC TWO OBJECTS EXACTLY ALIKE WOULD HAVE A DISTANCE OF ZERO ONE OF THE MOST POPULAR EXAMPLES IS EUCLIDEAN DISTANCE TO BE A ‘TRUE’ METRIC IT MUST OBEY THE FOLLOWING FOUR CONDITIONS

1 DA B 0 FORALL AANDB

2 DA B 0 IF ANDONLYIFA B POSITIVE DEFINITENESS

3 DA B DB A SYMMETRY

4 DA C DA B DB C THE TRIANGLE INEQUALITY

KERNELS ARE MEASURES OF SIMILARITY IE SA B SA C IF OBJECTSAANDBARE CONSIDERED “MORE SIMILAR” THAN OBJECTSAANDC A KERNEL MUST ALSO BE POSITIVE SEMIDEFINITE

THERE ARE A NUMBER OF WAYS TO CONVERT BETWEEN A DISTANCE METRIC AND A SIMILARITY MEASURE SUCH AS A KERNEL LET DBE THE DISTANCE AND SBE THE KERNEL

1S NPEXPD GAMMA WHERE ONE HEURISTIC FOR CHOOSING GAMMA IS1 NUMFEATURES

2S 1 D NPMAXD

THE DISTANCES BETWEEN THE ROW VECTORS OF XAND THE ROW VECTORS OF YCAN BE EVALUATED USING PAIRWISEDISTANCES
IFYIS OMITTED THE PAIRWISE DISTANCES OF THE ROW VECTORS OF XARE CALCULATED SIMILARLY PAIRWISE
PAIRWISEKERNELS CAN BE USED TO CALCULATE THE KERNEL BETWEEN XANDYUSING DIFFERENT KERNEL FUNCTIONS SEE
THE API REFERENCE FOR MORE DETAILS

```
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT PAIRWISEDISTANCES
 FROM SKLEARNMETRICSPAIRWISE IMPORT PAIRWISEKERNELS
X  NPARRAY2 3 3 5 5 8
Y  NPARRAY1 0 2 1
PAIRWISEDISTANCESX Y METRICMANHATTAN
ARRAY 4 2
 7 5
12 10
PAIRWISEDISTANCESX METRICMANHATTAN
ARRAY0 3 8
3 0 5
8 5 0
PAIRWISEKERNELSX Y METRICLINEAR
ARRAY 2 7
 3 11
 5 18
```

COSINE SIMILARITY

COSINESIMILARITY COMPUTES THE L2NORMALIZED DOT PRODUCT OF VECTORS THAT IS IF □AND□ARE ROW VECTORS THEIR
COSINE SIMILARITY □IS DEFINED AS

□□ □ □□⊤
‖□‖‖□‖

THIS IS CALLED COSINE SIMILARITY BECAUSE EUCLIDEAN L2 NORMALIZATION PROJECTS THE VECTORS ONTO THE UNIT SPHERE AND
THEIR DOT PRODUCT IS THEN THE COSINE OF THE ANGLE BETWEEN THE POINTS DENOTED BY THE VECTORS
THIS KERNEL IS A POPULAR CHOICE FOR COMPUTING THE SIMILARITY OF DOCUMENTS REPRESENTED AS TFIDF VECTORS
COSINESIMILARITY ACCEPTSSCIPYSPARSE MATRICES NOTE THAT THE TFIDF FUNCTIONALITY IN SKLEARN
FEATUREEXTRACTIONTEXT CAN PRODUCE NORMALIZED VECTORS IN WHICH CASE COSINESIMILARITY IS EQUIV
ALENT TOLINEARKERNEL ONLY SLOWER

REFERENCES

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VERSITY PRESS HTTPSNLPSTANFORDEDUIRBOOKHTMLHTMLEDITIONTHEVECTORSPACEMODELFORSCORING1HTML

LINEAR KERNEL

THE FUNCTION LINEARKERNEL COMPUTES THE LINEAR KERNEL THAT IS A SPECIAL CASE OF POLYNOMIALKERNEL WITH
DEGREE1 ANDCOEF00 HOMOGENEOUS IF XANDYARE COLUMN VECTORS THEIR LINEAR KERNEL IS

□□ □ □⊤□

POLYNOMIAL KERNEL

THE FUNCTION POLYNOMIALKERNEL COMPUTES THE DEGREED POLYNOMIAL KERNEL BETWEEN TWO VECTORS THE POLYNO
MIAL KERNEL REPRESENTS THE SIMILARITY BETWEEN TWO VECTORS CONCEPTUALLY THE POLYNOMIAL KERNELS CONSIDERS NOT ONLY THE SIMILARITY BETWEEN VECTORS UNDER THE SAME DIMENSION BUT ALSO ACROSS DIMENSIONS WHEN USED IN MACHINE LEARNING ALGORITHMS THIS ALLOWS TO ACCOUNT FOR FEATURE INTERACTION

THE POLYNOMIAL KERNEL IS DEFINED AS

□□ □ □□⊤□□0□

WHERE

•XYARE THE INPUT VECTORS

•DIS THE KERNEL DEGREE

IF□0 0THE KERNEL IS SAID TO BE HOMOGENEOUS

SIGMOID KERNEL

THE FUNCTION SIGMOIDKERNEL COMPUTES THE SIGMOID KERNEL BETWEEN TWO VECTORS THE SIGMOID KERNEL IS ALSO KNOWN AS HYPERBOLIC TANGENT OR MULTILAYER PERCEPTRON BECAUSE IN THE NEURAL NETWORK FIELD IT IS OFTEN USED AS NEURON ACTIVATION FUNCTION IT IS DEFINED AS

□□ □ TANH □□⊤□□0

WHERE

•XYARE THE INPUT VECTORS

•□IS KNOWN AS SLOPE

•□0IS KNOWN AS INTERCEPT

RBF KERNEL

THE FUNCTION RBFKERNEL COMPUTES THE RADIAL BASIS FUNCTION RBF KERNEL BETWEEN TWO VECTORS THIS KERNEL IS DEFINED AS

□□ □ EXP−□‖□−□‖2

WHEREXANDYARE THE INPUT VECTORS IF □□−2THE KERNEL IS KNOWN AS THE GAUSSIAN KERNEL OF VARIANCE □2

LAPLACIAN KERNEL

THE FUNCTION LAPLACIANKERNEL IS A VARIANT ON THE RADIAL BASIS FUNCTION KERNEL DEFINED AS

□□ □ EXP−□‖□−□‖1

WHEREXANDYARE THE INPUT VECTORS AND ‖□−□‖1IS THE MANHATTAN DISTANCE BETWEEN THE INPUT VECTORS

IT HAS PROVEN USEFUL IN ML APPLIED TO NOISELESS DATA SEE EG MACHINE LEARNING FOR QUANTUM MECHANICS IN A NUTSHELL

CHISQUARED KERNEL
THE CHISQUARED KERNEL IS A VERY POPULAR CHOICE FOR TRAINING NONLINEAR SVMS IN COMPUTER VISION APPLICATIONS IT CAN BE COMPUTED USING CHI2KERNEL AND THEN PASSED TO AN SKLEARNSVMSVC WITHKERNELPRECOMPUTED

```
 FROM SKLEARNSVM IMPORT SVC
 FROM SKLEARNMETRICSPAIRWISE IMPORT CHI2KERNEL
X  0 1 1 0 2 8 7 3
Y  0 1 0 1
K  CHI2KERNELX GAMMA5
K
ARRAY1  036787944 089483932 058364548
036787944 1  051341712 083822343
089483932 051341712 1  07768366
058364548 083822343 07768366  1
SVM  SVCKERNELPRECOMPUTEDFITK Y
SVMPREDICTK
ARRAY0 1 0 1
```

IT CAN ALSO BE DIRECTLY USED AS THE KERNEL ARGUMENT

```
SVM  SVCKERNELCHI2KERNELFITX Y
SVMPREDICTX
ARRAY0 1 0 1
```

THE CHI SQUARED KERNEL IS GIVEN BY

□□ □ EXP
−□∑
□□□−□□2
□□ □□

THE DATA IS ASSUMED TO BE NONNEGATIVE AND IS OFTEN NORMALIZED TO HAVE AN L1NORM OF ONE THE NORMALIZATION IS RATIONALIZED WITH THE CONNECTION TO THE CHI SQUARED DISTANCE WHICH IS A DISTANCE BETWEEN DISCRETE PROBABILITY DISTRIBUTIONS

THE CHI SQUARED KERNEL IS MOST COMMONLY USED ON HISTOGRAMS BAGS OF VISUAL WORDS

REFERENCES

• ZHANG J AND MARSZALEK M AND LAZEBNIK S AND SCHMID C LOCAL FEATURES AND KERNELS FOR CLASSIFICATION OF TEXTURE AND OBJECT CATEGORIES A COMPREHENSIVE STUDY INTERNATIONAL JOURNAL OF COMPUTER VISION 2007 HTTPSRESEARCHMICROSOFTCOMENUSUMPEOPLEMANIKPROJECTSTRADEOFFPAPERSZHANGIJCV06PDF

359 TRANSFORMING THE PREDICTION TARGET Y

THESE ARE TRANSFORMERS THAT ARE NOT INTENDED TO BE USED ON FEATURES ONLY ON SUPERVISED LEARNING TARGETS SEE ALSO TRANSFORMING TARGET IN REGRESSION IF YOU WANT TO TRANSFORM THE PREDICTION TARGET FOR LEARNING BUT EVALUATE THE MODEL IN THE ORIGINAL UNTRANSFORMED SPACE

LABEL BINARIZATION

LABELBINARIZER IS A UTILITY CLASS TO HELP CREATE A LABEL INDICATOR MATRIX FROM A LIST OF MULTICLASS LABELS

```
 FROM SKLEARN IMPORT PREPROCESSING
LB  PREPROCESSINGLABELBINARIZER
LBFIT1 2 6 4 2
LABELBINARIZERNEGLABEL0 POSLABEL1 SPARSEOUTPUTFALSE
LBCLASSES
ARRAY1 2 4 6
LBTRANSFORM1 6
ARRAY1 0 0 0
0 0 0 1
```
FOR MULTIPLE LABELS PER INSTANCE USE MULTILABELBINARIZER
```
LB  PREPROCESSINGMULTILABELBINARIZER
LBFITTRANSFORM1 2 3
ARRAY1 1 0
0 0 1
LBCLASSES
ARRAY1 2 3
```
LABEL ENCODING

LABELENCODER IS A UTILITY CLASS TO HELP NORMALIZE LABELS SUCH THAT THEY CONTAIN ONLY VALUES BETWEEN 0 AND NCLASSES 1 THIS IS SOMETIMES USEFUL FOR WRITING EFFICIENT CYTHON ROUTINES LABELENCODER CAN BE USED AS FOLLOWS
```
 FROM SKLEARN IMPORT PREPROCESSING
LE  PREPROCESSINGLABELENCODER
LEFIT1 2 2 6
LABELENCODER
LECLASSES
ARRAY1 2 6
LETRANSFORM1 1 2 6
ARRAY0 0 1 2
LEINVERSETRANSFORM0 0 1 2
ARRAY1 1 2 6
```
IT CAN ALSO BE USED TO TRANSFORM NONNUMERICAL LABELS AS LONG AS THEY ARE HASHABLE AND COMPARABLE TO NUMERICAL LABELS
```
LE  PREPROCESSINGLABELENCODER
LEFITPARIS PARIS TOKYO AMSTERDAM
LABELENCODER
LISTLECLASSES
AMSTERDAM PARIS TOKYO
LETRANSFORMTOKYO TOKYO PARIS
ARRAY2 2 1
LISTLEINVERSETRANSFORM2 2 1
TOKYO TOKYO PARIS
```
36 DATASET LOADING UTILITIES

THESKLEARNDATASETS PACKAGE EMBEDS SOME SMALL TOY DATASETS AS INTRODUCED IN THE GETTING STARTED SECTION

THIS PACKAGE ALSO FEATURES HELPERS TO FETCH LARGER DATASETS COMMONLY USED BY THE MACHINE LEARNING COMMUNITY TO BENCHMARK ALGORITHMS ON DATA THAT COMES FROM THE ‘REAL WORLD’

TO EVALUATE THE IMPACT OF THE SCALE OF THE DATASET NSAMPLES ANDNFEATURES WHILE CONTROLLING THE STATISTICAL PROPERTIES OF THE DATA TYPICALLY THE CORRELATION AND INFORMATIVENESS OF THE FEATURES IT IS ALSO POSSIBLE TO GENERATE SYNTHETIC DATA

361 GENERAL DATASET API

THERE ARE THREE MAIN KINDS OF DATASET INTERFACES THAT CAN BE USED TO GET DATASETS DEPENDING ON THE DESIRED TYPE OF DATASET

THE DATASET LOADERS THEY CAN BE USED TO LOAD SMALL STANDARD DATASETS DESCRIBED IN THE TOY DATASETS SECTION

THE DATASET FETCHERS THEY CAN BE USED TO DOWNLOAD AND LOAD LARGER DATASETS DESCRIBED IN THE REAL WORLD DATASETS SECTION

BOTH LOADERS AND FETCHERS FUNCTIONS RETURN A DICTIONARYLIKE OBJECT HOLDING AT LEAST TWO ITEMS AN ARRAY OF SHAPE NSAMPLES NFEATURES WITH KEYDATA EXCEPT FOR 20NEWSGROUPS AND A NUMPY ARRAY OF LENGTH NSAMPLES CONTAINING THE TARGET VALUES WITH KEY TARGET

IT'S ALSO POSSIBLE FOR ALMOST ALL OF THESE FUNCTION TO CONSTRAIN THE OUTPUT TO BE A TUPLE CONTAINING ONLY THE DATA AND THE TARGET BY SETTING THE RETURNXY PARAMETER TO TRUE

THE DATASETS ALSO CONTAIN A FULL DESCRIPTION IN THEIR DESCR ATTRIBUTE AND SOME CONTAIN FEATURENAMES AND TARGETNAMES SEE THE DATASET DESCRIPTIONS BELOW FOR DETAILS

THE DATASET GENERATION FUNCTIONS THEY CAN BE USED TO GENERATE CONTROLLED SYNTHETIC DATASETS DESCRIBED IN THE GENERATED DATASETS SECTION

THESE FUNCTIONS RETURN A TUPLE X Y CONSISTING OF A NSAMPLES NFEATURES NUMPY ARRAY XAND AN ARRAY OF LENGTHNSAMPLES CONTAINING THE TARGETS Y

IN ADDITION THERE ARE ALSO MISCELLANEOUS TOOLS TO LOAD DATASETS OF OTHER FORMATS OR FROM OTHER LOCATIONS DESCRIBED IN THELOADING OTHER DATASETS SECTION

362 TOY DATASETS

SCIKITLEARN COMES WITH A FEW SMALL STANDARD DATASETS THAT DO NOT REQUIRE TO DOWNLOAD ANY FILE FROM SOME EXTERNAL WEBSITE

THEY CAN BE LOADED USING THE FOLLOWING FUNCTIONS

LOADBOSTON RETURNXY LOAD AND RETURN THE BOSTON HOUSEPRICES DATASET REGRES
SION

LOADIRIS RETURNXY LOAD AND RETURN THE IRIS DATASET CLASSIFICATION

LOADDIABETES RETURNXY LOAD AND RETURN THE DIABETES DATASET REGRESSION

LOADDIGITS NCLASS RETURNXY LOAD AND RETURN THE DIGITS DATASET CLASSIFICATION

LOADLINNERUD RETURNXY LOAD AND RETURN THE LINNERUD DATASET MULTIVARIATE REGRES
SION

LOADWINE RETURNXY LOAD AND RETURN THE WINE DATASET CLASSIFICATION

LOADBREASTCANCER RETURNXY LOAD AND RETURN THE BREAST CANCER WISCONSIN DATASET CLAS
SIFICATION

THESE DATASETS ARE USEFUL TO QUICKLY ILLUSTRATE THE BEHAVIOR OF THE VARIOUS ALGORITHMS IMPLEMENTED IN SCIKITLEARN THEY ARE HOWEVER OFTEN TOO SMALL TO BE REPRESENTATIVE OF REAL WORLD MACHINE LEARNING TASKS

SCIKITLEARN USER GUIDE RELEASE 0213
BOSTON HOUSE PRICES DATASET
DATA SET CHARACTERISTICS
NUMBER OF INSTANCES 506
NUMBER OF ATTRIBUTES 13 NUMERICCATEGORICAL PREDICTIVE MEDIAN VALUE ATTRIBUTE 14 IS USU
ALLY THE TARGET
ATTRIBUTE INFORMATION IN ORDER
• CRIM PER CAPITA CRIME RATE BY TOWN
• ZN PROPORTION OF RESIDENTIAL LAND ZONED FOR LOTS OVER 25000 SQFT
• INDUS PROPORTION OF NONRETAIL BUSINESS ACRES PER TOWN
• CHAS CHARLES RIVER DUMMY VARIABLE 1 IF TRACT BOUNDS RIVER 0 OTHERWISE
• NOX NITRIC OXIDES CONCENTRATION PARTS PER 10 MILLION
• RM AVERAGE NUMBER OF ROOMS PER DWELLING
• AGE PROPORTION OF OWNEROCCUPIED UNITS BUILT PRIOR TO 1940
• DIS WEIGHTED DISTANCES TO FIVE BOSTON EMPLOYMENT CENTRES
• RAD INDEX OF ACCESSIBILITY TO RADIAL HIGHWAYS
• TAX FULLVALUE PROPERTYTAX RATE PER 10000
• PTRATIO PUPILTEACHER RATIO BY TOWN
• B 1000BK 0632 WHERE BK IS THE PROPORTION OF BLACKS BY TOWN
• LSTAT LOWER STATUS OF THE POPULATION
• MEDV MEDIAN VALUE OF OWNEROCCUPIED HOMES IN 1000’S
MISSING ATTRIBUTE VALUES NONE
CREATOR HARRISON D AND RUBINFELD DL
THIS IS A COPY OF UCI ML HOUSING DATASET HTTPSARCHIVEICSUCIEDUMLMACHINELEARNINGDATABASESHOUSING
THIS DATASET WAS TAKEN FROM THE STATLIB LIBRARY WHICH IS MAINTAINED AT CARNEGIE MELLON UNIVERSITY
THE BOSTON HOUSEPRICE DATA OF HARRISON D AND RUBINFELD DL ‘HEDONIC PRICES AND THE DEMAND FOR CLEAN AIR’ J
ENVIRON ECONOMICS MANAGEMENT VOL5 81102 1978 USED IN BELSLEY KUH WELSCH ‘REGRESSION DIAGNOSTICS
’ WILEY 1980 NB VARIOUS TRANSFORMATIONS ARE USED IN THE TABLE ON PAGES 244261 OF THE LATTER
THE BOSTON HOUSEPRICE DATA HAS BEEN USED IN MANY MACHINE LEARNING PAPERS THAT ADDRESS REGRESSION PROBLEMS
REFERENCES
• BELSLEY KUH WELSCH ‘REGRESSION DIAGNOSTICS IDENTIFYING INFLUENTIAL DATA AND SOURCES OF COLLINEARITY’
WILEY 1980 244261
• QUINLANR 1993 COMBINING INSTANCEBASED AND MODELBASED LEARNING IN PROCEEDINGS ON THE TENTH
INTERNATIONAL CONFERENCE OF MACHINE LEARNING 236243 UNIVERSITY OF MASSACHUSETTS AMHERST MORGAN
KAUFMANN

SCIKITLEARN USER GUIDE RELEASE 0213
IRIS PLANTS DATASET
DATA SET CHARACTERISTICS
NUMBER OF INSTANCES 150 50 IN EACH OF THREE CLASSES
NUMBER OF ATTRIBUTES 4 NUMERIC PREDICTIVE ATTRIBUTES AND THE CLASS
ATTRIBUTE INFORMATION
• SEPAL LENGTH IN CM
• SEPAL WIDTH IN CM
• PETAL LENGTH IN CM
• PETAL WIDTH IN CM
•CLASS
–IRISSETOSA
–IRISVERSICOLOUR
–IRISVIRGINICA
SUMMARY STATISTICS
SEPAL LENGTH 43 79 584 083 07826
SEPAL WIDTH 20 44 305 043 04194
PETAL LENGTH 10 69 376 176 09490 HIGH
PETAL WIDTH 01 25 120 076 09565 HIGH
MISSING ATTRIBUTE VALUES NONE
CLASS DISTRIBUTION 333 FOR EACH OF 3 CLASSES
CREATOR RA FISHER
DONOR MICHAEL MARSHALL MARSHALLPLUIOARCNASAGOV
DATE JULY 1988
THE FAMOUS IRIS DATABASE FIRST USED BY SIR RA FISHER THE DATASET IS TAKEN FROM FISHER’S PAPER NOTE THAT IT’S THE SAME AS IN R BUT NOT AS IN THE UCI MACHINE LEARNING REPOSITORY WHICH HAS TWO WRONG DATA POINTS
THIS IS PERHAPS THE BEST KNOWN DATABASE TO BE FOUND IN THE PATTERN RECOGNITION LITERATURE FISHER’S PAPER IS A CLASSIC IN THE FIELD AND IS REFERENCED FREQUENTLY TO THIS DAY SEE DUDA HART FOR EXAMPLE THE DATA SET CONTAINS 3 CLASSES OF 50 INSTANCES EACH WHERE EACH CLASS REFERS TO A TYPE OF IRIS PLANT ONE CLASS IS LINEARLY SEPARABLE FROM THE OTHER 2 THE LATTER ARE NOT LINEARLY SEPARABLE FROM EACH OTHER
REFERENCES
• FISHER RA “THE USE OF MULTIPLE MEASUREMENTS IN TAXONOMIC PROBLEMS” ANNUAL EUGENICS 7 PART II 179188 1936 ALSO IN “CONTRIBUTIONS TO MATHEMATICAL STATISTICS” JOHN WILEY NY 1950
• DUDA RO HART PE 1973 PATTERN CLASSIFICATION AND SCENE ANALYSIS Q327D83 JOHN WILEY SONS ISBN 0471223611 SEE PAGE 218
• DASARATHY BV 1980 “NOSING AROUND THE NEIGHBORHOOD A NEW SYSTEM STRUCTURE AND CLASSIFICATION RULE FOR RECOGNITION IN PARTIALLY EXPOSED ENVIRONMENTS” IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE V OL PAMI2 NO 1 6771

• GATES GW 1972 “THE REDUCED NEAREST NEIGHBOR RULE” IEEE TRANSACTIONS ON INFORMATION THEORY MAY 1972 431433
• SEE ALSO 1988 MLC PROCEEDINGS 5464 CHEESEMAN ET AL”S AUTOCLASS II CONCEPTUAL CLUSTERING SYSTEM FINDS 3 CLASSES IN THE DATA
• MANY MANY MORE

DIABETES DATASET

TEN BASELINE VARIABLES AGE SEX BODY MASS INDEX AVERAGE BLOOD PRESSURE AND SIX BLOOD SERUM MEASUREMENTS WERE OBTAINED FOR EACH OF N 442 DIABETES PATIENTS AS WELL AS THE RESPONSE OF INTEREST A QUANTITATIVE MEASURE OF DISEASE PROGRESSION ONE YEAR AFTER BASELINE

DATA SET CHARACTERISTICS

NUMBER OF INSTANCES 442

NUMBER OF ATTRIBUTES FIRST 10 COLUMNS ARE NUMERIC PREDICTIVE VALUES

TARGET COLUMN 11 IS A QUANTITATIVE MEASURE OF DISEASE PROGRESSION ONE YEAR AFTER BASELINE

ATTRIBUTE INFORMATION

• AGE
• SEX
• BODY MASS INDEX
• AVERAGE BLOOD PRESSURE
• S1
• S2
• S3
• S4
• S5
• S6

NOTE EACH OF THESE 10 FEATURE VARIABLES HAVE BEEN MEAN CENTERED AND SCALED BY THE STANDARD DEVIATION TIMES NSAMPLES IE THE SUM OF SQUARES OF EACH COLUMN TOTALS 1

SOURCE URL HTTPSWWW4STATNCSUEDUBOOSVARSELECTDIABETESHTML

FOR MORE INFORMATION SEE BRADLEY EFRON TREVOR HASTIE IAIN JOHNSTONE AND ROBERT TIBSHIRANI 2004 “LEAST AN GLE REGRESSION” ANNALS OF STATISTICS WITH DISCUSSION 407499 HTTPSWEBSTANFORDEDUHASTIEPAPERSLARS LEASTANGLE2002PDF

OPTICAL RECOGNITION OF HANDWRITTEN DIGITS DATASET

DATA SET CHARACTERISTICS

NUMBER OF INSTANCES 5620

NUMBER OF ATTRIBUTES 64

ATTRIBUTE INFORMATION 8X8 IMAGE OF INTEGER PIXELS IN THE RANGE 016

SCIKITLEARN USER GUIDE RELEASE 0213
MISSING ATTRIBUTE VALUES NONE
CREATOR
5 ALPAYDIN ALPAYDIN ‘’ BOUNEDUTR
DATE JULY 1998
THIS IS A COPY OF THE TEST SET OF THE UCI ML HANDWRITTEN DIGITS DATASETS HTTPSARCHIVEICSUCIEDUMLDATASETSOPTICAL RECOGNITIONOFHANDWRITTENDIGITS
THE DATA SET CONTAINS IMAGES OF HANDWRITTEN DIGITS 10 CLASSES WHERE EACH CLASS REFERS TO A DIGIT
PREPROCESSING PROGRAMS MADE AVAILABLE BY NIST WERE USED TO EXTRACT NORMALIZED BITMAPS OF HANDWRITTEN DIGITS FROM A PREPRINTED FORM FROM A TOTAL OF 43 PEOPLE 30 CONTRIBUTED TO THE TRAINING SET AND DIFFERENT 13 TO THE TEST SET 32X32 BITMAPS ARE DIVIDED INTO NONOVERLAPPING BLOCKS OF 4X4 AND THE NUMBER OF ON PIXELS ARE COUNTED IN EACH BLOCK THIS GENERATES AN INPUT MATRIX OF 8X8 WHERE EACH ELEMENT IS AN INTEGER IN THE RANGE 016 THIS REDUCES DIMENSIONALITY AND GIVES INVARIANCE TO SMALL DISTORTIONS
FOR INFO ON NIST PREPROCESSING ROUTINES SEE M D GARRIS J L BLUE G T CANDELA D L DIMMICK J GEIST P J GROTHER S A JANET AND C L WILSON NIST FORMBASED HANDPRINT RECOGNITION SYSTEM NISTIR 5469 1994
REFERENCES
• C KAYNAK 1995 METHODS OF COMBINING MULTIPLE CLASSIFIERS AND THEIR APPLICATIONS TO HANDWRITTEN DIGIT RECOGNITION MSC THESIS INSTITUTE OF GRADUATE STUDIES IN SCIENCE AND ENGINEERING BOGAZICI UNIVERSITY
• 5 ALPAYDIN C KAYNAK 1998 CASCADING CLASSIFIERS KYBERNETIKA
• KEN TANG AND PONNUTHURAI N SUGANTHAN AND XI YAO AND A KAI QIN LINEAR DIMENSIONALITYREDUCTION USING RELEVANCE WEIGHTED LDA SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING NANYANG TECHNOLOGICAL UNIVERSITY 2005
• CLAUDIO GENTILE A NEW APPROXIMATE MAXIMAL MARGIN CLASSIFICATION ALGORITHM NIPS 2000
LINNERRUD DATASET
DATA SET CHARACTERISTICS
NUMBER OF INSTANCES 20
NUMBER OF ATTRIBUTES 3
MISSING ATTRIBUTE VALUES NONE
THE LINNERUD DATASET CONSTAINS TWO SMALL DATASET
•PHYSIOLOGICAL CSV CONTAINING 20 OBSERVATIONS ON 3 EXERCISE VARIABLES WEIGHT WAIST AND PULSE
•EXERCISE CSV CONTAINING 20 OBSERVATIONS ON 3 PHYSIOLOGICAL VARIABLES CHINS SITUPS AND JUMPS
REFERENCES
• TENENHAUS M 1998 LA REGRESSION PLS THEORIE ET PRATIQUE PARIS EDITIONS TECHNIC
WINE RECOGNITION DATASET
DATA SET CHARACTERISTICS

SCIKITLEARN USER GUIDE RELEASE 0213
NUMBER OF INSTANCES 178 50 IN EACH OF THREE CLASSES
NUMBER OF ATTRIBUTES 13 NUMERIC PREDICTIVE ATTRIBUTES AND THE CLASS
ATTRIBUTE INFORMATION
• ALCOHOL
• MALIC ACID
• ASH
• ALCALINITY OF ASH
• MAGNESIUM
• TOTAL PHENOLS
• FLAVANOIDS
• NONFLAVANOID PHENOLS
• PROANTHOCYANINS
• COLOR INTENSITY
• HUE
• OD280OD315 OF DILUTED WINES
• PROLINE
•CLASS
–CLASS0
–CLASS1
–CLASS2
SUMMARY STATISTICS
ALCOHOL 110 148 130 08
MALIC ACID 074 580 234 112
ASH 136 323 236 027
ALCALINITY OF ASH 106 300 195 33
MAGNESIUM 700 1620 997 143
TOTAL PHENOLS 098 388 229 063
FLAVANOIDS 034 508 203 100
NONFLAVANOID PHENOLS 013 066 036 012
PROANTHOCYANINS 041 358 159 057
COLOUR INTENSITY 13 130 51 23
HUE 048 171 096 023
OD280OD315 OF DILUTED WINES 127 400 261 071
PROLINE 278 1680 746 315
MISSING ATTRIBUTE VALUES NONE
CLASS DISTRIBUTION CLASS0 59 CLASS1 71 CLASS2 48
CREATOR RA FISHER
DONOR MICHAEL MARSHALL MARSHALLPLUIOARCNASAGOV

SCIKITLEARN USER GUIDE RELEASE 0213
DATE JULY 1988
THIS IS A COPY OF UCI ML WINE RECOGNITION DATASETS HTTPSARCHIVEICSUCIEDUMLMACHINELEARNINGDATABASESWINE
WINEDATA
THE DATA IS THE RESULTS OF A CHEMICAL ANALYSIS OF WINES GROWN IN THE SAME REGION IN ITALY BY THREE DIFFERENT CULTIVATORS
THERE ARE THIRTEEN DIFFERENT MEASUREMENTS TAKEN FOR DIFFERENT CONSTITUENTS FOUND IN THE THREE TYPES OF WINE
ORIGINAL OWNERS
FORINA M ET AL PARVUS AN EXTENDIBLE PACKAGE FOR DATA EXPLORATION CLASSIFICATION AND CORRELATION INSTITUTE OF
PHARMACEUTICAL AND FOOD ANALYSIS AND TECHNOLOGIES VIA BRIGATA SALERNO 16147 GENOA ITALY
CITATION
LICHMAN M 2013 UCI MACHINE LEARNING REPOSITORY HTTPSARCHIVEICSUCIEDUML IRVINE CA UNIVERSITY OF
CALIFORNIA SCHOOL OF INFORMATION AND COMPUTER SCIENCE
REFERENCES
1 S AEBERHARD D COOMANS AND O DE VEL COMPARISON OF CLASSIFIERS IN HIGH DIMENSIONAL SETTINGS TECH REP
NO 9202 1992 DEPT OF COMPUTER SCIENCE AND DEPT OF MATHEMATICS AND STATISTICS JAMES COOK UNIVERSITY OF
NORTH QUEENSLAND ALSO SUBMITTED TO TECHNOMETRICS
THE DATA WAS USED WITH MANY OTHERS FOR COMPARING VARIOUS CLASSIFIERS THE CLASSES ARE SEPARABLE THOUGH ONLY RDA
HAS ACHIEVED 100 CORRECT CLASSIFICATION RDA 100 QDA 994 LDA 989 1NN 961 ZTRANSFORMED
DATA ALL RESULTS USING THE LEAVEONEOUT TECHNIQUE
2 S AEBERHARD D COOMANS AND O DE VEL “THE CLASSIFICATION PERFORMANCE OF RDA” TECH REP
NO 9201 1992 DEPT OF COMPUTER SCIENCE AND DEPT OF MATHEMATICS AND STATISTICS JAMES COOK UNIVERSITY OF
NORTH QUEENSLAND ALSO SUBMITTED TO JOURNAL OF CHEMOMETRICS
BREAST CANCER WISCONSIN DIAGNOSTIC DATASET
DATA SET CHARACTERISTICS
NUMBER OF INSTANCES 569
NUMBER OF ATTRIBUTES 30 NUMERIC PREDICTIVE ATTRIBUTES AND THE CLASS
ATTRIBUTE INFORMATION
• RADIUS MEAN OF DISTANCES FROM CENTER TO POINTS ON THE PERIMETER
• TEXTURE STANDARD DEVIATION OF GRAYSCALE VALUES
• PERIMETER
• AREA
• SMOOTHNESS LOCAL VARIATION IN RADIUS LENGTHS
• COMPACTNESS PERIMETER2 AREA 10
• CONCAVITY SEVERITY OF CONCAVE PORTIONS OF THE CONTOUR
• CONCAVE POINTS NUMBER OF CONCAVE PORTIONS OF THE CONTOUR
• SYMMETRY
• FRACTAL DIMENSION “COASTLINE APPROXIMATION” 1

THE MEAN STANDARD ERROR AND “WORST” OR LARGEST MEAN OF THE THREE LARGEST VALUES OF THESE FEATURES WERE COMPUTED FOR EACH IMAGE RESULTING IN 30 FEATURES FOR INSTANCE FIELD 3 IS MEAN RADIUS FIELD 13 IS RADIUS SE FIELD 23 IS WORST RADIUS

- CLASS
  - WDBCMALIGNANT
  - WDBCBENIGN

SUMMARY STATISTICS

RADIUS MEAN 6981 2811
TEXTURE MEAN 971 3928
PERIMETER MEAN 4379 1885
AREA MEAN 1435 25010
SMOOTHNESS MEAN 0053 0163
COMPACTNESS MEAN 0019 0345
CONCAVITY MEAN 00 0427
CONCAVE POINTS MEAN 00 0201
SYMMETRY MEAN 0106 0304
FRACTAL DIMENSION MEAN 005 0097
RADIUS STANDARD ERROR 0112 2873
TEXTURE STANDARD ERROR 036 4885
PERIMETER STANDARD ERROR 0757 2198
AREA STANDARD ERROR 6802 5422
SMOOTHNESS STANDARD ERROR 0002 0031
COMPACTNESS STANDARD ERROR 0002 0135
CONCAVITY STANDARD ERROR 00 0396
CONCAVE POINTS STANDARD ERROR 00 0053
SYMMETRY STANDARD ERROR 0008 0079
FRACTAL DIMENSION STANDARD ERROR 0001 003
RADIUS WORST 793 3604
TEXTURE WORST 1202 4954
PERIMETER WORST 5041 2512
AREA WORST 1852 42540
SMOOTHNESS WORST 0071 0223
COMPACTNESS WORST 0027 1058
CONCAVITY WORST 00 1252
CONCAVE POINTS WORST 00 0291
SYMMETRY WORST 0156 0664
FRACTAL DIMENSION WORST 0055 0208

MISSING ATTRIBUTE VALUES NONE

CLASS DISTRIBUTION 212 MALIGNANT 357 BENIGN

CREATOR DR WILLIAM H WOLBERG W NICK STREET OLVI L MANGASARIAN

DONOR NICK STREET

DATE NOVEMBER 1995

THIS IS A COPY OF UCI ML BREAST CANCER WISCONSIN DIAGNOSTIC DATASETS HTTPSGOOGLU2UWZ2

FEATURES ARE COMPUTED FROM A DIGITIZED IMAGE OF A FINE NEEDLE ASPIRATE FNA OF A BREAST MASS THEY DESCRIBE CHARACTERISTICS OF THE CELL NUCLEI PRESENT IN THE IMAGE

SEPARATING PLANE DESCRIBED ABOVE WAS OBTAINED USING MULTISURFACE METHODTREE MSMT K P BENNETT “DECISION TREE CONSTRUCTION VIA LINEAR PROGRAMMING” PROCEEDINGS OF THE 4TH MIDWEST ARTIFICIAL INTELLIGENCE AND COGNITIVE SCIENCE SOCIETY PP 97101 1992 A CLASSIFICATION METHOD WHICH USES LINEAR PROGRAMMING TO CONSTRUCT A DECISION TREE RELEVANT FEATURES WERE SELECTED USING AN EXHAUSTIVE SEARCH IN THE SPACE OF 14 FEATURES AND 13 SEPARATING PLANES THE ACTUAL LINEAR PROGRAM USED TO OBTAIN THE SEPARATING PLANE IN THE 3DIMENSIONAL SPACE IS THAT DESCRIBED IN K P BENNETT AND O L MANGASARIAN “ROBUST LINEAR PROGRAMMING DISCRIMINATION OF TWO LINEARLY INSEPARABLE SETS” OPTIMIZATION METHODS AND SOFTWARE 1 1992 2334

THIS DATABASE IS ALSO AVAILABLE THROUGH THE UW CS FTP SERVER

FTP FTPCSWISCEDU CD MATHPROGCPODATASETMACHINELEARNWDBC

REFERENCES

• WN STREET WH WOLBERG AND OL MANGASARIAN NUCLEAR FEATURE EXTRACTION FOR BREAST TUMOR DIAGNOSIS ISTSPIE 1993 INTERNATIONAL SYMPOSIUM ON ELECTRONIC IMAGING SCIENCE AND TECHNOLOGY VOLUME 1905 PAGES 861870 SAN JOSE CA 1993

• OL MANGASARIAN WN STREET AND WH WOLBERG BREAST CANCER DIAGNOSIS AND PROGNOSIS VIA LINEAR PROGRAM MING OPERATIONS RESEARCH 434 PAGES 570577 JULYAUGUST 1995

• WH WOLBERG WN STREET AND OL MANGASARIAN MACHINE LEARNING TECHNIQUES TO DIAGNOSE BREAST CANCER FROM FINENEEDLE ASPIRATES CANCER LETTERS 77 1994 163171

363 REAL WORLD DATASETS

SCIKITLEARN PROVIDES TOOLS TO LOAD LARGER DATASETS DOWNLOADING THEM IF NECESSARY

THEY CAN BE LOADED USING THE FOLLOWING FUNCTIONS

FETCHOLIVETTIFACES DATAHOME SHUFFLE LOAD THE OLIVETTI FACES DATASET FROM ATT CLASSIFICATION

FETCH20NEWSGROUPS DATAHOME SUBSET LOAD THE FILENAMES AND DATA FROM THE 20 NEWSGROUPS DATASET CLASSIFICATION

FETCH20NEWSGROUPSVECTORIZED SUBSET LOAD THE 20 NEWSGROUPS DATASET AND VECTORIZE IT INTO TOKEN COUNTS CLASSIFICATION

FETCHLFWPEOPLE DATAHOME FUNNELED LOAD THE LABELED FACES IN THE WILD LFW PEOPLE DATASET CLASSIFICATION

FETCHLFWPAIRS SUBSET DATAHOME LOAD THE LABELED FACES IN THE WILD LFW PAIRS DATASET CLASSIFICATION

FETCHCOVTYPE DATAHOME LOAD THE COVERTYPE DATASET CLASSIFICATION

FETCHRCV1 DATAHOME SUBSET LOAD THE RCV1 MULTILABEL DATASET CLASSIFICATION

FETCHKDDCUP99 SUBSET DATAHOME SHUFFLE LOAD THE KDDCUP99 DATASET CLASSIFICATION

FETCHCALIFORNIAHOUSING DATAHOME LOAD THE CALIFORNIA HOUSING DATASET REGRESSION

THE OLIVETTI FACES DATASET

THIS DATASET CONTAINS A SET OF FACE IMAGES TAKEN BETWEEN APRIL 1992 AND APRIL 1994 AT ATT LABORATORIES CAM BRIDGE THE SKLEARNDATASETSFETCHOLIVETTIFACES FUNCTION IS THE DATA FETCHING CACHING FUNCTION THAT DOWNLOADS THE DATA ARCHIVE FROM ATT

AS DESCRIBED ON THE ORIGINAL WEBSITE

THERE ARE TEN DIFFERENT IMAGES OF EACH OF 40 DISTINCT SUBJECTS FOR SOME SUBJECTS THE IMAGES WERE TAKEN

AT DIFFERENT TIMES VARYING THE LIGHTING FACIAL EXPRESSIONS OPEN CLOSED EYES SMILING NOT SMILING AND
FACIAL DETAILS GLASSES NO GLASSES ALL THE IMAGES WERE TAKEN AGAINST A DARK HOMOGENEOUS BACKGROUND
WITH THE SUBJECTS IN AN UPRIGHT FRONTAL POSITION WITH TOLERANCE FOR SOME SIDE MOVEMENT
DATA SET CHARACTERISTICS
CLASSES 40
SAMPLES TOTAL 400
DIMENSIONALITY 4096
FEATURES REAL BETWEEN 0 AND 1
THE IMAGE IS QUANTIZED TO 256 GREY LEVELS AND STORED AS UNSIGNED 8BIT INTEGERS THE LOADER WILL CONVERT THESE TO FLOATING
POINT VALUES ON THE INTERVAL 0 1 WHICH ARE EASIER TO WORK WITH FOR MANY ALGORITHMS
THE “TARGET” FOR THIS DATABASE IS AN INTEGER FROM 0 TO 39 INDICATING THE IDENTITY OF THE PERSON PICTURED HOWEVER WITH
ONLY 10 EXAMPLES PER CLASS THIS RELATIVELY SMALL DATASET IS MORE INTERESTING FROM AN UNSUPERVISED OR SEMISUPERVISED
PERSPECTIVE
THE ORIGINAL DATASET CONSISTED OF 92 X 112 WHILE THE VERSION AVAILABLE HERE CONSISTS OF 64X64 IMAGES
WHEN USING THESE IMAGES PLEASE GIVE CREDIT TO ATT LABORATORIES CAMBRIDGE
THE 20 NEWSGROUPS TEXT DATASET
THE 20 NEWSGROUPS DATASET COMPRISES AROUND 18000 NEWSGROUPS POSTS ON 20 TOPICS SPLIT IN TWO SUBSETS ONE FOR
TRAINING OR DEVELOPMENT AND THE OTHER ONE FOR TESTING OR FOR PERFORMANCE EVALUATION THE SPLIT BETWEEN THE TRAIN
AND TEST SET IS BASED UPON A MESSAGES POSTED BEFORE AND AFTER A SPECIFIC DATE
THIS MODULE CONTAINS TWO LOADERS THE FIRST ONE SKLEARNDATASETSFETCH20NEWSGROUPS RETURNS A LIST
OF THE RAW TEXTS THAT CAN BE FED TO TEXT FEATURE EXTRACTORS SUCH AS SKLEARNFEATUREEXTRACTIONTEXT
COUNTVECTORIZER WITH CUSTOM PARAMETERS SO AS TO EXTRACT FEATURE VECTORS THE SECOND ONE SKLEARN
DATASETSFETCH20NEWSGROUPSVECTORIZED RETURNS READYTOUSE FEATURES IE IT IS NOT NECESSARY TO USE
A FEATURE EXTRACTOR
DATA SET CHARACTERISTICS
CLASSES 20
SAMPLES TOTAL 18846
DIMENSIONALITY 1
FEATURES TEXT
USAGE
THESKLEARNDATASETSFETCH20NEWSGROUPS FUNCTION IS A DATA FETCHING CACHING FUNCTIONS THAT DOWN
LOADS THE DATA ARCHIVE FROM THE ORIGINAL 20 NEWSGROUPS WEBSITE EXTRACTS THE ARCHIVE CONTENTS IN THE
SCIKITLEARNDATA20NEWSHOME FOLDER AND CALLS THE SKLEARNDATASETSLOADFILES ON EITHER THE
TRAINING OR TESTING SET FOLDER OR BOTH OF THEM
 FROM SKLEARNDATASETS IMPORT FETCH20NEWSGROUPS
NEWSGROUPSTRAIN FETCH20NEWSGROUPSSUBSETTRAIN
 FROM PPRINT IMPORT PPRINT
PPRINTLISTNEWSGROUPSTRAINTARGETNAMES
ALTATHEISM
COMPGRAPHICS

SCIKITLEARN USER GUIDE RELEASE 0213
COMPOSMSWINDOWSMISC
COMPSYSIBMPCHARDWARE
COMPSYSMACHARDWARE
COMPWINDOWSX
MISCFORSALE
RECAUTOS
RECMOTORCYCLES
RECSPORTBASEBALL
RECSPORTHOCKEY
SCICRYPT
SCIELECTRONICS
SCIMED
SCISPACE
SOCRELIGIONCHRISTIAN
TALKPOLITICSGUNS
TALKPOLITICSMIDEAST
TALKPOLITICSMISC
TALKRELIGIONMISC
THE REAL DATA LIES IN THE FILENAMES ANDTARGET ATTRIBUTES THE TARGET ATTRIBUTE IS THE INTEGER INDEX OF THE CATEGORY
NEWSGROUPSTRAINFILENAMESSHAPE
11314
NEWSGROUPSTRAINTARGETSHAPE
11314
NEWSGROUPSTRAINTARGET10
ARRAY 7 4 4 1 14 16 13 3 2 4
IT IS POSSIBLE TO LOAD ONLY A SUBSELECTION OF THE CATEGORIES BY PASSING THE LIST OF THE CATEGORIES TO LOAD TO THE SKLEARN
DATASETSFETCH20NEWSGROUPS FUNCTION
CATS ALTATHEISM SCISPACE
NEWSGROUPSTRAIN FETCH20NEWSGROUPSSUBSETTRAIN CATEGORIESCATS
LISTNEWSGROUPSTRAINTARGETNAMES
ALTATHEISM SCISPACE
NEWSGROUPSTRAINFILENAMESSHAPE
1073
NEWSGROUPSTRAINTARGETSHAPE
1073
NEWSGROUPSTRAINTARGET10
ARRAY0 1 1 1 0 1 1 0 0 0
CONVERTING TEXT TO VECTORS
IN ORDER TO FEED PREDICTIVE OR CLUSTERING MODELS WITH THE TEXT DATA ONE FIRST NEED TO TURN THE TEXT INTO VECTORS
OF NUMERICAL VALUES SUITABLE FOR STATISTICAL ANALYSIS THIS CAN BE ACHIEVED WITH THE UTILITIES OF THE SKLEARN
FEATUREEXTRACTIONTEXT AS DEMONSTRATED IN THE FOLLOWING EXAMPLE THAT EXTRACT TFIDF VECTORS OF UNIGRAM
TOKENS FROM A SUBSET OF 20NEWS
 FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFVECTORIZER
CATEGORIES ALTATHEISM TALKRELIGIONMISC
 COMPGRAPHICS SCISPACE
NEWSGROUPSTRAIN FETCH20NEWSGROUPSSUBSETTRAIN
 CATEGORIESCATEGORIES
VECTORIZER TFIDFVECTORIZER

SCIKITLEARN USER GUIDE RELEASE 0213
VECTORS VECTORIZERFITTRANSFORMNEWSGROUPSTRAINDATA
VECTORSSHAPE
2034 34118
THE EXTRACTED TFIDF VECTORS ARE VERY SPARSE WITH AN AVERAGE OF 159 NONZERO COMPONENTS BY SAMPLE IN A MORE THAN 30000DIMENSIONAL SPACE LESS THAN 5 NONZERO FEATURES
VECTORSNNZ FLOATVECTORSSHAPE0
15901327
SKLEARNDATASETSFETCH20NEWSGROUPSVECTORIZED IS A FUNCTION WHICH RETURNS READYTOUSE TOKEN COUNTS FEATURES INSTEAD OF FILE NAMES
FILTERING TEXT FOR MORE REALISTIC TRAINING
IT IS EASY FOR A CLASSIFIER TO OVERFIT ON PARTICULAR THINGS THAT APPEAR IN THE 20 NEWSGROUPS DATA SUCH AS NEWSGROUP HEADERS MANY CLASSIFIERS ACHIEVE VERY HIGH FSCORES BUT THEIR RESULTS WOULD NOT GENERALIZE TO OTHER DOCUMENTS THAT AREN'T FROM THIS WINDOW OF TIME
FOR EXAMPLE LET'S LOOK AT THE RESULTS OF A MULTINOMIAL NAIVE BAYES CLASSIFIER WHICH IS FAST TO TRAIN AND ACHIEVES A DECENT FSCORE
```
 FROM SKLEARNNAIVEBAYES IMPORT MULTINOMIALNB
 FROM SKLEARN IMPORT METRICS
NEWSGROUPSTEST  FETCH20NEWSGROUPSSUBSETTEST
 CATEGORIESCATEGORIES
VECTORSTEST  VECTORIZERTRANSFORMNEWSGROUPSTESTDATA
CLF  MULTINOMIALNBALPHA01
CLFFITVECTORS NEWSGROUPSTRAINTARGET
MULTINOMIALNBALPHA001 CLASSPRIORNONE FITPRIORTRUE
PRED  CLFPREDICTVECTORSTEST
METRICSF1SCORENEWSGROUPSTESTTARGET PRED AVERAGEMACRO
088213
```
THE EXAMPLE CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES SHUFFLES THE TRAINING AND TEST DATA INSTEAD OF SEGMENTING BY TIME AND IN THAT CASE MULTINOMIAL NAIVE BAYES GETS A MUCH HIGHER FSCORE OF 088 ARE YOU SUSPICIOUS YET OF WHAT'S GOING ON INSIDE THIS CLASSIFIER
LET'S TAKE A LOOK AT WHAT THE MOST INFORMATIVE FEATURES ARE
```
 IMPORT NUMPY AS NP
 DEF SHOWTOP10CLASSIFIER VECTORIZER CATEGORIES
 FEATURENAMES  NPASARRAYVECTORIZERGETFEATURENAMES
 FOR I CATEGORY INENUMERATECATEGORIES
 TOP10  NPARGSORTCLASSIFIERCOEFI10
 PRINTSS  CATEGORY  JOINFEATURENAMESTOP10

SHOWTOP10CLF VECTORIZER NEWSGROUPSTRAINTARGETNAMES
ALTATHEISM EDU IT AND IN YOU THAT IS OF TO THE
COMPGRAPHICS EDU IN GRAPHICS IT IS FOR AND OF TO THE
SCISPACE EDU IT THAT IS IN AND SPACE TO OF THE
TALKRELIGIONMISC NOT IT YOU IN IS THAT AND TO OF THE
```
YOU CAN NOW SEE MANY THINGS THAT THESE FEATURES HAVE OVERFIT TO

• ALMOST EVERY GROUP IS DISTINGUISHED BY WHETHER HEADERS SUCH AS NNTPPOSTINGHOST AND
DISTRIBUTION APPEAR MORE OR LESS OFTEN
• ANOTHER SIGNIFICANT FEATURE INVOLVES WHETHER THE SENDER IS AFFILIATED WITH A UNIVERSITY AS INDICATED EITHER BY THEIR
HEADERS OR THEIR SIGNATURE
• THE WORD “ARTICLE” IS A SIGNIFICANT FEATURE BASED ON HOW OFTEN PEOPLE QUOTE PREVIOUS POSTS LIKE THIS “IN ARTICLE
ARTICLE ID NAME EMAIL ADDRESS WROTE”
• OTHER FEATURES MATCH THE NAMES AND EMAIL ADDRESSES OF PARTICULAR PEOPLE WHO WERE POSTING AT THE TIME
WITH SUCH AN ABUNDANCE OF CLUES THAT DISTINGUISH NEWSGROUPS THE CLASSIFIERS BARELY HAVE TO IDENTIFY TOPICS FROM TEXT AT
ALL AND THEY ALL PERFORM AT THE SAME HIGH LEVEL
FOR THIS REASON THE FUNCTIONS THAT LOAD 20 NEWSGROUPS DATA PROVIDE A PARAMETER CALLED REMOVE TELLING IT WHAT
KINDS OF INFORMATION TO STRIP OUT OF EACH FILE REMOVE SHOULD BE A TUPLE CONTAINING ANY SUBSET OF HEADERS
FOOTERS QUOTES TELLING IT TO REMOVE HEADERS SIGNATURE BLOCKS AND QUOTATION BLOCKS RESPECTIVELY
NEWSGROUPSTEST FETCH20NEWSGROUPSSUBSETTEST
REMOVEHEADERS FOOTERS QUOTES
CATEGORIESCATEGORIES
VECTORSTEST VECTORIZERTRANSFORMNEWSGROUPSTESTDATA
PRED CLFPREDICTVECTORSTEST
METRICSF1SCOREPRED NEWSGROUPSTESTTARGET AVERAGEMACRO
077310
THIS CLASSIFIER LOST OVER A LOT OF ITS FSCORE JUST BECAUSE WE REMOVED METADATA THAT HAS LITTLE TO DO WITH TOPIC CLASSIFI
CATION IT LOSES EVEN MORE IF WE ALSO STRIP THIS METADATA FROM THE TRAINING DATA
NEWSGROUPSTRAIN FETCH20NEWSGROUPSSUBSETTRAIN
REMOVEHEADERS FOOTERS QUOTES
CATEGORIESCATEGORIES
VECTORS VECTORIZERFITTRANSFORMNEWSGROUPSTRAINDATA
CLF MULTINOMIALNBALPHA01
CLFFITVECTORS NEWSGROUPSTRAINTARGET
MULTINOMIALNBALPHA001 CLASSPRIORNONE FITPRIORTRUE
VECTORSTEST VECTORIZERTRANSFORMNEWSGROUPSTESTDATA
PRED CLFPREDICTVECTORSTEST
METRICSF1SCORENEWSGROUPSTESTTARGET PRED AVERAGEMACRO
076995
SOME OTHER CLASSIFIERS COPE BETTER WITH THIS HARDER VERSION OF THE TASK TRY RUNNING SAMPLE PIPELINE FOR TEXT FEATURE
EXTRACTION AND EVALUATION WITH AND WITHOUT THE FILTER OPTION TO COMPARE THE RESULTS
RECOMMENDATION
WHEN EVALUATING TEXT CLASSIFIERS ON THE 20 NEWSGROUPS DATA YOU SHOULD STRIP NEWSGROUPRELATED METADATA IN
SCIKITLEARN YOU CAN DO THIS BY SETTING REMOVEHEADERS FOOTERS QUOTES THE FSCORE WILL
BE LOWER BECAUSE IT IS MORE REALISTIC
EXAMPLES
•SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES

THE LABELED FACES IN THE WILD FACE RECOGNITION DATASET

THIS DATASET IS A COLLECTION OF JPEG PICTURES OF FAMOUS PEOPLE COLLECTED OVER THE INTERNET ALL DETAILS ARE AVAILABLE ON THE OFFICIAL WEBSITE

HTTPVISWWWCSUMASSEDULFW

EACH PICTURE IS CENTERED ON A SINGLE FACE THE TYPICAL TASK IS CALLED FACE VERIFICATION GIVEN A PAIR OF TWO PICTURES A BINARY CLASSIFIER MUST PREDICT WHETHER THE TWO IMAGES ARE FROM THE SAME PERSON

AN ALTERNATIVE TASK FACE RECOGNITION OR FACE IDENTIFICATION IS GIVEN THE PICTURE OF THE FACE OF AN UNKNOWN PERSON IDENTIFY THE NAME OF THE PERSON BY REFERRING TO A GALLERY OF PREVIOUSLY SEEN PICTURES OF IDENTIFIED PERSONS

BOTH FACE VERIFICATION AND FACE RECOGNITION ARE TASKS THAT ARE TYPICALLY PERFORMED ON THE OUTPUT OF A MODEL TRAINED TO PERFORM FACE DETECTION THE MOST POPULAR MODEL FOR FACE DETECTION IS CALLED VIOLAJONES AND IS IMPLEMENTED IN THE OPENCV LIBRARY THE LFW FACES WERE EXTRACTED BY THIS FACE DETECTOR FROM VARIOUS ONLINE WEBSITES

DATA SET CHARACTERISTICS

CLASSES 5749

SAMPLES TOTAL 13233

DIMENSIONALITY 5828

FEATURES REAL BETWEEN 0 AND 255

USAGE

SCIKITLEARN PROVIDES TWO LOADERS THAT WILL AUTOMATICALLY DOWNLOAD CACHE PARSE THE METADATA FILES DECODE THE JPEG AND CONVERT THE INTERESTING SLICES INTO MEMMAPPED NUMPY ARRAYS THIS DATASET SIZE IS MORE THAN 200 MB THE FIRST LOAD TYPICALLY TAKES MORE THAN A COUPLE OF MINUTES TO FULLY DECODE THE RELEVANT PART OF THE JPEG FILES INTO NUMPY ARRAYS IF THE DATASET HAS BEEN LOADED ONCE THE FOLLOWING TIMES THE LOADING TIMES LESS THAN 200MS BY USING A MEMMAPPED VERSION MEMOIZED ON THE DISK IN THE SCIKITLEARNDATALFWHOME FOLDER USING JOBLIB

THE FIRST LOADER IS USED FOR THE FACE IDENTIFICATION TASK A MULTICLASS CLASSIFICATION TASK HENCE SUPERVISED LEARNING

```
 FROM SKLEARNDATASETS IMPORT FETCHLFWPEOPLE
LFWPEOPLE  FETCHLFWPEOPLEMINFACESPERPERSON70 RESIZE04
 FOR NAMEINLFWPEOPLETARGETNAMES
 PRINTNAME

ARIEL SHARON
COLIN POWELL
DONALD RUMSFELD
GEORGE W BUSH
GERHARD SCHROEDER
HUGO CHAVEZ
TONY BLAIR
```

THE DEFAULT SLICE IS A RECTANGULAR SHAPE AROUND THE FACE REMOVING MOST OF THE BACKGROUND

```
LFWPEOPLEDATADTYPE
DTYPEFLOAT32
LFWPEOPLEDATASHAPE
1288 1850
```

LFWPEOPLEIMAGESSHAPE
1288 50 37
EACH OF THE 1140 FACES IS ASSIGNED TO A SINGLE PERSON ID IN THE TARGET ARRAY
LFWPEOPLETARGETSHAPE
1288
LISTLFWPEOPLETARGET10
5 6 3 1 0 1 3 4 3 0
THE SECOND LOADER IS TYPICALLY USED FOR THE FACE VERIFICATION TASK EACH SAMPLE IS A PAIR OF TWO PICTURE BELONGING OR NOT TO THE SAME PERSON
FROM SKLEARNDATASETS IMPORT FETCHLFWPAIRS
LFWPAIRSTRAIN FETCHLFWPAIRSSUBSETTRAIN
LISTLFWPAIRSTRAINTARGETNAMES
DIFFERENT PERSONS SAME PERSON
LFWPAIRSTRAINPAIRSSHAPE
2200 2 62 47
LFWPAIRSTRAINDATASHAPE
2200 5828
LFWPAIRSTRAINTARGETSHAPE
2200
BOTH FOR THE SKLEARNDATASETSFETCHLFWPEOPLE ANDSKLEARNDATASETSFETCHLFWPAIRS FUNCTION IT IS POSSIBLE TO GET AN ADDITIONAL DIMENSION WITH THE RGB COLOR CHANNELS BY PASSING COLORTRUE IN THAT CASE THE SHAPE WILL BE 2200 2 62 47 3
THESKLEARNDATASETSFETCHLFWPAIRS DATASETS IS SUBDIVIDED INTO 3 SUBSETS THE DEVELOPMENT TRAIN SET THE DEVELOPMENT TEST SET AND AN EVALUATION 10FOLDS SET MEANT TO COMPUTE PERFORMANCE METRICS USING A 10FOLDS CROSS VALIDATION SCHEME
REFERENCES
• LABELED FACES IN THE WILD A DATABASE FOR STUDYING FACE RECOGNITION IN UNCONSTRAINED ENVIRONMENTS GARY B HUANG MANU RAMESH TAMARA BERG AND ERIK LEARNEDMILLER UNIVERSITY OF MASSACHUSETTS AMHERST TECHNICAL REPORT 0749 OCTOBER 2007
EXAMPLES
FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
FOREST COVERTYPES
THE SAMPLES IN THIS DATASET CORRESPOND TO 30×30M PATCHES OF FOREST IN THE US COLLECTED FOR THE TASK OF PREDICTING EACH PATCH’S COVER TYPE IE THE DOMINANT SPECIES OF TREE THERE ARE SEVEN COVERTYPES MAKING THIS A MULTICLASS CLASSIFICATION PROBLEM EACH SAMPLE HAS 54 FEATURES DESCRIBED ON THE DATASET’S HOMEPAGE SOME OF THE FEATURES ARE BOOLEAN INDICATORS WHILE OTHERS ARE DISCRETE OR CONTINUOUS MEASUREMENTS

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DATA SET CHARACTERISTICS
CLASSES 7
SAMPLES TOTAL 581012
DIMENSIONALITY 54
FEATURES INT
SKLEARNDATASETSFETCHCOVTYPE WILL LOAD THE COVERTYPE DATASET IT RETURNS A DICTIONARYLIKE OBJECT WITH
THE FEATURE MATRIX IN THE DATA MEMBER AND THE TARGET VALUES IN TARGET THE DATASET WILL BE DOWNLOADED FROM THE
WEB IF NECESSARY
RCV1 DATASET
REUTERS CORPUS V OLUME I RCV1 IS AN ARCHIVE OF OVER 800000 MANUALLY CATEGORIZED NEWSWIRE STORIES MADE AVAILABLE
BY REUTERS LTD FOR RESEARCH PURPOSES THE DATASET IS EXTENSIVELY DESCRIBED IN1
DATA SET CHARACTERISTICS
CLASSES 103
SAMPLES TOTAL 804414
DIMENSIONALITY 47236
FEATURES REAL BETWEEN 0 AND 1
SKLEARNDATASETSFETCHRCV1 WILL LOAD THE FOLLOWING VERSION RCV1V2 VECTORS FULL SETS TOPICS MULTIL
ABELS
 FROM SKLEARNDATASETS IMPORT FETCHRCV1
RCV1 FETCHRCV1
IT RETURNS A DICTIONARYLIKE OBJECT WITH THE FOLLOWING ATTRIBUTES
DATA THE FEATURE MATRIX IS A SCIPY CSR SPARSE MATRIX WITH 804414 SAMPLES AND 47236 FEATURES NONZERO VALUES
CONTAINS COSINENORMALIZED LOG TFIDF VECTORS A NEARLY CHRONOLOGICAL SPLIT IS PROPOSED IN1 THE FIRST 23149 SAMPLES
ARE THE TRAINING SET THE LAST 781265 SAMPLES ARE THE TESTING SET THIS FOLLOWS THE OFFICIAL LYRL2004 CHRONOLOGICAL
SPLIT THE ARRAY HAS 016 OF NON ZERO VALUES
RCV1DATASHAPE
804414 47236
TARGET THE TARGET VALUES ARE STORED IN A SCIPY CSR SPARSE MATRIX WITH 804414 SAMPLES AND 103 CATEGORIES EACH
SAMPLE HAS A VALUE OF 1 IN ITS CATEGORIES AND 0 IN OTHERS THE ARRAY HAS 315 OF NON ZERO VALUES
RCV1TARGETSHAPE
804414 103
SAMPLEID EACH SAMPLE CAN BE IDENTIFIED BY ITS ID RANGING WITH GAPS FROM 2286 TO 810596
RCV1SAMPLEID3
ARRAY2286 2287 2288 DTYPEUINT32
1LEWIS D D YANG Y ROSE T G LI F 2004 RCV1 A NEW BENCHMARK COLLECTION FOR TEXT CATEGORIZATION RESEARCH THE JOURNAL OF
MACHINE LEARNING RESEARCH 5 361397

TARGETNAMES THE TARGET VALUES ARE THE TOPICS OF EACH SAMPLE EACH SAMPLE BELONGS TO AT LEAST ONE TOPIC AND
TO UP TO 17 TOPICS THERE ARE 103 TOPICS EACH REPRESENTED BY A STRING THEIR CORPUS FREQUENCIES SPAN FIVE ORDERS OF
MAGNITUDE FROM 5 OCCURRENCES FOR ‘GMIL’ TO 381327 FOR ‘CCAT’
RCV1TARGETNAMES3TOLIST
E11 ECAT M11
THE DATASET WILL BE DOWNLOADED FROM THE RCV1 HOMEPAGE IF NECESSARY THE COMPRESSED SIZE IS ABOUT 656 MB
REFERENCES
KDDCUP 99 DATASET
THE KDD CUP ‘99 DATASET WAS CREATED BY PROCESSING THE TCPDUMP PORTIONS OF THE 1998 DARPA INTRUSION DETECTION
SYSTEM IDS EVALUATION DATASET CREATED BY MIT LINCOLN LAB 1 THE ARTIFICIAL DATA DESCRIBED ON THE DATASET’S
HOMEPAGE WAS GENERATED USING A CLOSED NETWORK AND HANDINJECTED ATTACKS TO PRODUCE A LARGE NUMBER OF DIFFERENT
TYPES OF ATTACK WITH NORMAL ACTIVITY IN THE BACKGROUND AS THE INITIAL GOAL WAS TO PRODUCE A LARGE TRAINING SET FOR
SUPERVISED LEARNING ALGORITHMS THERE IS A LARGE PROPORTION 801 OF ABNORMAL DATA WHICH IS UNREALISTIC IN REAL WORLD
AND INAPPROPRIATE FOR UNSUPERVISED ANOMALY DETECTION WHICH AIMS AT DETECTING ‘ABNORMAL’ DATA IE
1 QUALITATIVELY DIFFERENT FROM NORMAL DATA
2 IN LARGE MINORITY AMONG THE OBSERVATIONS
WE THUS TRANSFORM THE KDD DATA SET INTO TWO DIFFERENT DATA SETS SA AND SF
SA IS OBTAINED BY SIMPLY SELECTING ALL THE NORMAL DATA AND A SMALL PROPORTION OF ABNORMAL DATA TO GIVES AN ANOMALY
PROPORTION OF 1
SF IS OBTAINED AS IN 2 BY SIMPLY PICKING UP THE DATA WHOSE ATTRIBUTE LOGGEDIN IS POSITIVE THUS FOCUSING ON THE
INTRUSION ATTACK WHICH GIVES A PROPORTION OF 03 OF ATTACK
HTTP AND SMTP ARE TWO SUBSETS OF SF CORRESPONDING WITH THIRD FEATURE EQUAL TO ‘HTTP’ RESP TO ‘SMTP’
GENERAL KDD STRUCTURE
SAMPLES TOTAL 4898431
DIMENSIONALITY 41
FEATURES DISCRETE INT OR CONTINUOUS FLOAT
TARGETS STR ‘NORMAL’ OR NAME OF THE ANOMALY TYPE
SA STRUCTURE
SAMPLES TOTAL 976158
DIMENSIONALITY 41
FEATURES DISCRETE INT OR CONTINUOUS FLOAT
TARGETS STR ‘NORMAL’ OR NAME OF THE ANOMALY TYPE
SF STRUCTURE
SAMPLES TOTAL 699691
DIMENSIONALITY 4
FEATURES DISCRETE INT OR CONTINUOUS FLOAT
TARGETS STR ‘NORMAL’ OR NAME OF THE ANOMALY TYPE

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HTTP STRUCTURE
SAMPLES TOTAL 619052
DIMENSIONALITY 3
FEATURES DISCRETE INT OR CONTINUOUS FLOAT
TARGETS STR ‘NORMAL’ OR NAME OF THE ANOMALY TYPE
SMTP STRUCTURE
SAMPLES TOTAL 95373
DIMENSIONALITY 3
FEATURES DISCRETE INT OR CONTINUOUS FLOAT
TARGETS STR ‘NORMAL’ OR NAME OF THE ANOMALY TYPE
SKLEARNDATASETSFETCHKDDCUP99 WILL LOAD THE KDDCUP99 DATASET IT RETURNS A DICTIONARYLIKE OBJECT WITH
THE FEATURE MATRIX IN THE DATA MEMBER AND THE TARGET VALUES IN TARGET THE DATASET WILL BE DOWNLOADED FROM THE
WEB IF NECESSARY
CALIFORNIA HOUSING DATASET
DATA SET CHARACTERISTICS
NUMBER OF INSTANCES 20640
NUMBER OF ATTRIBUTES 8 NUMERIC PREDICTIVE ATTRIBUTES AND THE TARGET
ATTRIBUTE INFORMATION
• MEDINC MEDIAN INCOME IN BLOCK
• HOUSEAGE MEDIAN HOUSE AGE IN BLOCK
• AVEROOMS AVERAGE NUMBER OF ROOMS
• AVEBEDRMS AVERAGE NUMBER OF BEDROOMS
• POPULATION BLOCK POPULATION
• AVEOCCUP AVERAGE HOUSE OCCUPANCY
• LATITUDE HOUSE BLOCK LATITUDE
• LONGITUDE HOUSE BLOCK LONGITUDE
MISSING ATTRIBUTE VALUES NONE
THIS DATASET WAS OBTAINED FROM THE STATLIB REPOSITORY HTTPLIBSTATCMUEDUDATASETS
THE TARGET VARIABLE IS THE MEDIAN HOUSE VALUE FOR CALIFORNIA DISTRICTS
THIS DATASET WAS DERIVED FROM THE 1990 US CENSUS USING ONE ROW PER CENSUS BLOCK GROUP A BLOCK GROUP IS THE
SMALLEST GEOGRAPHICAL UNIT FOR WHICH THE US CENSUS BUREAU PUBLISHES SAMPLE DATA A BLOCK GROUP TYPICALLY HAS A
POPULATION OF 600 TO 3000 PEOPLE
IT CAN BE DOWNLOADEDLOADED USING THE SKLEARNDATASETSFETCHCALIFORNIAHOUSING FUNCTION
REFERENCES

• PACE R KELLEY AND RONALD BARRY SPARSE SPATIAL AUTOREGRESSIONS STATISTICS AND PROBABILITY LETTERS 33
1997 291297
364 GENERATED DATASETS
IN ADDITION SCIKITLEARN INCLUDES VARIOUS RANDOM SAMPLE GENERATORS THAT CAN BE USED TO BUILD ARTIFICIAL DATASETS OF CONTROLLED SIZE AND COMPLEXITY
GENERATORS FOR CLASSIFICATION AND CLUSTERING
THESE GENERATORS PRODUCE A MATRIX OF FEATURES AND CORRESPONDING DISCRETE TARGETS
SINGLE LABEL
BOTHMAKEBLOBS ANDMAKECLASSIFICATION CREATE MULTICLASS DATASETS BY ALLOCATING EACH CLASS ONE OR MORE NORMALLYDISTRIBUTED CLUSTERS OF POINTS MAKEBLOBS PROVIDES GREATER CONTROL REGARDING THE CENTERS AND STANDARD DE VIATIONS OF EACH CLUSTER AND IS USED TO DEMONSTRATE CLUSTERING MAKECLASSIFICATION SPECIALISES IN INTRODUCING NOISE BY WAY OF CORRELATED REDUNDANT AND UNINFORMATIVE FEATURES MULTIPLE GAUSSIAN CLUSTERS PER CLASS AND LINEAR TRANSFORMATIONS OF THE FEATURE SPACE
MAKEGAUSSIANQUANTILES DIVIDES A SINGLE GAUSSIAN CLUSTER INTO NEAREQUALSIZE CLASSES SEPARATED BY CONCENTRIC HYPERSPHERES MAKEHASTIE102 GENERATES A SIMILAR BINARY 10DIMENSIONAL PROBLEM
MAKECIRCLES ANDMAKEMOONS GENER
ATE 2D BINARY CLASSIFICATION DATASETS THAT ARE CHALLENGING TO CERTAIN ALGORITHMS EG CENTROIDBASED CLUSTERING OR LINEAR CLASSIFICATION INCLUDING OPTIONAL GAUSSIAN NOISE THEY ARE USEFUL FOR VISUALISATION MAKECIRCLES PRODUCES GAUS SIAN DATA WITH A SPHERICAL DECISION BOUNDARY FOR BINARY CLASSIFICATION WHILE MAKEMOONS PRODUCES TWO INTERLEAVING HALF CIRCLES

MULTILABEL
MAKEMULTILABELCLASSIFICATION GENERATES RANDOM SAMPLES WITH MULTIPLE LABELS REFLECTING A BAG OF WORDS DRAWN FROM A MIXTURE OF TOPICS THE NUMBER OF TOPICS FOR EACH DOCUMENT IS DRAWN FROM A POISSON DISTRIBUTION AND THE TOPICS THEMSELVES ARE DRAWN FROM A FIXED RANDOM DISTRIBUTION SIMILARLY THE NUMBER OF WORDS IS DRAWN FROM POISSON WITH WORDS DRAWN FROM A MULTINOMIAL WHERE EACH TOPIC DEFINES A PROBABILITY DISTRIBUTION OVER WORDS SIMPLIFICATIONS WITH RESPECT TO TRUE BAGOFWORDS MIXTURES INCLUDE

- PERTOPIC WORD DISTRIBUTIONS ARE INDEPENDENTLY DRAWN WHERE IN REALITY ALL WOULD BE AFFECTED BY A SPARSE BASE DISTRIBUTION AND WOULD BE CORRELATED
- FOR A DOCUMENT GENERATED FROM MULTIPLE TOPICS ALL TOPICS ARE WEIGHTED EQUALLY IN GENERATING ITS BAG OF WORDS
- DOCUMENTS WITHOUT LABELS WORDS AT RANDOM RATHER THAN FROM A BASE DISTRIBUTION

BICLUSTERING
MAKEBICLUSTERS SHAPE NCLUSTERS NOISE GENERATE AN ARRAY WITH CONSTANT BLOCK DIAGONAL STRUCTURE FOR BICLUSTERING
MAKECHECKERBOARD SHAPE NCLUSTERS GENERATE AN ARRAY WITH BLOCK CHECKERBOARD STRUCTURE FOR BI CLUSTERING
GENERATORS FOR REGRESSION
MAKEREGRESSION PRODUCES REGRESSION TARGETS AS AN OPTIONALLYSPARSE RANDOM LINEAR COMBINATION OF RANDOM FEATURES WITH NOISE ITS INFORMATIVE FEATURES MAY BE UNCORRELATED OR LOW RANK FEW FEATURES ACCOUNT FOR MOST OF THE VARIANCE
OTHER REGRESSION GENERATORS GENERATE FUNCTIONS DETERMINISTICALLY FROM RANDOMIZED FEATURES MAKESPARSEUNCORRELATED PRODUCES A TARGET AS A LINEAR COMBINATION OF FOUR FEATURES WITH FIXED COEFFICIENTS OTHERS ENCODE EXPLICITLY NONLINEAR RELATIONS MAKEFRIEDMAN1 IS RELATED BY POLYNOMIAL AND SINE TRANSFORMS MAKEFRIEDMAN2 INCLUDES FEATURE MULTIPLICATION AND RECIPROCATION AND MAKEFRIEDMAN3 IS SIMILAR WITH AN ARCTAN TRANSFORMATION ON THE TARGET
GENERATORS FOR MANIFOLD LEARNING
MAKESCURVE NSAMPLES NOISE RANDOMSTATE GENERATE AN S CURVE DATASET
MAKESWISSROLL NSAMPLES NOISE RANDOMSTATE GENERATE A SWISS ROLL DATASET

GENERATORS FOR DECOMPOSITION
MAKELOWRANKMATRIX NSAMPLES GENERATE A MOSTLY LOW RANK MATRIX WITH BELLSHAPED SINGU
LAR VALUES
MAKESPARSECODEDSIGNAL NSAMPLES GENERATE A SIGNAL AS A SPARSE COMBINATION OF DICTIONARY EL
EMENTS
MAKESPDMATRIX NDIM RANDOMSTATE GENERATE A RANDOM SYMMETRIC POSITIVEDEFINITE MATRIX
MAKESPARSESPDMATRIX DIM ALPHA GENERATE A SPARSE SYMMETRIC DEFINITE POSITIVE MATRIX
365 LOADING OTHER DATASETS
SAMPLE IMAGES
SCIKITLEARN ALSO EMBED A COUPLE OF SAMPLE JPEG IMAGES PUBLISHED UNDER CREATIVE COMMONS LICENSE BY THEIR AUTHORS
THOSE IMAGES CAN BE USEFUL TO TEST ALGORITHMS AND PIPELINE ON 2D DATA
LOADSAMPLEIMAGES LOAD SAMPLE IMAGES FOR IMAGE MANIPULATION
LOADSAMPLEIMAGE IMAGENAME LOAD THE NUMPY ARRAY OF A SINGLE SAMPLE IMAGE
WARNING THE DEFAULT CODING OF IMAGES IS BASED ON THE UINT8 DTYPE TO SPARE MEMORY OFTEN MACHINE LEARNING
ALGORITHMS WORK BEST IF THE INPUT IS CONVERTED TO A FLOATING POINT REPRESENTATION FIRST ALSO IF YOU PLAN TO USE
MATPLOTLIBPYPLPTIMSHOW DON’T FORGET TO SCALE TO THE RANGE 0 1 AS DONE IN THE FOLLOWING EXAMPLE
EXAMPLES
•COLOR QUANTIZATION USING KMEANS
DATASETS IN SVMLIGHT LIBSVM FORMAT
SCIKITLEARN INCLUDES UTILITY FUNCTIONS FOR LOADING DATASETS IN THE SVMLIGHT LIBSVM FORMAT IN THIS FORMAT EACH LINE
TAKES THE FORM LABEL FEATUREIDFEATUREVALUE FEATUREIDFEATUREVALUE
THIS FORMAT IS ESPECIALLY SUITABLE FOR SPARSE DATASETS IN THIS MODULE SCIPY SPARSE CSR MATRICES ARE USED FOR XAND
NUMPY ARRAYS ARE USED FOR Y
YOU MAY LOAD A DATASET LIKE AS FOLLOWS
FROM SKLEARNDATASETS IMPORT LOADSVMLIGHTFILE
XTRAIN YTRAIN LOADSVMLIGHTFILEPATHTOTRAINDATASETTXT

YOU MAY ALSO LOAD TWO OR MORE DATASETS AT ONCE
XTRAIN YTRAIN XTEST YTEST LOADSVMLIGHTFILES
 PATHTOTRAINDATASETTXT PATHTOTESTDATASETTXT

IN THIS CASE XTRAIN ANDXTEST ARE GUARANTEED TO HAVE THE SAME NUMBER OF FEATURES ANOTHER WAY TO ACHIEVE THE SAME RESULT IS TO FIX THE NUMBER OF FEATURES
XTEST YTEST LOADSVMLIGHTFILE
 PATHTOTESTDATASETTXT NFEATURESXTRAINSHAPE1

RELATED LINKS
PUBLIC DATASETS IN SVMLIGHT LIBSVM FORMAT HTTPSWWWCSIENTUEDUTWCJLINLIBSVMTOOLSDATASETS
FASTER APICOMPATIBLE IMPLEMENTATION HTTPSGITHUBCOMMBLONDELSVMLIGHTLOADER
DOWNLOADING DATASETS FROM THE OPENMLORG REPOSITORY
OPENMLORG IS A PUBLIC REPOSITORY FOR MACHINE LEARNING DATA AND EXPERIMENTS THAT ALLOWS EVERYBODY TO UPLOAD OPEN DATASETS
THESKLEARNDATASETS PACKAGE IS ABLE TO DOWNLOAD DATASETS FROM THE REPOSITORY USING THE FUNCTION SKLEARN DATASETSFETCHOPENML
FOR EXAMPLE TO DOWNLOAD A DATASET OF GENE EXPRESSIONS IN MICE BRAINS
 FROM SKLEARNDATASETS IMPORT FETCHOPENML
MICE FETCHOPENMLNAMEMICEPROTEIN VERSION4
TO FULLY SPECIFY A DATASET YOU NEED TO PROVIDE A NAME AND A VERSION THOUGH THE VERSION IS OPTIONAL SEE DATASET VERSIONS BELOW THE DATASET CONTAINS A TOTAL OF 1080 EXAMPLES BELONGING TO 8 DIFFERENT CLASSES
MICEDATASHAPE
1080 77
MICETARGETSHAPE
1080
NPUNIQUEMICETARGET
ARRAYCCSM CCSS CSCM CSCS TCSM TCSS TSCM TSCS
‘→ DTYPEOBJECT
YOU CAN GET MORE INFORMATION ON THE DATASET BY LOOKING AT THE DESCR ANDDETAILS ATTRIBUTES
PRINTMICEDESCR
AUTHOR CLARA HIGUERA KATHELEEN J GARDINER KRZYSZTOF J CIOS
SOURCE UCIHTTPSARCHIVEICSUCIEDUMLDATASETSMICEPROTEINEXPRESSION
‘→2015
PLEASE CITE HIGUERA C GARDINER KJ CIOS KJ 2015 SELFORGANIZING
FEATURE MAPS IDENTIFY PROTEINS CRITICAL TO LEARNING IN A MOUSE MODEL OF DOWN
SYNDROME PLOS ONE 106 E0129126
MICEDETAILS
ID 40966 NAME MICEPROTEIN VERSION 4 FORMAT ARFF
UPLOADDATE 20171108T160015 LICENCE PUBLIC

SCIKITLEARN USER GUIDE RELEASE 0213
URL HTTPSWWWOPENMLORGDATAV1DOWNLOAD17928620MICEPROTEINARFF
FILEID 17928620 DEFAULTTARGETATTRIBUTE CLASS
ROWIDATTRIBUTE MOUSEID
IGNOREATTRIBUTE GENOTYPE TREATMENT BEHAVIOR
TAG OPENMLCC18 STUDY135 STUDY98 STUDY99
VISIBILITY PUBLIC STATUS ACTIVE
MD5CHECKSUM 3C479A6885BFA0438971388283A1CE32
THEDESCR CONTAINS A FREETEXT DESCRIPTION OF THE DATA WHILE DETAILS CONTAINS A DICTIONARY OF METADATA STORED
BY OPENML LIKE THE DATASET ID FOR MORE DETAILS SEE THE OPENML DOCUMENTATION THE DATAID OF THE MICE PROTEIN
DATASET IS 40966 AND YOU CAN USE THIS OR THE NAME TO GET MORE INFORMATION ON THE DATASET ON THE OPENML WEBSITE
MICEURL
HTTPSWWWOPENMLORGD40966
THEDATAID ALSO UNIQUELY IDENTIFIES A DATASET FROM OPENML
MICE FETCHOPENMLDATAID40966
MICEDETAILS
ID 4550 NAME MICEPROTEIN VERSION 1 FORMAT ARFF
CREATOR
UPLOADDATE 20160217T143249 LICENCE PUBLIC URL
HTTPSWWWOPENMLORGDATAV1DOWNLOAD1804243MICEPROTEINARFF FILEID
1804243 DEFAULTTARGETATTRIBUTE CLASS CITATION HIGUERA C
GARDINER KJ CIOS KJ 2015 SELFORGANIZING FEATURE MAPS IDENTIFY PROTEINS
CRITICAL TO LEARNING IN A MOUSE MODEL OF DOWN SYNDROME PLOS ONE 106
E0129126 WEB LINK JOURNALPONE0129126 TAG OPENML100 STUDY14
STUDY34 VISIBILITY PUBLIC STATUS ACTIVE MD5CHECKSUM
3C479A6885BFA0438971388283A1CE32
DATASET VERSIONS
A DATASET IS UNIQUELY SPECIFIED BY ITS DATAID BUT NOT NECESSARILY BY ITS NAME SEVERAL DIFFERENT “VERSIONS” OF A
DATASET WITH THE SAME NAME CAN EXIST WHICH CAN CONTAIN ENTIRELY DIFFERENT DATASETS IF A PARTICULAR VERSION OF A DATASET
HAS BEEN FOUND TO CONTAIN SIGNIFICANT ISSUES IT MIGHT BE DEACTIVATED USING A NAME TO SPECIFY A DATASET WILL YIELD THE
EARLIEST VERSION OF A DATASET THAT IS STILL ACTIVE THAT MEANS THAT FETCHOPENMLNAMEMICEPROTEIN CAN
YIELD DIFFERENT RESULTS AT DIFFERENT TIMES IF EARLIER VERSIONS BECOME INACTIVE YOU CAN SEE THAT THE DATASET WITH DATAID
40966 THAT WE FETCHED ABOVE IS THE VERSION 1 OF THE “MICEPROTEIN” DATASET
MICEDETAILSVERSION
1
IN FACT THIS DATASET ONLY HAS ONE VERSION THE IRIS DATASET ON THE OTHER HAND HAS MULTIPLE VERSIONS
IRIS FETCHOPENMLNAMEIRIS
IRISDETAILSVERSION
1
IRISDETAILSID
61
IRIS61 FETCHOPENMLDATAID61
IRIS61DETAILSVERSION
1
IRIS61DETAILSID
61

SCIKITLEARN USER GUIDE RELEASE 0213
IRIS969 FETCHOPENMLDATAID969
IRIS969DETAILSVERSION
3
IRIS969DETAILSID
969
SPECIFYING THE DATASET BY THE NAME “IRIS” YIELDS THE LOWEST VERSION VERSION 1 WITH THE DATAID 61 TO MAKE SURE YOU ALWAYS GET THIS EXACT DATASET IT IS SAFEST TO SPECIFY IT BY THE DATASET DATAID THE OTHER DATASET WITH DATAID 969 IS VERSION 3 VERSION 2 HAS BECOME INACTIVE AND CONTAINS A BINARIZED VERSION OF THE DATA
NPUNIQUEIRIS969TARGET
ARRAYN P DTYPEOBJECT
YOU CAN ALSO SPECIFY BOTH THE NAME AND THE VERSION WHICH ALSO UNIQUELY IDENTIFIES THE DATASET
IRISVERSION3 FETCHOPENMLNAMEIRIS VERSION3
IRISVERSION3DETAILSVERSION
3
IRISVERSION3DETAILSID
969
REFERENCES
• VANSCHOREN VAN RIJN BISCHL AND TORGO “OPENML NETWORKED SCIENCE IN MACHINE LEARNING” ACM SIGKDD EXPLORATIONS NEWSLETTER 152 4960 2014
LOADING FROM EXTERNAL DATASETS
SCIKITLEARN WORKS ON ANY NUMERIC DATA STORED AS NUMPY ARRAYS OR SCIPY SPARSE MATRICES OTHER TYPES THAT ARE CONVERTIBLE TO NUMERIC ARRAYS SUCH AS PANDAS DATAFRAME ARE ALSO ACCEPTABLE
HERE ARE SOME RECOMMENDED WAYS TO LOAD STANDARD COLUMNAR DATA INTO A FORMAT USABLE BY SCIKITLEARN
• PANDASIO PROVIDES TOOLS TO READ DATA FROM COMMON FORMATS INCLUDING CSV EXCEL JSON AND SQL DATAFRAMES MAY ALSO BE CONSTRUCTED FROM LISTS OF TUPLES OR DICTS PANDAS HANDLES HETEROGENEOUS DATA SMOOTHLY AND PROVIDES TOOLS FOR MANIPULATION AND CONVERSION INTO A NUMERIC ARRAY SUITABLE FOR SCIKITLEARN
• SCIPYIO SPECIALIZES IN BINARY FORMATS OFTEN USED IN SCIENTIFIC COMPUTING CONTEXT SUCH AS MAT AND ARFF
• NUMPYROUTINESIO FOR STANDARD LOADING OF COLUMNAR DATA INTO NUMPY ARRAYS
• SCIKITLEARN’S DATASETSLOADSVMLIGHTFILE FOR THE SVMLIGHT OR LIBSVM SPARSE FORMAT
• SCIKITLEARN’S DATASETSLOADFILES FOR DIRECTORIES OF TEXT FILES WHERE THE NAME OF EACH DIRECTORY IS THE NAME OF EACH CATEGORY AND EACH FILE INSIDE OF EACH DIRECTORY CORRESPONDS TO ONE SAMPLE FROM THAT CATEGORY
FOR SOME MISCELLANEOUS DATA SUCH AS IMAGES VIDEOS AND AUDIO YOU MAY WISH TO REFER TO
• SKIMAGEIO OR IMAGEIO FOR LOADING IMAGES AND VIDEOS INTO NUMPY ARRAYS
• SCIPYIOWAVFILEREAD FOR READING WA V FILES INTO A NUMPY ARRAY
CATEGORICAL OR NOMINAL FEATURES STORED AS STRINGS COMMON IN PANDAS DATAFRAMES WILL NEED CONVERTING TO NUMERICAL FEATURES USING SKLEARNPREPROCESSINGONEHOTENCODER ORSKLEARNPREPROCESSING ORDINALENCODER OR SIMILAR SEE PREPROCESSING DATA

NOTE IF YOU MANAGE YOUR OWN NUMERICAL DATA IT IS RECOMMENDED TO USE AN OPTIMIZED FILE FORMAT SUCH AS HDF5 TO REDUCE DATA LOAD TIMES VARIOUS LIBRARIES SUCH AS H5PY PYTABLES AND PANDAS PROVIDES A PYTHON INTERFACE FOR READING AND WRITING DATA IN THAT FORMAT

37 COMPUTING WITH SCIKITLEARN

371 STRATEGIES TO SCALE COMPUTATIONALLY BIGGER DATA

FOR SOME APPLICATIONS THE AMOUNT OF EXAMPLES FEATURES OR BOTH ANDOR THE SPEED AT WHICH THEY NEED TO BE PROCESSED ARE CHALLENGING FOR TRADITIONAL APPROACHES IN THESE CASES SCIKITLEARN HAS A NUMBER OF OPTIONS YOU CAN CONSIDER TO MAKE YOUR SYSTEM SCALE

SCALING WITH INSTANCES USING OUTOFCORE LEARNING

OUTOFCORE OR “EXTERNAL MEMORY” LEARNING IS A TECHNIQUE USED TO LEARN FROM DATA THAT CANNOT FIT IN A COMPUTER’S MAIN MEMORY RAM

HERE IS A SKETCH OF A SYSTEM DESIGNED TO ACHIEVE THIS GOAL

1 A WAY TO STREAM INSTANCES

2 A WAY TO EXTRACT FEATURES FROM INSTANCES

3 AN INCREMENTAL ALGORITHM

STREAMING INSTANCES

BASICALLY 1 MAY BE A READER THAT YIELDS INSTANCES FROM FILES ON A HARD DRIVE A DATABASE FROM A NETWORK STREAM ETC HOWEVER DETAILS ON HOW TO ACHIEVE THIS ARE BEYOND THE SCOPE OF THIS DOCUMENTATION

EXTRACTING FEATURES

2 COULD BE ANY RELEVANT WAY TO EXTRACT FEATURES AMONG THE DIFFERENT FEATURE EXTRACTION METHODS SUPPORTED BY SCIKIT LEARN HOWEVER WHEN WORKING WITH DATA THAT NEEDS VECTORIZATION AND WHERE THE SET OF FEATURES OR VALUES IS NOT KNOWN IN ADVANCE ONE SHOULD TAKE EXPLICIT CARE A GOOD EXAMPLE IS TEXT CLASSIFICATION WHERE UNKNOWN TERMS ARE LIKELY TO BE FOUND DURING TRAINING IT IS POSSIBLE TO USE A STATEFUL VECTORIZER IF MAKING MULTIPLE PASSES OVER THE DATA IS REASONABLE FROM AN APPLICATION POINT OF VIEW OTHERWISE ONE CAN TURN UP THE DIFFICULTY BY USING A STATELESS FEATURE EXTRACTOR CURRENTLY THE PREFERRED WAY TO DO THIS IS TO USE THE SOCALLED HASHING TRICK AS IMPLEMENTED BY SKLEARN FEATUREEXTRACTIONFEATUREHASHER FOR DATASETS WITH CATEGORICAL VARIABLES REPRESENTED AS LIST OF PYTHON DICTS ORSKLEARNFEATUREEXTRACTIONTEXTHASHINGVECTORIZER FOR TEXT DOCUMENTS

INCREMENTAL LEARNING

FINALLY FOR 3 WE HAVE A NUMBER OF OPTIONS INSIDE SCIKITLEARN ALTHOUGH NOT ALL ALGORITHMS CAN LEARN INCREMENTALLY IE WITHOUT SEEING ALL THE INSTANCES AT ONCE ALL ESTIMATORS IMPLEMENTING THE PARTIALFIT API ARE CANDIDATES ACTUALLY THE ABILITY TO LEARN INCREMENTALLY FROM A MINIBATCH OF INSTANCES SOMETIMES CALLED “ONLINE LEARNING” IS KEY TO OUTOFCORE LEARNING AS IT GUARANTEES THAT AT ANY GIVEN TIME THERE WILL BE ONLY A SMALL AMOUNT OF INSTANCES IN THE

MAIN MEMORY CHOOSING A GOOD SIZE FOR THE MINIBATCH THAT BALANCES RELEVANCY AND MEMORY FOOTPRINT COULD INVOLVE SOME TUNING1

HERE IS A LIST OF INCREMENTAL ESTIMATORS FOR DIFFERENT TASKS

•CLASSIFICATION
–SKLEARNNAIVEBAYESMULTINOMIALNB
–SKLEARNNAIVEBAYESBERNOULLINB
–SKLEARNLINEARMODELPERCEPTRON
–SKLEARNLINEARMODELSGDCLASSIFIER
–SKLEARNLINEARMODELPASSIVEAGGRESSIVECLASSIFIER
–SKLEARNNEURALNETWORKMLPCLASSIFIER
•REGRESSION
–SKLEARNLINEARMODELSGDREGRESSOR
–SKLEARNLINEARMODELPASSIVEAGGRESSIVEREGRESSOR
–SKLEARNNEURALNETWORKMLPREGRESSOR
•CLUSTERING
–SKLEARNCLUSTERMINIBATCHKMEANS
–SKLEARNCLUSTERBIRCH
•DECOMPOSITION FEATURE EXTRACTION
–SKLEARNDECOMPOSITIONMINIBATCHDICTIONARYLEARNING
–SKLEARNDECOMPOSITIONINCREMENTALPCA
–SKLEARNDECOMPOSITIONLATENTDIRICHLETALLOCATION
•PREPROCESSING
–SKLEARNPREPROCESSINGSTANDARDSCALER
–SKLEARNPREPROCESSINGMINMAXSCALER
–SKLEARNPREPROCESSINGMAXABSSCALER

FOR CLASSIFICATION A SOMEWHAT IMPORTANT THING TO NOTE IS THAT ALTHOUGH A STATELESS FEATURE EXTRACTION ROUTINE MAY BE ABLE TO COPE WITH NEWUNSEEN ATTRIBUTES THE INCREMENTAL LEARNER ITSELF MAY BE UNABLE TO COPE WITH NEWUNSEEN TARGETS CLASSES IN THIS CASE YOU HAVE TO PASS ALL THE POSSIBLE CLASSES TO THE FIRST PARTIALFIT CALL USING THE CLASSES PARAMETER

ANOTHER ASPECT TO CONSIDER WHEN CHOOSING A PROPER ALGORITHM IS THAT NOT ALL OF THEM PUT THE SAME IMPORTANCE ON EACH EXAMPLE OVER TIME NAMELY THE PERCEPTRON IS STILL SENSITIVE TO BADLY LABELED EXAMPLES EVEN AFTER MANY EXAMPLES WHEREAS THE SGDANDPASSIVEAGGRESSIVE FAMILIES ARE MORE ROBUST TO THIS KIND OF ARTIFACTS CONVERSELY THE LATTER ALSO TEND TO GIVE LESS IMPORTANCE TO REMARKABLY DIFFERENT YET PROPERLY LABELED EXAMPLES WHEN THEY COME LATE IN THE STREAM AS THEIR LEARNING RATE DECREASES OVER TIME

1DEPENDING ON THE ALGORITHM THE MINIBATCH SIZE CAN INFLUENCE RESULTS OR NOT SGD PASSIVEAGGRESSIVE AND DISCRETE NAIVEBAYES ARE ONLINE AND ARE NOT AFFECTED BY BATCH SIZE CONVERSELY MINIBATCHKMEANS CONVERGENCE RATE IS AFFECTED BY THE BATCH SIZE ALSO IT CAN VARY DRAMATICALLY WITH BATCH SIZE

EXAMPLES
FINALLY WE HAVE A FULLFLEDGED EXAMPLE OF OUTOFCORE CLASSIFICATION OF TEXT DOCUMENTS IT IS AIMED AT PROVIDING A STARTING POINT FOR PEOPLE WANTING TO BUILD OUTOFCORE LEARNING SYSTEMS AND DEMONSTRATES MOST OF THE NOTIONS DISCUSSED ABOVE
FURTHERMORE IT ALSO SHOWS THE EVOLUTION OF THE PERFORMANCE OF DIFFERENT ALGORITHMS WITH THE NUMBER OF PROCESSED EXAMPLES
NOW LOOKING AT THE COMPUTATION TIME OF THE DIFFERENT PARTS WE SEE THAT THE VECTORIZATION IS MUCH MORE EXPENSIVE THAN LEARNING ITSELF FROM THE DIFFERENT ALGORITHMS MULTINOMIALNB IS THE MOST EXPENSIVE BUT ITS OVERHEAD CAN BE MITIGATED BY INCREASING THE SIZE OF THE MINIBATCHES EXERCISE CHANGE MINIBATCHSIZE TO 100 AND 10000 IN THE PROGRAM AND COMPARE

NOTES
372 COMPUTATIONAL PERFORMANCE
FOR SOME APPLICATIONS THE PERFORMANCE MAINLY LATENCY AND THROUGHPUT AT PREDICTION TIME OF ESTIMATORS IS CRUCIAL IT MAY ALSO BE OF INTEREST TO CONSIDER THE TRAINING THROUGHPUT BUT THIS IS OFTEN LESS IMPORTANT IN A PRODUCTION SETUP WHERE IT OFTEN TAKES PLACE OFFLINE
WE WILL REVIEW HERE THE ORDERS OF MAGNITUDE YOU CAN EXPECT FROM A NUMBER OF SCIKITLEARN ESTIMATORS IN DIFFERENT CONTEXTS AND PROVIDE SOME TIPS AND TRICKS FOR OVERCOMING PERFORMANCE BOTTLENECKS
PREDICTION LATENCY IS MEASURED AS THE ELAPSED TIME NECESSARY TO MAKE A PREDICTION EG IN MICROSECONDS LATENCY IS OFTEN VIEWED AS A DISTRIBUTION AND OPERATIONS ENGINEERS OFTEN FOCUS ON THE LATENCY AT A GIVEN PERCENTILE OF THIS DISTRIBUTION EG THE 90 PERCENTILE
PREDICTION THROUGHPUT IS DEFINED AS THE NUMBER OF PREDICTIONS THE SOFTWARE CAN DELIVER IN A GIVEN AMOUNT OF TIME EG IN PREDICTIONS PER SECOND
AN IMPORTANT ASPECT OF PERFORMANCE OPTIMIZATION IS ALSO THAT IT CAN HURT PREDICTION ACCURACY INDEED SIMPLER MODELS EG LINEAR INSTEAD OF NONLINEAR OR WITH FEWER PARAMETERS OFTEN RUN FASTER BUT ARE NOT ALWAYS ABLE TO TAKE INTO ACCOUNT THE SAME EXACT PROPERTIES OF THE DATA AS MORE COMPLEX ONES
PREDICTION LATENCY
ONE OF THE MOST STRAIGHTFORWARD CONCERNS ONE MAY HAVE WHEN USINGCHOOSING A MACHINE LEARNING TOOLKIT IS THE LATENCY AT WHICH PREDICTIONS CAN BE MADE IN A PRODUCTION ENVIRONMENT
THE MAIN FACTORS THAT INFLUENCE THE PREDICTION LATENCY ARE
1 NUMBER OF FEATURES

A LAST MAJOR PARAMETER IS ALSO THE POSSIBILITY TO DO PREDICTIONS IN BULK OR ONEATATIME MODE
BULK VERSUS ATOMIC MODE
IN GENERAL DOING PREDICTIONS IN BULK MANY INSTANCES AT THE SAME TIME IS MORE EFFICIENT FOR A NUMBER OF REASONS BRANCHING PREDICTABILITY CPU CACHE LINEAR ALGEBRA LIBRARIES OPTIMIZATIONS ETC HERE WE SEE ON A SETTING WITH FEW FEATURES THAT INDEPENDENTLY OF ESTIMATOR CHOICE THE BULK MODE IS ALWAYS FASTER AND FOR SOME OF THEM BY 1 TO 2 ORDERS OF MAGNITUDE

TO BENCHMARK DIFFERENT ESTIMATORS FOR YOUR CASE YOU CAN SIMPLY CHANGE THE NFEATURES PARAMETER IN THIS EXAMPLE
PREDICTION LATENCY THIS SHOULD GIVE YOU AN ESTIMATE OF THE ORDER OF MAGNITUDE OF THE PREDICTION LATENCY
CONFIGURING SCIKITLEARN FOR REDUCED VALIDATION OVERHEAD
SCIKITLEARN DOES SOME VALIDATION ON DATA THAT INCREASES THE OVERHEAD PER CALL TO PREDICT AND SIMILAR FUNCTIONS
IN PARTICULAR CHECKING THAT FEATURES ARE FINITE NOT NAN OR INFINITE INVOLVES A FULL PASS OVER THE DATA IF YOU EN
SURE THAT YOUR DATA IS ACCEPTABLE YOU MAY SUPPRESS CHECKING FOR FINITENESS BY SETTING THE ENVIRONMENT VARIABLE
SKLEARNASSUMEFINITE TO A NONEMPTY STRING BEFORE IMPORTING SCIKITLEARN OR CONFIGURE IT IN PYTHON WITH
SKLEARNSETCONFIG FOR MORE CONTROL THAN THESE GLOBAL SETTINGS A CONFIGCONTEXT ALLOWS YOU TO SET THIS
CONFIGURATION WITHIN A SPECIFIED CONTEXT

```
 IMPORT SKLEARN
 WITH SKLEARNCONFIGCONTEXTASSUMEFINITE TRUE
 PASS  DO LEARNINGPREDICTION HERE WITH REDUCED VALIDATION
```

NOTE THAT THIS WILL AFFECT ALL USES OF SKLEARNUTILSASSERTALLFINITE WITHIN THE CONTEXT
INFLUENCE OF THE NUMBER OF FEATURES
OBVIOUSLY WHEN THE NUMBER OF FEATURES INCREASES SO DOES THE MEMORY CONSUMPTION OF EACH EXAMPLE INDEED FOR A
MATRIX OF □INSTANCES WITH □FEATURES THE SPACE COMPLEXITY IS IN □□□ FROM A COMPUTING PERSPECTIVE IT ALSO
MEANS THAT THE NUMBER OF BASIC OPERATIONS EG MULTIPLICATIONS FOR VECTORMATRIX PRODUCTS IN LINEAR MODELS INCREASES
TOO HERE IS A GRAPH OF THE EVOLUTION OF THE PREDICTION LATENCY WITH THE NUMBER OF FEATURES

OVERALL YOU CAN EXPECT THE PREDICTION TIME TO INCREASE AT LEAST LINEARLY WITH THE NUMBER OF FEATURES NONLINEAR CASES CAN HAPPEN DEPENDING ON THE GLOBAL MEMORY FOOTPRINT AND ESTIMATOR

INFLUENCE OF THE INPUT DATA REPRESENTATION

SCIPY PROVIDES SPARSE MATRIX DATA STRUCTURES WHICH ARE OPTIMIZED FOR STORING SPARSE DATA THE MAIN FEATURE OF SPARSE FORMATS IS THAT YOU DON'T STORE ZEROS SO IF YOUR DATA IS SPARSE THEN YOU USE MUCH LESS MEMORY A NONZERO VALUE IN A SPARSE CSR OR CSC REPRESENTATION WILL ONLY TAKE ON AVERAGE ONE 32BIT INTEGER POSITION THE 64 BIT FLOATING POINT VALUE AN ADDITIONAL 32BIT PER ROW OR COLUMN IN THE MATRIX USING SPARSE INPUT ON A DENSE OR SPARSE LINEAR MODEL CAN SPEEDUP PREDICTION BY QUITE A BIT AS ONLY THE NON ZERO VALUED FEATURES IMPACT THE DOT PRODUCT AND THUS THE MODEL PREDICTIONS HENCE IF YOU HAVE 100 NON ZEROS IN 1E6 DIMENSIONAL SPACE YOU ONLY NEED 100 MULTIPLY AND ADD OPERATION INSTEAD OF 1E6

CALCULATION OVER A DENSE REPRESENTATION HOWEVER MAY LEVERAGE HIGHLY OPTIMISED VECTOR OPERATIONS AND MULTITHREADING IN BLAS AND TENDS TO RESULT IN FEWER CPU CACHE MISSES SO THE SPARSITY SHOULD TYPICALLY BE QUITE HIGH 10 NONZEROS MAX TO BE CHECKED DEPENDING ON THE HARDWARE FOR THE SPARSE INPUT REPRESENTATION TO BE FASTER THAN THE DENSE INPUT REPRESENTATION ON A MACHINE WITH MANY CPUS AND AN OPTIMIZED BLAS IMPLEMENTATION

HERE IS SAMPLE CODE TO TEST THE SPARSITY OF YOUR INPUT

```
DEFSPARSITYRATIOX
RETURN10  NPCOUNTNONZEROX  FLOATXSHAPE0 XSHAPE1
PRINTINPUT SPARSITY RATIO SPARSITYRATIOX
```

AS A RULE OF THUMB YOU CAN CONSIDER THAT IF THE SPARSITY RATIO IS GREATER THAN 90 YOU CAN PROBABLY BENEFIT FROM SPARSE FORMATS CHECK SCIPY'S SPARSE MATRIX FORMATS DOCUMENTATION FOR MORE INFORMATION ON HOW TO BUILD OR CONVERT YOUR DATA TO SPARSE MATRIX FORMATS MOST OF THE TIME THE CSR ANDCSC FORMATS WORK BEST

INFLUENCE OF THE MODEL COMPLEXITY

GENERALLY SPEAKING WHEN MODEL COMPLEXITY INCREASES PREDICTIVE POWER AND LATENCY ARE SUPPOSED TO INCREASE IN CREASING PREDICTIVE POWER IS USUALLY INTERESTING BUT FOR MANY APPLICATIONS WE WOULD BETTER NOT INCREASE PREDICTION LATENCY TOO MUCH WE WILL NOW REVIEW THIS IDEA FOR DIFFERENT FAMILIES OF SUPERVISED MODELS

FORSKLEARNLINEARMODEL EG LASSO ELASTICNET SGDCLASSIFIERREGRESSOR RIDGE RIDGECLASSIFIER PAS SIVEAGGRESSIVECLASSIFIERREGRESSOR LINEARSVC LOGISTICREGRESSION THE DECISION FUNCTION THAT IS APPLIED AT PRE DICTION TIME IS THE SAME A DOT PRODUCT SO LATENCY SHOULD BE EQUIVALENT

HERE IS AN EXAMPLE USING SKLEARNLINEARMODELSTOCHASTICGRADIENTSGDCLASSIFIER WITH THE ELASTICNET PENALTY THE REGULARIZATION STRENGTH IS GLOBALLY CONTROLLED BY THE ALPHA PARAMETER WITH A SUFFICIENTLY HIGHALPHA ONE CAN THEN INCREASE THE L1RATIO PARAMETER OF ELASTICNET TO ENFORCE VARIOUS LEVELS OF SPARSITY IN THE MODEL COEFFICIENTS HIGHER SPARSITY HERE IS INTERPRETED AS LESS MODEL COMPLEXITY AS WE NEED FEWER COEFFICIENTS TO DESCRIBE IT FULLY OF COURSE SPARSITY INFLUENCES IN TURN THE PREDICTION TIME AS THE SPARSE DOTPRODUCT TAKES TIME ROUGHLY PROPORTIONAL TO THE NUMBER OF NONZERO COEFFICIENTS

FOR THESKLEARNSVM FAMILY OF ALGORITHMS WITH A NONLINEAR KERNEL THE LATENCY IS TIED TO THE NUMBER OF SUPPORT VECTORS THE FEWER THE FASTER LATENCY AND THROUGHPUT SHOULD ASYMPTOTICALLY GROW LINEARLY WITH THE NUMBER OF SUPPORT VECTORS IN A SVC OR SVR MODEL THE KERNEL WILL ALSO INFLUENCE THE LATENCY AS IT IS USED TO COMPUTE THE PROJECTION OF THE INPUT VECTOR ONCE PER SUPPORT VECTOR IN THE FOLLOWING GRAPH THE NUPARAMETER OF SKLEARNSVM CLASSESNUSVR WAS USED TO INFLUENCE THE NUMBER OF SUPPORT VECTORS

FORSKLEARNENSEMBLE OF TREES EG RANDOMFOREST GBT EXTRATREES ETC THE NUMBER OF TREES AND THEIR DEPTH PLAY THE MOST IMPORTANT ROLE LATENCY AND THROUGHPUT SHOULD SCALE LINEARLY WITH THE NUMBER OF TREES IN THIS CASE WE USED DIRECTLY THE NESTIMATORS PARAMETER OF SKLEARNENSEMBLEGRADIENTBOOSTING GRADIENTBOOSTINGREGRESSOR

IN ANY CASE BE WARNED THAT DECREASING MODEL COMPLEXITY CAN HURT ACCURACY AS MENTIONED ABOVE FOR INSTANCE A NON LINEARLY SEPARABLE PROBLEM CAN BE HANDLED WITH A SPEEDY LINEAR MODEL BUT PREDICTION POWER WILL VERY LIKELY SUFFER IN THE PROCESS

FEATURE EXTRACTION LATENCY

MOST SCIKITLEARN MODELS ARE USUALLY PRETTY FAST AS THEY ARE IMPLEMENTED EITHER WITH COMPILED CYTHON EXTENSIONS OR OPTIMIZED COMPUTING LIBRARIES ON THE OTHER HAND IN MANY REAL WORLD APPLICATIONS THE FEATURE EXTRACTION PROCESS IE TURNING RAW DATA LIKE DATABASE ROWS OR NETWORK PACKETS INTO NUMPY ARRAYS GOVERNS THE OVERALL PREDICTION TIME FOR EXAMPLE ON THE REUTERS TEXT CLASSIFICATION TASK THE WHOLE PREPARATION READING AND PARSING SGML FILES TOKENIZING THE TEXT AND HASHING IT INTO A COMMON VECTOR SPACE IS TAKING 100 TO 500 TIMES MORE TIME THAN THE ACTUAL PREDICTION CODE DEPENDING ON THE CHOSEN MODEL

IN MANY CASES IT IS THUS RECOMMENDED TO CAREFULLY TIME AND PROFILE YOUR FEATURE EXTRACTION CODE AS IT MAY BE A GOOD PLACE TO START OPTIMIZING WHEN YOUR OVERALL LATENCY IS TOO SLOW FOR YOUR APPLICATION

PREDICTION THROUGHPUT

ANOTHER IMPORTANT METRIC TO CARE ABOUT WHEN SIZING PRODUCTION SYSTEMS IS THE THROUGHPUT IE THE NUMBER OF PREDICTIONS YOU CAN MAKE IN A GIVEN AMOUNT OF TIME HERE IS A BENCHMARK FROM THE PREDICTION LATENCY EXAMPLE THAT MEASURES THIS QUANTITY FOR A NUMBER OF ESTIMATORS ON SYNTHETIC DATA

THESE THROUGHPUTS ARE ACHIEVED ON A SINGLE PROCESS AN OBVIOUS WAY TO INCREASE THE THROUGHPUT OF YOUR APPLICATION IS TO SPAWN ADDITIONAL INSTANCES USUALLY PROCESSES IN PYTHON BECAUSE OF THE GIL THAT SHARE THE SAME MODEL ONE MIGHT ALSO ADD MACHINES TO SPREAD THE LOAD A DETAILED EXPLANATION ON HOW TO ACHIEVE THIS IS BEYOND THE SCOPE OF THIS DOCUMENTATION THOUGH

TIPS AND TRICKS

LINEAR ALGEBRA LIBRARIES

AS SCIKITLEARN RELIES HEAVILY ON NUMPYSCIPY AND LINEAR ALGEBRA IN GENERAL IT MAKES SENSE TO TAKE EXPLICIT CARE OF THE VERSIONS OF THESE LIBRARIES BASICALLY YOU OUGHT TO MAKE SURE THAT NUMPY IS BUILT USING AN OPTIMIZED BLAS LAPACK LIBRARY

NOT ALL MODELS BENEFIT FROM OPTIMIZED BLAS AND LAPACK IMPLEMENTATIONS FOR INSTANCE MODELS BASED ON RANDOM IZED DECISION TREES TYPICALLY DO NOT RELY ON BLAS CALLS IN THEIR INNER LOOPS NOR DO KERNEL SVMS SVCSVRNUSVC NUSVR ON THE OTHER HAND A LINEAR MODEL IMPLEMENTED WITH A BLAS DGEMM CALL VIA NUMPYDOT WILL TYPICALLY BENEFIT HUGELY FROM A TUNED BLAS IMPLEMENTATION AND LEAD TO ORDERS OF MAGNITUDE SPEEDUP OVER A NONOPTIMIZED BLAS

YOU CAN DISPLAY THE BLAS LAPACK IMPLEMENTATION USED BY YOUR NUMPY SCIPY SCIKITLEARN INSTALL WITH THE FOLLOWING COMMANDS

```
FROM NUMPYDISTUTILSSYSTEMINFO IMPORT GETINFO
PRINTGETINFOBLASOPT
PRINTGETINFOLAPACKOPT
```

OPTIMIZED BLAS LAPACK IMPLEMENTATIONS INCLUDE

• ATLAS NEED HARDWARE SPECIFIC TUNING BY REBUILDING ON THE TARGET MACHINE

• OPENBLAS
• MKL
• APPLE ACCELERATE AND VECLIB FRAMEWORKS OSX ONLY
MORE INFORMATION CAN BE FOUND ON THE SCIPY INSTALL PAGE AND IN THIS BLOG POST FROM DANIEL NOURI WHICH HAS SOME NICE STEP BY STEP INSTALL INSTRUCTIONS FOR DEBIAN UBUNTU
LIMITING WORKING MEMORY
SOME CALCULATIONS WHEN IMPLEMENTED USING STANDARD NUMPY VECTORIZED OPERATIONS INVOLVE USING A LARGE AMOUNT OF TEMPORARY MEMORY THIS MAY POTENTIALLY EXHAUST SYSTEM MEMORY WHERE COMPUTATIONS CAN BE PERFORMED IN FIXED MEMORY CHUNKS WE ATTEMPT TO DO SO AND ALLOW THE USER TO HINT AT THE MAXIMUM SIZE OF THIS WORKING MEMORY DE FAULTING TO 1GB USING SKLEARNSETCONFIG ORCONFIGCONTEXT THE FOLLOWING SUGGESTS TO LIMIT TEMPORARY WORKING MEMORY TO 128 MIB

```
IMPORT SKLEARN
WITH SKLEARNCONFIGCONTEXTWORKINGMEMORY128
PASS  DO CHUNKED WORK HERE
```

AN EXAMPLE OF A CHUNKED OPERATION ADHERING TO THIS SETTING IS METRICPAIRWISEDISTANCESCHUNKED WHICH FACILITATES COMPUTING ROWWISE REDUCTIONS OF A PAIRWISE DISTANCE MATRIX
MODEL COMPRESSION
MODEL COMPRESSION IN SCIKITLEARN ONLY CONCERNS LINEAR MODELS FOR THE MOMENT IN THIS CONTEXT IT MEANS THAT WE WANT TO CONTROL THE MODEL SPARSITY IE THE NUMBER OF NONZERO COORDINATES IN THE MODEL VECTORS IT IS GENERALLY A GOOD IDEA TO COMBINE MODEL SPARSITY WITH SPARSE INPUT DATA REPRESENTATION
HERE IS SAMPLE CODE THAT ILLUSTRATES THE USE OF THE SPARSIFY METHOD

```
CLF  SGDREGRESSORPENALTYELASTICNET L1RATIO025
CLFFITXTRAIN YTRAINSPARSIFY
CLFPREDICTXTEST
```

IN THIS EXAMPLE WE PREFER THE ELASTICNET PENALTY AS IT IS OFTEN A GOOD COMPROMISE BETWEEN MODEL COMPACTNESS AND PREDICTION POWER ONE CAN ALSO FURTHER TUNE THE L1RATIO PARAMETER IN COMBINATION WITH THE REGULARIZATION STRENGTHALPHA TO CONTROL THIS TRADEOFF
A TYPICAL BENCHMARK ON SYNTHETIC DATA YIELDS A 30 DECREASE IN LATENCY WHEN BOTH THE MODEL AND INPUT ARE SPARSE WITH 0000024 AND 0027400 NONZERO COEFFICIENTS RATIO RESPECTIVELY YOUR MILEAGE MAY VARY DEPENDING ON THE SPARSITY AND SIZE OF YOUR DATA AND MODEL FURTHERMORE SPARSIFYING CAN BE VERY USEFUL TO REDUCE THE MEMORY USAGE OF PREDICTIVE MODELS DEPLOYED ON PRODUCTION SERVERS
MODEL RESHAPING
MODEL RESHAPING CONSISTS IN SELECTING ONLY A PORTION OF THE AVAILABLE FEATURES TO FIT A MODEL IN OTHER WORDS IF A MODEL DISCARDS FEATURES DURING THE LEARNING PHASE WE CAN THEN STRIP THOSE FROM THE INPUT THIS HAS SEVERAL BENEFITS FIRSTLY IT REDUCES MEMORY AND THEREFORE TIME OVERHEAD OF THE MODEL ITSELF IT ALSO ALLOWS TO DISCARD EXPLICIT FEATURE SELECTION COMPONENTS IN A PIPELINE ONCE WE KNOW WHICH FEATURES TO KEEP FROM A PREVIOUS RUN FINALLY IT CAN HELP REDUCE PROCESSING TIME AND IO USAGE UPSTREAM IN THE DATA ACCESS AND FEATURE EXTRACTION LAYERS BY NOT COLLECTING AND BUILDING FEATURES THAT ARE DISCARDED BY THE MODEL FOR INSTANCE IF THE RAW DATA COME FROM A DATABASE IT CAN MAKE IT POSSIBLE TO WRITE SIMPLER AND FASTER QUERIES OR REDUCE IO USAGE BY MAKING THE QUERIES RETURN LIGHTER RECORDS AT THE

MOMENT RESHAPING NEEDS TO BE PERFORMED MANUALLY IN SCIKITLEARN IN THE CASE OF SPARSE INPUT PARTICULARLY IN CSR FORMAT IT IS GENERALLY SUFFICIENT TO NOT GENERATE THE RELEVANT FEATURES LEAVING THEIR COLUMNS EMPTY

LINKS

•SCIKITLEARN DEVELOPER PERFORMANCE DOCUMENTATION

• SCIPY SPARSE MATRIX FORMATS DOCUMENTATION

373 PARALLELISM RESOURCE MANAGEMENT AND CONFIGURATION

PARALLEL AND DISTRIBUTED COMPUTING

SCIKITLEARN USES THE JOBLIB LIBRARY TO ENABLE PARALLEL COMPUTING INSIDE ITS ESTIMATORS SEE THE JOBLIB DOCUMENTATION FOR THE SWITCHES TO CONTROL PARALLEL COMPUTING

NOTE THAT BY DEFAULT SCIKITLEARN USES ITS EMBEDDED VENDORED VERSION OF JOBLIB A CONFIGURATION SWITCH DOCUMENTED BELOW CONTROLS THIS BEHAVIOR

CONFIGURATION SWITCHES

PYTHON RUNTIME

SKLEARNSETCONFIG CONTROLS THE FOLLOWING BEHAVIORS

ASSUMEFINITE USED TO SKIP VALIDATION WHICH ENABLES FASTER COMPUTATIONS BUT MAY LEAD TO SEGMENTATION FAULTS IF THE DATA CONTAINS NANS

WORKINGMEMORY THE OPTIMAL SIZE OF TEMPORARY ARRAYS USED BY SOME ALGORITMS

ENVIRONMENT VARIABLES

THESE ENVIRONMENT VARIABLES SHOULD BE SET BEFORE IMPORTING SCIKITLEARN

SKLEARNSITEJOBLIB WHEN THIS ENVIRONMENT VARIABLE IS SET TO A NON ZERO VALUE SCIKITLEARN USES THE SITE JOBLIB RATHER THAN ITS VENDORED VERSION CONSEQUENTLY JOBLIB MUST BE INSTALLED FOR SCIKITLEARN TO RUN NOTE THAT USING THE SITE JOBLIB IS AT YOUR OWN RISKS THE VERSIONS OF SCIKITLEARN AND JOBLIB NEED TO BE COMPATIBLE CURRENTLY JOBLIB 011 IS SUPPORTED IN ADDITION DUMPS FROM JOBLIBMEMORY MIGHT BE INCOMPATIBLE AND YOU MIGHT LOOSE SOME CACHES AND HAVE TO REDOWNLOAD SOME DATASETS DEPRECATED SINCE VERSION 021 AS OF VERSION 021 THIS PARAMETER HAS NO EFFECT VENDORED JOBLIB WAS REMOVED AND SITE JOBLIB IS ALWAYS USED

SKLEARNASSUMEFINITE SETS THE DEFAULT VALUE FOR THE ASSUMEFINITE ARGUMENT OF SKLEARNSETCONFIG

SKLEARNWORKINGMEMORY SETS THE DEFAULT VALUE FOR THE LIMITING WORKING MEMORY ARGUMENT OFSKLEARNSETCONFIG

SKLEARNSEED SETS THE SEED OF THE GLOBAL RANDOM GENERATOR WHEN RUNNING THE TESTS FOR REPRODUCIBIL ITY

SKLEARNSKIPNETWORKTESTS WHEN THIS ENVIRONMENT VARIABLE IS SET TO A NON ZERO VALUE THE TESTS THAT NEED NETWORK ACCESS ARE SKIPPED

CHAPTER
FOUR
GLOSSARY OF COMMON TERMS AND API ELEMENTS
THIS GLOSSARY HOPES TO DEFINITIVELY REPRESENT THE TACIT AND EXPLICIT CONVENTIONS APPLIED IN SCIKITLEARN AND ITS API WHILE PROVIDING A REFERENCE FOR USERS AND CONTRIBUTORS IT AIMS TO DESCRIBE THE CONCEPTS AND EITHER DETAIL THEIR CORRESPONDING API OR LINK TO OTHER RELEVANT PARTS OF THE DOCUMENTATION WHICH DO SO BY LINKING TO GLOSSARY ENTRIES FROM THE API REFERENCE AND USER GUIDE WE MAY MINIMIZE REDUNDANCY AND INCONSISTENCY
WE BEGIN BY LISTING GENERAL CONCEPTS AND ANY THAT DIDN’T FIT ELSEWHERE BUT MORE SPECIFIC SETS OF RELATED TERMS ARE LISTED BELOW CLASS APIS AND ESTIMATOR TYPES TARGET TYPES METHODS PARAMETERS ATTRIBUTES DATA AND SAMPLE PROPERTIES
41 GENERAL CONCEPTS
1D
1D ARRAY ONEDIMENSIONAL ARRAY A NUMPY ARRAY WHOSE SHAPE HAS LENGTH 1 A VECTOR
2D
2D ARRAY TWODIMENSIONAL ARRAY A NUMPY ARRAY WHOSE SHAPE HAS LENGTH 2 OFTEN REPRESENTS A MATRIX
API REFERS TO BOTH THE SPECIFIC INTERFACES FOR ESTIMATORS IMPLEMENTED IN SCIKITLEARN AND THE GENERALIZED CONVENTIONS ACROSS TYPES OF ESTIMATORS AS DESCRIBED IN THIS GLOSSARY AND OVERVIEWED IN THE CONTRIBUTOR DOCUMENTATION
THE SPECIFIC INTERFACES THAT CONSTITUTE SCIKITLEARN’S PUBLIC API ARE LARGELY DOCUMENTED IN API REFERENCE HOW EVER WE LESS FORMALLY CONSIDER ANYTHING AS PUBLIC API IF NONE OF THE IDENTIFIERS REQUIRED TO ACCESS IT BEGINS WITH WE GENERALLY TRY TO MAINTAIN BACKWARDS COMPATIBILITY FOR ALL OBJECTS IN THE PUBLIC API
PRIVATE API INCLUDING FUNCTIONS MODULES AND METHODS BEGINNING ARE NOT ASSURED TO BE STABLE
ARRAYLIKE THE MOST COMMON DATA FORMAT FOR INPUT TO SCIKITLEARN ESTIMATORS AND FUNCTIONS ARRAYLIKE IS ANY TYPE OBJECT FOR WHICH NUMPYASARRAY WILL PRODUCE AN ARRAY OF APPROPRIATE SHAPE USUALLY 1 OR 2DIMENSIONAL OF APPROPRIATE DTYPE USUALLY NUMERIC
THIS INCLUDES
• A NUMPY ARRAY
• A LIST OF NUMBERS
• A LIST OF LENGTHK LISTS OF NUMBERS FOR SOME FIXED LENGTH K
• APANDASDATAFRAME WITH ALL COLUMNS NUMERIC
• A NUMERIC PANDASSERIES
IT EXCLUDES
• ASPARSE MATRIX
• AN ITERATOR

• A GENERATOR
NOTE THAT OUTPUT FROM SCIKITLEARN ESTIMATORS AND FUNCTIONS EG PREDICTIONS SHOULD GENERALLY BE ARRAYS OR SPARSE MATRICES OR LISTS THEREOF AS IN MULTIOUTPUT TREEDECISIONTREECLASSIFIER 'SPREDICTPROBA AN ESTIMATOR WHERE PREDICT RETURNS A LIST OR A PANDASSERIES IS NOT VALID
ATTRIBUTE
ATTRIBUTES WE MOSTLY USE ATTRIBUTE TO REFER TO HOW MODEL INFORMATION IS STORED ON AN ESTIMATOR DURING FITTING ANY PUBLIC ATTRIBUTE STORED ON AN ESTIMATOR INSTANCE IS REQUIRED TO BEGIN WITH AN ALPHABETIC CHARACTER AND END IN A SINGLE UNDERSCORE IF IT IS SET IN FITORPARTIALFIT THESE ARE WHAT IS DOCUMENTED UNDER AN ESTIMATOR'S ATTRIBUTES DOCUMENTATION THE INFORMATION STORED IN ATTRIBUTES IS USUALLY EITHER SUFFICIENT STATISTICS USED FOR PREDICTION OR TRANSFORMATION TRANSDUCTIVE OUTPUTS SUCH AS LABELS OREMBEDDING OR DIAGNOSTIC DATA SUCH AS FEATUREIMPORTANCES COMMON ATTRIBUTES ARE LISTED BELOW
A PUBLIC ATTRIBUTE MAY HAVE THE SAME NAME AS A CONSTRUCTOR PARAMETER WITH AAPPENDED THIS IS USED TO STORE A VALIDATED OR ESTIMATED VERSION OF THE USER'S INPUT FOR EXAMPLE DECOMPOSITIONPCA IS CONSTRUCTED WITH ANNCOMPONENTS PARAMETER FROM THIS TOGETHER WITH OTHER PARAMETERS AND THE DATA PCA ESTIMATES THE ATTRIBUTENCOMPONENTS
FURTHER PRIVATE ATTRIBUTES USED IN PREDICTIONTRANSFORMATIONETC MAY ALSO BE SET WHEN FITTING THESE BEGIN WITH A SINGLE UNDERSCORE AND ARE NOT ASSURED TO BE STABLE FOR PUBLIC ACCESS
A PUBLIC ATTRIBUTE ON AN ESTIMATOR INSTANCE THAT DOES NOT END IN AN UNDERSCORE SHOULD BE THE STORED UNMODIFIED VALUE OF AN INIT PARAMETER OF THE SAME NAME BECAUSE OF THIS EQUIVALENCE THESE ARE DOCUMENTED UNDER AN ESTIMATOR'S PARAMETERS DOCUMENTATION
BACKWARDS COMPATIBILITY WE GENERALLY TRY TO MAINTAIN BACKWARDS COMPATIBILITY IE INTERFACES AND BEHAVIORS MAY BE EXTENDED BUT NOT CHANGED OR REMOVED FROM RELEASE TO RELEASE BUT THIS COMES WITH SOME EXCEPTIONS
PUBLIC API ONLY THE BEHAVIOUR OF OBJECTS ACCESSED THROUGH PRIVATE IDENTIFIERS THOSE BEGINNING MAY BE CHANGED ARBITRARILY BETWEEN VERSIONS
AS DOCUMENTED WE WILL GENERALLY ASSUME THAT THE USERS HAVE ADHERED TO THE DOCUMENTED PARAMETER TYPES AND RANGES IF THE DOCUMENTATION ASKS FOR A LIST AND THE USER GIVES A TUPLE WE DO NOT ASSURE CONSISTENT BEHAVIOR FROM VERSION TO VERSION
DEPRECATION BEHAVIORS MAY CHANGE FOLLOWING A DEPRECATION PERIOD USUALLY TWO RELEASES LONG WARNINGS ARE ISSUED USING PYTHON'S WARNINGS MODULE
KEYWORD ARGUMENTS WE MAY SOMETIMES ASSUME THAT ALL OPTIONAL PARAMETERS OTHER THAN X AND Y TO FITAND SIMILAR METHODS ARE PASSED AS KEYWORD ARGUMENTS ONLY AND MAY BE POSITIONALLY REORDERED
BUG FIXES AND ENHANCEMENTS BUG FIXES AND – LESS OFTEN – ENHANCEMENTS MAY CHANGE THE BEHAVIOR OF ESTIMATORS INCLUDING THE PREDICTIONS OF AN ESTIMATOR TRAINED ON THE SAME DATA AND RANDOMSTATE WHEN THIS HAPPENS WE ATTEMPT TO NOTE IT CLEARLY IN THE CHANGELOG
SERIALIZATION WE MAKE NO ASSURANCES THAT PICKLING AN ESTIMATOR IN ONE VERSION WILL ALLOW IT TO BE UNPICKLED TO AN EQUIVALENT MODEL IN THE SUBSEQUENT VERSION FOR ESTIMATORS IN THE SKLEARN PACKAGE WE ISSUE A WARNING WHEN THIS UNPICKLING IS ATTEMPTED EVEN IF IT MAY HAPPEN TO WORK SEE SECURITY MAINTAINABILITY LIMITATIONS
UTILSESTIMATORCHECKSCHECKESTIMATOR WE PROVIDE LIMITED BACKWARDS COMPATIBILITY ASSURANCES FOR THE ESTIMATOR CHECKS WE MAY ADD EXTRA REQUIREMENTS ON ESTIMATORS TESTED WITH THIS FUNCTION USUALLY WHEN THESE WERE INFORMALLY ASSUMED BUT NOT FORMALLY TESTED
DESPITE THIS INFORMAL CONTRACT WITH OUR USERS THE SOFTWARE IS PROVIDED AS IS AS STATED IN THE LICENCE WHEN A RELEASE INADVERTENTLY INTRODUCES CHANGES THAT ARE NOT BACKWARDS COMPATIBLE THESE ARE KNOWN AS SOFTWARE REGRESSIONS
CALLABLE A FUNCTION CLASS OR AN OBJECT WHICH IMPLEMENTS THE CALL METHOD ANYTHING THAT RETURNS TRUE WHEN THE ARGUMENT OF CALLABLE

CATEGORICAL FEATURE A CATEGORICAL OR NOMINAL FEATURE IS ONE THAT HAS A FINITE SET OF DISCRETE VALUES ACROSS THE POP ULATION OF DATA THESE ARE COMMONLY REPRESENTED AS COLUMNS OF INTEGERS OR STRINGS STRINGS WILL BE REJECTED BY MOST SCIKITLEARN ESTIMATORS AND INTEGERS WILL BE TREATED AS ORDINAL OR COUNTVALUED FOR THE USE WITH MOST ESTIMATORS CATEGORICAL VARIABLES SHOULD BE ONEHOT ENCODED NOTABLE EXCEPTIONS INCLUDE TREEBASED MODELS SUCH AS RANDOM FORESTS AND GRADIENT BOOSTING MODELS THAT OFTEN WORK BETTER AND FASTER WITH INTEGERCODED CATEGOR ICAL VARIABLES ORDINALENCODER HELPS ENCODING STRINGVALUED CATEGORICAL FEATURES AS ORDINAL INTEGERS AND ONEHOTENCODER CAN BE USED TO ONEHOT ENCODE CATEGORICAL FEATURES SEE ALSO ENCODING CATEGORICAL FEATURES AND THE CATEGORICALENCODING PACKAGE FOR TOOLS RELATED TO ENCODING CATEGORICAL FEATURES

CLONE

CLONED TO COPY AN ESTIMATOR INSTANCE AND CREATE A NEW ONE WITH IDENTICAL PARAMETERS BUT WITHOUT ANY FITTED ATTRIBUTES USINGCLONE

WHENFIT IS CALLED A METAESTIMATOR USUALLY CLONES A WRAPPED ESTIMATOR INSTANCE BEFORE FITTING THE CLONED INSTANCE EXCEPTIONS FOR LEGACY REASONS INCLUDE PIPELINE ANDFEATUREUNION

COMMON TESTS THIS REFERS TO THE TESTS RUN ON ALMOST EVERY ESTIMATOR CLASS IN SCIKITLEARN TO CHECK THEY COMPLY WITH BASIC API CONVENTIONS THEY ARE AVAILABLE FOR EXTERNAL USE THROUGH UTILSESTIMATORCHECKS CHECKESTIMATOR WITH MOST OF THE IMPLEMENTATION IN SKLEARNUTILSESTIMATORCHECKSPY

NOTE SOME EXCEPTIONS TO THE COMMON TESTING REGIME ARE CURRENTLY HARDCODED INTO THE LIBRARY BUT WE HOPE TO REPLACE THIS BY MARKING EXCEPTIONAL BEHAVIOURS ON THE ESTIMATOR USING SEMANTIC ESTIMATOR TAGS

DEPRECATION WE USE DEPRECATION TO SLOWLY VIOLATE OUR BACKWARDS COMPATIBILITY ASSURANCES USUALLY TO TO

- CHANGE THE DEFAULT VALUE OF A PARAMETER OR
- REMOVE A PARAMETER ATTRIBUTE METHOD CLASS ETC

WE WILL ORDINARILY ISSUE A WARNING WHEN A DEPRECATED ELEMENT IS USED ALTHOUGH THERE MAY BE LIMITATIONS TO THIS FOR INSTANCE WE WILL RAISE A WARNING WHEN SOMEONE SETS A PARAMETER THAT HAS BEEN DEPRECATED BUT MAY NOT WHEN THEY ACCESS THAT PARAMETER'S ATTRIBUTE ON THE ESTIMATOR INSTANCE

SEE THE CONTRIBUTORS' GUIDE

DIMENSIONALITY MAY BE USED TO REFER TO THE NUMBER OF FEATURES IE NFEATURES OR COLUMNS IN A 2D FEATURE MATRIX DIMENSIONS ARE HOWEVER ALSO USED TO REFER TO THE LENGTH OF A NUMPY ARRAY'S SHAPE DISTINGUISHING A 1D ARRAY FROM A 2D MATRIX

DOCSTRING THE EMBEDDED DOCUMENTATION FOR A MODULE CLASS FUNCTION ETC USUALLY IN CODE AS A STRING AT THE BEGINNING OF THE OBJECT'S DEFINITION AND ACCESSIBLE AS THE OBJECT'S DOC ATTRIBUTE

WE TRY TO ADHERE TO PEP257 AND FOLLOW NUMPYDOC CONVENTIONS

DOUBLE UNDERSCORE

DOUBLE UNDERSCORE NOTATION WHEN SPECIFYING PARAMETER NAMES FOR NESTED ESTIMATORS MAY BE USED TO SEPARATE BETWEEN PARENT AND CHILD IN SOME CONTEXTS THE MOST COMMON USE IS WHEN SETTING PARAMETERS THROUGH A META ESTIMATOR WITH SETPARAMS AND HENCE IN SPECIFYING A SEARCH GRID IN PARAMETER SEARCH SEE PARAMETER IT IS ALSO USED INPIPELINEPIPELINEFIT FOR PASSING SAMPLE PROPERTIES TO THEFIT METHODS OF ESTIMATORS IN THE PIPELINE

DTYPE

DATA TYPE NUMPY ARRAYS ASSUME A HOMOGENEOUS DATA TYPE THROUGHOUT AVAILABLE IN THE DTYPE ATTRIBUTE OF AN ARRAY OR SPARSE MATRIX WE GENERALLY ASSUME SIMPLE DATA TYPES FOR SCIKITLEARN DATA FLOAT OR INTEGER WE MAY SUPPORT OBJECT OR STRING DATA TYPES FOR ARRAYS BEFORE ENCODING OR VECTORIZING OUR ESTIMATORS DO NOT WORK WITH STRUCT ARRAYS FOR INSTANCE

TODO MENTION EFFICIENCY AND PRECISION ISSUES CASTING POLICY

DUCK TYPING WE TRY TO APPLY DUCK TYPING TO DETERMINE HOW TO HANDLE SOME INPUT VALUES EG CHECKING WHETHER A GIVEN ESTIMATOR IS A CLASSIFIER THAT IS WE AVOID USING ISINSTANCE WHERE POSSIBLE AND RELY ON THE PRESENCE OR ABSENCE OF ATTRIBUTES TO DETERMINE AN OBJECT'S BEHAVIOUR SOME NUANCE IS REQUIRED WHEN FOLLOWING THIS APPROACH

• FOR SOME ESTIMATORS AN ATTRIBUTE MAY ONLY BE AVAILABLE ONCE IT IS FITTED FOR INSTANCE WE CANNOT A PRIORI DETERMINE IF PREDICTPROBA IS AVAILABLE IN A GRID SEARCH WHERE THE GRID INCLUDES ALTERNATING BETWEEN A PROBABILISTIC AND A NONPROBABILISTIC PREDICTOR IN THE FINAL STEP OF THE PIPELINE IN THE FOLLOWING WE CAN ONLY DETERMINE IF CLF IS PROBABILISTIC AFTER FITTING IT ON SOME DATA

```
 FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
 FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
CLF  GRIDSEARCHCVSGDCLASSIFIER
 PARAMGRIDLOSS LOG HINGE
```

THIS MEANS THAT WE CAN ONLY CHECK FOR DUCKTYPED ATTRIBUTES AFTER FITTING AND THAT WE MUST BE CAREFUL TO MAKE METAESTIMATORS ONLY PRESENT ATTRIBUTES ACCORDING TO THE STATE OF THE UNDERLYING ESTIMATOR AFTER FITTING

• CHECKING IF AN ATTRIBUTE IS PRESENT USING HASATTR IS IN GENERAL JUST AS EXPENSIVE AS GETTING THE ATTRIBUTE GETATTR OR DOT NOTATION IN SOME CASES GETTING THE ATTRIBUTE MAY INDEED BE EXPENSIVE EG FOR SOME IMPLEMENTATIONS OF FEATUREIMPORTANCES WHICH MAY SUGGEST THIS IS AN API DESIGN FLAW SO CODE WHICH DOESHASATTR FOLLOWED BY GETATTR SHOULD BE AVOIDED GETATTR WITHIN A TRYEXCEPT BLOCK IS PRE FERRED

• FOR DETERMINING SOME ASPECTS OF AN ESTIMATOR'S EXPECTATIONS OR SUPPORT FOR SOME FEATURE WE USE ESTIMATOR TAGS INSTEAD OF DUCK TYPING

EARLY STOPPING THIS CONSISTS IN STOPPING AN ITERATIVE OPTIMIZATION METHOD BEFORE THE CONVERGENCE OF THE TRAINING LOSS TO AVOID OVERFITTING THIS IS GENERALLY DONE BY MONITORING THE GENERALIZATION SCORE ON A VALIDATION SET WHEN AVAILABLE IT IS ACTIVATED THROUGH THE PARAMETER EARLYSTOPPING OR BY SETTING A POSITIVE NITERNOCHANGE

ESTIMATOR INSTANCE WE SOMETIMES USE THIS TERMINOLOGY TO DISTINGUISH AN ESTIMATOR CLASS FROM A CONSTRUCTED INSTANCE FOR EXAMPLE IN THE FOLLOWING CLS IS AN ESTIMATOR CLASS WHILE EST1 ANDEST2 ARE INSTANCES

```
CLS  RANDOMFORESTCLASSIFIER
EST1  CLS
EST2  RANDOMFORESTCLASSIFIER
```

EXAMPLES WE TRY TO GIVE EXAMPLES OF BASIC USAGE FOR MOST FUNCTIONS AND CLASSES IN THE API

• AS DOCTESTS IN THEIR DOCSTRINGS IE WITHIN THE SKLEARN LIBRARY CODE ITSELF

• AS EXAMPLES IN THE EXAMPLE GALLERY RENDERED USING SPHINXGALLERY FROM SCRIPTS IN THE EXAMPLES DIREC TORY EXEMPLIFYING KEY FEATURES OR PARAMETERS OF THE ESTIMATORFUNCTION THESE SHOULD ALSO BE REFERENCED FROM THE USER GUIDE

• SOMETIMES IN THE USER GUIDE BUILT FROM DOC ALONGSIDE A TECHNICAL DESCRIPTION OF THE ESTIMATOR

EVALUATION METRIC

EVALUATION METRICS EVALUATION METRICS GIVE A MEASURE OF HOW WELL A MODEL PERFORMS WE MAY USE THIS TERM SPECIF ICALLY TO REFER TO THE FUNCTIONS IN METRICS DISREGARDING METRICSPAIRWISE AS DISTINCT FROM THE SCORE METHOD AND THE SCORING API USED IN CROSS VALIDATION SEE MODEL EVALUATION QUANTIFYING THE QUALITY OF PREDIC TIONS

THESE FUNCTIONS USUALLY ACCEPT A GROUND TRUTH OR THE RAW DATA WHERE THE METRIC EVALUATES CLUSTERING WITHOUT A GROUND TRUTH AND A PREDICTION BE IT THE OUTPUT OF PREDICT YPRED OF PREDICTPROBA YPROBA OR OF AN ARBITRARY SCORE FUNCTION INCLUDING DECISIONFUNCTION YSCORE FUNCTIONS ARE USUALLY NAMED TO END WITH SCORE IF A GREATER SCORE INDICATES A BETTER MODEL AND LOSS IF A LESSER SCORE INDICATES A BETTER MODEL THIS DIVERSITY OF INTERFACE MOTIVATES THE SCORING API

NOTE THAT SOME ESTIMATORS CAN CALCULATE METRICS THAT ARE NOT INCLUDED IN METRICS AND ARE ESTIMATORSPECIFIC NOTABLY MODEL LIKELIHOODS

ESTIMATOR TAGS A PROPOSED FEATURE EG 8022 BY WHICH THE CAPABILITIES OF AN ESTIMATOR ARE DESCRIBED THROUGH A SET OF SEMANTIC TAGS THIS WOULD ENABLE SOME RUNTIME BEHAVIORS BASED ON ESTIMATOR INSPECTION BUT IT ALSO ALLOWS EACH ESTIMATOR TO BE TESTED FOR APPROPRIATE INVARIANCES WHILE BEING EXCEPTED FROM OTHER COMMON TESTS

SOME ASPECTS OF ESTIMATOR TAGS ARE CURRENTLY DETERMINED THROUGH THE DUCK TYPING OF METHODS LIKE PREDICTPROBA AND THROUGH SOME SPECIAL ATTRIBUTES ON ESTIMATOR OBJECTS

ESTIMATORTYPE THIS STRINGVALUED ATTRIBUTE IDENTIFIES AN ESTIMATOR AS BEING A CLASSIFIER REGRESSOR ETC IT IS SET BY MIXINS SUCH AS BASECLASSIFIERMIXIN BUT NEEDS TO BE MORE EXPLICITLY ADOPTED ON A META ESTIMATOR ITS VALUE SHOULD USUALLY BE CHECKED BY WAY OF A HELPER SUCH AS BASEISCLASSIFIER

PAIRWISE THIS BOOLEAN ATTRIBUTE INDICATES WHETHER THE DATA X PASSED TOFIT AND SIMILAR METHODS CONSISTS OF PAIRWISE MEASURES OVER SAMPLES RATHER THAN A FEATURE REPRESENTATION FOR EACH SAMPLE IT IS USUALLY TRUE WHERE AN ESTIMATOR HAS A METRIC ORAFFINITY ORKERNEL PARAMETER WITH VALUE ‘PRECOMPUTED’ ITS PRIMARY PURPOSE IS THAT WHEN A METAESTIMATOR EXTRACTS A SUBSAMPLE OF DATA INTENDED FOR A PAIRWISE ESTIMATOR THE DATA NEEDS TO BE INDEXED ON BOTH AXES WHILE OTHER DATA IS INDEXED ONLY ON THE FIRST AXIS

FEATURE

FEATURES

FEATURE VECTOR IN THE ABSTRACT A FEATURE IS A FUNCTION IN ITS MATHEMATICAL SENSE MAPPING A SAMPLED OBJECT TO A NU MERIC OR CATEGORICAL QUANTITY “FEATURE” IS ALSO COMMONLY USED TO REFER TO THESE QUANTITIES BEING THE INDIVIDUAL ELEMENTS OF A VECTOR REPRESENTING A SAMPLE IN A DATA MATRIX FEATURES ARE REPRESENTED AS COLUMNS EACH COLUMN CONTAINS THE RESULT OF APPLYING A FEATURE FUNCTION TO A SET OF SAMPLES

ELSEWHERE FEATURES ARE KNOWN AS ATTRIBUTES PREDICTORS REGRESSORS OR INDEPENDENT VARIABLES

NEARLY ALL ESTIMATORS IN SCIKITLEARN ASSUME THAT FEATURES ARE NUMERIC FINITE AND NOT MISSING EVEN WHEN THEY HAVE SEMANTICALLY DISTINCT DOMAINS AND DISTRIBUTIONS CATEGORICAL ORDINAL COUNTVALUED REALVALUED INTERVAL SEE ALSO CATEGORICAL FEATURE ANDMISSING VALUES

NFEATURES INDICATES THE NUMBER OF FEATURES IN A DATASET

FITTING CALLING FITORFITTRANSFORM FITPREDICT ETC ON AN ESTIMATOR

FITTED THE STATE OF AN ESTIMATOR AFTER FITTING

THERE IS NO CONVENTIONAL PROCEDURE FOR CHECKING IF AN ESTIMATOR IS FITTED HOWEVER AN ESTIMATOR THAT IS NOT FITTED

• SHOULD RAISE EXCEPTIONSNOTFITTEDERROR WHEN A PREDICTION METHOD PREDICT TRANSFORM ETC IS CALLED UTILSVALIDATIONCHECKISFITTED IS USED INTERNALLY FOR THIS PURPOSE

• SHOULD NOT HAVE ANY ATTRIBUTES BEGINNING WITH AN ALPHABETIC CHARACTER AND ENDING WITH AN UNDERSCORE NOTE THAT A DESCRIPTOR FOR THE ATTRIBUTE MAY STILL BE PRESENT ON THE CLASS BUT HASATTR SHOULD RETURN FALSE

FUNCTION WE PROVIDE AD HOC FUNCTION INTERFACES FOR MANY ALGORITHMS WHILE ESTIMATOR CLASSES PROVIDE A MORE CONSIS TENT INTERFACE

IN PARTICULAR SCIKITLEARN MAY PROVIDE A FUNCTION INTERFACE THAT FITS A MODEL TO SOME DATA AND RETURNS THE LEARNT MODEL PARAMETERS AS IN LINEARMODELENETPATH FOR TRANSDUCTIVE MODELS THIS ALSO RETURNS THE EM BEDDING OR CLUSTER LABELS AS IN MANIFOLDSPECTRALEMBEDDING ORCLUSTERDBSCAN MANY PREPRO CESSING TRANSFORMERS ALSO PROVIDE A FUNCTION INTERFACE AKIN TO CALLING FITTRANSFORM AS INPREPROCESSING MAXABSSCALE USERS SHOULD BE CAREFUL TO AVOID DATA LEAKAGE WHEN MAKING USE OF THESE FITTRANSFORM EQUIVALENT FUNCTIONS

WE DO NOT HAVE A STRICT POLICY ABOUT WHEN TO OR WHEN NOT TO PROVIDE FUNCTION FORMS OF ESTIMATORS BUT MAINTAINERS SHOULD CONSIDER CONSISTENCY WITH EXISTING INTERFACES AND WHETHER PROVIDING A FUNCTION WOULD LEAD USERS ASTRAY FROM BEST PRACTICES AS REGARDS DATA LEAKAGE ETC

GALLERY SEEEXAMPLES
HYPERPARAMETER
HYPERPARAMETER SEEPARAMETER
IMPUTE
IMPUTATION MOST MACHINE LEARNING ALGORITHMS REQUIRE THAT THEIR INPUTS HAVE NO MISSING VALUES AND WILL NOT WORK IF THIS REQUIREMENT IS VIOLATED ALGORITHMS THAT ATTEMPT TO FILL IN OR IMPUTE MISSING VALUES ARE REFERRED TO AS IMPUTATION ALGORITHMS
INDEXABLE ANARRAYLIKE SPARSE MATRIX PANDAS DATAFRAME OR SEQUENCE USUALLY A LIST
INDUCTION
INDUCTIVE INDUCTIVE CONTRASTED WITH TRANSDUCTIVE MACHINE LEARNING BUILDS A MODEL OF SOME DATA THAT CAN THEN BE APPLIED TO NEW INSTANCES MOST ESTIMATORS IN SCIKITLEARN ARE INDUCTIVE HAVING PREDICT ANDOR TRANSFORM METHODS
JOBLIB A PYTHON LIBRARY HTTPSJOBLIBREADTHEDOCSIO USED IN SCIKITLEARN TO FACILITE SIMPLE PARALLELISM AND CACHING JOBLIB IS ORIENTED TOWARDS EFFICIENTLY WORKING WITH NUMPY ARRAYS SUCH AS THROUGH USE OF MEMORY MAPPING SEE PARALLEL AND DISTRIBUTED COMPUTING FOR MORE INFORMATION
LABEL INDICATOR MATRIX
MULTILABEL INDICATOR MATRIX
MULTILABEL INDICATOR MATRICES THE FORMAT USED TO REPRESENT MULTILABEL DATA WHERE EACH ROW OF A 2D ARRAY OR SPARSE MATRIX CORRESPONDS TO A SAMPLE EACH COLUMN CORRESPONDS TO A CLASS AND EACH ELEMENT IS 1 IF THE SAMPLE IS LABELED WITH THE CLASS AND 0 IF NOT
LEAKAGE
DATA LEAKAGE A PROBLEM IN CROSS VALIDATION WHERE GENERALIZATION PERFORMANCE CAN BE OVERESTIMATED SINCE KNOWL EDGE OF THE TEST DATA WAS INADVERTENTLY INCLUDED IN TRAINING A MODEL THIS IS A RISK FOR INSTANCE WHEN APPLYING ATRANSFORMER TO THE ENTIRETY OF A DATASET RATHER THAN EACH TRAINING PORTION IN A CROSS VALIDATION SPLIT WE AIM TO PROVIDE INTERFACES SUCH AS PIPELINE ANDMODELSELECTION THAT SHIELD THE USER FROM DATA LEAKAGE
MEMMAPPING
MEMORY MAP
MEMORY MAPPING A MEMORY EFFICIENCY STRATEGY THAT KEEPS DATA ON DISK RATHER THAN COPYING IT INTO MAIN MEMORY MEMORY MAPS CAN BE CREATED FOR ARRAYS THAT CAN BE READ WRITTEN OR BOTH USING NUMPYMEMMAP WHEN USING JOBLIB TO PARALLELIZE OPERATIONS IN SCIKITLEARN IT MAY AUTOMATICALLY MEMMAP LARGE ARRAYS TO REDUCE MEMORY DUPLICATION OVERHEAD IN MULTIPROCESSING
MISSING VALUES MOST SCIKITLEARN ESTIMATORS DO NOT WORK WITH MISSING VALUES WHEN THEY DO EG IN IMPUTE SIMPLEIMPUTER NAN IS THE PREFERRED REPRESENTATION OF MISSING VALUES IN FLOAT ARRAYS IF THE ARRAY HAS INTEGER DTYPE NAN CANNOT BE REPRESENTED FOR THIS REASON WE SUPPORT SPECIFYING ANOTHER MISSINGVALUES VALUE WHEN IMPUTATION OR LEARNING CAN BE PERFORMED IN INTEGER SPACE UNLABELED DATA IS A SPECIAL CASE OF MISSING VALUES IN THE TARGET
NFEATURES THE NUMBER OF FEATURES
NOUTPUTS THE NUMBER OF OUTPUTS IN THE TARGET
NSAMPLES THE NUMBER OF SAMPLES
NTARGETS SYNONYM FOR NOUTPUTS
NARRATIVE DOCS

NARRATIVE DOCUMENTATION AN ALIAS FOR USER GUIDE IE DOCUMENTATION WRITTEN IN DOCMODULES UNLIKE THE API REFERENCE PROVIDED THROUGH DOCSTRINGS THE USER GUIDE AIMS TO
• GROUP TOOLS PROVIDED BY SCIKITLEARN TOGETHER THEMATICALLY OR IN TERMS OF USAGE
• MOTIVATE WHY SOMEONE WOULD USE EACH PARTICULAR TOOL OFTEN THROUGH COMPARISON
• PROVIDE BOTH INTUITIVE AND TECHNICAL DESCRIPTIONS OF TOOLS
• PROVIDE OR LINK TO EXAMPLES OF USING KEY FEATURES OF A TOOL
NPA SHORTHAND FOR NUMPY DUE TO THE CONVENTIONAL IMPORT STATEMENT
IMPORT NUMPY AS NP
ONLINE LEARNING WHERE A MODEL IS ITERATIVELY UPDATED BY RECEIVING EACH BATCH OF GROUND TRUTH TARGETS SOON AFTER MAKING PREDICTIONS ON CORRESPONDING BATCH OF DATA INTRINSICALLY THE MODEL MUST BE USABLE FOR PREDICTION AFTER EACH BATCH SEE PARTIALFIT
OUTOFCORE AN EFFICIENCY STRATEGY WHERE NOT ALL THE DATA IS STORED IN MAIN MEMORY AT ONCE USUALLY BY PERFORMING LEARNING ON BATCHES OF DATA SEE PARTIALFIT
OUTPUTS INDIVIDUAL SCALARCATEGORICAL VARIABLES PER SAMPLE IN THE TARGET FOR EXAMPLE IN MULTILABEL CLASSIFICATION EACH POSSIBLE LABEL CORRESPONDS TO A BINARY OUTPUT ALSO CALLED RESPONSES TASKS ORTARGETS SEE MULTICLASS MULTIOUTPUT ANDCONTINUOUS MULTIOUTPUT
PAIR A TUPLE OF LENGTH TWO
PARAMETER
PARAMETERS
PARAM
PARAMS WE MOSTLY USE PARAMETER TO REFER TO THE ASPECTS OF AN ESTIMATOR THAT CAN BE SPECIFIED IN ITS CONSTRUCTION FOR EXAMPLEMAXDEPTH ANDRANDOMSTATE ARE PARAMETERS OF RANDOMFORESTCLASSIFIER PARAMETERS TO AN ESTIMATOR’S CONSTRUCTOR ARE STORED UNMODIFIED AS ATTRIBUTES ON THE ESTIMATOR INSTANCE AND CONVENTIONALLY START WITH AN ALPHABETIC CHARACTER AND END WITH AN ALPHANUMERIC CHARACTER EACH ESTIMATOR’S CONSTRUCTOR PARAM ETERS ARE DESCRIBED IN THE ESTIMATOR’S DOCSTRING
WE DO NOT USE PARAMETERS IN THE STATISTICAL SENSE WHERE PARAMETERS ARE VALUES THAT SPECIFY A MODEL AND CAN BE ESTIMATED FROM DATA WHAT WE CALL PARAMETERS MIGHT BE WHAT STATISTICIANS CALL HYPERPARAMETERS TO THE MODEL ASPECTS FOR CONFIGURING MODEL STRUCTURE THAT ARE OFTEN NOT DIRECTLY LEARNT FROM DATA HOWEVER OUR PARAMETERS ARE ALSO USED TO PRESCRIBE MODELING OPERATIONS THAT DO NOT AFFECT THE LEARNT MODEL SUCH AS NJOBS FOR CONTROLLING PARALLELISM
WHEN TALKING ABOUT THE PARAMETERS OF A METAESTIMATOR WE MAY ALSO BE INCLUDING THE PARAMETERS OF THE ESTIMATORS WRAPPED BY THE METAESTIMATOR ORDINARILY THESE NESTED PARAMETERS ARE DENOTED BY USING ADOUBLE UNDERSCORE TO SEPARATE BETWEEN THE ESTIMATORASPARAMETER AND ITS PARAMETER THUS CLF BAGGINGCLASSIFIERBASEESTIMATORDECISIONTREECLASSIFIERMAXDEPTH3 HAS A DEEP PARAMETER BASEESTIMATORMAXDEPTH WITH VALUE 3 WHICH IS ACCESSIBLE WITH CLF BASEESTIMATORMAXDEPTH ORCLFGETPARAMSBASEESTIMATORMAXDEPTH
THE LIST OF PARAMETERS AND THEIR CURRENT VALUES CAN BE RETRIEVED FROM AN ESTIMATOR INSTANCE USING ITS GETPARAMS METHOD
BETWEEN CONSTRUCTION AND FITTING PARAMETERS MAY BE MODIFIED USING SETPARAMS TO ENABLE THIS PARAMETERS ARE NOT ORDINARILY VALIDATED OR ALTERED WHEN THE ESTIMATOR IS CONSTRUCTED OR WHEN EACH PARAMETER IS SET PARAMETER VALIDATION IS PERFORMED WHEN FITIS CALLED
COMMON PARAMETERS ARE LISTED BELOW
PAIRWISE METRIC

PAIRWISE METRICS IN ITS BROAD SENSE A PAIRWISE METRIC DEFINES A FUNCTION FOR MEASURING SIMILARITY OR DISSIMILARITY BETWEEN TWO SAMPLES WITH EACH ORDINARILY REPRESENTED AS A FEATURE VECTOR WE PARTICULARLY PROVIDE IMPLEMENTATIONS OF DISTANCE METRICS AS WELL AS IMPROPER METRICS LIKE COSINE DISTANCE THROUGH METRICS PAIRWISEDISTANCES AND OF KERNEL FUNCTIONS A CONSTRAINED CLASS OF SIMILARITY FUNCTIONS IN METRICS PAIRWISEKERNELS THESE CAN COMPUTE PAIRWISE DISTANCE MATRICES THAT ARE SYMMETRIC AND HENCE STORE DATA REDUNDANTLY

SEE ALSO PRECOMPUTED ANDMETRIC

NOTE THAT FOR MOST DISTANCE METRICS WE RELY ON IMPLEMENTATIONS FROM SCIPYSPATIALDISTANCE BUT MAY REIMPLEMENT FOR EFFICIENCY IN OUR CONTEXT THE NEIGHBORS MODULE ALSO DUPLICATES SOME METRIC IMPLEMENTATIONS FOR INTEGRATION WITH EFFICIENT BINARY TREE SEARCH DATA STRUCTURES

PDA SHORTHAND FOR PANDAS DUE TO THE CONVENTIONAL IMPORT STATEMENT

IMPORT PANDAS AS PD

PRECOMPUTED WHERE ALGORITHMS RELY ON PAIRWISE METRICS AND CAN BE COMPUTED FROM PAIRWISE METRICS ALONE WE OFTEN ALLOW THE USER TO SPECIFY THAT THE XPROVIDED IS ALREADY IN THE PAIRWISE DISSIMILARITY SPACE RATHER THAN IN A FEATURE SPACE THAT IS WHEN PASSED TO FIT IT IS A SQUARE SYMMETRIC MATRIX WITH EACH VECTOR INDICATING DISSIMILARITY TO EVERY SAMPLE AND WHEN PASSED TO PREDICTIONTRANSFORMATION METHODS EACH ROW CORRESPONDS TO A TESTING SAMPLE AND EACH COLUMN TO A TRAINING SAMPLE

USE OF PRECOMPUTED X IS USUALLY INDICATED BY SETTING A METRIC AFFINITY ORKERNEL PARAMETER TO THE STRING ‘PRECOMPUTED’ AN ESTIMATOR SHOULD MARK ITSELF AS BEING PAIRWISE IF THIS IS THE CASE

RECTANGULAR DATA THAT CAN BE REPRESENTED AS A MATRIX WITH SAMPLES ON THE FIRST AXIS AND A FIXED FINITE SET OF FEATURES ON THE SECOND IS CALLED RECTANGULAR

THIS TERM EXCLUDES SAMPLES WITH NONVECTORIAL STRUCTURE SUCH AS TEXT AN IMAGE OF ARBITRARY SIZE A TIME SERIES OF ARBITRARY LENGTH A SET OF VECTORS ETC THE PURPOSE OF A VECTORIZER IS TO PRODUCE RECTANGULAR FORMS OF SUCH DATA

SAMPLE

SAMPLES WE USUALLY USE THIS TERM AS A NOUN TO INDICATE A SINGLE FEATURE VECTOR ELSEWHERE A SAMPLE IS CALLED AN INSTANCE DATA POINT OR OBSERVATION NSAMPLES INDICATES THE NUMBER OF SAMPLES IN A DATASET BEING THE NUMBER OF ROWS IN A DATA ARRAY X

SAMPLE PROPERTY

SAMPLE PROPERTIES A SAMPLE PROPERTY IS DATA FOR EACH SAMPLE EG AN ARRAY OF LENGTH NSAMPLES PASSED TO AN ESTIMATOR METHOD OR A SIMILAR FUNCTION ALONGSIDE BUT DISTINCT FROM THE FEATURES X AND TARGET Y THE MOST PROMINENT EXAMPLE IS SAMPLEWEIGHT SEE OTHERS AT DATA AND SAMPLE PROPERTIES

AS OF VERSION 019 WE DO NOT HAVE A CONSISTENT APPROACH TO HANDLING SAMPLE PROPERTIES AND THEIR ROUTING IN METAESTIMATORS THOUGH AFITPARAMS PARAMETER IS OFTEN USED

SCIKITLEARNCONTRIB A VENUE FOR PUBLISHING SCIKITLEARNCOMPATIBLE LIBRARIES THAT ARE BROADLY AUTHORIZED BY THE CORE DEVELOPERS AND THE CONTRIB COMMUNITY BUT NOT MAINTAINED BY THE CORE DEVELOPER TEAM SEE HTTPS SCIKITLEARNCONTRIBGITHUBIO

SCIKITLEARN ENHANCEMENT PROPOSALS

SLEP

SLEPS CHANGES TO THE API PRINCIPLES AND CHANGES TO DEPENDENCIES OR SUPPORTED VERSIONS HAPPEN VIA A SLEP AND FOLLOWS THE DECISIONMAKING PROCESS OUTLINED IN SCIKITLEARN GOVERNANCE AND DECISIONMAKING FOR ALL VOTES A PROPOSAL MUST HAVE BEEN MADE PUBLIC AND DISCUSSED BEFORE THE VOTE SUCH PROPOSAL MUST BE A CONSOLIDATED DOCUMENT IN THE FORM OF A ‘SCIKITLEARN ENHANCEMENT PROPOSAL’ SLEP RATHER THAN A LONG DISCUSSION ON AN ISSUE A SLEP MUST BE SUBMITTED AS A PULLREQUEST TO ENHANCEMENT PROPOSALS USING THE SLEP TEMPLATE

SEMISUPERVISED

SEMISUPERVISED LEARNING

SEMISUPERVISED LEARNING WHERE THE EXPECTED PREDICTION LABEL OR GROUND TRUTH IS ONLY AVAILABLE FOR SOME SAMPLES PROVIDED AS TRAINING DATA WHEN FITTING THE MODEL WE CONVENTIONALLY APPLY THE LABEL 1TOUNLABELED SAMPLES IN SEMISUPERVISED CLASSIFICATION

SPARSE MATRIX A REPRESENTATION OF TWODIMENSIONAL NUMERIC DATA THAT IS MORE MEMORY EFFICIENT THE CORRESPONDING DENSE NUMPY ARRAY WHERE ALMOST ALL ELEMENTS ARE ZERO WE USE THE SCIPYSPARSE FRAMEWORK WHICH PROVIDES SEVERAL UNDERLYING SPARSE DATA REPRESENTATIONS OR FORMATS SOME FORMATS ARE MORE EFFICIENT THAN OTHERS FOR PARTICULAR TASKS AND WHEN A PARTICULAR FORMAT PROVIDES ESPECIAL BENEFIT WE TRY TO DOCUMENT THIS FACT IN SCIKIT LEARN PARAMETER DESCRIPTIONS

SOME SPARSE MATRIX FORMATS NOTABLY CSR CSC COO AND LIL DISTINGUISH BETWEEN IMPLICIT ANDEXPLICIT ZEROS EXPLICIT ZEROS ARE STORED IE THEY CONSUME MEMORY IN A DATA ARRAY IN THE DATA STRUCTURE WHILE IMPLICIT ZEROS CORRESPOND TO EVERY ELEMENT NOT OTHERWISE DEFINED IN EXPLICIT STORAGE

TWO SEMANTICS FOR SPARSE MATRICES ARE USED IN SCIKITLEARN

MATRIX SEMANTICS THE SPARSE MATRIX IS INTERPRETED AS AN ARRAY WITH IMPLICIT AND EXPLICIT ZEROS BEING INTERPRETED AS THE NUMBER 0 THIS IS THE INTERPRETATION MOST OFTEN ADOPTED EG WHEN SPARSE MATRICES ARE USED FOR FEATURE MATRICES OR MULTILABEL INDICATOR MATRICES

GRAPH SEMANTICS AS WITHSCIPYSPARSECSGRAPH EXPLICIT ZEROS ARE INTERPRETED AS THE NUMBER 0 BUT IMPLICIT ZEROS INDICATE A MASKED OR ABSENT VALUE SUCH AS THE ABSENCE OF AN EDGE BETWEEN TWO VER TICES OF A GRAPH WHERE AN EXPLICIT VALUE INDICATES AN EDGE'S WEIGHT THIS INTERPRETATION IS ADOPTED TO REPRESENT CONNECTIVITY IN CLUSTERING IN REPRESENTATIONS OF NEAREST NEIGHBORHOODS EG NEIGHBORS KNEIGHBORSGRAPH AND FOR PRECOMPUTED DISTANCE REPRESENTATION WHERE ONLY DISTANCES IN THE NEIGH BORHOOD OF EACH POINT ARE REQUIRED

WHEN WORKING WITH SPARSE MATRICES WE ASSUME THAT IT IS SPARSE FOR A GOOD REASON AND AVOID WRITING CODE THAT DENSIFIES A USERPROVIDED SPARSE MATRIX INSTEAD MAINTAINING SPARSITY OR RAISING AN ERROR IF NOT POSSIBLE IE IF AN ESTIMATOR DOES NOT CANNOT SUPPORT SPARSE MATRICES

SUPERVISED

SUPERVISED LEARNING LEARNING WHERE THE EXPECTED PREDICTION LABEL OR GROUND TRUTH IS AVAILABLE FOR EACH SAMPLE WHEN FITTING THE MODEL PROVIDED AS Y THIS IS THE APPROACH TAKEN IN A CLASSIFIER ORREGRESSOR AMONG OTHER ESTIMATORS

TARGET

TARGETS THEDEPENDENT VARIABLE INSUPERVISED AND SEMISUPERVISED LEARNING PASSED AS YTO AN ESTIMATOR'S FITMETHOD ALSO KNOWN AS DEPENDENT VARIABLE OUTCOME VARIABLE RESPONSE VARIABLE GROUND TRUTH ORLABEL SCIKITLEARN WORKS WITH TARGETS THAT HAVE MINIMAL STRUCTURE A CLASS FROM A FINITE SET A FINITE REALVALUED NUMBER MULTIPLE CLASSES OR MULTIPLE NUMBERS SEE TARGET TYPES

TRANSDUCTION

TRANSDUCTIVE A TRANSDUCTIVE CONTRASTED WITH INDUCTIVE MACHINE LEARNING METHOD IS DESIGNED TO MODEL A SPE CIFIC DATASET BUT NOT TO APPLY THAT MODEL TO UNSEEN DATA EXAMPLES INCLUDE MANIFOLDTSNE CLUSTER AGGLOMERATIVECLUSTERING ANDNEIGHBORSLOCALOUTLIERFACTOR

UNLABELED

UNLABELED DATA SAMPLES WITH AN UNKNOWN GROUND TRUTH WHEN FITTING EQUIVALENTLY MISSING VALUES IN THE TARGET SEE ALSOSEMISUPERVISED ANDUNSUPERVISED LEARNING

UNSUPERVISED

UNSUPERVISED LEARNING LEARNING WHERE THE EXPECTED PREDICTION LABEL OR GROUND TRUTH IS NOT AVAILABLE FOR EACH SAMPLE WHEN FITTING THE MODEL AS IN CLUSTERERS ANDOUTLIER DETECTORS UNSUPERVISED ESTIMATORS IGNORE ANY Y PASSED TO FIT

42 CLASS APIS AND ESTIMATOR TYPES
CLASSIFIER
CLASSIFIERS ASUPERVISED ORSEMISUPERVISED PREDICTOR WITH A FINITE SET OF DISCRETE POSSIBLE OUTPUT VALUES
A CLASSIFIER SUPPORTS MODELING SOME OF BINARY MULTICLASS MULTILABEL ORMULTICLASS MULTIOUTPUT TARGETS WITHIN SCIKITLEARN ALL CLASSIFIERS SUPPORT MULTICLASS CLASSIFICATION DEFAULTING TO USING A ONEVSREST STRATEGY OVER THE BINARY CLASSIFICATION PROBLEM
CLASSIFIERS MUST STORE A CLASSES ATTRIBUTE AFTER FITTING AND USUALLY INHERIT FROM BASECLASSIFIERMIXIN WHICH SETS THEIR ESTIMATORTYPE ATTRIBUTE
A CLASSIFIER CAN BE DISTINGUISHED FROM OTHER ESTIMATORS WITH ISCLASSIFIER
A CLASSIFIER MUST IMPLEMENT
•FIT
•PREDICT
•SCORE
IT MAY ALSO BE APPROPRIATE TO IMPLEMENT DECISIONFUNCTION PREDICTPROBA ANDPREDICTLOGPROBA
CLUSTERER
CLUSTERERS AUNSUPERVISED PREDICTOR WITH A FINITE SET OF DISCRETE OUTPUT VALUES
A CLUSTERER USUALLY STORES LABELS AFTER FITTING AND MUST DO SO IF IT IS TRANSDUCTIVE
A CLUSTERER MUST IMPLEMENT
•FIT
•FITPREDICT IFTRANSDUCTIVE
•PREDICT IFINDUCTIVE
DENSITY ESTIMATOR TODO
ESTIMATOR
ESTIMATORS AN OBJECT WHICH MANAGES THE ESTIMATION AND DECODING OF A MODEL THE MODEL IS ESTIMATED AS A DETERMINISTIC FUNCTION OF
•PARAMETERS PROVIDED IN OBJECT CONSTRUCTION OR WITH SETPARAMS
• THE GLOBAL NUMPYRANDOM RANDOM STATE IF THE ESTIMATOR'S RANDOMSTATE PARAMETER IS SET TO NONE AND
• ANY DATA OR SAMPLE PROPERTIES PASSED TO THE MOST RECENT CALL TO FITFITTRANSFORM ORFITPREDICT OR DATA SIMILARLY PASSED IN A SEQUENCE OF CALLS TO PARTIALFIT
THE ESTIMATED MODEL IS STORED IN PUBLIC AND PRIVATE ATTRIBUTES ON THE ESTIMATOR INSTANCE FACILITATING DECODING THROUGH PREDICTION AND TRANSFORMATION METHODS
ESTIMATORS MUST PROVIDE A FITMETHOD AND SHOULD PROVIDE SETPARAMS ANDGETPARAMS ALTHOUGH THESE ARE USUALLY PROVIDED BY INHERITANCE FROM BASEBASEESTIMATOR
THE CORE FUNCTIONALITY OF SOME ESTIMATORS MAY ALSO BE AVAILABLE AS A FUNCTION
FEATURE EXTRACTOR
FEATURE EXTRACTORS ATRANSFORMER WHICH TAKES INPUT WHERE EACH SAMPLE IS NOT REPRESENTED AS AN ARRAYLIKE OBJECT OF FIXED LENGTH AND PRODUCES AN ARRAYLIKE OBJECT OF FEATURES FOR EACH SAMPLE AND THUS A 2DIMENSIONAL ARRAYLIKE FOR A SET OF SAMPLES IN OTHER WORDS IT LOSSILY MAPS A NONRECTANGULAR DATA REPRESENTATION INTO RECTANGULAR DATA

FEATURE EXTRACTORS MUST IMPLEMENT AT LEAST
•FIT
•TRANSFORM
•GETFEATURENAMES
METAESTIMATOR
METAESTIMATORS
METAESTIMATOR
METAESTIMATORS ANESTIMATOR WHICH TAKES ANOTHER ESTIMATOR AS A PARAMETER EXAMPLES INCLUDE PIPELINE
PIPELINE MODELSELECTIONGRIDSEARCHCV FEATURESELECTIONSELECTFROMMODEL AND
ENSEMBLEBAGGINGCLASSIFIER
IN A METAESTIMATOR'S FITMETHOD ANY CONTAINED ESTIMATORS SHOULD BE CLONED BEFORE THEY ARE FIT ALTHOUGH FIXME
PIPELINE AND FEATUREUNION DO NOT DO THIS CURRENTLY AN EXCEPTION TO THIS IS THAT AN ESTIMATOR MAY EXPLIC
ITLY DOCUMENT THAT IT ACCEPTS A PREFITTED ESTIMATOR EG USING PREFITTRUE INFEATURESELECTION
SELECTFROMMODEL ONE KNOWN ISSUE WITH THIS IS THAT THE PREFITTED ESTIMATOR WILL LOSE ITS MODEL IF THE
METAESTIMATOR IS CLONED A METAESTIMATOR SHOULD HAVE FIT CALLED BEFORE PREDICTION EVEN IF ALL CONTAINED
ESTIMATORS ARE PREFITTED
IN CASES WHERE A METAESTIMATOR'S PRIMARY BEHAVIORS EG PREDICT ORTRANSFORM IMPLEMENTATION ARE FUNCTIONS
OF PREDICTIONTRANSFORMATION METHODS OF THE PROVIDED BASE ESTIMATOR OR MULTIPLE BASE ESTIMATORS A META
ESTIMATOR SHOULD PROVIDE AT LEAST THE STANDARD METHODS PROVIDED BY THE BASE ESTIMATOR IT MAY NOT BE POSSIBLE
TO IDENTIFY WHICH METHODS ARE PROVIDED BY THE UNDERLYING ESTIMATOR UNTIL THE METAESTIMATOR HAS BEEN FITTED
SEE ALSO DUCK TYPING FOR WHICH UTILSMETAESTIMATORSIFDELEGATEHASMETHOD MAY HELP IT
SHOULD ALSO PROVIDE OR MODIFY THE ESTIMATOR TAGS ANDCLASSES ATTRIBUTE PROVIDED BY THE BASE ESTIMATOR
METAESTIMATORS SHOULD BE CAREFUL TO VALIDATE DATA AS MINIMALLY AS POSSIBLE BEFORE PASSING IT TO AN UNDERLYING
ESTIMATOR THIS SAVES COMPUTATION TIME AND MAY FOR INSTANCE ALLOW THE UNDERLYING ESTIMATOR TO EASILY WORK
WITH DATA THAT IS NOT RECTANGULAR
OUTLIER DETECTOR
OUTLIER DETECTORS ANUNSUPERVISED BINARY PREDICTOR WHICH MODELS THE DISTINCTION BETWEEN CORE AND OUTLYING SAMPLES
OUTLIER DETECTORS MUST IMPLEMENT
•FIT
•FITPREDICT IFTRANSDUCTIVE
•PREDICT IFINDUCTIVE
INDUCTIVE OUTLIER DETECTORS MAY ALSO IMPLEMENT DECISIONFUNCTION TO GIVE A NORMALIZED INLIER SCORE WHERE OUTLIERS
HAVE SCORE BELOW 0 SCORESAMPLES MAY PROVIDE AN UNNORMALIZED SCORE PER SAMPLE
PREDICTOR
PREDICTORS ANESTIMATOR SUPPORTING PREDICT ANDOR FITPREDICT THIS ENCOMPASSES CLASSIFIER REGRESSOR OUTLIER DETEC
TORANDCLUSTERER
IN STATISTICS "PREDICTORS" REFERS TO FEATURES
REGRESSOR
REGRESSORS ASUPERVISED ORSEMISUPERVISED PREDICTOR WITH CONTINUOUS OUTPUT VALUES
REGRESSORS USUALLY INHERIT FROM BASEREGRESSORMIXIN WHICH SETS THEIR ESTIMATORTYPE ATTRIBUTE
A REGRESSOR CAN BE DISTINGUISHED FROM OTHER ESTIMATORS WITH ISREGRESSOR

A REGRESSOR MUST IMPLEMENT
•FIT
•PREDICT
•SCORE
TRANSFORMER
TRANSFORMERS AN ESTIMATOR SUPPORTING TRANSFORM ANDOR FITTRANSFORM A PURELY TRANSDUCTIVE TRANSFORMER SUCH AS MANIFOLDTSNE MAY NOT IMPLEMENT TRANSFORM
VECTORIZER
VECTORIZERS SEEFEATURE EXTRACTOR
THERE ARE FURTHER APIS SPECIFICALLY RELATED TO A SMALL FAMILY OF ESTIMATORS SUCH AS
CROSSVALIDATION SPLITTER
CV SPLITTER
CROSSVALIDATION GENERATOR A NONESTIMATOR FAMILY OF CLASSES USED TO SPLIT A DATASET INTO A SEQUENCE OF TRAIN AND TEST PORTIONS SEE CROSSVALIDATION EVALUATING ESTIMATOR PERFORMANCE BY PROVIDING SPLIT ANDGETNSPLITS METH ODS NOTE THAT UNLIKE ESTIMATORS THESE DO NOT HAVE FITMETHODS AND DO NOT PROVIDE SETPARAMS ORGETPARAMS PARAMETER VALIDATION MAY BE PERFORMED IN INIT
CROSSVALIDATION ESTIMATOR AN ESTIMATOR THAT HAS BUILTIN CROSSVALIDATION CAPABILITIES TO AUTOMATICALLY SELECT THE BEST HYPERPARAMETERS SEE THE USER GUIDE SOME EXAMPLE OF CROSSVALIDATION ESTIMATORS ARE ELASTICNETCV AND LOGISTICREGRESSIONCV CROSSVALIDATION ESTIMATORS ARE NAMED ESTIMATORCV AND TEND TO BE ROUGHLY EQUIVALENT TO GRIDSEARCHCVESTIMATOR THE ADVANTAGE OF USING A CROSSVALIDATION ESTIMATOR OVER THE CANONICAL ESTIMATOR CLASS ALONG WITH GRID SEARCH IS THAT THEY CAN TAKE ADVANTAGE OF WARMSTARTING BY REUSING PRECOMPUTED RESULTS IN THE PREVIOUS STEPS OF THE CROSSVALIDATION PROCESS THIS GENERALLY LEADS TO SPEED IMPROVEMENTS AN EXCEPTION IS THE RIDGECV CLASS WHICH CAN INSTEAD PERFORM EFFICIENT LEAVEONEOUT CV
SCORER A NONESTIMATOR CALLABLE OBJECT WHICH EVALUATES AN ESTIMATOR ON GIVEN TEST DATA RETURNING A NUMBER UNLIKE EVALUATION METRICS A GREATER RETURNED NUMBER MUST CORRESPOND WITH A BETTER SCORE SEE THE SCORING PARAMETER DEFINING MODEL EVALUATION RULES
FURTHER EXAMPLES
•NEIGHBORSDISTANCEMETRIC
•GAUSSIANPROCESSKERNELSKERNEL
•TREECRITERION
43 TARGET TYPES
BINARY A CLASSIFICATION PROBLEM CONSISTING OF TWO CLASSES A BINARY TARGET MAY REPRESENTED AS FOR A MULTICLASS PROBLEM BUT WITH ONLY TWO LABELS A BINARY DECISION FUNCTION IS REPRESENTED AS A 1D ARRAY
SEMANTICALLY ONE CLASS IS OFTEN CONSIDERED THE “POSITIVE” CLASS UNLESS OTHERWISE SPECIFIED EG USING POSLABEL INEVALUATION METRICS WE CONSIDER THE CLASS LABEL WITH THE GREATER VALUE NUMERICALLY OR LEXICOGRAPHICALLY AS THE POSITIVE CLASS OF LABELS 0 1 1 IS THE POSITIVE CLASS OF 1 2 2 IS THE POSITIVE CLASS OF ‘NO’ ‘YES’ ‘YES’ IS THE POSITIVE CLASS OF ‘NO’ ‘YES’ ‘NO’ IS THE POSITIVE CLASS THIS AFFECTS THE OUTPUT OF DECISIONFUNCTION FOR INSTANCE
NOTE THAT A DATASET SAMPLED FROM A MULTICLASS YOR A CONTINUOUS YMAY APPEAR TO BE BINARY

TYPEOFTARGET WILL RETURN ‘BINARY’ FOR BINARY INPUT OR A SIMILAR ARRAY WITH ONLY A SINGLE CLASS PRESENT
CONTINUOUS A REGRESSION PROBLEM WHERE EACH SAMPLE’S TARGET IS A FINITE FLOATING POINT NUMBER REPRESENTED AS A 1DIMENSIONAL ARRAY OF FLOATS OR SOMETIMES INTS
TYPEOFTARGET WILL RETURN ‘CONTINUOUS’ FOR CONTINUOUS INPUT BUT IF THE DATA IS ALL INTEGERS IT WILL BE IDENTIFIED AS ‘MULTICLASS’
CONTINUOUS MULTIOUTPUT
MULTIOUTPUT CONTINUOUS A REGRESSION PROBLEM WHERE EACH SAMPLE’S TARGET CONSISTS OF NOUTPUTS OUTPUTS EACH ONE A FINITE FLOATING POINT NUMBER FOR A FIXED INT NOUTPUTS 1 IN A PARTICULAR DATASET
CONTINUOUS MULTIOUTPUT TARGETS ARE REPRESENTED AS MULTIPLE CONTINUOUS TARGETS HORIZONTALLY STACKED INTO AN ARRAY OF SHAPENSAMPLES NOUTPUTS
TYPEOFTARGET WILL RETURN ‘CONTINUOUSMULTIOUTPUT’ FOR CONTINUOUS MULTIOUTPUT INPUT BUT IF THE DATA IS ALL INTEGERS IT WILL BE IDENTIFIED AS ‘MULTICLASSMULTIOUTPUT’
MULTICLASS A CLASSIFICATION PROBLEM CONSISTING OF MORE THAN TWO CLASSES A MULTICLASS TARGET MAY BE REPRESENTED AS A 1DIMENSIONAL ARRAY OF STRINGS OR INTEGERS A 2D COLUMN VECTOR OF INTEGERS IE A SINGLE OUTPUT IN MULTIOUTPUT TERMS IS ALSO ACCEPTED
WE DO NOT OFFICIALLY SUPPORT OTHER ORDERABLE HASHABLE OBJECTS AS CLASS LABELS EVEN IF ESTIMATORS MAY HAPPEN TO WORK WHEN GIVEN CLASSIFICATION TARGETS OF SUCH TYPE
FOR SEMISUPERVISED CLASSIFICATION UNLABELED SAMPLES SHOULD HAVE THE SPECIAL LABEL 1 IN Y
WITHIN SCKITLEARN ALL ESTIMATORS SUPPORTING BINARY CLASSIFICATION ALSO SUPPORT MULTICLASS CLASSIFICATION USING ONEVSREST BY DEFAULT
APREPROCESSINGLABELENCODER HELPS TO CANONICALIZE MULTICLASS TARGETS AS INTEGERS
TYPEOFTARGET WILL RETURN ‘MULTICLASS’ FOR MULTICLASS INPUT THE USER MAY ALSO WANT TO HANDLE ‘BINARY’ INPUT IDENTICALLY TO ‘MULTICLASS’
MULTICLASS MULTIOUTPUT
MULTIOUTPUT MULTICLASS A CLASSIFICATION PROBLEM WHERE EACH SAMPLE’S TARGET CONSISTS OF NOUTPUTS OUTPUTS EACH A CLASS LABEL FOR A FIXED INT NOUTPUTS 1 IN A PARTICULAR DATASET EACH OUTPUT HAS A FIXED SET OF AVAILABLE CLASSES AND EACH SAMPLE IS LABELLED WITH A CLASS FOR EACH OUTPUT AN OUTPUT MAY BE BINARY OR MULTICLASS AND IN THE CASE WHERE ALL OUTPUTS ARE BINARY THE TARGET IS MULTILABEL
MULTICLASS MULTIOUTPUT TARGETS ARE REPRESENTED AS MULTIPLE MULTICLASS TARGETS HORIZONTALLY STACKED INTO AN ARRAY OF SHAPENSAMPLES NOUTPUTS
XXX FOR SIMPLICITY WE MAY NOT ALWAYS SUPPORT STRING CLASS LABELS FOR MULTICLASS MULTIOUTPUT AND INTEGER CLASS LABELS SHOULD BE USED
MULTIOUTPUT PROVIDES ESTIMATORS WHICH ESTIMATE MULTIOUTPUT PROBLEMS USING MULTIPLE SINGLEOUTPUT ESTIMA TORS THIS MAY NOT FULLY ACCOUNT FOR DEPENDENCIES AMONG THE DIFFERENT OUTPUTS WHICH METHODS NATIVELY HANDLING THE MULTIOUTPUT CASE EG DECISION TREES NEAREST NEIGHBORS NEURAL NETWORKS MAY DO BETTER
TYPEOFTARGET WILL RETURN ‘MULTICLASSMULTIOUTPUT’ FOR MULTICLASS MULTIOUTPUT INPUT
MULTILABEL AMULTICLASS MULTIOUTPUT TARGET WHERE EACH OUTPUT IS BINARY THIS MAY BE REPRESENTED AS A 2D DENSE ARRAY OR SPARSE MATRIX OF INTEGERS SUCH THAT EACH COLUMN IS A SEPARATE BINARY TARGET WHERE POSITIVE LABELS ARE INDICATED WITH 1 AND NEGATIVE LABELS ARE USUALLY 1 OR 0 SPARSE MULTILABEL TARGETS ARE NOT SUPPORTED EVERYWHERE THAT DENSE MULTILABEL TARGETS ARE SUPPORTED
SEMANTICALLY A MULTILABEL TARGET CAN BE THOUGHT OF AS A SET OF LABELS FOR EACH SAMPLE WHILE NOT USED INTER NALLYPREPROCESSINGMULTILABELBINARIZER IS PROVIDED AS A UTILITY TO CONVERT FROM A LIST OF SETS REPRESENTATION TO A 2D ARRAY OR SPARSE MATRIX ONEHOT ENCODING A MULTICLASS TARGET WITH PREPROCESSING LABELBINARIZER TURNS IT INTO A MULTILABEL PROBLEM

TYPEOFTARGET WILL RETURN ‘MULTILABELINDICATOR’ FOR MULTILABEL INPUT WHETHER SPARSE OR DENSE
MULTIOUTPUT
MULTIOUTPUT A TARGET WHERE EACH SAMPLE HAS MULTIPLE CLASSIFICATIONREGRESSION LABELS SEE MULTICLASS MULTIOUTPUT
ANDCONTINUOUS MULTIOUTPUT WE DO NOT CURRENTLY SUPPORT MODELLING MIXED CLASSIFICATION AND REGRESSION TARGETS
44 METHODS
DECISIONFUNCTION IN A FITTED CLASSIFIER OROUTLIER DETECTOR PREDICTS A “SOFT” SCORE FOR EACH SAMPLE IN RELATION
TO EACH CLASS RATHER THAN THE “HARD” CATEGORICAL PREDICTION PRODUCED BY PREDICT ITS INPUT IS USUALLY ONLY SOME
OBSERVED DATA X
IF THE ESTIMATOR WAS NOT ALREADY FITTED CALLING THIS METHOD SHOULD RAISE A EXCEPTIONSNOTFITTEDERROR
OUTPUT CONVENTIONS
BINARY CLASSIFICATION A 1DIMENSIONAL ARRAY WHERE VALUES STRICTLY GREATER THAN ZERO INDICATE THE POSITIVE CLASS
IE THE LAST CLASS IN CLASSES
MULTICLASS CLASSIFICATION A 2DIMENSIONAL ARRAY WHERE THE ROWWISE ARGMAXIMUM IS THE PREDICTED CLASS
COLUMNS ARE ORDERED ACCORDING TO CLASSES
MULTILABEL CLASSIFICATION SCIKITLEARN IS INCONSISTENT IN ITS REPRESENTATION OF MULTILABEL DECISION FUNCTIONS
SOME ESTIMATORS REPRESENT IT LIKE MULTICLASS MULTIOUTPUT IE A LIST OF 2D ARRAYS EACH WITH TWO COLUMNS
OTHERS REPRESENT IT WITH A SINGLE 2D ARRAY WHOSE COLUMNS CORRESPOND TO THE INDIVIDUAL BINARY CLASSIFICATION
DECISIONS THE LATTER REPRESENTATION IS AMBIGUOUSLY IDENTICAL TO THE MULTICLASS CLASSIFICATION FORMAT THOUGH
ITS SEMANTICS DIFFER IT SHOULD BE INTERPRETED LIKE IN THE BINARY CASE BY THRESHOLDING AT 0
TODO THIS GIST HIGLIGHTS THE USE OF THE DIFFERENT FORMATS FOR MULTILABEL
MULTIOUTPUT CLASSIFICATION A LIST OF 2D ARRAYS CORRESPONDING TO EACH MULTICLASS DECISION FUNCTION
OUTLIER DETECTION A 1DIMENSIONAL ARRAY WHERE A VALUE GREATER THAN OR EQUAL TO ZERO INDICATES AN INLIER
FIT THEFIT METHOD IS PROVIDED ON EVERY ESTIMATOR IT USUALLY TAKES SOME SAMPLESXTARGETSYIF THE MODEL IS
SUPERVISED AND POTENTIALLY OTHER SAMPLE PROPERTIES SUCH AS SAMPLEWEIGHT IT SHOULD
• CLEAR ANY PRIOR ATTRIBUTES STORED ON THE ESTIMATOR UNLESS WARMSTART IS USED
• VALIDATE AND INTERPRET ANY PARAMETERS IDEALLY RAISING AN ERROR IF INVALID
• VALIDATE THE INPUT DATA
• ESTIMATE AND STORE MODEL ATTRIBUTES FROM THE ESTIMATED PARAMETERS AND PROVIDED DATA AND
• RETURN THE NOW FITTED ESTIMATOR TO FACILITATE METHOD CHAINING
TARGET TYPES DESCRIBES POSSIBLE FORMATS FOR Y
FITPREDICT USED ESPECIALLY FOR UNSUPERVISED TRANSDUCTIVE ESTIMATORS THIS FITS THE MODEL AND RETURNS THE PRE
DICTIONS SIMILAR TO PREDICT ON THE TRAINING DATA IN CLUSTERERS THESE PREDICTIONS ARE ALSO STORED IN THE LABELS
ATTRIBUTE AND THE OUTPUT OF FITPREDICTX IS USUALLY EQUIVALENT TO FITXPREDICTX THE PA
RAMETERS TO FITPREDICT ARE THE SAME AS THOSE TO FIT
FITTRANSFORM A METHOD ON TRANSFORMERS WHICH FITS THE ESTIMATOR AND RETURNS THE TRANSFORMED TRAINING
DATA IT TAKES PARAMETERS AS IN FITAND ITS OUTPUT SHOULD HAVE THE SAME SHAPE AS CALLING FITX
TRANSFORMX THERE ARE NONETHELESS RARE CASES WHERE FITTRANSFORMX ANDFITX
TRANSFORMX DO NOT RETURN THE SAME VALUE WHEREIN TRAINING DATA NEEDS TO BE HANDLED DIFFERENTLY DUE
TO MODEL BLENDING IN STACKED ENSEMBLES FOR INSTANCE SUCH CASES SHOULD BE CLEARLY DOCUMENTED TRANSDUCTIVE
TRANSFORMERS MAY ALSO PROVIDE FITTRANSFORM BUT NOT TRANSFORM

ONE REASON TO IMPLEMENT FITTRANSFORM IS THAT PERFORMING FIT ANDTRANSFORM SEPARATELY WOULD BE LESS EFFICIENT THAN TOGETHER BASETRANSFORMERMIXIN PROVIDES A DEFAULT IMPLEMENTATION PROVIDING A CONSIS TENT INTERFACE ACROSS TRANSFORMERS WHERE FITTRANSFORM IS OR IS NOT SPECIALISED
ININDUCTIVE LEARNING – WHERE THE GOAL IS TO LEARN A GENERALISED MODEL THAT CAN BE APPLIED TO NEW DATA – USERS SHOULD BE CAREFUL NOT TO APPLY FITTRANSFORM TO THE ENTIRETY OF A DATASET IE TRAINING AND TEST DATA TOGETHER BEFORE FURTHER MODELLING AS THIS RESULTS IN DATA LEAKAGE
GETFEATURENAMES PRIMARILY FOR FEATURE EXTRACTORS BUT ALSO USED FOR OTHER TRANSFORMERS TO PROVIDE STRING NAMES FOR EACH COLUMN IN THE OUTPUT OF THE ESTIMATOR'S TRANSFORM METHOD IT OUTPUTS A LIST OF STRINGS AND MAY TAKE A LIST OF STRINGS AS INPUT CORRESPONDING TO THE NAMES OF INPUT COLUMNS FROM WHICH OUTPUT COLUMN NAMES CAN BE GENERATED BY DEFAULT INPUT FEATURES ARE NAMED X0 X1
GETNSPLITS ON A CV SPLITTER NOT AN ESTIMATOR RETURNS THE NUMBER OF ELEMENTS ONE WOULD GET IF ITERATING THROUGH THE RETURN VALUE OF SPLIT GIVEN THE SAME PARAMETERS TAKES THE SAME PARAMETERS AS SPLIT
GETPARAMS GETS ALL PARAMETERS AND THEIR VALUES THAT CAN BE SET USING SETPARAMS A PARAMETER DEEP CAN BE USED WHEN SET TO FALSE TO ONLY RETURN THOSE PARAMETERS NOT INCLUDING IE NOT DUE TO INDIRECTION VIA CONTAINED ESTIMATORS
MOST ESTIMATORS ADOPT THE DEFINITION FROM BASEBASEESTIMATOR WHICH SIMPLY ADOPTS THE PARAMETERS DE FINED FORINIT PIPELINEPIPELINE AMONG OTHERS REIMPLEMENTS GETPARAMS TO DECLARE THE ESTIMATORS NAMED IN ITS STEPS PARAMETERS AS THEMSELVES BEING PARAMETERS
PARTIALFIT FACILITATES FITTING AN ESTIMATOR IN AN ONLINE FASHION UNLIKE FIT REPEATEDLY CALLING PARTIALFIT DOES NOT CLEAR THE MODEL BUT UPDATES IT WITH RESPECT TO THE DATA PROVIDED THE PORTION OF DATA PROVIDED TO PARTIALFIT MAY BE CALLED A MINIBATCH EACH MINIBATCH MUST BE OF CONSISTENT SHAPE ETC IN ITERATIVE ESTIMATORS PARTIALFIT OFTEN ONLY PERFORMS A SINGLE ITERATION
PARTIALFIT MAY ALSO BE USED FOR OUTOFCORE LEARNING ALTHOUGH USUALLY LIMITED TO THE CASE WHERE LEARNING CAN BE PERFORMED ONLINE IE THE MODEL IS USABLE AFTER EACH PARTIALFIT AND THERE IS NO SEPARATE PROCESSING NEEDED TO FINALIZE THE MODEL CLUSTERBIRCH INTRODUCES THE CONVENTION THAT CALLING PARTIALFITX WILL PRODUCE A MODEL THAT IS NOT FINALIZED BUT THE MODEL CAN BE FINALIZED BY CALLING PARTIALFIT IE WITHOUT PASSING A FURTHER MINIBATCH
GENERALLY ESTIMATOR PARAMETERS SHOULD NOT BE MODIFIED BETWEEN CALLS TO PARTIALFIT ALTHOUGH PARTIALFIT SHOULD VALIDATE THEM AS WELL AS THE NEW MINIBATCH OF DATA IN CONTRAST WARMSTART IS USED TO REPEATEDLY FIT THE SAME ESTIMATOR WITH THE SAME DATA BUT VARYING PARAMETERS LIKEFITPARTIALFIT SHOULD RETURN THE ESTIMATOR OBJECT
TO CLEAR THE MODEL A NEW ESTIMATOR SHOULD BE CONSTRUCTED FOR INSTANCE WITH BASECLONE
PREDICT MAKES A PREDICTION FOR EACH SAMPLE USUALLY ONLY TAKING XAS INPUT BUT SEE UNDER REGRESSOR OUTPUT CON VENTIONS BELOW IN A CLASSIFIER ORREGRESSOR THIS PREDICTION IS IN THE SAME TARGET SPACE USED IN FITTING EG ONE OF 'RED' 'AMBER' 'GREEN' IF THE YIN FITTING CONSISTED OF THESE STRINGS DESPITE THIS EVEN WHEN YPASSED TO FIT IS A LIST OR OTHER ARRAYLIKE THE OUTPUT OF PREDICT SHOULD ALWAYS BE AN ARRAY OR SPARSE MATRIX IN A CLUSTERER OR OUTLIER DETECTOR THE PREDICTION IS AN INTEGER
IF THE ESTIMATOR WAS NOT ALREADY FITTED CALLING THIS METHOD SHOULD RAISE A EXCEPTIONSNOTFITTEDERROR
OUTPUT CONVENTIONS
CLASSIFIER AN ARRAY OF SHAPE NSAMPLESNSAMPLES NOUTPUTS MULTILABEL DATA MAY BE REP RESENTED AS A SPARSE MATRIX IF A SPARSE MATRIX WAS USED IN FITTING EACH ELEMENT SHOULD BE ONE OF THE VALUES IN THE CLASSIFIER'S CLASSES ATTRIBUTE
CLUSTERER AN ARRAY OF SHAPE NSAMPLES WHERE EACH VALUE IS FROM 0 TO NCLUSTERS 1 IF THE CORRE SPONDING SAMPLE IS CLUSTERED AND 1 IF THE SAMPLE IS NOT CLUSTERED AS IN CLUSTERDBSCAN
OUTLIER DETECTOR AN ARRAY OF SHAPE NSAMPLES WHERE EACH VALUE IS 1 FOR AN OUTLIER AND 1 OTHERWISE

REGRESSOR A NUMERIC ARRAY OF SHAPE NSAMPLES USUALLY FLOAT64 SOME REGRESSORS HAVE EXTRA OPTIONS IN THEIRPREDICT METHOD ALLOWING THEM TO RETURN STANDARD DEVIATION RETURNSTDTRUE OR COVARIANCE RETURNCOVTRUE RELATIVE TO THE PREDICTED VALUE IN THIS CASE THE RETURN VALUE IS A TUPLE OF ARRAYS CORRESPONDING TO PREDICTION MEAN STD COV AS REQUIRED
PREDICTLOGPROBA THE NATURAL LOGARITHM OF THE OUTPUT OF PREDICTPROBA PROVIDED TO FACILITATE NUMERICAL STA BILITY
PREDICTPROBA A METHOD IN CLASSIFIERS ANDCLUSTERERS THAT ARE ABLE TO RETURN PROBABILITY ESTIMATES FOR EACH CLASSCLUSTER ITS INPUT IS USUALLY ONLY SOME OBSERVED DATA X
IF THE ESTIMATOR WAS NOT ALREADY FITTED CALLING THIS METHOD SHOULD RAISE A EXCEPTIONSNOTFITTEDERROR
OUTPUT CONVENTIONS ARE LIKE THOSE FOR DECISIONFUNCTION EXCEPT IN THE BINARY CLASSIFICATION CASE WHERE ONE COLUMN IS OUTPUT FOR EACH CLASS WHILE DECISIONFUNCTION OUTPUTS A 1D ARRAY FOR BINARY AND MULTICLASS PREDICTIONS EACH ROW SHOULD ADD TO 1
LIKE OTHER METHODS PREDICTPROBA SHOULD ONLY BE PRESENT WHEN THE ESTIMATOR CAN MAKE PROBABILISTIC PRE DICTIONS SEE DUCK TYPING THIS MEANS THAT THE PRESENCE OF THE METHOD MAY DEPEND ON ESTIMATOR PARAMETERS EG INLINEARMODELSGDCLASSIFIER OR TRAINING DATA EG IN MODELSELECTIONGRIDSEARCHCV AND MAY ONLY APPEAR AFTER FITTING
SCORE A METHOD ON AN ESTIMATOR USUALLY A PREDICTOR WHICH EVALUATES ITS PREDICTIONS ON A GIVEN DATASET AND RETURNS A SINGLE NUMERICAL SCORE A GREATER RETURN VALUE SHOULD INDICATE BETTER PREDICTIONS ACCURACY IS USED FOR CLASSIFIERS AND R2 FOR REGRESSORS BY DEFAULT
IF THE ESTIMATOR WAS NOT ALREADY FITTED CALLING THIS METHOD SHOULD RAISE A EXCEPTIONSNOTFITTEDERROR
SOME ESTIMATORS IMPLEMENT A CUSTOM ESTIMATORSPECIFIC SCORE FUNCTION OFTEN THE LIKELIHOOD OF THE DATA UNDER THE MODEL
SCORESAMPLES TODO
IF THE ESTIMATOR WAS NOT ALREADY FITTED CALLING THIS METHOD SHOULD RAISE A EXCEPTIONSNOTFITTEDERROR
SETPARAMS AVAILABLE IN ANY ESTIMATOR TAKES KEYWORD ARGUMENTS CORRESPONDING TO KEYS IN GETPARAMS EACH IS PROVIDED A NEW VALUE TO ASSIGN SUCH THAT CALLING GETPARAMS AFTERSETPARAMS WILL REFLECT THE CHANGED PA RAMETERS MOST ESTIMATORS USE THE IMPLEMENTATION IN BASEBASEESTIMATOR WHICH HANDLES NESTED PARAME TERS AND OTHERWISE SETS THE PARAMETER AS AN ATTRIBUTE ON THE ESTIMATOR THE METHOD IS OVERRIDDEN IN PIPELINE PIPELINE AND RELATED ESTIMATORS
SPLIT ON A CV SPLITTER NOT AN ESTIMATOR THIS METHOD ACCEPTS PARAMETERS XYGROUPS WHERE ALL MAY BE OP TIONAL AND RETURNS AN ITERATOR OVER TRAINIDX TESTIDX PAIRS EACH OF TRAINTESTIDX IS A 1D INTEGER ARRAY WITH VALUES FROM 0 FROM XSHAPE0 1 OF ANY LENGTH SUCH THAT NO VALUES APPEAR IN BOTH SOME TRAINIDX AND ITS CORRESPONDING TESTIDX
TRANSFORM IN A TRANSFORMER TRANSFORMS THE INPUT USUALLY ONLY X INTO SOME TRANSFORMED SPACE CONVENTIONALLY NOTATED AS XT OUTPUT IS AN ARRAY OR SPARSE MATRIX OF LENGTH NSAMPLES AND WITH NUMBER OF COLUMNS FIXED AFTER FITTING
IF THE ESTIMATOR WAS NOT ALREADY FITTED CALLING THIS METHOD SHOULD RAISE A EXCEPTIONSNOTFITTEDERROR
45 PARAMETERS
THESE COMMON PARAMETER NAMES SPECIFICALLY USED IN ESTIMATOR CONSTRUCTION SEE CONCEPT PARAMETER SOMETIMES ALSO APPEAR AS PARAMETERS OF FUNCTIONS OR NONESTIMATOR CONSTRUCTORS
CLASSWEIGHT USED TO SPECIFY SAMPLE WEIGHTS WHEN FITTING CLASSIFIERS AS A FUNCTION OF THE TARGET CLASS WHERE SAMPLEWEIGHT IS ALSO SUPPORTED AND GIVEN IT IS MULTIPLIED BY THE CLASSWEIGHT CONTRIBUTION SIMILARLY

WHERECLASSWEIGHT IS USED IN A MULTIOUTPUT INCLUDING MULTILABEL TASKS THE WEIGHTS ARE MULTIPLIED ACROSS
OUTPUTS IE COLUMNS OF Y
BY DEFAULT ALL SAMPLES HAVE EQUAL WEIGHT SUCH THAT CLASSES ARE EFFECTIVELY WEIGHTED BY THEIR THEIR PREVALENCE IN
THE TRAINING DATA THIS COULD BE ACHIEVED EXPLICITLY WITH CLASSWEIGHTLABEL1 1 LABEL2 1
 FOR ALL CLASS LABELS
MORE GENERALLY CLASSWEIGHT IS SPECIFIED AS A DICT MAPPING CLASS LABELS TO WEIGHTS CLASSLABEL
WEIGHT SUCH THAT EACH SAMPLE OF THE NAMED CLASS IS GIVEN THAT WEIGHT
CLASSWEIGHTBALANCED CAN BE USED TO GIVE ALL CLASSES EQUAL WEIGHT BY GIVING EACH SAMPLE A
WEIGHT INVERSELY RELATED TO ITS CLASS'S PREVALENCE IN THE TRAINING DATA NSAMPLES NCLASSES NP
BINCOUNTY CLASS WEIGHTS WILL BE USED DIFFERENTLY DEPENDING ON THE ALGORITHM FOR LINEAR MODELS SUCH
AS LINEAR SVM OR LOGISTIC REGRESSION THE CLASS WEIGHTS WILL ALTER THE LOSS FUNCTION BY WEIGHTING THE LOSS OF EACH
SAMPLE BY ITS CLASS WEIGHT FOR TREEBASED ALGORITHMS THE CLASS WEIGHTS WILL BE USED FOR REWEIGHTING THE SPLITTING
CRITERION NOTE HOWEVER THAT THIS REBALANCING DOES NOT TAKE THE WEIGHT OF SAMPLES IN EACH CLASS INTO ACCOUNT
FOR MULTIOUTPUT CLASSIFICATION A LIST OF DICTS IS USED TO SPECIFY WEIGHTS FOR EACH OUTPUT FOR EXAMPLE FOR FOUR
CLASS MULTILABEL CLASSIFICATION WEIGHTS SHOULD BE 0 1 1 1 0 1 1 5 0 1
1 1 0 1 1 1 INSTEAD OF11 25 31 41
THECLASSWEIGHT PARAMETER IS VALIDATED AND INTERPRETED WITH UTILSCOMPUTECLASSWEIGHT
CV DETERMINES A CROSS VALIDATION SPLITTING STRATEGY AS USED IN CROSSVALIDATION BASED ROUTINES CV
IS ALSO AVAILABLE IN ESTIMATORS SUCH AS MULTIOUTPUTCLASSIFIERCHAIN ORCALIBRATION
CALIBRATEDCLASSIFIERCV WHICH USE THE PREDICTIONS OF ONE ESTIMATOR AS TRAINING DATA FOR ANOTHER TO
NOT OVERFIT THE TRAINING SUPERVISION
POSSIBLE INPUTS FOR CVARE USUALLY
• AN INTEGER SPECIFYING THE NUMBER OF FOLDS IN KFOLD CROSS VALIDATION KFOLD WILL BE STRATIFIED OVER CLASSES
IF THE ESTIMATOR IS A CLASSIFIER DETERMINED BY BASEISCLASSIFIER AND THE TARGETS MAY REPRESENT A
BINARY OR MULTICLASS BUT NOT MULTIOUTPUT CLASSIFICATION PROBLEM DETERMINED BY UTILSMULTICLASS
TYPEOFTARGET
• ACROSSVALIDATION SPLITTER INSTANCE REFER TO THE USER GUIDE FOR SPLITTERS AVAILABLE WITHIN SCIKITLEARN
• AN ITERABLE YIELDING TRAINTEST SPLITS
WITH SOME EXCEPTIONS ESPECIALLY WHERE NOT USING CROSS VALIDATION AT ALL IS AN OPTION THE DEFAULT IS 3FOLD AND
WILL CHANGE TO 5FOLD IN VERSION 022
CVVALUES ARE VALIDATED AND INTERPRETED WITH UTILSCHECKCV
KERNEL TODO
MAXITER FOR ESTIMATORS INVOLVING ITERATIVE OPTIMIZATION THIS DETERMINES THE MAXIMUM NUMBER OF ITERA
TIONS TO BE PERFORMED IN FIT IFMAXITER ITERATIONS ARE RUN WITHOUT CONVERGENCE A EXCEPTIONS
CONVERGENCEWARNING SHOULD BE RAISED NOTE THAT THE INTERPRETATION OF "A SINGLE ITERATION" IS INCONSISTENT
ACROSS ESTIMATORS SOME BUT NOT ALL USE IT TO MEAN A SINGLE EPOCH IE A PASS OVER EVERY SAMPLE IN THE DATA
FIXME PERHAPS WE SHOULD HAVE SOME COMMON TESTS ABOUT THE RELATIONSHIP BETWEEN CONVERGENCEWARNING AND
MAXITER
MEMORY SOME ESTIMATORS MAKE USE OF JOBLIBMEMORY TO STORE PARTIAL SOLUTIONS DURING FITTING THUS WHEN FIT
IS CALLED AGAIN THOSE PARTIAL SOLUTIONS HAVE BEEN MEMOIZED AND CAN BE REUSED
AMEMORY PARAMETER CAN BE SPECIFIED AS A STRING WITH A PATH TO A DIRECTORY OR A JOBLIBMEMORY INSTANCE
OR AN OBJECT WITH A SIMILAR INTERFACE IE A CACHE METHOD CAN BE USED
MEMORY VALUES ARE VALIDATED AND INTERPRETED WITH UTILSVALIDATIONCHECKMEMORY

METRIC AS A PARAMETER THIS IS THE SCHEME FOR DETERMINING THE DISTANCE BETWEEN TWO DATA POINTS SEE METRICS PAIRWISEDISTANCES IN PRACTICE FOR SOME ALGORITHMS AN IMPROPER DISTANCE METRIC ONE THAT DOES NOT OBEY THE TRIANGLE INEQUALITY SUCH AS COSINE DISTANCE MAY BE USED
XXX HIERARCHICAL CLUSTERING USES AFFINITY WITH THIS MEANING
WE ALSO USE METRIC TO REFER TO EVALUATION METRICS BUT AVOID USING THIS SENSE AS A PARAMETER NAME
NCOMPONENTS THE NUMBER OF FEATURES WHICH A TRANSFORMER SHOULD TRANSFORM THE INPUT INTO SEE COMPONENTS FOR THE SPECIAL CASE OF AFFINE PROJECTION
NITERNOCHANGE NUMBER OF ITERATIONS WITH NO IMPROVEMENT TO WAIT BEFORE STOPPING THE ITERATIVE PROCEDURE THIS IS ALSO KNOWN AS A PATIENCE PARAMETER IT IS TYPICALLY USED WITH EARLY STOPPING TO AVOID STOPPING TOO EARLY
NJOBS THIS IS USED TO SPECIFY HOW MANY CONCURRENT PROCESSESTHREADS SHOULD BE USED FOR PARALLELIZED ROUTINES SCIKITLEARN USES ONE PROCESSOR FOR ITS PROCESSING BY DEFAULT ALTHOUGH IT ALSO MAKES USE OF NUMPY WHICH MAY BE CONFIGURED TO USE A THREADED NUMERICAL PROCESSOR LIBRARY LIKE MKL SEE FAQ
NJOBS IS AN INT SPECIFYING THE MAXIMUM NUMBER OF CONCURRENTLY RUNNING JOBS IF SET TO 1 ALL CPUS ARE USED IF 1 IS GIVEN NO JOBLIB LEVEL PARALLELISM IS USED AT ALL WHICH IS USEFUL FOR DEBUGGING EVEN WITH NJOBS 1 PARALLELISM MAY OCCUR DUE TO NUMERICAL PROCESSING LIBRARIES SEE FAQ FOR NJOBS BELOW 1 NCPUS 1 NJOBS ARE USED THUS FOR NJOBS 2 ALL CPUS BUT ONE ARE USED
NJOBSNONE MEANS UNSET IT WILL GENERALLY BE INTERPRETED AS NJOBS1 UNLESS THE CURRENT JOBLIB PARALLEL BACKEND CONTEXT SPECIFIES OTHERWISE
THE USE OFNJOBS BASED PARALLELISM IN ESTIMATORS VARIES
• MOST OFTEN PARALLELISM HAPPENS IN FITTING BUT SOMETIMES PARALLELISM HAPPENS IN PREDICTION EG IN RANDOM FORESTS
• SOME PARALLELISM USES A MULTITHREADING BACKEND BY DEFAULT SOME A MULTIPROCESSING BACKEND IT IS POS SIBLE TO OVERRIDE THE DEFAULT BACKEND BY USING SKLEARNUTILSPARALLELBACKEND
• WHETHER PARALLEL PROCESSING IS HELPFUL AT IMPROVING RUNTIME DEPENDS ON MANY FACTORS AND IT'S USUALLY A GOOD IDEA TO EXPERIMENT RATHER THAN ASSUMING THAT INCREASING THE NUMBER OF JOBS IS ALWAYS A GOOD THING IT CAN BE HIGHLY DETRIMENTAL TO PERFORMANCE TO RUN MULTIPLE COPIES OF SOME ESTIMATORS OR FUNCTIONS IN PARALLEL
NESTED USES OF NJOBS BASED PARALLELISM WITH THE SAME BACKEND WILL RESULT IN AN EXCEPTION SO GRIDSEARCHCVONEVSRESTCLASSIFIERSVC NJOBS2 NJOBS2 WON'T WORK
WHENNJOBS IS NOT 1 THE ESTIMATOR BEING PARALLELIZED MUST BE PICKLABLE THIS MEANS FOR INSTANCE THAT LAMBDAS CANNOT BE USED AS ESTIMATOR PARAMETERS
RANDOMSTATE WHENEVER RANDOMIZATION IS PART OF A SCIKITLEARN ALGORITHM A RANDOMSTATE PARAMETER MAY BE PROVIDED TO CONTROL THE RANDOM NUMBER GENERATOR USED NOTE THAT THE MERE PRESENCE OF RANDOMSTATE DOESN'T MEAN THAT RANDOMIZATION IS ALWAYS USED AS IT MAY BE DEPENDENT ON ANOTHER PARAMETER EG SHUFFLE BEING SET
RANDOMSTATE 'S VALUE MAY BE
NONE DEFAULT USE THE GLOBAL RANDOM STATE FROM NUMPYRANDOM
AN INTEGER USE A NEW RANDOM NUMBER GENERATOR SEEDED BY THE GIVEN INTEGER TO MAKE A RANDOMIZED AL GORITHM DETERMINISTIC IE RUNNING IT MULTIPLE TIMES WILL PRODUCE THE SAME RESULT AN ARBITRARY INTEGER RANDOMSTATE CAN BE USED HOWEVER IT MAY BE WORTHWHILE CHECKING THAT YOUR RESULTS ARE STABLE ACROSS A NUMBER OF DIFFERENT DISTINCT RANDOM SEEDS POPULAR INTEGER RANDOM SEEDS ARE 0 AND 42
ANUMPYRANDOMRANDOMSTATE INSTANCE USE THE PROVIDED RANDOM STATE ONLY AFFECTING OTHER USERS OF THE SAME RANDOM STATE INSTANCE CALLING FIT MULTIPLE TIMES WILL REUSE THE SAME INSTANCE AND WILL PRODUCE DIFFERENT RESULTS

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UTILSCHECKRANDOMSTATE IS USED INTERNALLY TO VALIDATE THE INPUT RANDOMSTATE AND RETURN A
RANDOMSTATE INSTANCE
SCORING SPECIFIES THE SCORE FUNCTION TO BE MAXIMIZED USUALLY BY CROSS VALIDATION OR – IN SOME CASES – MULTIPLE
SCORE FUNCTIONS TO BE REPORTED THE SCORE FUNCTION CAN BE A STRING ACCEPTED BY METRICSGETSCORER OR A
CALLABLE SCORER NOT TO BE CONFUSED WITH AN EVALUATION METRIC AS THE LATTER HAVE A MORE DIVERSE API SCORING
MAY ALSO BE SET TO NONE IN WHICH CASE THE ESTIMATOR'S SCORE METHOD IS USED SEE THE SCORING PARAMETER
DEFINING MODEL EVALUATION RULES IN THE USER GUIDE
WHERE MULTIPLE METRICS CAN BE EVALUATED SCORING MAY BE GIVEN EITHER AS A LIST OF UNIQUE STRINGS OR A DICT WITH
NAMES AS KEYS AND CALLABLES AS VALUES NOTE THAT THIS DOES NOTSPECIFY WHICH SCORE FUNCTION IS TO BE MAXIMISED
AND ANOTHER PARAMETER SUCH AS REFIT MAY BE USED FOR THIS PURPOSE
THESCORING PARAMETER IS VALIDATED AND INTERPRETED USING METRICSCHECKSCORING
VERBOSE LOGGING IS NOT HANDLED VERY CONSISTENTLY IN SCIKITLEARN AT PRESENT BUT WHEN IT IS PROVIDED AS AN OPTION
THEVERBOSE PARAMETER IS USUALLY AVAILABLE TO CHOOSE NO LOGGING SET TO FALSE ANY TRUE VALUE SHOULD ENABLE
SOME LOGGING BUT LARGER INTEGERS EG ABOVE 10 MAY BE NEEDED FOR FULL VERBOSITY VERBOSE LOGS ARE USUALLY
PRINTED TO STANDARD OUTPUT ESTIMATORS SHOULD NOT PRODUCE ANY OUTPUT ON STANDARD OUTPUT WITH THE DEFAULT
VERBOSE SETTING
WARMSTART WHEN FITTING AN ESTIMATOR REPEATEDLY ON THE SAME DATASET BUT FOR MULTIPLE PARAMETER VALUES SUCH AS
TO FIND THE VALUE MAXIMIZING PERFORMANCE AS IN GRID SEARCH IT MAY BE POSSIBLE TO REUSE ASPECTS OF THE MODEL
LEARNT FROM THE PREVIOUS PARAMETER VALUE SAVING TIME WHEN WARMSTART IS TRUE THE EXISTING FITTED MODEL
ATTRIBUTES ARE USED TO INITIALISE THE NEW MODEL IN A SUBSEQUENT CALL TO FIT
NOTE THAT THIS IS ONLY APPLICABLE FOR SOME MODELS AND SOME PARAMETERS AND EVEN SOME ORDERS OF PARAMETER
VALUES FOR EXAMPLE WARMSTART MAY BE USED WHEN BUILDING RANDOM FORESTS TO ADD MORE TREES TO THE FOREST
INCREASING NESTIMATORS BUT NOT TO REDUCE THEIR NUMBER
PARTIALFIT ALSO RETAINS THE MODEL BETWEEN CALLS BUT DIFFERS WITH WARMSTART THE PARAMETERS CHANGE AND THE
DATA IS MOREORLESS CONSTANT ACROSS CALLS TO FIT WITHPARTIALFIT THE MINIBATCH OF DATA CHANGES AND
MODEL PARAMETERS STAY FIXED
THERE ARE CASES WHERE YOU WANT TO USE WARMSTART TO FIT ON DIFFERENT BUT CLOSELY RELATED DATA FOR EXAM
PLE ONE MAY INITIALLY FIT TO A SUBSET OF THE DATA THEN FINETUNE THE PARAMETER SEARCH ON THE FULL DATASET FOR
CLASSIFICATION ALL DATA IN A SEQUENCE OF WARMSTART CALLS TOFIT MUST INCLUDE SAMPLES FROM EACH CLASS
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SEE CONCEPT ATTRIBUTE
CLASSES A LIST OF CLASS LABELS KNOWN TO THE CLASSIFIER MAPPING EACH LABEL TO A NUMERICAL INDEX USED IN THE
MODEL REPRESENTATION OUR OUTPUT FOR INSTANCE THE ARRAY OUTPUT FROM PREDICTPROBA HAS COLUMNS ALIGNED WITH
CLASSES FOR MULTIOUTPUT CLASSIFIERS CLASSES SHOULD BE A LIST OF LISTS WITH ONE CLASS LISTING FOR EACH
OUTPUT FOR EACH OUTPUT THE CLASSES SHOULD BE SORTED NUMERICALLY OR LEXICOGRAPHICALLY FOR STRINGS
CLASSES AND THE MAPPING TO INDICES IS OFTEN MANAGED WITH PREPROCESSINGLABELENCODER
COMPONENTS AN AFFINE TRANSFORMATION MATRIX OF SHAPE NCOMPONENTS NFEATURES USED IN MANY LIN
EARTRANSFORMERS WHERE NCOMPONENTS IS THE NUMBER OF OUTPUT FEATURES AND NFEATURES IS THE NUMBER OF INPUT
FEATURES
SEE ALSO COMPONENTS WHICH IS A SIMILAR ATTRIBUTE FOR LINEAR PREDICTORS
COEF THE WEIGHTCOEFFICIENT MATRIX OF A GENERALISED LINEAR MODEL PREDICTOR OF SHAPENFEATURES FOR BINARY
CLASSIFICATION AND SINGLEOUTPUT REGRESSION NCLASSES NFEATURES FOR MULTICLASS CLASSIFICATION AND
NTARGETS NFEATURES FOR MULTIOUTPUT REGRESSION NOTE THIS DOES NOT INCLUDE THE INTERCEPT OR BIAS
TERM WHICH IS STORED IN INTERCEPT
46 ATTRIBUTES 681

WHEN AVAILABLE FEATUREIMPORTANCES IS NOT USUALLY PROVIDED AS WELL BUT CAN BE CALCULATED AS THE NORM
OF EACH FEATURE'S ENTRY IN COEF
SEE ALSO COMPONENTS WHICH IS A SIMILAR ATTRIBUTE FOR LINEAR TRANSFORMERS
EMBEDDING AN EMBEDDING OF THE TRAINING DATA IN MANIFOLD LEARNING ESTIMATORS WITH SHAPE NSAMPLES
NCOMPONENTS IDENTICAL TO THE OUTPUT OF FITTRANSFORM SEE ALSO LABELS
NITER THE NUMBER OF ITERATIONS ACTUALLY PERFORMED WHEN FITTING AN ITERATIVE ESTIMATOR THAT MAY STOP UPON CON
VERGENCE SEE ALSO MAXITER
FEATUREIMPORTANCES A VECTOR OF SHAPE NFEATURES AVAILABLE IN SOME PREDICTORS TO PROVIDE A RELATIVE
MEASURE OF THE IMPORTANCE OF EACH FEATURE IN THE PREDICTIONS OF THE MODEL
LABELS A VECTOR CONTAINING A CLUSTER LABEL FOR EACH SAMPLE OF THE TRAINING DATA IN CLUSTERERS IDENTICAL TO THE OUTPUT
OFFITPREDICT SEE ALSO EMBEDDING
47 DATA AND SAMPLE PROPERTIES
SEE CONCEPT SAMPLE PROPERTY
GROUPS USED IN CROSS VALIDATION ROUTINES TO IDENTIFY SAMPLES WHICH ARE CORRELATED EACH VALUE IS AN IDENTIFIER SUCH
THAT IN A SUPPORTING CV SPLITTER SAMPLES FROM SOME GROUPS VALUE MAY NOT APPEAR IN BOTH A TRAINING SET AND
ITS CORRESPONDING TEST SET SEE CROSSVALIDATION ITERATORS FOR GROUPED DATA
SAMPLEWEIGHT A RELATIVE WEIGHT FOR EACH SAMPLE INTUITIVELY IF ALL WEIGHTS ARE INTEGERS A WEIGHTED MODEL OR
SCORE SHOULD BE EQUIVALENT TO THAT CALCULATED WHEN REPEATING THE SAMPLE THE NUMBER OF TIMES SPECIFIED IN THE
WEIGHT WEIGHTS MAY BE SPECIFIED AS FLOATS SO THAT SAMPLE WEIGHTS ARE USUALLY EQUIVALENT UP TO A CONSTANT
POSITIVE SCALING FACTOR
FIXME IS THIS INTERPRETATION ALWAYS THE CASE IN PRACTICE WE HAVE NO COMMON TESTS
SOME ESTIMATORS SUCH AS DECISION TREES SUPPORT NEGATIVE WEIGHTS FIXME THIS FEATURE OR ITS ABSENCE MAY NOT
BE TESTED OR DOCUMENTED IN MANY ESTIMATORS
THIS IS NOT ENTIRELY THE CASE WHERE OTHER PARAMETERS OF THE MODEL CONSIDER THE NUMBER OF SAMPLES IN A REGION
AS WITHMINSAMPLES INCLUSTERDBSCAN IN THIS CASE A COUNT OF SAMPLES BECOMES TO A SUM OF THEIR
WEIGHTS
IN CLASSIFICATION SAMPLE WEIGHTS CAN ALSO BE SPECIFIED AS A FUNCTION OF CLASS WITH THE CLASSWEIGHT ESTIMATOR
PARAMETER
XDENOTES DATA THAT IS OBSERVED AT TRAINING AND PREDICTION TIME USED AS INDEPENDENT VARIABLES IN LEARNING THE
NOTATION IS UPPERCASE TO DENOTE THAT IT IS ORDINARILY A MATRIX SEE RECTANGULAR WHEN A MATRIX EACH SAMPLE MAY
BE REPRESENTED BY A FEATURE VECTOR OR A VECTOR OF PRECOMPUTED DISSIMILARITY WITH EACH TRAINING SAMPLE XMAY
ALSO NOT BE A MATRIX AND MAY REQUIRE A FEATURE EXTRACTOR OR APAIRWISE METRIC TO TURN IT INTO ONE BEFORE LEARNING
A MODEL
XT SHORTHAND FOR "TRANSFORMED X"
Y
YDENOTES DATA THAT MAY BE OBSERVED AT TRAINING TIME AS THE DEPENDENT VARIABLE IN LEARNING BUT WHICH IS UNAVAILABLE
AT PREDICTION TIME AND IS USUALLY THE TARGET OF PREDICTION THE NOTATION MAY BE UPPERCASE TO DENOTE THAT IT IS
A MATRIX REPRESENTING MULTIOUTPUT TARGETS FOR INSTANCE BUT USUALLY WE USE YAND SOMETIMES DO SO EVEN WHEN
MULTIPLE OUTPUTS ARE ASSUMED

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FIVE
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51 MISCELLANEOUS EXAMPLES
MISCELLANEOUS AND INTRODUCTORY EXAMPLES FOR SCIKITLEARN
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
511 COMPACT ESTIMATOR REPRESENTATIONS
THIS EXAMPLE ILLUSTRATES THE USE OF THE PRINTCHANGEDONLY GLOBAL PARAMETER
SETTING PRINTCHANGEDONLY TO TRUE WILL ALTERATE THE REPRESENTATION OF ESTIMATORS TO ONLY SHOW THE PARAMETERS THAT HAVE BEEN SET TO NONDEFAULT VALUES THIS CAN BE USED TO HAVE MORE COMPACT REPRESENTATIONS
OUT
```
DEFAULT REPRESENTATION
LOGISTICREGRESSIONC10 CLASSWEIGHTNONE DUALFALSE FITINTERCEPTTRUE
INTERCEPTSCALING1 L1RATIONONE MAXITER100
MULTICLASSWARN NJOBSNONE PENALTYL1
RANDOMSTATENONE SOLVERWARN TOL00001 VERBOSE0
WARMSTARTFALSE
WITH CHANGEDONLY OPTION
LOGISTICREGRESSIONPENALTYL1
```
PRINTDOC
```
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARN IMPORT SETCONFIG
LR  LOGISTICREGRESSIONPENALTYL1
PRINTDEFAULT REPRESENTATION
PRINTLR
 LOGISTICREGRESSIONC10 CLASSWEIGHTNONE DUALFALSE FITINTERCEPTTRUE
 INTERCEPTSCALING1 L1RATIONONE MAXITER100
```

SCIKITLEARN USER GUIDE RELEASE 0213
MULTICLASSWARN NJOBSNONE PENALTYL1
RANDOMSTATENONE SOLVERWARN TOL00001 VERBOSE0
WARMSTARTFALSE
SETCONFIGPRINTCHANGEDONLYTRUE
PRINTNWITH CHANGEDONLY OPTION
PRINTLR
LOGISTICREGRESSIONPENALTYL1
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0003 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
512 ISOTONIC REGRESSION
AN ILLUSTRATION OF THE ISOTONIC REGRESSION ON GENERATED DATA THE ISOTONIC REGRESSION FINDS A NONDECREASING APPROX IMATION OF A FUNCTION WHILE MINIMIZING THE MEAN SQUARED ERROR ON THE TRAINING DATA THE BENEFIT OF SUCH A MODEL IS THAT IT DOES NOT ASSUME ANY FORM FOR THE TARGET FUNCTION SUCH AS LINEARITY FOR COMPARISON A LINEAR REGRESSION IS ALSO PRESENTED
PRINTDOC
684 CHAPTER 5 EXAMPLES

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AUTHOR NELLE VAROQUAUX NELLEVAROQUAUXGMAILCOM
ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
LICENSE BSD
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBCOLLECTIONS IMPORT LINECOLLECTION
FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION
FROM SKLEARNISOTONIC IMPORT ISOTONICREGRESSION
FROM SKLEARNUTILS IMPORT CHECKRANDOMSTATE
N 100
X NPARANGEN
RS CHECKRANDOMSTATE0
Y RSRANDINT50 50 SIZEN 50 NPLOG1PNPARANGEN

FIT ISOTONICREGRESSION AND LINEARREGRESSION MODELS
IR ISOTONICREGRESSION
Y IRFITTRANSFORMX Y
LR LINEARREGRESSION
LRFITX NPNEWAXIS Y X NEEDS TO BE 2D FOR LINEARREGRESSION

PLOT RESULT
SEGMENTS I YI I YI FORIINRANGEN
LC LINECOLLECTIONSEGMENTS ZORDER0
LCSETARRAYNPONESLENY
LCSETLINEWIDTHSNPFULLN 05
FIG PLTFIGURE
PLTPLOTX Y R MARKERSIZE12
PLTPLOTX Y B MARKERSIZE12
PLTPLOTX LRPREDICTX NPNEWAXIS B
PLTGCAADDCOLLECTIONLC
PLTLEGENDDATA ISOTONIC FIT LINEAR FIT LOCLOWER RIGHT
PLTTITLEISOTONIC REGRESSION
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0056 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
513 FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS
THIS EXAMPLE SHOWS THE USE OF MULTIOUTPUT ESTIMATOR TO COMPLETE IMAGES THE GOAL IS TO PREDICT THE LOWER HALF OF A FACE GIVEN ITS UPPER HALF
THE FIRST COLUMN OF IMAGES SHOWS TRUE FACES THE NEXT COLUMNS ILLUSTRATE HOW EXTREMELY RANDOMIZED TREES K NEAREST NEIGHBORS LINEAR REGRESSION AND RIDGE REGRESSION COMPLETE THE LOWER HALF OF THOSE FACES

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OUT
DOWNLOADING OLIVETTI FACES FROM HTTPSNDOWNLOADERFIGSHARECOMFILES5976027 TO
↪HOMECIRCLECISCIKITLEARNDATA
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SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT FETCHOLIVETTIFACES
FROM SKLEARNUTILSVALIDATION IMPORT CHECKRANDOMSTATE
FROM SKLEARNENSEMBLE IMPORT EXTRATREESREGRESSOR
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSREGRESSOR
FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION
FROM SKLEARNLINEARMODEL IMPORT RIDGECV
LOAD THE FACES DATASETS
DATA FETCHOLIVETTIFACES
TARGETS DATATARGET
DATA DATAIMAGESRESHAPELENDATAIMAGES 1
TRAIN DATATARGETS 30
TEST DATATARGETS 30 TEST ON INDEPENDENT PEOPLE
TEST ON A SUBSET OF PEOPLE
NFACES 5
RNG CHECKRANDOMSTATE4
FACEIDS RNGRANDINTTESTSHAPE0 SIZENFACES
TEST TESTFACEIDS
NPIXELS DATASHAPE1
UPPER HALF OF THE FACES
XTRAIN TRAIN NPIXELS 1 2
LOWER HALF OF THE FACES
YTRAIN TRAIN NPIXELS 2
XTEST TEST NPIXELS 1 2
YTEST TEST NPIXELS 2
FIT ESTIMATORS
ESTIMATORS
EXTRA TREES EXTRATREESREGRESSORNESTIMATORS10 MAXFEATURES32
RANDOMSTATE0
KNN KNEIGHBORSREGRESSOR
LINEAR REGRESSION LINEARREGRESSION
RIDGE RIDGECV

YTESTPREDICT DICT
FORNAME ESTIMATOR INESTIMATORSITEMS
ESTIMATORFITXTRAIN YTRAIN
YTESTPREDICTNAME ESTIMATORPREDICTXTEST
PLOT THE COMPLETED FACES
IMAGESHAPE 64 64
NCOLS 1 LENESTIMATORS
PLTFIGUREFIGSIZE2 NCOLS 226 NFACES
PLTSUPTITLEFACE COMPLETION WITH MULTIOUTPUT ESTIMATORS SIZE16
FORIINRANGENFACES
TRUEFACE NPHSTACKXTESTI YTESTI

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IFI
SUB PLTSUBPLOTNFACES NCOLS I NCOLS 1
ELSE
SUB PLTSUBPLOTNFACES NCOLS I NCOLS 1
TITLETRUE FACES
SUBAXISOFF
SUBIMSHOWTRUEFACERESHAPEIMAGESHAPE
CMAPPLTCMGRAY
INTERPOLATIONNEAREST
FORJ ESTINENUMERATESORTEDESTIMATORS
COMPLETEDFACE NPHSTACKXTESTI YTESTPREDICTESTI
IFI
SUB PLTSUBPLOTNFACES NCOLS I NCOLS 2 J
ELSE
SUB PLTSUBPLOTNFACES NCOLS I NCOLS 2 J
TITLEEST
SUBAXISOFF
SUBIMSHOWCOMPLETEDFACERESHAPEIMAGESHAPE
CMAPPLTCMGRAY
INTERPOLATIONNEAREST
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3749 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
514 MULTILABEL CLASSIFICATION
THIS EXAMPLE SIMULATES A MULTILABEL DOCUMENT CLASSIFICATION PROBLEM THE DATASET IS GENERATED RANDOMLY BASED ON THE FOLLOWING PROCESS
• PICK THE NUMBER OF LABELS N POISSONNLABELS
• N TIMES CHOOSE A CLASS C C MULTINOMIALTHETA
• PICK THE DOCUMENT LENGTH K POISSONLENGTH
• K TIMES CHOOSE A WORD W MULTINOMIALTHETAC
IN THE ABOVE PROCESS REJECTION SAMPLING IS USED TO MAKE SURE THAT N IS MORE THAN 2 AND THAT THE DOCUMENT LENGTH IS NEVER ZERO LIKEWISE WE REJECT CLASSES WHICH HAVE ALREADY BEEN CHOSEN THE DOCUMENTS THAT ARE ASSIGNED TO BOTH CLASSES ARE PLOTTED SURROUNDED BY TWO COLORED CIRCLES
THE CLASSIFICATION IS PERFORMED BY PROJECTING TO THE FIRST TWO PRINCIPAL COMPONENTS FOUND BY PCA AND CCA FOR VISUAL ISATION PURPOSES FOLLOWED BY USING THE SKLEARNMULTICLASSONEVSRESTCLASSIFIER METACLASSIFIER USING TWO SVCS WITH LINEAR KERNELS TO LEARN A DISCRIMINATIVE MODEL FOR EACH CLASS NOTE THAT PCA IS USED TO PERFORM AN UNSUPERVISED DIMENSIONALITY REDUCTION WHILE CCA IS USED TO PERFORM A SUPERVISED ONE
NOTE IN THE PLOT “UNLABELED SAMPLES” DOES NOT MEAN THAT WE DON’T KNOW THE LABELS AS IN SEMISUPERVISED LEARNING BUT THAT THE SAMPLES SIMPLY DO NOTHAVE A LABEL

PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKEMULTILABELCLASSIFICATION
FROM SKLEARNMULTICLASS IMPORT ONEVSRESTCLASSIFIER
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNCROSSDECOMPOSITION IMPORT CCA
DEFPLOTHYPERPLANECLF MINX MAXX LINESTYLE LABEL
 GET THE SEPARATING HYPERPLANE
W CLFCOEF0
A W0 W1
XX NPLINSPACEMINX 5 MAXX 5 MAKE SURE THE LINE IS LONG ENOUGH
YY AXX CLFINTERCEPT0 W1
PLTPLOTXX YY LINESTYLE LABELLABEL
DEFPLOTSUBFIGUREX Y SUBPLOT TITLE TRANSFORM
IFTRANSFORM PCA
X PCANCOMPONENTS2FITTRANSFORMX
ELIFTRANSFORM CCA
X CCANCOMPONENTS2FITX YTRANSFORMX

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ELSE
RAISEVALUEERROR
MINX NPMINX 0
MAXX NPMAXX 0
MINY NPMINX 1
MAXY NPMAXX 1
CLASSIF ONEVSRESTCLASSIFIERSVCKERNELLINEAR
CLASSIFFITX Y
PLTSUBPLOT2 2 SUBPLOT
PLTTITLETITLE
ZEROCLASS NPWHEREY 0
ONECLASS NPWHEREY 1
PLTSCATTERX 0 X 1 S40 CGRAY EDGECOLORS0 0 0
PLTSCATTERXZEROCLASS 0 XZEROCLASS 1 S160 EDGECOLORSB
FACECOLORSNONE LINEWIDTHS2 LABELCLASS 1
PLTSCATTERXONECLASS 0 XONECLASS 1 S80 EDGECOLORSORANGE
FACECOLORSNONE LINEWIDTHS2 LABELCLASS 2
PLOTHYPERPLANECLASSIFESTIMATORS0 MINX MAXX K
BOUNDARY NFOR CLASS 1
PLOTHYPERPLANECLASSIFESTIMATORS1 MINX MAXX K
BOUNDARY NFOR CLASS 2
PLTXTICKS
PLTYTICKS
PLTXLIMMINX 5 MAXX MAXX 5 MAXX
PLTYLIMMINY 5 MAXY MAXY 5 MAXY
IFSUBPLOT 2
PLTXLABELFIRST PRINCIPAL COMPONENT
PLTYLABELSECOND PRINCIPAL COMPONENT
PLTLEGENDLOCUPPER LEFT
PLTFIGUREFIGSIZE8 6
X Y MAKEMULTILABELCLASSIFICATIONNCLASSES2 NLABELS1
ALLOWUNLABELEDTRUE
RANDOMSTATE1
PLOTSUBFIGUREX Y 1 WITH UNLABELED SAMPLES CCA CCA
PLOTSUBFIGUREX Y 2 WITH UNLABELED SAMPLES PCA PCA
X Y MAKEMULTILABELCLASSIFICATIONNCLASSES2 NLABELS1
ALLOWUNLABELEDFALSE
RANDOMSTATE1
PLOTSUBFIGUREX Y 3 WITHOUT UNLABELED SAMPLES CCA CCA
PLOTSUBFIGUREX Y 4 WITHOUT UNLABELED SAMPLES PCA PCA
PLTSUBPLOTSADJUST04 02 97 94 09 2
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0093 SECONDS
690 CHAPTER 5 EXAMPLES

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
515 COMPARING ANOMALY DETECTION ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS
THIS EXAMPLE SHOWS CHARACTERISTICS OF DIFFERENT ANOMALY DETECTION ALGORITHMS ON 2D DATASETS DATASETS CONTAIN ONE OR TWO MODES REGIONS OF HIGH DENSITY TO ILLUSTRATE THE ABILITY OF ALGORITHMS TO COPE WITH MULTIMODAL DATA
FOR EACH DATASET 15 OF SAMPLES ARE GENERATED AS RANDOM UNIFORM NOISE THIS PROPORTION IS THE VALUE GIVEN TO THE NU PARAMETER OF THE ONECLASSSVM AND THE CONTAMINATION PARAMETER OF THE OTHER OUTLIER DETECTION ALGORITHMS DECISION BOUNDARIES BETWEEN INLIERS AND OUTLIERS ARE DISPLAYED IN BLACK EXCEPT FOR LOCAL OUTLIER FACTOR LOF AS IT HAS NO PREDICT METHOD TO BE APPLIED ON NEW DATA WHEN IT IS USED FOR OUTLIER DETECTION
THESKLEARNSVMONECLASSSVM IS KNOWN TO BE SENSITIVE TO OUTLIERS AND THUS DOES NOT PERFORM VERY WELL FOR OUTLIER DETECTION THIS ESTIMATOR IS BEST SUITED FOR NOVELTY DETECTION WHEN THE TRAINING SET IS NOT CONTAMINATED BY OUTLIERS THAT SAID OUTLIER DETECTION IN HIGHDIMENSION OR WITHOUT ANY ASSUMPTIONS ON THE DISTRIBUTION OF THE INLYING DATA IS VERY CHALLENGING AND A ONECLASS SVM MIGHT GIVE USEFUL RESULTS IN THESE SITUATIONS DEPENDING ON THE VALUE OF ITS HYPERPARAMETERS
SKLEARNCOVARIANCEELLIPTICENVELOPE ASSUMES THE DATA IS GAUSSIAN AND LEARNS AN ELLIPSE IT THUS DE GRADES WHEN THE DATA IS NOT UNIMODAL NOTICE HOWEVER THAT THIS ESTIMATOR IS ROBUST TO OUTLIERS
SKLEARNENSEMBLEISOLATIONFOREST ANDSKLEARNNEIGHBORSLOCALOUTLIERFACTOR SEEM TO PERFORM REASONABLY WELL FOR MULTIMODAL DATA SETS THE ADVANTAGE OF SKLEARNNEIGHBORS LOCALOUTLIERFACTOR OVER THE OTHER ESTIMATORS IS SHOWN FOR THE THIRD DATA SET WHERE THE TWO MODES HAVE DIFFERENT DENSITIES THIS ADVANTAGE IS EXPLAINED BY THE LOCAL ASPECT OF LOF MEANING THAT IT ONLY COMPARES THE SCORE OF ABNOR MALITY OF ONE SAMPLE WITH THE SCORES OF ITS NEIGHBORS
FINALLY FOR THE LAST DATA SET IT IS HARD TO SAY THAT ONE SAMPLE IS MORE ABNORMAL THAN ANOTHER SAMPLE AS THEY ARE UNIFORMLY DISTRIBUTED IN A HYPERCUBE EXCEPT FOR THE SKLEARNSVMONECLASSSVM WHICH OVERFITS A LITTLE ALL ESTIMATORS PRESENT DECENT SOLUTIONS FOR THIS SITUATION IN SUCH A CASE IT WOULD BE WISE TO LOOK MORE CLOSELY AT THE SCORES OF ABNORMALITY OF THE SAMPLES AS A GOOD ESTIMATOR SHOULD ASSIGN SIMILAR SCORES TO ALL THE SAMPLES
WHILE THESE EXAMPLES GIVE SOME INTUITION ABOUT THE ALGORITHMS THIS INTUITION MIGHT NOT APPLY TO VERY HIGH DIMENSIONAL DATA
FINALLY NOTE THAT PARAMETERS OF THE MODELS HAVE BEEN HERE HANDPICKED BUT THAT IN PRACTICE THEY NEED TO BE ADJUSTED IN THE ABSENCE OF LABELLED DATA THE PROBLEM IS COMPLETELY UNSUPERVISED SO MODEL SELECTION CAN BE A CHALLENGE

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AUTHOR ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
ALBERT THOMAS ALBERTTHOMASTELECOMPARISTECHFR
LICENSE BSD 3 CLAUSE
IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIB
IMPORT MATPLOTLIBPYPLOT AS PLT

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FROM SKLEARN IMPORT SVM
FROM SKLEARNDATASETS IMPORT MAKEMOONS MAKEBLOBS
FROM SKLEARNCOVARIANCE IMPORT ELLIPTICENVELOPE
FROM SKLEARNENSEMBLE IMPORT ISOLATIONFOREST
FROM SKLEARNNEIGHBORS IMPORT LOCALOUTLIERFACTOR
PRINTDOC
MATPLOTLIBRCPARAMSCONTOURNEGATIVELINESTYLE SOLID
 EXAMPLE SETTINGS
NSAMPLES 300
OUTLIERSFRACTION 015
NOUTLIERS INTOUTLIERSFRACTION NSAMPLES
NINLIERS NSAMPLES NOUTLIERS
 DEFINE OUTLIERANOMALY DETECTION METHODS TO BE COMPARED
ANOMALYALGORITHMS
ROBUST COVARIANCE ELLIPTICENVELOPECONTAMINATIONOUTLIERSFRACTION
ONECLASS SVM SVMONECLASSSVMNUOUTLIERSFRACTION KERNELRBF
GAMMA01
ISOLATION FOREST ISOLATIONFORESTBEHAVIOURNEW
CONTAMINATIONOUTLIERSFRACTION
RANDOMSTATE42
LOCAL OUTLIER FACTOR LOCALOUTLIERFACTOR
NNEIGHBORS35 CONTAMINATIONOUTLIERSFRACTION
 DEFINE DATASETS
BLOBSPARAMS DICTRANDOMSTATE0 NSAMPLESNINLIERS NFEATURES2
DATASETS
MAKEBLOBSCENTERS0 0 0 0 CLUSTERSTD05
BLOBSPARAMS0
MAKEBLOBSCENTERS2 2 2 2 CLUSTERSTD05 05
BLOBSPARAMS0
MAKEBLOBSCENTERS2 2 2 2 CLUSTERSTD15 3
BLOBSPARAMS0
4MAKEMOONSNSAMPLESNSAMPLES NOISE05 RANDOMSTATE00
NPARRAY05 025
14NPRANDOMRANDOMSTATE42RANDNSAMPLES 2 05
 COMPARE GIVEN CLASSIFIERS UNDER GIVEN SETTINGS
XX YY NPMESHGRIDNPLINSPACE7 7 150
NPLINSPACE7 7 150
PLTFIGUREFIGSIZELENANOMALYALGORITHMS 2 3 125
PLTSUBPLOTSADJUSTLEFT02 RIGHT98 BOTTOM001 TOP96 WSPACE05
HSPACE01
PLOTNUM 1
RNG NPRANDOMRANDOMSTATE42
FORIDATASET X INENUMERATEDATASETS
 ADD OUTLIERS
X NPCONCATENATEX RNGUNIFORMLOW6 HIGH6
SIZENOUTLIERS 2 AXIS0
FORNAME ALGORITHM INANOMALYALGORITHMS

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T0 TIMETIME
ALGORITHMFITX
T1 TIMETIME
PLTSUBPLOTLENDATASETS LENANOMALYALGORITHMS PLOTNUM
IFIDATASET 0
PLTTITLENAME SIZE18
 FIT THE DATA AND TAG OUTLIERS
IFNAME LOCAL OUTLIER FACTOR
YPRED ALGORITHMFITPREDICTX
ELSE
YPRED ALGORITHMFITXPREDICTX
 PLOT THE LEVELS LINES AND THE POINTS
IFNAME LOCAL OUTLIER FACTOR LOF DOES NOT IMPLEMENT PREDICT
Z ALGORITHMPREDICTNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
PLTCONTOURXX YY Z LEVELS0 LINEWIDTHS2 COLORSBLACK
COLORS NPARRAY377EB8 FF7F00
PLTSCATTERX 0 X 1 S10 COLORCOLORSYPRED 1 2
PLTXLIM7 7
PLTYLIM7 7
PLTXTICKS
PLTYTICKS
PLTTEXT99 01 2FS T1 T0LSTRIP0
TRANSFORMPLTGCATRANSAXES SIZE15
HORIZONTALALIGNMENTRIGHT
PLOTNUM 1
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3491 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
516 THE JOHNSONLINDENSTRAUSS BOUND FOR EMBEDDING WITH RANDOM PROJECTIONS
THE JOHNSONLINDENSTRAUSS LEMMA STATES THAT ANY HIGH DIMENSIONAL DATASET CAN BE RANDOMLY PROJECTED INTO A LOWER DIMENSIONAL EUCLIDEAN SPACE WHILE CONTROLLING THE DISTORTION IN THE PAIRWISE DISTANCES
THEORETICAL BOUNDS
THE DISTORTION INTRODUCED BY A RANDOM PROJECTION PIS ASSERTED BY THE FACT THAT PIS DEFINING AN EPSEMBEDDING WITH GOOD PROBABILITY AS DEFINED BY
1−□□□‖□−□‖2‖□□−□□‖21 □□□‖□−□‖2
WHERE U AND V ARE ANY ROWS TAKEN FROM A DATASET OF SHAPE NSAMPLES NFEATURES AND P IS A PROJECTION BY A RANDOM GAUSSIAN N0 1 MATRIX WITH SHAPE NCOMPONENTS NFEATURES OR A SPARSE ACHLIOPTAS MATRIX
THE MINIMUM NUMBER OF COMPONENTS TO GUARANTEES THE EPSEMBEDDING IS GIVEN BY
□□□□□□□□□□□ 4□□□□□□□□□□□ □□□22−□□□33

THE FIRST PLOT SHOWS THAT WITH AN INCREASING NUMBER OF SAMPLES NSAMPLES THE MINIMAL NUMBER OF DIMENSIONS NCOMPONENTS INCREASED LOGARITHMICALLY IN ORDER TO GUARANTEE AN EPSEMBEDDING
THE SECOND PLOT SHOWS THAT AN INCREASE OF THE ADMISSIBLE DISTORTION EPS ALLOWS TO REDUCE DRASTICALLY THE MINIMAL NUMBER OF DIMENSIONS NCOMPONENTS FOR A GIVEN NUMBER OF SAMPLES NSAMPLES
EMPIRICAL VALIDATION
WE VALIDATE THE ABOVE BOUNDS ON THE DIGITS DATASET OR ON THE 20 NEWSGROUPS TEXT DOCUMENT TFIDF WORD FREQUENCIES DATASET
• FOR THE DIGITS DATASET SOME 8X8 GRAY LEVEL PIXELS DATA FOR 500 HANDWRITTEN DIGITS PICTURES ARE RANDOMLY PROJECTED TO SPACES FOR VARIOUS LARGER NUMBER OF DIMENSIONS NCOMPONENTS
• FOR THE 20 NEWSGROUPS DATASET SOME 500 DOCUMENTS WITH 100K FEATURES IN TOTAL ARE PROJECTED USING A SPARSE RANDOM MATRIX TO SMALLER EUCLIDEAN SPACES WITH VARIOUS VALUES FOR THE TARGET NUMBER OF DIMENSIONS NCOMPONENTS
THE DEFAULT DATASET IS THE DIGITS DATASET TO RUN THE EXAMPLE ON THE TWENTY NEWSGROUPS DATASET PASS THE –TWENTY NEWSGROUPS COMMAND LINE ARGUMENT TO THIS SCRIPT
FOR EACH VALUE OF NCOMPONENTS WE PLOT
• 2D DISTRIBUTION OF SAMPLE PAIRS WITH PAIRWISE DISTANCES IN ORIGINAL AND PROJECTED SPACES AS X AND Y AXIS RESPEC TIVELY
• 1D HISTOGRAM OF THE RATIO OF THOSE DISTANCES PROJECTED ORIGINAL
WE CAN SEE THAT FOR LOW VALUES OF NCOMPONENTS THE DISTRIBUTION IS WIDE WITH MANY DISTORTED PAIRS AND A SKEWED DISTRIBUTION DUE TO THE HARD LIMIT OF ZERO RATIO ON THE LEFT AS DISTANCES ARE ALWAYS POSITIVES WHILE FOR LARGER VALUES OF NCOMPONENTS THE DISTORTION IS CONTROLLED AND THE DISTANCES ARE WELL PRESERVED BY THE RANDOM PROJECTION
REMARKS
ACCORDING TO THE JL LEMMA PROJECTING 500 SAMPLES WITHOUT TOO MUCH DISTORTION WILL REQUIRE AT LEAST SEVERAL THOUSANDS DIMENSIONS IRRESPECTIVE OF THE NUMBER OF FEATURES OF THE ORIGINAL DATASET
HENCE USING RANDOM PROJECTIONS ON THE DIGITS DATASET WHICH ONLY HAS 64 FEATURES IN THE INPUT SPACE DOES NOT MAKE SENSE IT DOES NOT ALLOW FOR DIMENSIONALITY REDUCTION IN THIS CASE
ON THE TWENTY NEWSGROUPS ON THE OTHER HAND THE DIMENSIONALITY CAN BE DECREASED FROM 56436 DOWN TO 10000 WHILE REASONABLY PRESERVING PAIRWISE DISTANCES

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51 MISCELLANEOUS EXAMPLES 701

•
OUT
EMBEDDING 500 SAMPLES WITH DIM 64 USING VARIOUS RANDOM PROJECTIONS
PROJECTED 500 SAMPLES FROM 64 TO 300 IN 0016S
RANDOM MATRIX WITH SIZE 0028MB
MEAN DISTANCES RATE 097 008
PROJECTED 500 SAMPLES FROM 64 TO 1000 IN 0048S
RANDOM MATRIX WITH SIZE 0096MB
MEAN DISTANCES RATE 099 005
PROJECTED 500 SAMPLES FROM 64 TO 10000 IN 0594S
RANDOM MATRIX WITH SIZE 0964MB
MEAN DISTANCES RATE 101 001
PRINTDOC
IMPORT SYS
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIB
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM DISTUTILSVERSION IMPORT LOOSEVERSION
FROM SKLEARNRANDOMPROJECTION IMPORT JOHNSONLINDENSTRAUSSMINDIM

```
FROM SKLEARNRANDOMPROJECTION IMPORT SPARSERANDOMPROJECTION
FROM SKLEARNDATASETS IMPORT FETCH20NEWSGROUPSVECTORIZED
FROM SKLEARNDATASETS IMPORT LOADDIGITS
FROM SKLEARNMETRICSPAIRWISE IMPORT EUCLIDEANDISTANCES
 NORMED IS BEING DEPRECATED IN FAVOR OF DENSITY IN HISTOGRAMS
IFLOOSEVERSIONMATPLOTLIBVERSION  21
DENSITYPARAM  DENSITY TRUE
ELSE
DENSITYPARAM  NORMED TRUE
 PART 1 PLOT THE THEORETICAL DEPENDENCY BETWEEN NCOMPONENTSMIN AND
 NSAMPLES
 RANGE OF ADMISSIBLE DISTORTIONS
EPSRANGE  NPLINSPACE01 099 5
COLORS  PLTCMBLUESNPLINSPACE03 10 LENEPSRANGE
 RANGE OF NUMBER OF SAMPLES OBSERVATION TO EMBED
NSAMPLESRANGE  NPLOGSPACE1 9 9
PLTFIGURE
FOREPS COLOR INZIPEPSRANGE COLORS
MINNCOMPONENTS  JOHNSONLINDENSTRAUSSMINDIMNSAMPLESRANGE EPSEPS
PLTLOGLOGNSAMPLESRANGE MINNCOMPONENTS COLORCOLOR
PLTLEGENDEPS  01F  EPS FOREPSINEPSRANGE LOCLOWER RIGHT
PLTXLABELNUMBER OF OBSERVATIONS TO EPSEMBED
PLTYLABELMINIMUM NUMBER OF DIMENSIONS
PLTTITLEJOHNSONLINDENSTRAUSS BOUNDS NNSAMPLES VS NCOMPONENTS
 RANGE OF ADMISSIBLE DISTORTIONS
EPSRANGE  NPLINSPACE001 099 100
 RANGE OF NUMBER OF SAMPLES OBSERVATION TO EMBED
NSAMPLESRANGE  NPLOGSPACE2 6 5
COLORS  PLTCMBLUESNPLINSPACE03 10 LENNSAMPLESRANGE
PLTFIGURE
FORNSAMPLES COLOR INZIPNSAMPLESRANGE COLORS
MINNCOMPONENTS  JOHNSONLINDENSTRAUSSMINDIMNSAMPLES EPSEPSRANGE
PLTSEMILOGYEPSRANGE MINNCOMPONENTS COLORCOLOR
PLTLEGENDNSAMPLES  D  NFORNINNSAMPLESRANGE LOCUPPER RIGHT
PLTXLABELDISTORTION EPS
PLTYLABELMINIMUM NUMBER OF DIMENSIONS
PLTTITLEJOHNSONLINDENSTRAUSS BOUNDS NNCOMPONENTS VS EPS
 PART 2 PERFORM SPARSE RANDOM PROJECTION OF SOME DIGITS IMAGES WHICH ARE
 QUITE LOW DIMENSIONAL AND DENSE OR DOCUMENTS OF THE 20 NEWSGROUPS DATASET
 WHICH IS BOTH HIGH DIMENSIONAL AND SPARSE
IFTWENTYNEWSGROUPS INSYSARGV
 NEED AN INTERNET CONNECTION HENCE NOT ENABLED BY DEFAULT
DATA  FETCH20NEWSGROUPSVECTORIZEDDATA500
ELSE
DATA  LOADDIGITSDATA500
```

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NSAMPLES NFEATURES DATASHAPE
PRINTEMBEDDING DSAMPLES WITH DIM DUSING VARIOUS RANDOM PROJECTIONS
 NSAMPLES NFEATURES
NCOMPONENTSRANGE NPARRAY300 1000 10000
DISTS EUCLIDEANDISTANCESDATA SQUAREDTRUERAVEL
 SELECT ONLY NONIDENTICAL SAMPLES PAIRS
NONZERO DISTS 0
DISTS DISTSNONZERO
FORNCOMPONENTS INNCOMPONENTSRANGE
T0 TIME
RP SPARSERANDOMPROJECTIONNCOMPONENTSNCOMPONENTS
PROJECTEDDATA RPFITTRANSFORMDATA
PRINTPROJECTED DSAMPLES FROM DTODIN03FS
 NSAMPLES NFEATURES NCOMPONENTS TIME T0
IFHASATTRRP COMPONENTS
NBYTES RPCOMPONENTSDATANBYTES
NBYTES RPCOMPONENTSINDICESNBYTES
PRINTRANDOM MATRIX WITH SIZE 03FMB NBYTES 1E6
PROJECTEDDISTS EUCLIDEANDISTANCES
PROJECTEDDATA SQUAREDTRUERAVELNONZERO
PLTFIGURE
PLTHEXBINDISTS PROJECTEDDISTS GRIDSIZE100 CMAPPLTCMPUBU
PLTXLABELPAIRWISE SQUARED DISTANCES IN ORIGINAL SPACE
PLTYLABELPAIRWISE SQUARED DISTANCES IN PROJECTED SPACE
PLTTITLEPAIRWISE DISTANCES DISTRIBUTION FOR NCOMPONENTS D
NCOMPONENTS
CB PLTCOLORBAR
CBSETLABELSAMPLE PAIRS COUNTS
RATES PROJECTEDDISTS DISTS
PRINTMEAN DISTANCES RATE 02F02F
 NPMEANRATES NPSTDRATES
PLTFIGURE
PLTHISTRATES BINS50 RANGE0 2 EDGECOLORK DENSITYPARAM
PLTXLABELSQUARED DISTANCES RATE PROJECTED ORIGINAL
PLTYLABELDISTRIBUTION OF SAMPLES PAIRS
PLTTITLEHISTOGRAM OF PAIRWISE DISTANCE RATES FOR NCOMPONENTS D
NCOMPONENTS
 TODO COMPUTE THE EXPECTED VALUE OF EPS AND ADD THEM TO THE PREVIOUS PLOT
 AS VERTICAL LINES REGION
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1837 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51 MISCELLANEOUS EXAMPLES 705

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517 COMPARISON OF KERNEL RIDGE REGRESSION AND SVR

BOTH KERNEL RIDGE REGRESSION KRR AND SVR LEARN A NONLINEAR FUNCTION BY EMPLOYING THE KERNEL TRICK IE THEY LEARN A LINEAR FUNCTION IN THE SPACE INDUCED BY THE RESPECTIVE KERNEL WHICH CORRESPONDS TO A NONLINEAR FUNCTION IN THE ORIGINAL SPACE THEY DIFFER IN THE LOSS FUNCTIONS RIDGE VERSUS EPSILONINSENSITIVE LOSS IN CONTRAST TO SVR FITTING A KRR CAN BE DONE IN CLOSEDFORM AND IS TYPICALLY FASTER FOR MEDIUMSIZED DATASETS ON THE OTHER HAND THE LEARNED MODEL IS NONSPARSE AND THUS SLOWER THAN SVR AT PREDICTIONTIME

THIS EXAMPLE ILLUSTRATES BOTH METHODS ON AN ARTIFICIAL DATASET WHICH CONSISTS OF A SINUSOIDAL TARGET FUNCTION AND STRONG NOISE ADDED TO EVERY FIFTH DATAPOINT THE FIRST FIGURE COMPARES THE LEARNED MODEL OF KRR AND SVR WHEN BOTH COM PLEXITYREGULARIZATION AND BANDWIDTH OF THE RBF KERNEL ARE OPTIMIZED USING GRIDSEARCH THE LEARNED FUNCTIONS ARE VERY SIMILAR HOWEVER FITTING KRR IS APPROX SEVEN TIMES FASTER THAN FITTING SVR BOTH WITH GRIDSEARCH HOWEVER PREDICTION OF 100000 TARGET VALUES IS MORE THAN TREE TIMES FASTER WITH SVR SINCE IT HAS LEARNED A SPARSE MODEL USING ONLY APPROX 13 OF THE 100 TRAINING DATAPOINTS AS SUPPORT VECTORS

THE NEXT FIGURE COMPARES THE TIME FOR FITTING AND PREDICTION OF KRR AND SVR FOR DIFFERENT SIZES OF THE TRAINING SET FITTING KRR IS FASTER THAN SVR FOR MEDIUM SIZED TRAINING SETS LESS THAN 1000 SAMPLES HOWEVER FOR LARGER TRAINING SETS SVR SCALES BETTER WITH REGARD TO PREDICTION TIME SVR IS FASTER THAN KRR FOR ALL SIZES OF THE TRAINING SET BECAUSE OF THE LEARNED SPARSE SOLUTION NOTE THAT THE DEGREE OF SPARSITY AND THUS THE PREDICTION TIME DEPENDS ON THE PARAMETERS EPSILON AND C OF THE SVR

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OUT

SVR COMPLEXITY AND BANDWIDTH SELECTED AND MODEL FITTED IN 0389 S
KRR COMPLEXITY AND BANDWIDTH SELECTED AND MODEL FITTED IN 0175 S
SUPPORT VECTOR RATIO 0320
SVR PREDICTION FOR 100000 INPUTS IN 0117 S
KRR PREDICTION FOR 100000 INPUTS IN 0141 S

AUTHORS JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDE


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IMPORT TIME
IMPORT NUMPY AS NP
FROM SKLEARNSVM IMPORT SVR
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNMODELSELECTION IMPORT LEARNINGCURVE
FROM SKLEARNKERNELRIDGE IMPORT KERNELRIDGE
IMPORT MATPLOTLIBPYPLOT AS PLT
```

```
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RNG  NPRANDOMRANDOMSTATE0

 GENERATE SAMPLE DATA
X  5RNGRAND10000 1
Y  NPSINXRAVEL
 ADD NOISE TO TARGETS
Y5  3 05  RNGRANDXSHAPE0  5
XPLOT  NPLINSPACE0 5 100000 NONE

 FIT REGRESSION MODEL
TRAINSIZE  100
SVR  GRIDSEARCHCVSVRKERNELRBF GAMMA01 CV5
PARAMGRIDC 1E0 1E1 1E2 1E3
GAMMA NPLOGSPACE2 2 5
KR  GRIDSEARCHCVKERNELRIDGEKERNELRBF GAMMA01 CV5
PARAMGRIDALPHA 1E0 01 1E2 1E3
GAMMA NPLOGSPACE2 2 5
T0  TIMETIME
SVRFITXTRAINSIZE YTRAINSIZE
SVRFIT  TIMETIME  T0
PRINTSVR COMPLEXITY AND BANDWIDTH SELECTED AND MODEL FITTED IN 3FS
 SVRFIT
T0  TIMETIME
KRFITXTRAINSIZE YTRAINSIZE
KRFIT  TIMETIME  T0
PRINTKRR COMPLEXITY AND BANDWIDTH SELECTED AND MODEL FITTED IN 3FS
 KRFIT
SVRATIO  SVRBESTESTIMATORSUPPORTSHAPE0  TRAINSIZE
PRINTSUPPORT VECTOR RATIO 3F  SVRATIO
T0  TIMETIME
YSVR  SVRPREDICTXPLOT
SVRPREDICT  TIMETIME  T0
PRINTSVR PREDICTION FOR DINPUTS IN 3FS
 XPLOTSHAPE0 SVRPREDICT
T0  TIMETIME
YKR  KRPREDICTXPLOT
KRPREDICT  TIMETIME  T0
PRINTKRR PREDICTION FOR DINPUTS IN 3FS
 XPLOTSHAPE0 KRPREDICT

 LOOK AT THE RESULTS
SVIND  SVRBESTESTIMATORSUPPORT
PLTSCATTERXSVIND YSVIND CR S50 LABELSVR SUPPORT VECTORS
ZORDER2 EDGECOLORS0 0 0
PLTSCATTERX100 Y100 CK LABELDATA ZORDER1
EDGECOLORS0 0 0
51 MISCELLANEOUS EXAMPLES 709
```

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PLTPLOTXPLOT YSVR CR
LABELSVR FIT 3FS PREDICT 3FS SVRFIT SVRPREDICT
PLTPLOTXPLOT YKR CG
LABELKRR FIT 3FS PREDICT 3FS KRFIT KRPREDICT
PLTXLABELDATA
PLTYLABELTARGET
PLTTITLESVR VERSUS KERNEL RIDGE
PLTLEGEND
 VISUALIZE TRAINING AND PREDICTION TIME
PLTFIGURE
 GENERATE SAMPLE DATA
X 5RNGRAND10000 1
Y NPSINXRAVEL
Y5 3 05 RNGRANDXSHAPE0 5
SIZES NPLOGSPACE1 4 7ASTYPENPINT
FORNAME ESTIMATOR INKRR KERNELRIDGEKERNELRBF ALPHA01
GAMMA10
SVR SVRKERNELRBF C1E1 GAMMA10ITEMS
TRAINTIME
TESTTIME
FORTRAINTESTSIZE INSIZES
T0 TIMETIME
ESTIMATORFITXTRAINTESTSIZE YTRAINTESTSIZE
TRAINTIMEAPPENDTIMETIME T0
T0 TIMETIME
ESTIMATORPREDICTXPLOT1000
TESTTIMEAPPENDTIMETIME T0
PLTPLOTSIZES TRAINTIME O COLORR IFNAME SVR ELSEG
LABELSTRAIN NAME
PLTPLOTSIZES TESTTIME O COLORR IFNAME SVR ELSEG
LABELSTEST NAME
PLTXSCALELOG
PLTYSCALELOG
PLTXLABELTRAIN SIZE
PLTYLABELTIME SECONDS
PLTTITLEEXECUTION TIME
PLTLEGENDLOCBEST
 VISUALIZE LEARNING CURVES
PLTFIGURE
SVR SVRKERNELRBF C1E1 GAMMA01
KR KERNELRIDGEKERNELRBF ALPHA01 GAMMA01
TRAINSIZES TRAINSCORESSVR TESTSCORESSVR
LEARNINGCURVESVR X100 Y100 TRAINSIZESNPLINSPACE01 1 10
SCORINGNEGMEANSQUAREDERROR CV10
TRAINSIZESABS TRAINSCORESKR TESTSCORESKR
LEARNINGCURVEKR X100 Y100 TRAINSIZESNPLINSPACE01 1 10
SCORINGNEGMEANSQUAREDERROR CV10
PLTPLOTTRAINSIZES TESTSCORESSVRMEAN1 O COLORR
LABELSVR
PLTPLOTTRAINSIZES TESTSCORESKRMEAN1 O COLORG

SCIKITLEARN USER GUIDE RELEASE 0213
LABELKRR
PLTXLABELTRAIN SIZE
PLTYLABELMEAN SQUARED ERROR
PLTTITLELEARNING CURVES
PLTLEGENDLOCBEST
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 13067 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
518 EXPLICIT FEATURE MAP APPROXIMATION FOR RBF KERNELS
AN EXAMPLE ILLUSTRATING THE APPROXIMATION OF THE FEATURE MAP OF AN RBF KERNEL
IT SHOWS HOW TO USE RBFSAMPLER ANDNYSTROEM TO APPROXIMATE THE FEATURE MAP OF AN RBF KERNEL FOR CLASSIFICATION
WITH AN SVM ON THE DIGITS DATASET RESULTS USING A LINEAR SVM IN THE ORIGINAL SPACE A LINEAR SVM USING THE APPROX
IMATE MAPPINGS AND USING A KERNELIZED SVM ARE COMPARED TIMINGS AND ACCURACY FOR VARYING AMOUNTS OF MONTE
CARLO SAMPLINGS IN THE CASE OF RBFSAMPLER WHICH USES RANDOM FOURIER FEATURES AND DIFFERENT SIZED SUBSETS OF THE
TRAINING SET FOR NYSTROEM FOR THE APPROXIMATE MAPPING ARE SHOWN
PLEASE NOTE THAT THE DATASET HERE IS NOT LARGE ENOUGH TO SHOW THE BENEFITS OF KERNEL APPROXIMATION AS THE EXACT SVM IS
STILL REASONABLY FAST
SAMPLING MORE DIMENSIONS CLEARLY LEADS TO BETTER CLASSIFICATION RESULTS BUT COMES AT A GREATER COST THIS MEANS THERE
IS A TRADEOFF BETWEEN RUNTIME AND ACCURACY GIVEN BY THE PARAMETER NCOMPONENTS NOTE THAT SOLVING THE LINEAR
SVM AND ALSO THE APPROXIMATE KERNEL SVM COULD BE GREATLY ACCELERATED BY USING STOCHASTIC GRADIENT DESCENT VIA
SKLEARNLINEARMODELSGDCLASSIFIER THIS IS NOT EASILY POSSIBLE FOR THE CASE OF THE KERNELIZED SVM
THE SECOND PLOT VISUALIZED THE DECISION SURFACES OF THE RBF KERNEL SVM AND THE LINEAR SVM WITH APPROXIMATE KERNEL
MAPS THE PLOT SHOWS DECISION SURFACES OF THE CLASSIFIERS PROJECTED ONTO THE FIRST TWO PRINCIPAL COMPONENTS OF THE DATA
THIS VISUALIZATION SHOULD BE TAKEN WITH A GRAIN OF SALT SINCE IT IS JUST AN INTERESTING SLICE THROUGH THE DECISION SURFACE
IN 64 DIMENSIONS IN PARTICULAR NOTE THAT A DATAPOINT REPRESENTED AS A DOT DOES NOT NECESSARILY BE CLASSIFIED INTO THE
REGION IT IS LYING IN SINCE IT WILL NOT LIE ON THE PLANE THAT THE FIRST TWO PRINCIPAL COMPONENTS SPAN
THE USAGE OF RBFSAMPLER ANDNYSTROEM IS DESCRIBED IN DETAIL IN KERNEL APPROXIMATION

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PRINTDOC
 AUTHOR GAEL VAROQUAUX GAEL DOT VAROQUAUX AT NORMALESUP DOT ORG
 ANDREAS MUELLER AMUELLERAISUNIBONNDE
 LICENSE BSD 3 CLAUSE
 STANDARD SCIENTIFIC PYTHON IMPORTS
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM TIME IMPORT TIME
 IMPORT DATASETS CLASSIFIERS AND PERFORMANCE METRICS
FROM SKLEARN IMPORT DATASETS SVM PIPELINE
FROM SKLEARNKERNELAPPROXIMATION IMPORT RBFSAMPLER
NYSTROEM
FROM SKLEARNDECOMPOSITION IMPORT PCA
 THE DIGITS DATASET
DIGITS  DATASETSLOADDIGITSNCLASS9
 TO APPLY AN CLASSIFIER ON THIS DATA WE NEED TO FLATTEN THE IMAGE TO
 TURN THE DATA IN A SAMPLES FEATURE MATRIX
NSAMPLES  LENDIGITSDATA
DATA  DIGITSDATA  16
DATA  DATAMEANAXIS0
 WE LEARN THE DIGITS ON THE FIRST HALF OF THE DIGITS
DATATRAIN TARGETSTRAIN  DATANSAMPLES  2
DIGITSTARGETNSAMPLES  2
 NOW PREDICT THE VALUE OF THE DIGIT ON THE SECOND HALF
DATATEST TARGETSTEST  DATANSAMPLES  2
DIGITSTARGETNSAMPLES  2
 DATATEST  SCALERTRANSFORMDATATEST
 CREATE A CLASSIFIER A SUPPORT VECTOR CLASSIFIER
KERNELSVM  SVMSVCGAMMA2
LINEARSVM  SVMLINEARSVC
 CREATE PIPELINE FROM KERNEL APPROXIMATION
 AND LINEAR SVM
FEATUREMAPFOURIER  RBFSAMPLERGAMMA2 RANDOMSTATE1
FEATUREMAPNYSTROEM  NYSTROEMGAMMA2 RANDOMSTATE1
FOURIERAPPROXSVM  PIPELINEPIPELINEFEATUREMAP FEATUREMAPFOURIER
SVM SVMLINEARSVC
NYSTROEMAPPROXSVM  PIPELINEPIPELINEFEATUREMAP FEATUREMAPNYSTROEM
SVM SVMLINEARSVC
 FIT AND PREDICT USING LINEAR AND KERNEL SVM
KERNELSVMTIME  TIME
KERNELSVMFITDATATRAIN TARGETSTRAIN
KERNELSVMSCORE  KERNELSVMSCOREDATATEST TARGETSTEST
KERNELSVMTIME  TIME  KERNELSVMTIME
LINEARSVMTIME  TIME
```

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LINEARSVMFITDATATRAIN TARGETSTRAIN
LINEARSVMSCORE LINEARSVMSCOREDATATEST TARGETSTEST
LINEARSVMTIME TIME LINEARSVMTIME
SAMPLESIZES 30 NPARANGE1 10
FOURIERSCORES
NYSTROEMSCORES
FOURIERTIMES
NYSTROEMTIMES
FORDINSAMPLESIZES
FOURIERAPPROXSVMSETPARAMSFEATUREMAPNCOMPONENTSD
NYSTROEMAPPROXSVMSETPARAMSFEATUREMAPNCOMPONENTSD
START TIME
NYSTROEMAPPROXSVMFITDATATRAIN TARGETSTRAIN
NYSTROEMTIMESAPPENDTIME START
START TIME
FOURIERAPPROXSVMFITDATATRAIN TARGETSTRAIN
FOURIERTIMESAPPENDTIME START
FOURIERSCORE FOURIERAPPROXSVMSCOREDATATEST TARGETSTEST
NYSTROEMSCORE NYSTROEMAPPROXSVMSCOREDATATEST TARGETSTEST
NYSTROEMSCORESAPPENDNYSTROEMSCORE
FOURIERSCORESAPPENDFOURIERSCORE
 PLOT THE RESULTS
PLTFIGUREFIGSIZE8 8
ACCURACY PLTSUBPLOT211
 SECOND Y AXIS FOR TIMEINGS
TIMESCALE PLTSUBPLOT212
ACCURACYPLOTSAMPLESIZES NYSTROEMSCORES LABELNYSTROEM APPROX KERNEL
TIMESCALEPLOTSAMPLESIZES NYSTROEMTIMES
LABELNYSTROEM APPROX KERNEL
ACCURACYPLOTSAMPLESIZES FOURIERSCORES LABELFOURIER APPROX KERNEL
TIMESCALEPLOTSAMPLESIZES FOURIERTIMES
LABELFOURIER APPROX KERNEL
 HORIZONTAL LINES FOR EXACT RBF AND LINEAR KERNELS
ACCURACYPLOTSAMPLESIZES0 SAMPLESIZES1
LINEARSVMSCORE LINEARSVMSCORE LABELLINEAR SVM
TIMESCALEPLOTSAMPLESIZES0 SAMPLESIZES1
LINEARSVMTIME LINEARSVMTIME LABELLINEAR SVM
ACCURACYPLOTSAMPLESIZES0 SAMPLESIZES1
KERNELSVMSCORE KERNELSVMSCORE LABELRBF SVM
TIMESCALEPLOTSAMPLESIZES0 SAMPLESIZES1
KERNELSVMTIME KERNELSVMTIME LABELRBF SVM
 VERTICAL LINE FOR DATASET DIMENSIONALITY 64
ACCURACYPLOT64 64 07 1 LABELNFEATURES
 LEGENDS AND LABELS
ACCURACYSETTITLECLASSIFICATION ACCURACY
TIMESCALESETTITLETRAINING TIMES
ACCURACYSETXLIMSAMPLESIZES0 SAMPLESIZES1

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ACCURACYSETXTICKS
ACCURACYSETYLIMNPMINFOURIERSCORES 1
TIMESCALESETXLABELSAMPLING STEPS TRANSFORMED FEATURE DIMENSION
ACCURACYSETYLABELCLASSIFICATION ACCURACY
TIMESCALESETYLABELTRAINING TIME IN SECONDS
ACCURACYLEGENDLOCBEST
TIMESCALELEGENDLOCBEST
 VISUALIZE THE DECISION SURFACE PROJECTED DOWN TO THE FIRST
 TWO PRINCIPAL COMPONENTS OF THE DATASET
PCA PCANCOMPONENTS8FITDATATRAIN
X PCATRANSFORMDATATRAIN
 GENERATE GRID ALONG FIRST TWO PRINCIPAL COMPONENTS
MULTIPLES NPARANGE2 2 01
 STEPS ALONG FIRST COMPONENT
FIRST MULTIPLES NPNEWAXIS PCACOMPONENTS0
 STEPS ALONG SECOND COMPONENT
SECOND MULTIPLES NPNEWAXIS PCACOMPONENTS1
 COMBINE
GRID FIRSTNPNEWAXIS   SECOND NPNEWAXIS
FLATGRID GRIDRESHAPE1 DATASHAPE1
 TITLE FOR THE PLOTS
TITLES SVC WITH RBF KERNEL
SVC LINEAR KERNEL NWITH FOURIER RBF FEATURE MAP N
NCOMPONENTS100
SVC LINEAR KERNEL NWITH NYSTROEM RBF FEATURE MAP N
NCOMPONENTS100
PLTTIGHTLAYOUT
PLTFIGUREFIGSIZE12 5
 PREDICT AND PLOT
FORI CLFINENUMERATEKERNELSVM NYSTROEMAPPROXSVM
FOURIERAPPROXSVM
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
PLTSUBPLOT1 3 I 1
Z CLFPREDICTFLATGRID
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEGRIDSHAPE1
PLTCONTOURFMULTIPLES MULTIPLES Z CMAPPLTCMPAIRED
PLTAXISOFF
 PLOT ALSO THE TRAINING POINTS
PLTSCATTERX 0 X 1 CTARGETSTRAIN CMAPPLTCMPAIRED
EDGECOLORS0 0 0
PLTTITLETITLESI
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2188 SECONDS
51 MISCELLANEOUS EXAMPLES 715

52 EXAMPLES BASED ON REAL WORLD DATASETS
APPLICATIONS TO REAL WORLD PROBLEMS WITH SOME MEDIUM SIZED DATASETS OR INTERACTIVE USER INTERFACE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
521 OUTLIER DETECTION ON A REAL DATA SET
THIS EXAMPLE ILLUSTRATES THE NEED FOR ROBUST COVARIANCE ESTIMATION ON A REAL DATA SET IT IS USEFUL BOTH FOR OUTLIER DETECTION AND FOR A BETTER UNDERSTANDING OF THE DATA STRUCTURE
WE SELECTED TWO SETS OF TWO VARIABLES FROM THE BOSTON HOUSING DATA SET AS AN ILLUSTRATION OF WHAT KIND OF ANALYSIS CAN BE DONE WITH SEVERAL OUTLIER DETECTION TOOLS FOR THE PURPOSE OF VISUALIZATION WE ARE WORKING WITH TWODIMENSIONAL EXAMPLES BUT ONE SHOULD BE AWARE THAT THINGS ARE NOT SO TRIVIAL IN HIGHDIMENSION AS IT WILL BE POINTED OUT
IN BOTH EXAMPLES BELOW THE MAIN RESULT IS THAT THE EMPIRICAL COVARIANCE ESTIMATE AS A NONROBUST ONE IS HIGHLY INFLUENCED BY THE HETEROGENEOUS STRUCTURE OF THE OBSERVATIONS ALTHOUGH THE ROBUST COVARIANCE ESTIMATE IS ABLE TO FOCUS ON THE MAIN MODE OF THE DATA DISTRIBUTION IT STICKS TO THE ASSUMPTION THAT THE DATA SHOULD BE GAUSSIAN DISTRIBUTED YIELDING SOME BIASED ESTIMATION OF THE DATA STRUCTURE BUT YET ACCURATE TO SOME EXTENT THE ONECLASS SVM DOES NOT ASSUME ANY PARAMETRIC FORM OF THE DATA DISTRIBUTION AND CAN THEREFORE MODEL THE COMPLEX SHAPE OF THE DATA MUCH BETTER
FIRST EXAMPLE
THE FIRST EXAMPLE ILLUSTRATES HOW ROBUST COVARIANCE ESTIMATION CAN HELP CONCENTRATING ON A RELEVANT CLUSTER WHEN AN OTHER ONE EXISTS HERE MANY OBSERVATIONS ARE CONFOUNDED INTO ONE AND BREAK DOWN THE EMPIRICAL COVARIANCE ESTIMA TION OF COURSE SOME SCREENING TOOLS WOULD HAVE POINTED OUT THE PRESENCE OF TWO CLUSTERS SUPPORT VECTOR MACHINES GAUSSIAN MIXTURE MODELS UNIVARIATE OUTLIER DETECTION BUT HAD IT BEEN A HIGHDIMENSIONAL EXAMPLE NONE OF THESE COULD BE APPLIED THAT EASILY
SECOND EXAMPLE
THE SECOND EXAMPLE SHOWS THE ABILITY OF THE MINIMUM COVARIANCE DETERMINANT ROBUST ESTIMATOR OF COVARIANCE TO CONCENTRATE ON THE MAIN MODE OF THE DATA DISTRIBUTION THE LOCATION SEEMS TO BE WELL ESTIMATED ALTHOUGH THE COVARIANCE IS HARD TO ESTIMATE DUE TO THE BANANASHAPED DISTRIBUTION ANYWAY WE CAN GET RID OF SOME OUTLYING OBSERVATIONS THE ONECLASS SVM IS ABLE TO CAPTURE THE REAL DATA STRUCTURE BUT THE DIFFICULTY IS TO ADJUST ITS KERNEL BANDWIDTH PARAMETER SO AS TO OBTAIN A GOOD COMPROMISE BETWEEN THE SHAPE OF THE DATA SCATTER MATRIX AND THE RISK OF OVERFITTING THE DATA

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PRINTDOC
 AUTHOR VIRGILE FRITSCH VIRGILEFRITSCHINRIAFR
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
FROM SKLEARNCOVARIANCE IMPORT ELLIPTICENVELOPE
FROM SKLEARNSVM IMPORT ONECLASSSVM
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIBFONTMANAGER
FROM SKLEARNDATASETS IMPORT LOADBOSTON
 GET DATA
X1  LOADBOSTONDATA 8 10  TWO CLUSTERS
X2  LOADBOSTONDATA 5 12  BANANASHAPED
 DEFINE CLASSIFIERS TO BE USED
CLASSIFIERS
EMPIRICAL COVARIANCE ELLIPTICENVELOPESUPPORTFRACTION1
CONTAMINATION0261
ROBUST COVARIANCE MINIMUM COVARIANCE DETERMINANT
ELLIPTICENVELOPECONTAMINATION0261
OCSVM ONECLASSSVMNU0261 GAMMA005
COLORS  M G B
LEGEND1
LEGEND2
```

```
 LEARN A FRONTIER FOR OUTLIER DETECTION WITH SEVERAL CLASSIFIERS
XX1 YY1  NPMESHGRIDNPLINSPACE8 28 500 NPLINSPACE3 40 500
XX2 YY2  NPMESHGRIDNPLINSPACE3 10 500 NPLINSPACE5 45 500
FORI CLFNAME CLF INENUMERATECLASSIFIERSITEMS
PLTFIGURE1
CLFFITX1
Z1  CLFDECISIONFUNCTIONNPCXX1RAVEL YY1RAVEL
Z1  Z1RESHAPEXX1SHAPE
LEGEND1CLFNAME  PLTCONTOUR
XX1 YY1 Z1 LEVELS0 LINEWIDTHS2 COLORSCOLORSI
PLTFIGURE2
CLFFITX2
Z2  CLFDECISIONFUNCTIONNPCXX2RAVEL YY2RAVEL
Z2  Z2RESHAPEXX2SHAPE
LEGEND2CLFNAME  PLTCONTOUR
XX2 YY2 Z2 LEVELS0 LINEWIDTHS2 COLORSCOLORSI
LEGEND1VALUESLIST  LISTLEGEND1VALUES
LEGEND1KEYSLIST  LISTLEGEND1KEYS
 PLOT THE RESULTS  SHAPE OF THE DATA POINTS CLOUD
PLTFIGURE1  TWO CLUSTERS
PLTTITLEOUTLIER DETECTION ON A REAL DATA SET BOSTON HOUSING
PLTSCATTERX1 0 X1 1 COLORBLACK
BBOXARGS  DICTBOXSTYLEROUND FC08
ARROWARGS  DICTARROWSTYLE
PLTANNOTATESEVERAL CONFOUNDED POINTS XY24 19
XYCOORDSDATA TEXTCOORDSDATA
XYTEXT13 10 BBOXBBOXARGS ARROWPROPSARROWARGS
PLTXLIMXX1MIN XX1MAX
PLTYLIMYY1MIN YY1MAX
PLTLEGENDLEGEND1VALUESLIST0COLLECTIONS0
LEGEND1VALUESLIST1COLLECTIONS0
LEGEND1VALUESLIST2COLLECTIONS0
LEGEND1KEYSLIST0 LEGEND1KEYSLIST1 LEGEND1KEYSLIST2
LOCUPPER CENTER
PROPMATPLOTLIBFONTMANAGERFONTPROPERTIESSIZE12
PLTYLABELACCESSIBILITY TO RADIAL HIGHWAYS
PLTXLABELPUPILTEACHER RATIO BY TOWN
LEGEND2VALUESLIST  LISTLEGEND2VALUES
LEGEND2KEYSLIST  LISTLEGEND2KEYS
PLTFIGURE2  BANANA SHAPE
PLTTITLEOUTLIER DETECTION ON A REAL DATA SET BOSTON HOUSING
PLTSCATTERX2 0 X2 1 COLORBLACK
PLTXLIMXX2MIN XX2MAX
PLTYLIMYY2MIN YY2MAX
PLTLEGENDLEGEND2VALUESLIST0COLLECTIONS0
LEGEND2VALUESLIST1COLLECTIONS0
LEGEND2VALUESLIST2COLLECTIONS0
LEGEND2KEYSLIST0 LEGEND2KEYSLIST1 LEGEND2KEYSLIST2
LOCUPPER CENTER
PROPMATPLOTLIBFONTMANAGERFONTPROPERTIESSIZE12
PLTYLABEL  LOWER STATUS OF THE POPULATION
PLTXLABELAVERAGE NUMBER OF ROOMS PER DWELLING
PLTSHOW
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TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3436 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
522 COMPRESSIVE SENSING TOMOGRAPHY RECONSTRUCTION WITH L1 PRIOR LASSO
THIS EXAMPLE SHOWS THE RECONSTRUCTION OF AN IMAGE FROM A SET OF PARALLEL PROJECTIONS ACQUIRED ALONG DIFFERENT ANGLES SUCH A DATASET IS ACQUIRED IN COMPUTED TOMOGRAPHY CT
WITHOUT ANY PRIOR INFORMATION ON THE SAMPLE THE NUMBER OF PROJECTIONS REQUIRED TO RECONSTRUCT THE IMAGE IS OF THE ORDER OF THE LINEAR SIZE LOF THE IMAGE IN PIXELS FOR SIMPLICITY WE CONSIDER HERE A SPARSE IMAGE WHERE ONLY PIXELS ON THE BOUNDARY OF OBJECTS HAVE A NONZERO VALUE SUCH DATA COULD CORRESPOND FOR EXAMPLE TO A CELLULAR MATERIAL NOTE HOWEVER THAT MOST IMAGES ARE SPARSE IN A DIFFERENT BASIS SUCH AS THE HAAR WAVELETS ONLY L7 PROJECTIONS ARE ACQUIRED THEREFORE IT IS NECESSARY TO USE PRIOR INFORMATION AVAILABLE ON THE SAMPLE ITS SPARSITY THIS IS AN EXAMPLE OF COMPRESSIVE SENSING
THE TOMOGRAPHY PROJECTION OPERATION IS A LINEAR TRANSFORMATION IN ADDITION TO THE DATAFIDELITY TERM CORRESPONDING TO A LINEAR REGRESSION WE PENALIZE THE L1 NORM OF THE IMAGE TO ACCOUNT FOR ITS SPARSITY THE RESULTING OPTIMIZATION PROBLEM IS CALLED THE LASSO WE USE THE CLASS SKLEARNLINEARMODELLASSO THAT USES THE COORDINATE DESCENT ALGORITHM IMPORTANTLY THIS IMPLEMENTATION IS MORE COMPUTATIONALLY EFFICIENT ON A SPARSE MATRIX THAN THE PROJECTION OPERATOR USED HERE
THE RECONSTRUCTION WITH L1 PENALIZATION GIVES A RESULT WITH ZERO ERROR ALL PIXELS ARE SUCCESSFULLY LABELED WITH 0 OR 1 EVEN IF NOISE WAS ADDED TO THE PROJECTIONS IN COMPARISON AN L2 PENALIZATION SKLEARNLINEARMODELRIDGE PRODUCES A LARGE NUMBER OF LABELING ERRORS FOR THE PIXELS IMPORTANT ARTIFACTS ARE OBSERVED ON THE RECONSTRUCTED IMAGE CONTRARY TO THE L1 PENALIZATION NOTE IN PARTICULAR THE CIRCULAR ARTIFACT SEPARATING THE PIXELS IN THE CORNERS THAT HAVE CONTRIBUTED TO FEWER PROJECTIONS THAN THE CENTRAL DISK
PRINTDOC
 AUTHOR EMMANUELLE GOUILLART EMMANUELLEGOUILLARTNSUPORG
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
FROM SCIPY IMPORT SPARSE
FROM SCIPY IMPORT NDIMAGE
FROM SKLEARNLINEARMODEL IMPORT LASSO

SCIKITLEARN USER GUIDE RELEASE 0213
FROM SKLEARNLINEARMODEL IMPORT RIDGE
IMPORT MATPLOTLIBPYPLOT AS PLT
DEFWEIGHTSX DX1 ORIG0
X NPRAVELX
FLOORX NPFLOORX ORIG DXASTYPENPINT64
ALPHA X ORIG FLOORX DX DX
RETURNNPHSTACKFLOORX FLOORX 1 NPHSTACK1 ALPHA ALPHA
DEFGENERATECENTERCOORDINATESLX
X Y NPMGRIDLX LXASTYPENPFLOAT64
CENTER LX 2
X 05 CENTER
Y 05 CENTER
RETURNX Y
DEFBUILDPROJECTIONOPERATORLX NDIR
 COMPUTE THE TOMOGRAPHY DESIGN MATRIX
PARAMETERS

LX INT
LINEAR SIZE OF IMAGE ARRAY
NDIR INT
NUMBER OF ANGLES AT WHICH PROJECTIONS ARE ACQUIRED
RETURNS

P SPARSE MATRIX OF SHAPE NDIR LX LX 2

X Y GENERATECENTERCOORDINATESLX
ANGLES NPLINSPACE0 NPPI NDIR ENDPOINTFALSE
DATAINDS WEIGHTS CAMERAINDS
DATAUNRAVELINDICES NPARANGELX 2
DATAUNRAVELINDICES NPHSTACKDATAUNRAVELINDICES
DATAUNRAVELINDICES
FORI ANGLE INENUMERATEANGLES
XROT NPCOSANGLE X NPSINANGLE Y
INDS W WEIGHTSXROT DX1 ORIGXMIN
MASK NPLOGICALANDINDS 0 INDS LX
WEIGHTS LISTWMASK
CAMERAINDS LISTINDSMASK I LX
DATAINDS LISTDATAUNRAVELINDICESMASK
PROJOPERATOR SPARSECOOMATRIXWEIGHTS CAMERAINDS DATAINDS
RETURNPROJOPERATOR
DEFGENERATESYNTHETICDATA
 SYNTHETIC BINARY DATA
RS NPRANDOMRANDOMSTATE0
NPTS 36
X Y NPOGRID0L 0L
MASKOUTER X L 2 2 Y L 2 2 L 2 2

SCIKITLEARN USER GUIDE RELEASE 0213
MASK NPZEROSL L
POINTS L RSRAND2 NPTS
MASKPOINTS0ASTYPENPINT POINTS1ASTYPENPINT 1
MASK NDIMAGEGAUSSIANFILTERMASK SIGMAL NPTS
RES NPLOGICALANDMASK MASKMEAN MASKOUTER
RETURNNPLOGICALXORRES NDIMAGEBINARYEROSIONRES
 GENERATE SYNTHETIC IMAGES AND PROJECTIONS
L 128
PROJOPERATOR BUILDPROJECTIONOPERATORL L 7
DATA GENERATESYNTHETICDATA
PROJ PROJOPERATOR DATARAVEL NPNEWAXIS
PROJ 015 NPRANDOMRANDN PROJSHAPE
 RECONSTRUCTION WITH L2 RIDGE PENALIZATION
RGRRIDGE RIDGEALPHA02
RGRRIDGEFITPROJOPERATOR PROJRAVEL
RECL2 RGRRIDGECOEFRESHAPEL L
 RECONSTRUCTION WITH L1 LASSO PENALIZATION
 THE BEST VALUE OF ALPHA WAS DETERMINED USING CROSS VALIDATION
 WITH LASSOCV
RGRLASSO LASSOALPHA0001
RGRLASSOFITPROJOPERATOR PROJRAVEL
RECL1 RGRLASSOCOEFRESHAPEL L
PLTFIGUREFIGSIZE8 33
PLTSUBPLOT131
PLTIMSHOWDATA CMAPPLTCMGRAY INTERPOLATIONNEAREST
PLTAXISOFF
PLTTITLEORIGINAL IMAGE
PLTSUBPLOT132
PLTIMSHOWRECL2 CMAPPLTCMGRAY INTERPOLATIONNEAREST
PLTTITLEL2 PENALIZATION
PLTAXISOFF
PLTSUBPLOT133
PLTIMSHOWRECL1 CMAPPLTCMGRAY INTERPOLATIONNEAREST
PLTTITLEL1 PENALIZATION
PLTAXISOFF
PLTSUBPLOTSADJUSTHSPACE001 WSPACE001 TOP1 BOTTOM0 LEFT0
RIGHT1
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 9761 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
523 TOPIC EXTRACTION WITH NONNEGATIVE MATRIX FACTORIZATION AND LATENT DIRICHLET
ALLOCATION
THIS IS AN EXAMPLE OF APPLYING SKLEARNDECOMPOSITIONNMF ANDSKLEARNDECOMPOSITION
LATENTDIRICHLETALLOCATION ON A CORPUS OF DOCUMENTS AND EXTRACT ADDITIVE MODELS OF THE TOPIC STRUCTURE

OF THE CORPUS THE OUTPUT IS A LIST OF TOPICS EACH REPRESENTED AS A LIST OF TERMS WEIGHTS ARE NOT SHOWN
NONNEGATIVE MATRIX FACTORIZATION IS APPLIED WITH TWO DIFFERENT OBJECTIVE FUNCTIONS THE FROBENIUS NORM AND THE GENERALIZED KULLBACKLEIBLER DIVERGENCE THE LATTER IS EQUIVALENT TO PROBABILISTIC LATENT SEMANTIC INDEXING
THE DEFAULT PARAMETERS NSAMPLES NFEATURES NCOMPONENTS SHOULD MAKE THE EXAMPLE RUNNABLE IN A COUPLE OF TENS OF SECONDS YOU CAN TRY TO INCREASE THE DIMENSIONS OF THE PROBLEM BUT BE AWARE THAT THE TIME COMPLEXITY IS POLYNOMIAL IN NMF IN LDA THE TIME COMPLEXITY IS PROPORTIONAL TO NSAMPLES ITERATIONS
OUT
LOADING DATASET
DONE IN 7911S
EXTRACTING TFIDF FEATURES FOR NMF
DONE IN 0268S
EXTRACTING TF FEATURES FOR LDA
DONE IN 0254S
FITTING THE NMF MODEL FROBENIUS NORM WITH TFIDF FEATURES NSAMPLES2000 AND N
‹→FEATURES1000
DONE IN 0406S
TOPICS IN NMF MODEL FROBENIUS NORM
TOPIC 0 JUST PEOPLE DON THINK LIKE KNOW TIME GOOD MAKE WAY REALLY SAY RIGHT VE WANT
‹→DID LL NEW USE YEARS
TOPIC 1 WINDOWS USE DOS USING WINDOW PROGRAM OS DRIVERS APPLICATION HELP SOFTWARE
‹→PC RUNNING MS SCREEN FILES VERSION CARD CODE WORK
TOPIC 2 GOD JESUS BIBLE FAITH CHRISTIAN CHRIST CHRISTIANS DOES HEAVEN SIN BELIEVE
‹→LORD LIFE CHURCH MARY ATHEISM BELIEF HUMAN LOVE RELIGION
TOPIC 3 THANKS KNOW DOES MAIL ADVANCE HI INFO INTERESTED EMAIL ANYBODY LOOKING CARD
‹→HELP LIKE APPRECIATED INFORMATION SEND LIST VIDEO NEED
TOPIC 4 CAR CARS TIRES MILES 00 NEW ENGINE INSURANCE PRICE CONDITION OIL POWER
‹→SPEED GOOD 000 BRAKE YEAR MODELS USED BOUGHT
TOPIC 5 EDU SOON COM SEND UNIVERSITY INTERNET MIT FTP MAIL CC PUB ARTICLE
‹→INFORMATION HOPE PROGRAM MAC EMAIL HOME CONTACT BLOOD
TOPIC 6 FILE PROBLEM FILES FORMAT WIN SOUND FTP PUB READ SAVE SITE HELP IMAGE
‹→AVAILABLE CREATE COPY RUNNING MEMORY SELF VERSION
TOPIC 7 GAME TEAM GAMES YEAR WIN PLAY SEASON PLAYERS NHL RUNS GOAL HOCKEY TORONTO
‹→DIVISION FLYERS PLAYER DEFENSE LEAFS BAD TEAMS
TOPIC 8 DRIVE DRIVES HARD DISK FLOPPY SOFTWARE CARD MAC COMPUTER POWER SCSI
‹→CONTROLLER APPLE MB 00 PC ROM SALE PROBLEM INTERNAL
TOPIC 9 KEY CHIP CLIPPER KEYS ENCRYPTION GOVERNMENT PUBLIC USE SECURE ENFORCEMENT
‹→PHONE NSA COMMUNICATIONS LAW ENCRYPTED SECURITY CLINTON USED LEGAL STANDARD
FITTING THE NMF MODEL GENERALIZED KULLBACKLEIBLER DIVERGENCE WITH TFIDF FEATURES
‹→NSAMPLES2000 AND NFEATURES1000
DONE IN 1769S
TOPICS IN NMF MODEL GENERALIZED KULLBACKLEIBLER DIVERGENCE
TOPIC 0 JUST PEOPLE DON LIKE DID KNOW MAKE REALLY RIGHT THINK SAY THINGS TIME LOOK
‹→WAY DIDN VE COURSE PROBABLY GOOD
TOPIC 1 HELP THANKS WINDOWS KNOW HI NEED USING DOES LOOKING ANYBODY APPRECIATED
‹→CARD MAIL SOFTWARE USE INFO EMAIL FTP AVAILABLE PC
TOPIC 2 DOES GOD BELIEVE KNOW MEAN TRUE CHRISTIANS READ POINT JESUS CHRISTIAN
‹→CHURCH COME PEOPLE FACT SAYS RELIGION SAY AGREE BIBLE
TOPIC 3 KNOW THANKS MAIL INTERESTED LIKE NEW JUST BIKE EMAIL EDU ADVANCE WANT
‹→CONTACT REALLY LIST HEARD COM POST HEAR INFORMATION
TOPIC 4 10 NEW 30 12 20 50 11 SALE 16 15 TIME 14 OLD POWER AGO GOOD 100 GREAT OFFER
‹→COST

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TOPIC 5 NUMBER 1993 DATA SUBJECT GOVERNMENT NEW NUMBERS PROVIDE INFORMATION SPACE
‹→FOLLOWING COM RESEARCH INCLUDE LARGE NOTE GROUP MAJOR TIME TALK
TOPIC 6 EDU PROBLEM FILE COM REMEMBER TRY SOON ARTICLE MIKE FILES CODE PROGRAM SUN
‹→FREE SEND THINK CASES MANAGER LITTLE CALLED
TOPIC 7 GAME YEAR TEAM GAMES WORLD FACT SECOND CASE WON SAID WIN DIVISION PLAY BEST
‹→CLEARLY CLAIM ALLOW EXAMPLE USED DOESN
TOPIC 8 THINK DON DRIVE HARD NEED BIT MAC MAKE SURE READ APPLE GOING COMES DISK
‹→COMPUTER CASE PRETTY DRIVES SOFTWARE VE
TOPIC 9 GOOD JUST USE LIKE DOESN GOT WAY DON LL GOING DOES CHIP BETTER DOING BAD
‹→KEY WANT SURE BIT CAR
FITTING LDA MODELS WITH TF FEATURES NSAMPLES2000 AND NFEATURES1000
DONE IN 3167S
TOPICS IN LDA MODEL
TOPIC 0 EDU COM MAIL SEND GRAPHICS FTP PUB AVAILABLE CONTACT UNIVERSITY LIST FAQ CA
‹→INFORMATION CS 1993 PROGRAM SUN UK MIT
TOPIC 1 DON LIKE JUST KNOW THINK VE WAY USE RIGHT GOOD GOING MAKE SURE LL POINT GOT
‹→NEED REALLY TIME DOESN
TOPIC 2 CHRISTIAN THINK ATHEISM FAITH PITTSBURGH NEW BIBLE RADIO GAMES ALT LOT JUST
‹→RELIGION LIKE BOOK READ PLAY TIME SUBJECT BELIEVE
TOPIC 3 DRIVE DISK WINDOWS THANKS USE CARD DRIVES HARD VERSION PC SOFTWARE FILE
‹→USING SCSI HELP DOES NEW DOS CONTROLLER 16
TOPIC 4 HIV HEALTH AIDS DISEASE APRIL MEDICAL CARE RESEARCH 1993 LIGHT INFORMATION
‹→STUDY NATIONAL SERVICE TEST LED 10 PAGE NEW DRUG
TOPIC 5 GOD PEOPLE DOES JUST GOOD DON JESUS SAY ISRAEL WAY LIFE KNOW TRUE FACT TIME
‹→LAW WANT BELIEVE MAKE THINK
TOPIC 6 55 10 11 18 15 TEAM GAME 19 PERIOD PLAY 23 12 13 FLYERS 20 25 22 17 24 16
TOPIC 7 CAR YEAR JUST CARS NEW ENGINE LIKE BIKE GOOD OIL INSURANCE BETTER TIRES 000
‹→THING SPEED MODEL BRAKE DRIVING PERFORMANCE
TOPIC 8 PEOPLE SAID DID JUST DIDN KNOW TIME LIKE WENT THINK CHILDREN CAME COME DON
‹→TOOK YEARS SAY DEAD TOLD STARTED
TOPIC 9 KEY SPACE LAW GOVERNMENT PUBLIC USE ENCRYPTION EARTH SECTION SECURITY MOON
‹→PROBE ENFORCEMENT KEYS STATES LUNAR MILITARY CRIME SURFACE TECHNOLOGY
 AUTHOR OLIVIER GRISEL OLIVIERGRISELENSTAORG
 LARS BUITINCK
 CHYIKWEI YAU CHYIKWEIYAUGMAILCOM
 LICENSE BSD 3 CLAUSE
FROM TIME IMPORT TIME
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFVECTORIZER COUNTVECTORIZER
FROM SKLEARNDECOMPOSITION IMPORT NMF LATENTDIRICHLETALLOCATION
FROM SKLEARNDATASETS IMPORT FETCH20NEWSGROUPS
NSAMPLES 2000
NFEATURES 1000
NCOMPONENTS 10
NTOPWORDS 20
DEFPRINTTOPWORDSMODEL FEATURENAMES NTOPWORDS

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SCIKITLEARN USER GUIDE RELEASE 0213
FORTOPICIDX TOPIC INENUMERATEMODELCOMPONENTS
MESSAGE  TOPIC  D   TOPICIDX
MESSAGE   JOINFEATURENAMESI
FORIINTOPICARGSORTNTOPWORDS  11
PRINTMESSAGE
PRINT
 LOAD THE 20 NEWSGROUPS DATASET AND VECTORIZE IT WE USE A FEW HEURISTICS
 TO FILTER OUT USELESS TERMS EARLY ON THE POSTS ARE STRIPPED OF HEADERS
 FOOTERS AND QUOTED REPLIES AND COMMON ENGLISH WORDS WORDS OCCURRING IN
 ONLY ONE DOCUMENT OR IN AT LEAST 95 OF THE DOCUMENTS ARE REMOVED
PRINTLOADING DATASET
T0  TIME
DATASET  FETCH20NEWSGROUPSSHUFFLETRUE RANDOMSTATE1
REMOVEHEADERS FOOTERS QUOTES
DATASAMPLES  DATASETDATANSAMPLES
PRINTDONE IN 03FS  TIME  T0
 USE TFIDF FEATURES FOR NMF
PRINTEXTRACTING TFIDF FEATURES FOR NMF
TFIDFVECTORIZER  TFIDFVECTORIZERMAXDF095 MINDF2
MAXFEATURESNFEATURES
STOPWORDSENGLISH
T0  TIME
TFIDF  TFIDFVECTORIZERFITTRANSFORMDATASAMPLES
PRINTDONE IN 03FS  TIME  T0
 USE TF RAW TERM COUNT FEATURES FOR LDA
PRINTEXTRACTING TF FEATURES FOR LDA
TFVECTORIZER  COUNTVECTORIZERMAXDF095 MINDF2
MAXFEATURESNFEATURES
STOPWORDSENGLISH
T0  TIME
TF  TFVECTORIZERFITTRANSFORMDATASAMPLES
PRINTDONE IN 03FS  TIME  T0
PRINT
 FIT THE NMF MODEL
PRINTFITTING THE NMF MODEL FROBENIUS NORM WITH TFIDF FEATURES
NSAMPLES DAND NFEATURES D
 NSAMPLES NFEATURES
T0  TIME
NMF  NMFNCOMPONENTSNCOMPONENTS RANDOMSTATE1
ALPHA1 L1RATIO5FITTFIDF
PRINTDONE IN 03FS  TIME  T0
PRINTNTOPICS IN NMF MODEL FROBENIUS NORM
TFIDFFEATURENAMES  TFIDFVECTORIZERGETFEATURENAMES
PRINTTOPWORDSNMF TFIDFFEATURENAMES NTOPWORDS
 FIT THE NMF MODEL
PRINTFITTING THE NMF MODEL GENERALIZED KULLBACKLEIBLER DIVERGENCE WITH
TFIDF FEATURES NSAMPLES DAND NFEATURES D
 NSAMPLES NFEATURES
T0  TIME
NMF  NMFNCOMPONENTSNCOMPONENTS RANDOMSTATE1
52 EXAMPLES BASED ON REAL WORLD DATASETS 725
```

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BETALOSSKULLBACKLEIBLER SOLVERMU MAXITER1000 ALPHA1
L1RATIO5FITTFIDF
PRINTDONE IN 03FS TIME T0
PRINTNTOPICS IN NMF MODEL GENERALIZED KULLBACKLEIBLER DIVERGENCE
TFIDFFEATURENAMES TFIDFVECTORIZERGETFEATURENAMES
PRINTTOPWORDSNMF TFIDFFEATURENAMES NTOPWORDS
PRINTFITTING LDA MODELS WITH TF FEATURES
NSAMPLES DAND NFEATURES D
 NSAMPLES NFEATURES
LDA LATENTDIRICHLETALLOCATIONNCOMPONENTSNCOMPONENTS MAXITER5
LEARNINGMETHODONLINE
LEARNINGOFFSET50
RANDOMSTATE0
T0 TIME
LDAFITTF
PRINTDONE IN 03FS TIME T0
PRINTNTOPICS IN LDA MODEL
TFFEATURENAMES TFVECTORIZERGETFEATURENAMES
PRINTTOPWORDSLDA TFFEATURENAMES NTOPWORDS
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 13781 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
524 FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
THE DATASET USED IN THIS EXAMPLE IS A PREPROCESSED EXCERPT OF THE “LABELED FACES IN THE WILD” AKA LFW
HTTPVISWWWCSUMASSEDULFWLFWFUNNELEDTGZ 233MB
EXPECTED RESULTS FOR THE TOP 5 MOST REPRESENTED PEOPLE IN THE DATASET
ARIEL SHARON 067 092 077 13
COLIN POWELL 075 078 076 60
DONALD RUMSFELD 078 067 072 27
GEORGE W BUSH 086 086 086 146
GERHARD SCHROEDER 076 076 076 25
HUGO CHAVEZ 067 067 067 15
TONY BLAIR 081 069 075 36
AVG TOTAL 080 080 080 322
726 CHAPTER 5 EXAMPLES

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OUT
TOTAL DATASET SIZE
NSAMPLES 1288
NFEATURES 1850
NCLASSES 7
EXTRACTING THE TOP 150 EIGENFACES FROM 966 FACES
DONE IN 0118S
PROJECTING THE INPUT DATA ON THE EIGENFACES ORTHONORMAL BASIS
DONE IN 0005S
FITTING THE CLASSIFIER TO THE TRAINING SET
DONE IN 36078S
BEST ESTIMATOR FOUND BY GRID SEARCH
SVCC10000 CLASSWEIGHTBALANCED GAMMA0005
PREDICTING PEOPLES NAMES ON THE TEST SET
DONE IN 0061S
PRECISION RECALL F1SCORE SUPPORT

SCIKITLEARN USER GUIDE RELEASE 0213
ARIEL SHARON 075 046 057 13
COLIN POWELL 079 087 083 60
DONALD RUMSFELD 094 063 076 27
GEORGE W BUSH 083 098 090 146
GERHARD SCHROEDER 091 080 085 25
HUGO CHAVEZ 100 053 070 15
TONY BLAIR 096 075 084 36
ACCURACY 085 322
MACRO AVG 088 072 078 322
WEIGHTED AVG 086 085 084 322
 6 2 0 5 0 0 0
 1 52 0 7 0 0 0
 1 3 17 6 0 0 0
 0 3 0 143 0 0 0
 0 1 0 3 20 0 1
 0 4 0 2 1 8 0
 0 1 1 6 1 0 27
FROM TIME IMPORT TIME
IMPORT LOGGING
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNDATASETS IMPORT FETCHLFWPEOPLE
FROM SKLEARNMETRICS IMPORT CLASSIFICATIONREPORT
FROM SKLEARNMETRICS IMPORT CONFUSIONMATRIX
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNSVM IMPORT SVC
PRINTDOC
 DISPLAY PROGRESS LOGS ON STDOUT
LOGGINGBASICCONFIGLEVELLOGGINGINFO FORMAT ASCTIMES MESSAGES

 DOWNLOAD THE DATA IF NOT ALREADY ON DISK AND LOAD IT AS NUMPY ARRAYS
LFWPEOPLE FETCHLFWPEOPLEMINFACESPERPERSON70 RESIZE04
 INTROSPECT THE IMAGES ARRAYS TO FIND THE SHAPES FOR PLOTTING
NSAMPLES H W LFWPEOPLEIMAGESSHAPE
 FOR MACHINE LEARNING WE USE THE 2 DATA DIRECTLY AS RELATIVE PIXEL
 POSITIONS INFO IS IGNORED BY THIS MODEL
X LFWPEOPLEDATA
NFEATURES XSHAPE1
 THE LABEL TO PREDICT IS THE ID OF THE PERSON
52 EXAMPLES BASED ON REAL WORLD DATASETS 729

SCIKITLEARN USER GUIDE RELEASE 0213
Y LFWPEOPLETARGET
TARGETNAMES LFWPEOPLETARGETNAMES
NCLASSES TARGETNAMESSHAPE0
PRINTTOTAL DATASET SIZE
PRINTNSAMPLES D NSAMPLES
PRINTNFEATURES D NFEATURES
PRINTNCLASSES D NCLASSES

 SPLIT INTO A TRAINING SET AND A TEST SET USING A STRATIFIED K FOLD
 SPLIT INTO A TRAINING AND TESTING SET
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLIT
X Y TESTSIZE025 RANDOMSTATE42

 COMPUTE A PCA EIGENFACES ON THE FACE DATASET TREATED AS UNLABELED
 DATASET UNSUPERVISED FEATURE EXTRACTION DIMENSIONALITY REDUCTION
NCOMPONENTS 150
PRINTEXTRACTING THE TOP DEIGENFACES FROM DFACES
 NCOMPONENTS XTRAINSHAPE0
T0 TIME
PCA PCANCOMPONENTSNCOMPONENTS SVDSOLVERRANDOMIZED
WHITENTRUEFITXTRAIN
PRINTDONE IN 03FS TIME T0
EIGENFACES PCACOMPONENTSRESHAPENCOMPONENTS H W
PRINTPROJECTING THE INPUT DATA ON THE EIGENFACES ORTHONORMAL BASIS
T0 TIME
XTRAINPCA PCATRANSFORMXTRAIN
XTESTPCA PCATRANSFORMXTEST
PRINTDONE IN 03FS TIME T0

 TRAIN A SVM CLASSIFICATION MODEL
PRINTFITTING THE CLASSIFIER TO THE TRAINING SET
T0 TIME
PARAMGRID C 1E3 5E3 1E4 5E4 1E5
GAMMA 00001 00005 0001 0005 001 01
CLF GRIDSEARCHCVSVCKERNELRBF CLASSWEIGHTBALANCED
PARAMGRID CV5 IIDFALSE
CLF CLFFITXTRAINPCA YTRAIN
PRINTDONE IN 03FS TIME T0
PRINTBEST ESTIMATOR FOUND BY GRID SEARCH
PRINTCLFBESTESTIMATOR

 QUANTITATIVE EVALUATION OF THE MODEL QUALITY ON THE TEST SET
PRINTPREDICTING PEOPLES NAMES ON THE TEST SET

SCIKITLEARN USER GUIDE RELEASE 0213
T0 TIME
YPRED CLFPREDICTXTESTPCA
PRINTDONE IN 03FS TIME T0
PRINTCLASSIFICATIONREPORTYTEST YPRED TARGETNAMESTARGETNAMES
PRINTCONFUSIONMATRIXYTEST YPRED LABELSRANGENCLASSES

 QUALITATIVE EVALUATION OF THE PREDICTIONS USING MATPLOTLIB
DEFPLOTGALLERYIMAGES TITLES H W NROW3 NCOL4
HELPER FUNCTION TO PLOT A GALLERY OF PORTRAITS
PLTFIGUREFIGSIZE18 NCOL 24 NROW
PLTSUBPLOTSADJUSTBOTTOM0 LEFT01 RIGHT99 TOP90 HSPACE35
FORIINRANGENROW NCOL
PLTSUBPLOTNROW NCOL I 1
PLTIMSHOWIMAGESIRESHAPEH W CMAPPLTCMGRAY
PLTTITLETITLESI SIZE12
PLTXTICKS
PLTYTICKS
 PLOT THE RESULT OF THE PREDICTION ON A PORTION OF THE TEST SET
DEFTITLEYPRED YTEST TARGETNAMES I
PREDNAME TARGETNAMESYPREDIRSPLIT 11
TRUENAME TARGETNAMESYTESTIRSPLIT 11
RETURNPREDICTED SNTRUE S PREDNAME TRUENAME
PREDICTIONTITLES TITLEYPRED YTEST TARGETNAMES I
FORIINRANGEYPREDSHAPE0
PLOTGALLERYXTEST PREDICTIONTITLES H W
 PLOT THE GALLERY OF THE MOST SIGNIFICATIVE EIGENFACES
EIGENFACETITLES EIGENFACE D IFORIINRANGEEIGENFACESSHAPE0
PLOTGALLERYEIGENFACES EIGENFACETITLES H W
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 59514 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
525 MODEL COMPLEXITY INFLUENCE
DEMONSTRATE HOW MODEL COMPLEXITY INFLUENCES BOTH PREDICTION ACCURACY AND COMPUTATIONAL PERFORMANCE
THE DATASET IS THE BOSTON HOUSING DATASET RESP 20 NEWSGROUPS FOR REGRESSION RESP CLASSIFICATION
FOR EACH CLASS OF MODELS WE MAKE THE MODEL COMPLEXITY VARY THROUGH THE CHOICE OF RELEVANT MODEL PARAMETERS AND
MEASURE THE INFLUENCE ON BOTH COMPUTATIONAL PERFORMANCE LATENCY AND PREDICTIVE POWER MSE OR HAMMING LOSS
52 EXAMPLES BASED ON REAL WORLD DATASETS 731

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OUT

BENCHMARKING SGDCLASSIFIERALPHA0001 L1RATIO025 LOSSMODIFIEDHUBER PENALTYELASTICNET

COMPLEXITY 4466 HAMMING LOSS MISCLASSIFICATION RATIO 02491 PRED TIME 0‹→021496S

BENCHMARKING SGDCLASSIFIERALPHA0001 L1RATIO05 LOSSMODIFIEDHUBER PENALTYELASTICNET

COMPLEXITY 1663 HAMMING LOSS MISCLASSIFICATION RATIO 02915 PRED TIME 0‹→017370S

BENCHMARKING SGDCLASSIFIERALPHA0001 L1RATIO075 LOSSMODIFIEDHUBER PENALTYELASTICNET

COMPLEXITY 880 HAMMING LOSS MISCLASSIFICATION RATIO 03180 PRED TIME 0‹→012989S

BENCHMARKING SGDCLASSIFIERALPHA0001 L1RATIO09 LOSSMODIFIEDHUBER PENALTYELASTICNET

COMPLEXITY 639 HAMMING LOSS MISCLASSIFICATION RATIO 03337 PRED TIME 0‹→011292S

BENCHMARKING NUSVRC10000 GAMMA30517578125E05 NU01

COMPLEXITY 69 MSE 318139 PRED TIME 0000283S

BENCHMARKING NUSVRC10000 GAMMA30517578125E05 NU025

COMPLEXITY 136 MSE 256140 PRED TIME 0000506S

BENCHMARKING NUSVRC10000 GAMMA30517578125E05

COMPLEXITY 244 MSE 223375 PRED TIME 0000868S

BENCHMARKING NUSVRC10000 GAMMA30517578125E05 NU075

COMPLEXITY 351 MSE 213688 PRED TIME 0001226S

BENCHMARKING NUSVRC10000 GAMMA30517578125E05 NU09

COMPLEXITY 404 MSE 211033 PRED TIME 0001402S

BENCHMARKING GRADIENTBOOSTINGREGRESSORNESTIMATORS10

SCIKITLEARN USER GUIDE RELEASE 0213
COMPLEXITY 10 MSE 290148 PRED TIME 0000093S
BENCHMARKING GRADIENTBOOSTINGREGRESSORNESTIMATORS50
COMPLEXITY 50 MSE 89630 PRED TIME 0000165S
BENCHMARKING GRADIENTBOOSTINGREGRESSOR
COMPLEXITY 100 MSE 77187 PRED TIME 0000227S
BENCHMARKING GRADIENTBOOSTINGREGRESSORNESTIMATORS200
COMPLEXITY 200 MSE 66955 PRED TIME 0000608S
BENCHMARKING GRADIENTBOOSTINGREGRESSORNESTIMATORS500
COMPLEXITY 500 MSE 71437 PRED TIME 0000776S
PRINTDOC
 AUTHOR EUSTACHE DIEMERT EUSTACHEDIEMERTFR
 LICENSE BSD 3 CLAUSE
IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MPLTOOLKITSAXESGRID1PARASITEAXES IMPORT HOSTSUBPLOT
FROM MPLTOOLKITSAXISARTISTAXISLINES IMPORT AXES
FROM SCIPYSPARSECSR IMPORT CSRMATRIX
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNUTILS IMPORT SHUFFLE
FROM SKLEARNMETRICS IMPORT MEANSQUAREDERROR
FROM SKLEARNSVMCLASSES IMPORT NUSVR
FROM SKLEARNENSEMBLEGRADIENTBOOSTING IMPORT GRADIENTBOOSTINGREGRESSOR
FROM SKLEARNLINEARMODELSTOCHASTICGRADIENT IMPORT SGDCLASSIFIER
FROM SKLEARNMETRICS IMPORT HAMMINGLOSS

 ROUTINES
 INITIALIZE RANDOM GENERATOR
NPRANDOMSEED0
DEFGENERATEDATACASE SPARSEFALSE
GENERATE REGRESSIONCLASSIFICATION DATA
BUNCH NONE
IFCASE REGRESSION
BUNCH DATASETSLOADBOSTON
ELIFCASE CLASSIFICATION
BUNCH DATASETSFETCH20NEWSGROUPSVECTORIZEDSUBSETALL
X Y SHUFFLEBUNCHDATA BUNCHTARGET
OFFSET INTXSHAPE0 08
XTRAIN YTRAIN XOFFSET YOFFSET
XTEST YTEST XOFFSET YOFFSET

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IFSPARSE
XTRAIN CSRMATRIXXTRAIN
XTEST CSRMATRIXXTEST
ELSE
XTRAIN NPARRAYXTRAIN
XTEST NPARRAYXTEST
YTEST NPARRAYYTEST
YTRAIN NPARRAYYTRAIN
DATA XTRAIN XTRAIN XTEST XTEST YTRAIN YTRAIN
YTEST YTEST
RETURNDATA
DEFBENCHMARKINFLUENCECONF

BENCHMARK INFLUENCE OF CHANGINGPARAM ON BOTH MSE AND LATENCY

PREDICTIONTIMES
PREDICTIONPOWERS
COMPLEXITIES
FORPARAMVALUE INCONFCHANGINGPARAMVALUES
CONFTUNEDPARAMSCONFCHANGINGPARAM PARAMVALUE
ESTIMATOR CONFESTIMATOR CONFTUNEDPARAMS
PRINTBENCHMARKING S ESTIMATOR
ESTIMATORFITCONFDATAXTRAIN CONFDATAYTRAIN
CONFPOSTFITHOOKESTIMATOR
COMPLEXITY CONFCOMPLEXITYCOMPUTERESTIMATOR
COMPLEXITIESAPPENDCOMPLEXITY
STARTTIME TIMETIME
FORINRANGECONFNSAMPLES
YPRED ESTIMATORPREDICTCONFDATAXTEST
ELAPSEDTIME TIMETIME STARTTIME FLOATCONFNSAMPLES
PREDICTIONTIMESAPPENDELAPSEDTIME
PREDSCORE CONFPREDICTIONPERFORMANCECOMPUTER
CONFDATAYTEST YPRED
PREDICTIONPOWERSAPPENDPREDSCORE
PRINTCOMPLEXITY DS4F PRED TIME FSN
COMPLEXITY CONFPREDICTIONPERFORMANCELABEL PREDSCORE
ELAPSEDTIME
RETURNPREDICTIONPOWERS PREDICTIONTIMES COMPLEXITIES
DEFPLOTINFLUENCECONF MSEVALUES PREDICTIONTIMES COMPLEXITIES

PLOT INFLUENCE OF MODEL COMPLEXITY ON BOTH ACCURACY AND LATENCY

PLTFIGUREFIGSIZE12 6
HOST HOSTSUBPLOT111 AXESCLASSAXES
PLTSUBPLOTSADJUSTRIGHT075
PAR1 HOSTTWINX
HOSTSETXLABELMODEL COMPLEXITY S CONFCOMPLEXITYLABEL
Y1LABEL CONFPREDICTIONPERFORMANCELABEL
Y2LABEL TIME S
HOSTSETYLABELY1LABEL
PAR1SETYLABELY2LABEL
P1 HOSTPLOTCOMPLEXITIES MSEVALUES B LABELPREDICTION ERROR
P2 PAR1PLOTCOMPLEXITIES PREDICTIONTIMES R
LABELLATENCY
52 EXAMPLES BASED ON REAL WORLD DATASETS 735

SCIKITLEARN USER GUIDE RELEASE 0213
HOSTLEGENDLOCUPPER RIGHT
HOSTAXISLEFTLABELSETCOLORP1GETCOLOR
PAR1AXISRIGHTLABELSETCOLORP2GETCOLOR
PLTTITLEINFLUENCE OF MODEL COMPLEXITY S CONFESTIMATORNAME
PLTSHOW
DEFCOUNTNONZEROCOEFFICIENTSESTIMATOR
A ESTIMATORCOEFTOARRAY
RETURNNPCOUNTNONZEROA

 MAIN CODE
REGRESSIONDATA GENERATEDATAREGRESSION
CLASSIFICATIONDATA GENERATEDATACLASSIFICATION SPARSETRUE
CONFIGURATIONS
ESTIMATOR SGDCLASSIFIER
TUNEDPARAMS PENALTY ELASTICNET ALPHA 0001 LOSS
MODIFIEDHUBER FITINTERCEPT TRUE TOL 1E3
CHANGINGPARAM L1RATIO
CHANGINGPARAMVALUES 025 05 075 09
COMPLEXITYLABEL NONZERO COEFFICIENTS
COMPLEXITYCOMPUTER COUNTNONZEROCOEFFICIENTS
PREDICTIONPERFORMANCECOMPUTER HAMMINGLOSS
PREDICTIONPERFORMANCELABEL HAMMING LOSS MISCLASSIFICATION RATIO
POSTFITHOOK LAMBDAX XSPARSIFY
DATA CLASSIFICATIONDATA
NSAMPLES 30
ESTIMATOR NUSVR
TUNEDPARAMS C 1E3 GAMMA 2 15
CHANGINGPARAM NU
CHANGINGPARAMVALUES 01 025 05 075 09
COMPLEXITYLABEL NSUPPORTVECTORS
COMPLEXITYCOMPUTER LAMBDAX LENXSUPPORTVECTORS
DATA REGRESSIONDATA
POSTFITHOOK LAMBDAX X
PREDICTIONPERFORMANCECOMPUTER MEANSQUAREDERROR
PREDICTIONPERFORMANCELABEL MSE
NSAMPLES 30
ESTIMATOR GRADIENTBOOSTINGREGRESSOR
TUNEDPARAMS LOSS LS
CHANGINGPARAM NESTIMATORS
CHANGINGPARAMVALUES 10 50 100 200 500
COMPLEXITYLABEL NTREES
COMPLEXITYCOMPUTER LAMBDAX XNESTIMATORS
DATA REGRESSIONDATA
POSTFITHOOK LAMBDAX X
PREDICTIONPERFORMANCECOMPUTER MEANSQUAREDERROR
PREDICTIONPERFORMANCELABEL MSE
NSAMPLES 30

FORCONFINCONFIGURATIONS
PREDICTIONPERFORMANCES PREDICTIONTIMES COMPLEXITIES
BENCHMARKINFLUENCECONF
PLOTINFLUENCECONF PREDICTIONPERFORMANCES PREDICTIONTIMES
COMPLEXITIES
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 35625 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

526 SPECIES DISTRIBUTION MODELING

MODELING SPECIES' GEOGRAPHIC DISTRIBUTIONS IS AN IMPORTANT PROBLEM IN CONSERVATION BIOLOGY IN THIS EXAMPLE WE MODEL THE GEOGRAPHIC DISTRIBUTION OF TWO SOUTH AMERICAN MAMMALS GIVEN PAST OBSERVATIONS AND 14 ENVIRONMENTAL VARIABLES SINCE WE HAVE ONLY POSITIVE EXAMPLES THERE ARE NO UNSUCCESSFUL OBSERVATIONS WE CAST THIS PROBLEM AS A DENSITY ESTIMATION PROBLEM AND USE THE ONECLASSSVM PROVIDED BY THE PACKAGE SKLEARNSVM AS OUR MODELING TOOL THE DATASET IS PROVIDED BY PHILLIPS ET AL 2006 IF AVAILABLE THE EXAMPLE USES BASEMAP TO PLOT THE COAST LINES AND NATIONAL BOUNDARIES OF SOUTH AMERICA

THE TWO SPECIES ARE

- "BRADYPUS VARIEGATUS" THE BROWNTHROATED SLOTH
- "MICRORYZOMYS MINUTUS" ALSO KNOWN AS THE FOREST SMALL RICE RAT A RODENT THAT LIVES IN PERU COLOMBIA ECUADOR PERU AND VENEZUELA

REFERENCES

- "MAXIMUM ENTROPY MODELING OF SPECIES GEOGRAPHIC DISTRIBUTIONS" S J PHILLIPS R P ANDERSON R E SCHAPIRE ECOLOGICAL MODELLING 190231259 2006

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OUT

MODELING DISTRIBUTION OF SPECIES BRADYPUS VARIEGATUS
 FIT ONECLASSSVM DONE
 PLOT COASTLINES FROM COVERAGE
 PREDICT SPECIES DISTRIBUTION
AREA UNDER THE ROC CURVE 0868443

MODELING DISTRIBUTION OF SPECIES MICRORYZOMYS MINUTUS
 FIT ONECLASSSVM DONE
 PLOT COASTLINES FROM COVERAGE
 PREDICT SPECIES DISTRIBUTION
AREA UNDER THE ROC CURVE 0993919
TIME ELAPSED 2018S
 AUTHORS PETER PRETTENHOFER PETERPRETTENHOFERGMAILCOM
 JAKE VANDERPLAS VANDERPLASASTROWASHINGTONEDU

 LICENSE BSD 3 CLAUSE
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETSBASE IMPORT BUNCH
FROM SKLEARNDATASETS IMPORT FETCHSPECIESDISTRIBUTIONS
FROM SKLEARNDATASETSSPECIESDISTRIBUTIONS IMPORT CONSTRUCTGRIDS
FROM SKLEARN IMPORT SVM METRICS
 IF BASEMAP IS AVAILABLE WELL USE IT
 OTHERWISE WELL IMPROVISE LATER
TRY
FROM MPLTOOLKITSBASEMAP IMPORT BASEMAP
BASEMAP TRUE
EXCEPTIMPORTERROR
BASEMAP FALSE
PRINTDOC
DEFCREATESPECIESBUNCHSPECIESNAME TRAIN TEST COVERAGES XGRID YGRID
CREATE A BUNCH WITH INFORMATION ABOUT A PARTICULAR ORGANISM
THIS WILL USE THE TESTTRAIN RECORD ARRAYS TO EXTRACT THE
DATA SPECIFIC TO THE GIVEN SPECIES NAME

BUNCH BUNCHNAME JOINSPECIESNAMESPLIT2
SPECIESNAME SPECIESNAMEENCODEASCII

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POINTS DICTTESTTEST TRAINTRAIN
FORLABEL PTS INPOINTSITEMS
 CHOOSE POINTS ASSOCIATED WITH THE DESIRED SPECIES
PTS PTSPTSSPECIES SPECIESNAME
BUNCHPTS S LABEL PTS
 DETERMINE COVERAGE VALUES FOR EACH OF THE TRAINING TESTING POINTS
IX NPSEARCHSORTEDXGRID PTSDD LONG
IY NPSEARCHSORTEDYGRID PTSDD LAT
BUNCHCOV S LABEL COVERAGES IY IXT
RETURNBUNCH
DEFPLOTSPECIESDISTRIBUTIONSPECIESBRADYPUSVARIEGATUS0
MICRORYZOMYSMINUTUS0

PLOT THE SPECIES DISTRIBUTION

IFLENSPECIES 2
PRINTNOTE WHEN MORE THAN TWO SPECIES ARE PROVIDED
 ONLY THE FIRST TWO WILL BE USED
T0 TIME
 LOAD THE COMPRESSED DATA
DATA FETCHSPECIESDISTRIBUTIONS
 SET UP THE DATA GRID
XGRID YGRID CONSTRUCTGRIDSDATA
 THE GRID IN XY COORDINATES
X Y NPMESHGRIDXGRID YGRID1
 CREATE A BUNCH FOR EACH SPECIES
BVBUNCH CREATESPECIESBUNCHSPECIES0
DATATRAIN DATATEST
DATACOVERAGES XGRID YGRID
MMBUNCH CREATESPECIESBUNCHSPECIES1
DATATRAIN DATATEST
DATACOVERAGES XGRID YGRID
 BACKGROUND POINTS GRID COORDINATES FOR EVALUATION
NPRANDOMSEED13
BACKGROUNDPOINTS NPCNPRANDOMRANDINTLOW0 HIGHDATANY
SIZE10000
NPRANDOMRANDINTLOW0 HIGHDATANX
SIZE10000T
 WELL MAKE USE OF THE FACT THAT COVERAGES6 HAS MEASUREMENTS AT ALL
 LAND POINTS THIS WILL HELP US DECIDE BETWEEN LAND AND WATER
LANDREFERENCE DATACOVERAGES6
 FIT PREDICT AND PLOT FOR EACH SPECIES
FORI SPECIES INENUMERATEBVBUNCH MMBUNCH
PRINT80
PRINTMODELING DISTRIBUTION OF SPECIES S SPECIESNAME

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 STANDARDIZE FEATURES
MEAN SPECIESCOVTRAINMEANAXIS0
STD SPECIESCOVTRAINSTDAXIS0
TRAINCOVERSTD SPECIESCOVTRAIN MEAN STD
 FIT ONECLASSSVM
PRINT FIT ONECLASSSVM   END
CLF SVMONECLASSSVMNU01 KERNELRBF GAMMA05
CLFFITTRAINCOVERSTD
PRINTDONE
 PLOT MAP OF SOUTH AMERICA
PLTSUBPLOT1 2 I 1
IFBASEMAP
PRINT PLOT COASTLINES USING BASEMAP
M BASEMAPPROJECTIONCYL LLCRNRLATYMIN
URCRNRLATYMAX LLCRNRLONXMIN
URCRNRLONXMAX RESOLUTIONC
MDRAWCOASTLINES
MDRAWCOUNTRIES
ELSE
PRINT PLOT COASTLINES FROM COVERAGE
PLTCONTOURX Y LANDREFERENCE
LEVELS9998 COLORSK
LINESTYLESSOLID
PLTXTICKS
PLTYTICKS
PRINT PREDICT SPECIES DISTRIBUTION
 PREDICT SPECIES DISTRIBUTION USING THE TRAINING DATA
Z NPONESDATANY DATANX DTYPENPFLOAT64
 WELL PREDICT ONLY FOR THE LAND POINTS
IDX NPWHERELANDREFERENCE 9999
COVERAGESLAND DATACOVERAGES IDX0 IDX1T
PRED CLFDECISIONFUNCTIONCOVERAGESLAND MEAN STD
Z PREDMIN
ZIDX0 IDX1 PRED
LEVELS NPLINSPACEZMIN ZMAX 25
ZLANDREFERENCE 9999 9999
 PLOT CONTOURS OF THE PREDICTION
PLTCONTOURFX Y Z LEVELSLEVELS CMAPPLTCMREDS
PLTCOLORBARFORMAT 2F
 SCATTER TRAININGTESTING POINTS
PLTSCATTERSPECIESPTSTRAINDD LONG SPECIESPTSTRAINDD LAT
S22 CBLACK
MARKER LABELTRAIN
PLTSCATTERSPECIESPTSTESTDD LONG SPECIESPTSTESTDD LAT
S22 CBLACK
MARKERX LABELTEST
PLTLEGEND
PLTTITLESPECIESNAME

SCIKITLEARN USER GUIDE RELEASE 0213
PLTAXISEQUAL
 COMPUTE AUC WITH REGARDS TO BACKGROUND POINTS
PREDBACKGROUND ZBACKGROUNDPOINTS0 BACKGROUNDPOINTS1
PREDTEST CLFDECISIONFUNCTIONSPECIESCOVTEST MEAN STD
SCORES NPRPREDTEST PREDBACKGROUND
Y NPRNPONESPREDTESTSHAPE NPZEROSPREDBACKGROUNDSHAPE
FPR TPR THRESHOLDS METRICSROCCURVEY SCORES
ROCAUC METRICSAUCFPR TPR
PLTTEXT35 70 AUC 3F ROCAUC HARIGHT
PRINTNAREA UNDER THE ROC CURVE F ROCAUC
PRINTNTIME ELAPSED 2FS TIME T0
PLOTSPECIESDISTRIBUTION
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 20185 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
527 VISUALIZING THE STOCK MARKET STRUCTURE
THIS EXAMPLE EMPLOYS SEVERAL UNSUPERVISED LEARNING TECHNIQUES TO EXTRACT THE STOCK MARKET STRUCTURE FROM VARIATIONS IN HISTORICAL QUOTES
THE QUANTITY THAT WE USE IS THE DAILY VARIATION IN QUOTE PRICE QUOTES THAT ARE LINKED TEND TO COFLUCTUATE DURING A DAY
LEARNING A GRAPH STRUCTURE
WE USE SPARSE INVERSE COVARIANCE ESTIMATION TO FIND WHICH QUOTES ARE CORRELATED CONDITIONALLY ON THE OTHERS SPECIFI CALLY SPARSE INVERSE COVARIANCE GIVES US A GRAPH THAT IS A LIST OF CONNECTION FOR EACH SYMBOL THE SYMBOLS THAT IT IS CONNECTED TOO ARE THOSE USEFUL TO EXPLAIN ITS FLUCTUATIONS
CLUSTERING
WE USE CLUSTERING TO GROUP TOGETHER QUOTES THAT BEHAVE SIMILARLY HERE AMONGST THE VARIOUS CLUSTERING TECHNIQUES AVAILABLE IN THE SCIKITLEARN WE USE AFFINITY PROPAGATION AS IT DOES NOT ENFORCE EQUALSIZE CLUSTERS AND IT CAN CHOOSE AUTOMATICALLY THE NUMBER OF CLUSTERS FROM THE DATA
NOTE THAT THIS GIVES US A DIFFERENT INDICATION THAN THE GRAPH AS THE GRAPH REFLECTS CONDITIONAL RELATIONS BETWEEN VARIABLES WHILE THE CLUSTERING REFLECTS MARGINAL PROPERTIES VARIABLES CLUSTERED TOGETHER CAN BE CONSIDERED AS HAVING A SIMILAR IMPACT AT THE LEVEL OF THE FULL STOCK MARKET
EMBEDDING IN 2D SPACE
FOR VISUALIZATION PURPOSES WE NEED TO LAY OUT THE DIFFERENT SYMBOLS ON A 2D CANVAS FOR THIS WE USE MANIFOLD LEARNING TECHNIQUES TO RETRIEVE 2D EMBEDDING
52 EXAMPLES BASED ON REAL WORLD DATASETS 741

VISUALIZATION
THE OUTPUT OF THE 3 MODELS ARE COMBINED IN A 2D GRAPH WHERE NODES REPRESENTS THE STOCKS AND EDGES THE
• CLUSTER LABELS ARE USED TO DEFINE THE COLOR OF THE NODES
• THE SPARSE COVARIANCE MODEL IS USED TO DISPLAY THE STRENGTH OF THE EDGES
• THE 2D EMBEDDING IS USED TO POSITION THE NODES IN THE PLAN
THIS EXAMPLE HAS A FAIR AMOUNT OF VISUALIZATIONRELATED CODE AS VISUALIZATION IS CRUCIAL HERE TO DISPLAY THE GRAPH ONE OF THE CHALLENGE IS TO POSITION THE LABELS MINIMIZING OVERLAP FOR THIS WE USE AN HEURISTIC BASED ON THE DIRECTION OF THE NEAREST NEIGHBOR ALONG EACH AXIS
OUT
CLUSTER 1 APPLE AMAZON YAHOO
CLUSTER 2 COMCAST CABLEVISION TIME WARNER
CLUSTER 3 CONOCOPHILLIPS CHEVRON TOTAL VALERO ENERGY EXXON
CLUSTER 4 CISCO DELL HP IBM MICROSOFT SAP TEXAS INSTRUMENTS
CLUSTER 5 BOEING GENERAL DYNAMICS NORTHROP GRUMMAN RAYTHEON
CLUSTER 6 AIG AMERICAN EXPRESS BANK OF AMERICA CATERPILLAR CVS DUPONT DE
‹→NEMOURS FORD GENERAL ELECTRICS GOLDMAN SACHS HOME DEPOT JPMORGAN CHASE
‹→MARRIOTT 3M RYDER WELLS FARGO WALMART
CLUSTER 7 MCDONALDS

CLUSTER 8 GLAXOSMITHKLINE NOVARTIS PFIZER SANOFIAVENTIS UNILEVER
CLUSTER 9 KELLOGG COCA COLA PEPSI
CLUSTER 10 COLGATEPALMOLIVE KIMBERLYCLARK PROCTER GAMBLE
CLUSTER 11 CANON HONDA NAVISTAR SONY TOYOTA XEROX
 AUTHOR GAEL VAROQUAUX GAELVAROQUAUXNORMALESUPORG
 LICENSE BSD 3 CLAUSE
IMPORT SYS
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBCOLLECTIONS IMPORT LINECOLLECTION
IMPORT PANDAS AS PD
FROM SKLEARN IMPORT CLUSTER COVARIANCE MANIFOLD
PRINTDOC

 RETRIEVE THE DATA FROM INTERNET
 THE DATA IS FROM 2003 2008 THIS IS REASONABLY CALM NOT TOO LONG AGO SO
 THAT WE GET HIGHTECH FIRMS AND BEFORE THE 2008 CRASH THIS KIND OF
 HISTORICAL DATA CAN BE OBTAINED FOR FROM APIS LIKE THE QUANDLCOM AND
 ALPHAVANTAGECO ONES
SYMBOLDICT
TOT TOTAL
XOM EXXON
CVX CHEVRON
COP CONOCOPHILLIPS
VLO VALERO ENERGY
MSFT MICROSOFT
IBM IBM
TWX TIME WARNER
CMCSA COMCAST
CVC CABLEVISION
YHOO YAHOO
DELL DELL
HPQ HP
AMZN AMAZON
TM TOYOTA
CAJ CANON
SNE SONY
F FORD
HMC HONDA
NAV NAVISTAR
NOC NORTHROP GRUMMAN
BA BOEING
KO COCA COLA

MMM 3M
MCD MCDONALD S
PEP PEPSI
K KELLOGG
UN UNILEVER
MAR MARRIOTT
PG PROCTER GAMBLE
CL COLGATEPALMOLIVE
GE GENERAL ELECTRICS
WFC WELLS FARGO
JPM JPMORGAN CHASE
AIG AIG
AXP AMERICAN EXPRESS
BAC BANK OF AMERICA
GS GOLDMAN SACHS
AAPL APPLE
SAP SAP
CSCO CISCO
TXN TEXAS INSTRUMENTS
XRX XEROX
WMT WALMART
HD HOME DEPOT
GSK GLAXOSMITHKLINE
PFE PFIZER
SNY SANOFIAVENTIS
NVS NOVARTIS
KMB KIMBERLYCLARK
R RYDER
GD GENERAL DYNAMICS
RTN RAYTHEON
CVS CVS
CAT CATERPILLAR
DD DUPONT DE NEMOURS
SYMBOLS NAMES NPARRAYSORTEDSYMBOLDICTITEMST
QUOTES
FORSYMBOLINSYMBOLS
PRINTFETCHING QUOTE HISTORY FOR R SYMBOL FILESYSSTDERR
URL HTTPSRAWGITHUBUSERCONTENTCOMSCIKITLEARNEXAMPLESDATA
MASTERFINANCIALDATACSV
QUOTESAPPENDPDREADCSVURLFORMATSYMBOL
CLOSEPRICES NPVSTACKQCLOSE FORQINQUOTES
OPENPRICES NPVSTACKQOPEN FORQINQUOTES
 THE DAILY VARIATIONS OF THE QUOTES ARE WHAT CARRY MOST INFORMATION
VARIATION CLOSEPRICES OPENPRICES

 LEARN A GRAPHICAL STRUCTURE FROM THE CORRELATIONS
EDGEMODEL COVARIANCEGRAPHICALLASSOCVCV5
 STANDARDIZE THE TIME SERIES USING CORRELATIONS RATHER THAN COVARIANCE
 IS MORE EFFICIENT FOR STRUCTURE RECOVERY

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X VARIATIONCOPYT
X XSTDAXIS0
EDGEMODELFITX

 CLUSTER USING AFFINITY PROPAGATION
 LABELS CLUSTERAFFINITYPROPAGATIONEDGEMODELCOVARIANCE
NLABELS LABELSMAX
FORIINRANGENLABELS 1
PRINTCLUSTER IS I 1 JOINNAMESLABELS I

 FIND A LOWDIMENSION EMBEDDING FOR VISUALIZATION FIND THE BEST POSITION OF
 THE NODES THE STOCKS ON A 2D PLANE
 WE USE A DENSE EIGENSOLVER TO ACHIEVE REPRODUCIBILITY ARPACK IS
 INITIATED WITH RANDOM VECTORS THAT WE DONT CONTROL IN ADDITION WE
 USE A LARGE NUMBER OF NEIGHBORS TO CAPTURE THE LARGESCALE STRUCTURE
NODEPOSITIONMODEL MANIFOLDLOCALLYLINEAREMBEDDING
NCOMPONENTS2 EIGENSOLVERDENSE NNEIGHBORS6
EMBEDDING NODEPOSITIONMODELFITTRANSFORMXTT

 VISUALIZATION
PLTFIGURE1 FACECOLORW FIGSIZE10 8
PLTCLF
AX PLTAXES0 0 1 1
PLTAXISOFF
 DISPLAY A GRAPH OF THE PARTIAL CORRELATIONS
PARTIALCORRELATIONS EDGEMODELPRECISIONCOPY
D 1 NPSQRTNPDIAGPARTIALCORRELATIONS
PARTIALCORRELATIONS D
PARTIALCORRELATIONS D NPNEWAXIS
NONZERO NPABSNPTRIUPARTIALCORRELATIONS K1 002
 PLOT THE NODES USING THE COORDINATES OF OUR EMBEDDING
PLTSCATTEREMBEDDING0 EMBEDDING1 S100 D2 CLABELS
CMAPPLTCMNIPYSPECTRAL
 PLOT THE EDGES
STARTIDX ENDIDX NPWHERENONZERO
 A SEQUENCE OF LINE0LINE1LINE2 WHERE
 LINEN X0 Y0 X1 Y1 XM YM
SEGMENTS EMBEDDING START EMBEDDING STOP
FORSTART STOP INZIPSTARTIDX ENDIDX
VALUES NPABSPARTIALCORRELATIONSNONZERO
LC LINECOLLECTIONSEGMENTS
ZORDER0 CMAPPLTCMHOTR
NORMPLTNORMALIZE0 7 VALUESMAX
LCSETARRAYVALUES
LCSETLINEWIDTHS15 VALUES
AXADDCOLLECTIONLC
 ADD A LABEL TO EACH NODE THE CHALLENGE HERE IS THAT WE WANT TO

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POSITION THE LABELS TO AVOID OVERLAP WITH OTHER LABELS
FORINDEX NAME LABEL X Y INENUMERATE
ZIPNAMES LABELS EMBEDDINGT
DX X EMBEDDING0
DXINDEX 1
DY Y EMBEDDING1
DYINDEX 1
THISDX DXNPARGMINNPABSDY
THISDY DYNPARGMINNPABSDX
IFTHISDX 0
HORIZONTALALIGNMENT LEFT
X X 002
ELSE
HORIZONTALALIGNMENT RIGHT
X X 002
IFTHISDY 0
VERTICALALIGNMENT BOTTOM
Y Y 002
ELSE
VERTICALALIGNMENT TOP
Y Y 002
PLTTEXTX Y NAME SIZE10
HORIZONTALALIGNMENTHORIZONTALALIGNMENT
VERTICALALIGNMENTVERTICALALIGNMENT
BBOXDICTFACECOLORW
EDGECOLORPLTCMNIPYSPECTRALLABEL FLOATNLABELS
ALPHA6
PLTXLIMEMBEDDING0MIN 15 EMBEDDING0PTP
EMBEDDING0MAX 10 EMBEDDING0PTP
PLTYLIMEMBEDDING1MIN 03 EMBEDDING1PTP
EMBEDDING1MAX 03 EMBEDDING1PTP
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 4857 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
528 WIKIPEDIA PRINCIPAL EIGENVECTOR
A CLASSICAL WAY TO ASSERT THE RELATIVE IMPORTANCE OF VERTICES IN A GRAPH IS TO COMPUTE THE PRINCIPAL EIGENVECTOR OF THE ADJACENCY MATRIX SO AS TO ASSIGN TO EACH VERTEX THE VALUES OF THE COMPONENTS OF THE FIRST EIGENVECTOR AS A CENTRALITY SCORE
HTTPSENWIKIPEDIAORGWIKIEIGENVECTORCENTRALITY
ON THE GRAPH OF WEBPAGES AND LINKS THOSE VALUES ARE CALLED THE PAGERANK SCORES BY GOOGLE
THE GOAL OF THIS EXAMPLE IS TO ANALYZE THE GRAPH OF LINKS INSIDE WIKIPEDIA ARTICLES TO RANK ARTICLES BY RELATIVE IMPORTANCE ACCORDING TO THIS EIGENVECTOR CENTRALITY
THE TRADITIONAL WAY TO COMPUTE THE PRINCIPAL EIGENVECTOR IS TO USE THE POWER ITERATION METHOD
HTTPSENWIKIPEDIAORGWIKIPOWERITERATION

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HERE THE COMPUTATION IS ACHIEVED THANKS TO MARTINSSON'S RANDOMIZED SVD ALGORITHM IMPLEMENTED IN SCIKITLEARN
THE GRAPH DATA IS FETCHED FROM THE DBPEDIA DUMPS DBPEDIA IS AN EXTRACTION OF THE LATENT STRUCTURED DATA OF THE WIKIPEDIA CONTENT
AUTHOR OLIVIER GRISEL OLIVIERGRISELENSTAORG
LICENSE BSD 3 CLAUSE
FROM BZ2 IMPORT BZ2FILE
IMPORT OS
FROM DATETIME IMPORT DATETIME
FROM PPRINT IMPORT PPRINT
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
FROM SCIPY IMPORT SPARSE
FROM JOBLIB IMPORT MEMORY
FROM SKLEARNDECOMPOSITION IMPORT RANDOMIZEDSVD
FROM URLLIBREQUEST IMPORT URLOPEN
PRINTDOC

WHERE TO DOWNLOAD THE DATA IF NOT ALREADY ON DISK
REDIRECTSURL HTTPDOWNLOADSDBPEDIAORG351ENREDIRECTSENNTBZ2
REDIRECTSFILENAME REDIRECTSURLRSPLIT 11
PAGELINKSURL HTTPDOWNLOADSDBPEDIAORG351ENPAGELINKSENNTBZ2
PAGELINKSFILENAME PAGELINKSURLRSPLIT 11
RESOURCES
REDIRECTSURL REDIRECTSFILENAME
PAGELINKSURL PAGELINKSFILENAME

FORURL FILENAME INRESOURCES
IF NOTOSPATHEXISTSFILENAME
PRINTDOWNLOADING DATA FROM S PLEASE WAIT URL
OPENER URLOPENURL
OPENFILENAME WBWRITEOPENERREAD
PRINT

LOADING THE REDIRECT FILES
MEMORY MEMORYCACHEDIR
DEFINDEXREDIRECTS INDEXMAP K
FIND THE INDEX OF AN ARTICLE NAME AFTER REDIRECT RESOLUTION
K REDIRECTSGETK K
RETURNINDEXMAPSETDEFAULTK LENINDEXMAP

```
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DBPEDIARESOURCEPREFIXLEN  LENHTTPDBPEDIAORGRESOURCE
SHORTNAMESLICE  SLICEDBPEDIARESOURCEPREFIXLEN  1 1
DEFSHORTNAMENTURI
REMOVE THE  AND  URI MARKERS AND THE COMMON URI PREFIX
RETURNNTURISHORTNAMESLICE
DEFGETREDIRECTSREDIRECTSFILENAME
PARSE THE REDIRECTIONS AND BUILD A TRANSITIVELY CLOSED MAP OUT OF IT
REDIRECTS
PRINTPARSING THE NT REDIRECT FILE
FORL LINE INENUMERATEBZ2FILEREDIRECTSFILENAME
SPLIT  LINESPLIT
IFLENSPLIT  4
PRINTIGNORING MALFORMED LINE   LINE
CONTINUE
REDIRECTSSHORTNAMESPLIT0  SHORTNAMESPLIT2
IFL  1000000  0
PRINTS LINE 08D  DATETIMENOWISOFORMAT L
 COMPUTE THE TRANSITIVE CLOSURE
PRINTCOMPUTING THE TRANSITIVE CLOSURE OF THE REDIRECT RELATION
FORL SOURCE INENUMERATEREDIRECTSKEYS
TRANSITIVETARGET  NONE
TARGET  REDIRECTSSOURCE
SEEN  SOURCE
WHILETRUE
TRANSITIVETARGET  TARGET
TARGET  REDIRECTSGETTARGET
IFTARGETISNONEORTARGETINSEEN
BREAK
SEENADDTARGET
REDIRECTSSOURCE  TRANSITIVETARGET
IFL  1000000  0
PRINTS LINE 08D  DATETIMENOWISOFORMAT L
RETURNREDIRECTS
 DISABLING JOBLIB AS THE PICKLING OF LARGE DICTS SEEMS MUCH TOO SLOW
MEMORYCACHE
DEFGETADJACENCYMATRIXREDIRECTSFILENAME PAGELINKSFILENAME LIMITNONE
EXTRACT THE ADJACENCY GRAPH AS A SCIPY SPARSE MATRIX
REDIRECTS ARE RESOLVED FIRST
RETURNS X THE SCIPY SPARSE ADJACENCY MATRIX REDIRECTS AS PYTHON
DICT FROM ARTICLE NAMES TO ARTICLE NAMES AND INDEXMAP A PYTHON DICT
FROM ARTICLE NAMES TO PYTHON INT ARTICLE INDEXES

PRINTCOMPUTING THE REDIRECT MAP
REDIRECTS  GETREDIRECTSREDIRECTSFILENAME
PRINTCOMPUTING THE INTEGER INDEX MAP
INDEXMAP  DICT
748 CHAPTER 5 EXAMPLES
```

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LINKS LIST
FORL LINE INENUMERATEBZ2FILEPAGELINKSFILENAME
SPLIT LINESPLIT
IFLENSPLIT 4
PRINTIGNORING MALFORMED LINE   LINE
CONTINUE
I INDEXREDIRECTS INDEXMAP SHORTNAMESPLIT0
J INDEXREDIRECTS INDEXMAP SHORTNAMESPLIT2
LINKSAPPENDI J
IFL 1000000 0
PRINTS LINE 08D DATETIMENOWISOFORMAT L
IFLIMITIS NOTNONEANDL LIMIT 1
BREAK
PRINTCOMPUTING THE ADJACENCY MATRIX
X SPARSELILMATRIXLENINDEXMAP LENINDEXMAP DTYPENPFLOAT32
FORI JINLINKS
XI J 10
DELLINKS
PRINTCONVERTING TO CSR REPRESENTATION
X XTOCSR
PRINTCSR CONVERSION DONE
RETURNX REDIRECTS INDEXMAP
 STOP AFTER 5M LINKS TO MAKE IT POSSIBLE TO WORK IN RAM
X REDIRECTS INDEXMAP GETADJACENCYMATRIX
REDIRECTSFILENAME PAGELINKSFILENAME LIMIT5000000
NAMES I NAME FORNAME I ININDEXMAPITEMS
PRINTCOMPUTING THE PRINCIPAL SINGULAR VECTORS USING RANDOMIZEDSVD
T0 TIME
U S V RANDOMIZEDSVDX 5 NITER3
PRINTDONE IN 03FS TIME T0
 PRINT THE NAMES OF THE WIKIPEDIA RELATED STRONGEST COMPONENTS OF THE
 PRINCIPAL SINGULAR VECTOR WHICH SHOULD BE SIMILAR TO THE HIGHEST EIGENVECTOR
PRINTTOP WIKIPEDIA PAGES ACCORDING TO PRINCIPAL SINGULAR VECTORS
PPRINTNAMESI FORIINNPABSUT0ARGSORT10
PPRINTNAMESI FORIINNPABSV0ARGSORT10
DEFCENTRALITYSCORESX ALPHA085 MAXITER100 TOL1E10
POWER ITERATION COMPUTATION OF THE PRINCIPAL EIGENVECTOR
THIS METHOD IS ALSO KNOWN AS GOOGLE PAGERANK AND THE IMPLEMENTATION
IS BASED ON THE ONE FROM THE NETWORKX PROJECT BSD LICENSED TOO
WITH COPYRIGHTS BY
ARIC HAGBERG HAGBERGLANLGOV
DAN SCHULT DSCHULTCOLGATEEDU
PIETER SWART SWARTLANLGOV

N XSHAPE0
X XCOPY
INCOMINGCOUNTS NPASARRAYXSUMAXIS1RAVEL

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PRINTNORMALIZING THE GRAPH
FORIININCOMINGCOUNTSNONZERO0
XDATAXINDPTRIXINDPTRI 1 10 INCOMINGCOUNTSI
DANGLE NPASARRAYNPWHERENPISCLOSEXSUMAXIS1 0
10 N 0RAVEL
SCORES NPFULLN 1 N DTYPENPFLOAT32 INITIAL GUESS
FORIINRANGEMAXITER
PRINTPOWER ITERATION D I
PREVSCORES SCORES
SCORES ALPHA SCORES X NPDOTDANGLE PREVSCORES
 1 ALPHA PREVSCORESSUM N
 CHECK CONVERGENCE NORMALIZED LINF NORM
SCORESMAX NPABSSCORESMAX
IFSCORESMAX 00
SCORESMAX 10
ERR NPABSSCORES PREVSCORESMAX SCORESMAX
PRINTERROR 06F ERR
IFERR N TOL
RETURNSCORES
RETURNSCORES
PRINTCOMPUTING PRINCIPAL EIGENVECTOR SCORE USING A POWER ITERATION METHOD
T0 TIME
SCORES CENTRALITYSCORESX MAXITER100 TOL1E10
PRINTDONE IN 03FS TIME T0
PPRINTNAMESI FORIINNPABSSCORESARGSORT10
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0000 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
529 LIBSVM GUI
A SIMPLE GRAPHICAL FRONTEND FOR LIBSVM MAINLY INTENDED FOR DIDACTIC PURPOSES YOU CAN CREATE DATA POINTS BY POINT
AND CLICK AND VISUALIZE THE DECISION REGION INDUCED BY DIFFERENT KERNELS AND PARAMETER SETTINGS
TO CREATE POSITIVE EXAMPLES CLICK THE LEFT MOUSE BUTTON TO CREATE NEGATIVE EXAMPLES CLICK THE RIGHT BUTTON
IF ALL EXAMPLES ARE FROM THE SAME CLASS IT USES A ONECLASS SVM
PRINTDOC
 AUTHOR PETER PRETTENHOER PETERPRETTENHOFERGMAILCOM

 LICENSE BSD 3 CLAUSE
IMPORT MATPLOTLIB
MATPLOTLIBUSETKAGG
FROM MATPLOTLIBBACKENDSBACKENDTKAGG IMPORT FIGURECANVASTKAGG
FROM MATPLOTLIBBACKENDSBACKENDTKAGG IMPORT NAVIGATIONTOOLBAR2TKAGG
FROM MATPLOTLIBFIGURE IMPORT FIGURE
FROM MATPLOTLIBCONTOUR IMPORT CONTOURSET
750 CHAPTER 5 EXAMPLES

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```
IMPORT SYS
IMPORT NUMPY AS NP
IMPORT TKINTER AS TK
FROM SKLEARN IMPORT SVM
FROM SKLEARNDATASETS IMPORT DUMPSVMLIGHTFILE
YMIN YMAX  50 50
XMIN XMAX  50 50
CLASS MODEL
THE MODEL WHICH HOLD THE DATA IT IMPLEMENTS THE
OBSERVABLE IN THE OBSERVER PATTERN AND NOTIFIES THE
REGISTERED OBSERVERS ON CHANGE EVENT

DEFINITSELF
SELFOBSERVERS
SELFSURFACE  NONE
SELFDATA
SELFCLS  NONE
SELFSURFACETYPE  0
DEFCHANGEDSELF EVENT
NOTIFY THE OBSERVERS
FOROBSERVER INSELFOBSERVERS
OBSERVERUPDATEEVENT SELF
DEFADDOBSERVERSELF OBSERVER
REGISTER AN OBSERVER
SELFOBSERVERSAPPENDOBSERVER
DEFSETSURFACESELF SURFACE
SELFSURFACE  SURFACE
DEFDUMPSVMLIGHTFILESELF FILE
DATA  NPARRAYSELFDATA
X  DATA 02
Y  DATA 2
DUMPSVMLIGHTFILEX Y FILE
CLASS CONTROLLER
DEFINITSELF MODEL
SELFMODEL  MODEL
SELFKERNEL  TKINTVAR
SELFSURFACETYPE  TKINTVAR
 WHETHER OR NOT A MODEL HAS BEEN FITTED
SELFFITTED  FALSE
DEFFITSELF
PRINTFIT THE MODEL
TRAIN  NPARRAYSELFMODELDATA
X  TRAIN 02
Y  TRAIN 2
```

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C FLOATSELFCOMPLEXITYGET
GAMMA FLOATSELFGAMMAGET
COEF0 FLOATSELFCOEF0GET
DEGREE INTSELFDEGREEGET
KERNELMAP 0 LINEAR 1 RBF 2 POLY
IFLENNPUNIQUEY 1
CLF SVMONECLASSSVMKERNELKERNELMAPSELFKERNELGET
GAMMAGAMMA COEF0COEF0 DEGREEDEGREE
CLFFITX
ELSE
CLF SVMSVCKERNELKERNELMAPSELFKERNELGET CC
GAMMAGAMMA COEF0COEF0 DEGREEDEGREE
CLFFITX Y
IFHASATTRCLF SCORE
PRINTACCURACY CLFSCOREX Y 100
X1 X2 Z SELFDECISIONSURFACECLF
SELFMODELCLF CLF
SELFMODELSETSURFACEX1 X2 Z
SELFMODELSURFACETYPE SELFSURFACETYPEGET
SELFFITTED TRUE
SELFMODELCHANGEDSURFACE
DEFDECISIONSURFACESELF CLS
DELTA 1
X NPARANGEXMIN XMAX DELTA DELTA
Y NPARANGEYMIN YMAX DELTA DELTA
X1 X2 NPMESHGRIDX Y
Z CLSDECISIONFUNCTIONNPCX1RAVEL X2RAVEL
Z ZRESHAPEX1SHAPE
RETURNX1 X2 Z
DEFCLEARDATASELF
SELFMODELDATA
SELFFITTED FALSE
SELFMODELCHANGEDCLEAR
DEFADDEXAMPLESELF X Y LABEL
SELFMODELDATAAPPENDX Y LABEL
SELFMODELCHANGEDEXAMPLEADDED
 UPDATE DECISION SURFACE IF ALREADY FITTED
SELFREFIT
DEFREFITSELF
REFIT THE MODEL IF ALREADY FITTED
IFSELFFITTED
SELFFIT
CLASS VIEW
TEST DOCSTRING
DEFINITSELF ROOT CONTROLLER
F FIGURE
AX FADDSUBPLOT111
AXSETXTICKS
AXSETYTICKS
AXSETXLIMXMIN XMAX
AXSETYLIMYMIN YMAX

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CANVAS FIGURECANVASTKAGGF MASTERROOT
CANVASSHOW
CANVASGETTKWIDGETPACKSIDETKTOP FILLTKBOTH EXPAND1
CANVASTKCANVASPACKSIDETKTOP FILLTKBOTH EXPAND1
CANVASMPLCONNECTBUTTONPRESSEVENT SELFONCLICK
TOOLBAR NAVIGATIONTOOLBAR2TKAGGCANVAS ROOT
TOOLBARUPDATE
SELFCONTROLLBAR CONTROLLBARROOT CONTROLLER
SELFF F
SELFAX AX
SELFCANVAS CANVAS
SELFCONTROLLER CONTROLLER
SELFCONTOURS
SELFCLABELS NONE
SELFPLOTKERNELS
DEFPLOTKERNELSSELF
SELFAXTEXT50 60 LINEAR UT V
SELFAXTEXT20 60 RRBF EXP GAMMA UV 2
SELFAXTEXT10 60 RPOLY GAMMA UT V RD
DEFONCLICKSELF EVENT
IFEVENTXDATA ANDEVENTYDATA
IFEVENTBUTTON 1
SELFCONTROLLERADDEXAMPLEEVENTXDATA EVENTYDATA 1
ELIFEVENTBUTTON 3
SELFCONTROLLERADDEXAMPLEEVENTXDATA EVENTYDATA 1
DEFUPDATEEXAMPLESELF MODEL IDX
X Y L MODELDATAIDX
IFL 1
COLOR W
ELIFL 1
COLOR K
SELFAXPLOTX Y SO COLOR SCALEX00 SCALEY00
DEFUPDATESELF EVENT MODEL
IFEVENT EXAMPLESLOADED
FORIINRANGELENMODELDATA
SELFUPDATEEXAMPLEMODEL I
IFEVENT EXAMPLEADDED
SELFUPDATEEXAMPLEMODEL 1
IFEVENT CLEAR
SELFAXCLEAR
SELFAXSETXTICKS
SELFAXSETYTICKS
SELFCONTOURS
SELFCLABELS NONE
SELFPLOTKERNELS
IFEVENT SURFACE
SELFREMOVESURFACE
SELFPLOTSUPPORTVECTORSMODELCLFSUPPORTVECTORS
SELFPLOTDECISIONSURFACEMODELSURFACE MODELSURFACETYPE
SELFCANVASDRAW

SCIKITLEARN USER GUIDE RELEASE 0213
DEFREMOVESURFACESELF
REMOVE OLD DECISION SURFACE
IFLENSELFCONTOURS 0
FORCONTOUR INSELFCONTOURS
IFISINSTANCECONTOUR CONTOURSET
FORLINESET INCONTOURCOLLECTIONS
LINESETREMOVE
ELSE
CONTOURREMOVE
SELFCONTOURS
DEFPLOTSUPPORTVECTORSSELF SUPPORTVECTORS
PLOT THE SUPPORT VECTORS BY PLACING CIRCLES OVER THE
CORRESPONDING DATA POINTS AND ADDS THE CIRCLE COLLECTION
TO THE CONTOURS LIST
CS SELFAXSCATTERSUPPORTVECTORS 0 SUPPORTVECTORS 1
S80 EDGECOLORSK FACECOLORSNONE
SELFCONTOURSAPPENDCS
DEFPLOTDECISIONSURFACESELF SURFACE TYPE
X1 X2 Z SURFACE
IFTYPE 0
LEVELS 10 00 10
LINESTYLES DASHED SOLID DASHED
COLORS K
SELFCONTOURSAPPENDSELFAXCONTOURX1 X2 Z LEVELS
COLORSCOLORS
LINESTYLESLINESTYLES
ELIFTYPE 1
SELFCONTOURSAPPENDSELFAXCONTOURFX1 X2 Z 10
CMAPMATPLOTLIBCMBONE
ORIGINLOWER ALPHA085
SELFCONTOURSAPPENDSELFAXCONTOURX1 X2 Z 00 COLORSK
LINESTYLESSOLID
ELSE
RAISEVALUEERRORSURFACE TYPE UNKNOWN
CLASS CONTROLLBAR
DEFINITSELF ROOT CONTROLLER
FM TKFRAMEROOT
KERNELGROUP TKFRAMEFM
TKRADIOBUTTONKERNELGROUP TEXTLINEAR VARIABLECONTROLLERKERNEL
VALUE0 COMMANDCONTROLLERREFITPACKANCHORTKW
TKRADIOBUTTONKERNELGROUP TEXTRBF VARIABLECONTROLLERKERNEL
VALUE1 COMMANDCONTROLLERREFITPACKANCHORTKW
TKRADIOBUTTONKERNELGROUP TEXTPOLY VARIABLECONTROLLERKERNEL
VALUE2 COMMANDCONTROLLERREFITPACKANCHORTKW
KERNELGROUPPACKSIDETKLEFT
VALBOX TKFRAMEFM
CONTROLLERCOMPLEXITY TKSTRINGVAR
CONTROLLERCOMPLEXITYSET10
C TKFRAMEVALBOX
TKLABELC TEXTC ANCHORE WIDTH7PACKSIDETKLEFT
TKENTRYC WIDTH6 TEXTVARIABLECONTROLLERCOMPLEXITYPACK
SIDETKLEFT

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CPACK
CONTROLLERGAMMA TKSTRINGVAR
CONTROLLERGAMMASET001
G TKFRAMEVALBOX
TKLABELG TEXTGAMMA ANCHORE WIDTH7PACKSIDETKLEFT
TKENTRYG WIDTH6 TEXTVARIABLECONTROLLERGAMMAPACKSIDETKLEFT
GPACK
CONTROLLERDEGREE TKSTRINGVAR
CONTROLLERDEGREESET3
D TKFRAMEVALBOX
TKLABELD TEXTDEGREE ANCHORE WIDTH7PACKSIDETKLEFT
TKENTRYD WIDTH6 TEXTVARIABLECONTROLLERDEGREEPACKSIDETKLEFT
DPACK
CONTROLLERCOEF0 TKSTRINGVAR
CONTROLLERCOEF0SET0
R TKFRAMEVALBOX
TKLABELR TEXTCOEF0 ANCHORE WIDTH7PACKSIDETKLEFT
TKENTRYR WIDTH6 TEXTVARIABLECONTROLLERCOEF0PACKSIDETKLEFT
RPACK
VALBOXPACKSIDETKLEFT
CMAPGROUP TKFRAMEFM
TKRADIOBUTTONCMAPGROUP TEXTHYPERPLANES
VARIABLECONTROLLERSURFACETYPE VALUE0
COMMANDCONTROLLERREFITPACKANCHORTKW
TKRADIOBUTTONCMAPGROUP TEXTSURFACE
VARIABLECONTROLLERSURFACETYPE VALUE1
COMMANDCONTROLLERREFITPACKANCHORTKW
CMAPGROUPPACKSIDETKLEFT
TRAINBUTTON TKBUTTONFM TEXTFIT WIDTH5
COMMANDCONTROLLERFIT
TRAINBUTTONPACK
FMPACKSIDETKLEFT
TKBUTTONFM TEXTCLEAR WIDTH5
COMMANDCONTROLLERCLEARDATAPACKSIDETKLEFT
DEFGETPARSER
FROM OPTPARSE IMPORT OPTIONPARSER
OP OPTIONPARSER
OPADDOPTIONOUTPUT
ACTIONSTORE TYPESTR DESTOUTPUT
HELPPATH WHERE TO DUMP DATA
RETURNOP
DEFMAINARGV
OP GETPARSER
OPTS ARGS OPPARSEARGSARGV1
ROOT TKTK
MODEL MODEL
CONTROLLER CONTROLLERMODEL
ROOTWMTITLESCIKITLEARN LIBSVM GUI
52 EXAMPLES BASED ON REAL WORLD DATASETS 755

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VIEW VIEWROOT CONTROLLER
MODELADDOBSERVERVIEW
TKMAINLOOP
IFOPTSOUTPUT
MODELDUMPSVMLIGHTFILEOPTSOUTPUT
IFNAME MAIN
MAINSYSARGV
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0000 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5210 PREDICTION LATENCY
THIS IS AN EXAMPLE SHOWING THE PREDICTION LATENCY OF VARIOUS SCIKITLEARN ESTIMATORS
THE GOAL IS TO MEASURE THE LATENCY ONE CAN EXPECT WHEN DOING PREDICTIONS EITHER IN BULK OR ATOMIC IE ONE BY ONE MODE
THE PLOTS REPRESENT THE DISTRIBUTION OF THE PREDICTION LATENCY AS A BOXPLOT
•

•

OUT

BENCHMARKING SGDREGRESSORALPHA001 L1RATIO025 PENALTYELASTICNET TOL00001
BENCHMARKING RANDOMFORESTREGRESSORNESTIMATORS100
BENCHMARKING SVR
BENCHMARKING WITH 100 FEATURES
BENCHMARKING WITH 250 FEATURES
BENCHMARKING WITH 500 FEATURES
EXAMPLE RUN IN 960S
AUTHORS EUSTACHE DIEMERT EUSTACHEDIEMERTFR
LICENSE BSD 3 CLAUSE

```
FROM COLLECTIONS IMPORT DEFAULTDICT
IMPORT TIME
IMPORT GC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNDATASETSSAMPLESGENERATOR IMPORT MAKEREGRESSION
FROM SKLEARNENSEMBLEFOREST IMPORT RANDOMFORESTREGRESSOR
FROM SKLEARNLINEARMODELRIDGE IMPORT RIDGE
FROM SKLEARNLINEARMODELSTOCHASTICGRADIENT IMPORT SGDREGRESSOR
FROM SKLEARNSVMCLASSES IMPORT SVR
FROM SKLEARNUTILS IMPORT SHUFFLE
```

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DEFNOTINSPHINX
 HACK TO DETECT WHETHER WE ARE RUNNING BY THE SPHINX BUILDER
RETURNFILE INGLOBALS
DEFATOMICBENCHMARKESTIMATORESTIMATOR XTEST VERBOSEFALSE
MEASURE RUNTIME PREDICTION OF EACH INSTANCE
NINSTANCES XTESTSHAPE0
RUNTIMES NPZEROSNINSTANCES DTYPENPFLOAT
FORIINRANGENINSTANCES
INSTANCE XTESTI
START TIMETIME
ESTIMATORPREDICTINSTANCE
RUNTIMESI TIMETIME START
IFVERBOSE
PRINTATOMICBENCHMARK RUNTIMES MINRUNTIMES NPPERCENTILE
RUNTIMES 50 MAXRUNTIMES
RETURNRUNTIMES
DEFBULKBENCHMARKESTIMATORESTIMATOR XTEST NBULKREPEATS VERBOSE
MEASURE RUNTIME PREDICTION OF THE WHOLE INPUT
NINSTANCES XTESTSHAPE0
RUNTIMES NPZEROSNBULKREPEATS DTYPENPFLOAT
FORIINRANGENBULKREPEATS
START TIMETIME
ESTIMATORPREDICTXTEST
RUNTIMESI TIMETIME START
RUNTIMES NPARRAYLISTMAP LAMBDAX X FLOATNINSTANCES RUNTIMES
IFVERBOSE
PRINTBULKBENCHMARK RUNTIMES MINRUNTIMES NPPERCENTILE
RUNTIMES 50 MAXRUNTIMES
RETURNRUNTIMES
DEFBENCHMARKESTIMATORESTIMATOR XTEST NBULKREPEATS30 VERBOSEFALSE

MEASURE RUNTIMES OF PREDICTION IN BOTH ATOMIC AND BULK MODE
PARAMETERS

ESTIMATOR ALREADY TRAINED ESTIMATOR SUPPORTING PREDICT
XTEST TEST INPUT
NBULKREPEATS HOW MANY TIMES TO REPEAT WHEN EVALUATING BULK MODE
RETURNS

ATOMICRUNTIMES BULKRUNTIMES A PAIR OF NPARRAY WHICH CONTAIN THE
RUNTIMES IN SECONDS

ATOMICRUNTIMES ATOMICBENCHMARKESTIMATORESTIMATOR XTEST VERBOSE
BULKRUNTIMES BULKBENCHMARKESTIMATORESTIMATOR XTEST NBULKREPEATS
VERBOSE
RETURNATOMICRUNTIMES BULKRUNTIMES

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DEFGENERATEDATASETNTRAIN NTEST NFEATURES NOISE01 VERBOSEFALSE
GENERATE A REGRESSION DATASET WITH THE GIVEN PARAMETERS
IFVERBOSE
PRINTGENERATING DATASET
X Y COEF MAKEREGRESSIONNSAMPLESNTRAIN NTEST
NFEATURESNFEATURES NOISENOISE COEFTRUE
RANDOMSEED 13
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLIT
X Y TRAINSIZENTRAIN TESTSIZENTEST RANDOMSTATERANDOMSEED
XTRAIN YTRAIN SHUFFLEXTRAIN YTRAIN RANDOMSTATERANDOMSEED
XSCALER STANDARDSCALER
XTRAIN XSCALERFITTRANSFORMXTRAIN
XTEST XSCALERTRANSFORMXTEST
YSCALER STANDARDSCALER
YTRAIN YSCALERFITTRANSFORMYTRAIN NONE 0
YTEST YSCALERTRANSFORMYTEST NONE 0
GCCOLLECT
IFVERBOSE
PRINTOK
RETURNXTRAIN YTRAIN XTEST YTEST
DEFBOXPLOTRUNTIMESRUNTIMES PREDTYPE CONFIGURATION

PLOT A NEW FIGURE WITH BOXPLOTS OF PREDICTION RUNTIMES
PARAMETERS

RUNTIMES LIST OF NPARRAY OF LATENCIES IN MICROSECONDS
CLSNAMES LIST OF ESTIMATOR CLASS NAMES THAT GENERATED THE RUNTIMES
PREDTYPE BULK OR ATOMIC

FIG AX1 PLTSUBPLOTSFIGSIZE10 6
BP PLTBOXPLOTRUNTIMES
CLSINFOS   SND S ESTIMATORCONFNAME
ESTIMATORCONFCOMPLEXITYCOMPUTER
ESTIMATORCONFINSTANCE
ESTIMATORCONFCOMPLEXITYLABEL FOR
ESTIMATORCONF INCONFIGURATIONESTIMATORS
PLTSETPAX1 XTICKLABELSCLSINFOS
PLTSETPBPBOXES COLORBLACK
PLTSETPBPWHISKERS COLORBLACK
PLTSETPBPFLIERS COLORRED MARKER
AX1YAXISGRIDTRUE LINESTYLE WHICHMAJOR COLORLIGHTGREY
ALPHA05
AX1SETAXISBELOWTRUE
AX1SETTITLEPREDICTION TIME PER INSTANCE SDFEATS

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PREDTYPECAPITALIZE
CONFIGURATIONNFEATURES
AX1SETYLABELPREDICTION TIME US
PLTSHOW
DEFBENCHMARKCONFIGURATION
RUN THE WHOLE BENCHMARK
XTRAIN YTRAIN XTEST YTEST GENERATEDATASET
CONFIGURATIONNTRAIN CONFIGURATIONNTEST
CONFIGURATIONNFEATURES
STATS
FORESTIMATORCONF INCONFIGURATIONESTIMATORS
PRINTBENCHMARKING ESTIMATORCONFINSTANCE
ESTIMATORCONFINSTANCEFITXTRAIN YTRAIN
GCCOLLECT
A B BENCHMARKESTIMATORESTIMATORCONFINSTANCE XTEST
STATSESTIMATORCONFNAME ATOMIC A BULK B
CLSNAMES ESTIMATORCONFNAME FORESTIMATORCONF INCONFIGURATION
ESTIMATORS
RUNTIMES 1E6 STATSCLFNAMEATOMIC FORCLFNAME INCLSNAMES
BOXPLOTRUNTIMESRUNTIMES ATOMIC CONFIGURATION
RUNTIMES 1E6 STATSCLFNAMEBULK FORCLFNAME INCLSNAMES
BOXPLOTRUNTIMESRUNTIMES BULK D CONFIGURATIONNTEST
CONFIGURATION
DEFNFEATUREINFLUENCEESTIMATORS NTRAIN NTEST NFEATURES PERCENTILE

ESTIMATE INFLUENCE OF THE NUMBER OF FEATURES ON PREDICTION TIME
PARAMETERS

ESTIMATORS DICT OF NAME STR ESTIMATOR TO BENCHMARK
NTRAIN NBER OF TRAINING INSTANCES INT
NTEST NBER OF TESTING INSTANCES INT
NFEATURES LIST OF FEATURESPACE DIMENSIONALITY TO TEST INT
PERCENTILE PERCENTILE AT WHICH TO MEASURE THE SPEED INT 0100
RETURNS

PERCENTILES DICTESTIMATORNAME
DICTNFEATURES PERCENTILEPERFINUS

PERCENTILES DEFAULTDICTDEFAULTDICT
FORNINNFEATURES
PRINTBENCHMARKING WITH DFEATURES N
XTRAIN YTRAIN XTEST YTEST GENERATEDATASETNTRAIN NTEST N
FORCLSNAME ESTIMATOR INESTIMATORSITEMS
ESTIMATORFITXTRAIN YTRAIN
GCCOLLECT
RUNTIMES BULKBENCHMARKESTIMATORESTIMATOR XTEST 30 FALSE

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PERCENTILESCLSNAMEN 1E6 NPPERCENTILERUNTIMES
PERCENTILE
RETURNPERCENTILES
DEFPLOTNFEATURESINFLUENCEPERCENTILES PERCENTILE
FIG AX1 PLTSUBPLOTSFIGSIZE10 6
COLORS R G B
FORI CLSNAME INENUMERATEPERCENTILESKEYS
X NPARRAYSORTEDN FORNINPERCENTILESCLSNAMEKEYS
Y NPARRAYPERCENTILESCLSNAMEN FORNINX
PLTPLOTX Y COLORCOLORSI
AX1YAXISGRIDTRUE LINESTYLE WHICHMAJOR COLORLIGHTGREY
ALPHA05
AX1SETAXISBELOWTRUE
AX1SETTITLEEVOLUTION OF PREDICTION TIME WITH FEATURES
AX1SETXLABELFEATURES
AX1SETYLABELPREDICTION TIME AT DILE US PERCENTILE
PLTSHOW
DEFBENCHMARKTHROUGHPUTSCONFIGURATION DURATIONSECS01
BENCHMARK THROUGHPUT FOR DIFFERENT ESTIMATORS
XTRAIN YTRAIN XTEST YTEST GENERATEDATASET
CONFIGURATIONNTRAIN CONFIGURATIONNTEST
CONFIGURATIONNFEATURES
THROUGHPUTS DICT
FORESTIMATORCONFIG INCONFIGURATIONESTIMATORS
ESTIMATORCONFIGINSTANCEFITXTRAIN YTRAIN
STARTTIME TIMETIME
NPREDICTIONS 0
WHILETIMETIME STARTTIME DURATIONSECS
ESTIMATORCONFIGINSTANCEPREDICTXTEST0
NPREDICTIONS 1
THROUGHPUTSESTIMATORCONFIGNAME NPREDICTIONS DURATIONSECS
RETURNTHROUGHPUTS
DEFPLOTBENCHMARKTHROUGHPUTTHROUGHPUTS CONFIGURATION
FIG AX PLTSUBPLOTSFIGSIZE10 6
COLORS R G B
CLSINFOS   SND S ESTIMATORCONFNAME
ESTIMATORCONFCOMPLEXITYCOMPUTER
ESTIMATORCONFINSTANCE
ESTIMATORCONFCOMPLEXITYLABEL FOR
ESTIMATORCONF INCONFIGURATIONESTIMATORS
CLSVALUES THROUGHPUTSESTIMATORCONFNAME FORESTIMATORCONF IN
CONFIGURATIONESTIMATORS
PLTBARRANGELENTHROUGHPUTS CLSVALUES WIDTH05 COLORCOLORS
AXSETXTICKSNPLINSPACE025 LENTHROUGHPUTS 075 LENTHROUGHPUTS
AXSETXTICKLABELSCLSINFOS FONTSIZE10
YMAX MAXCLSVALUES 12
AXSETYLIM0 YMAX
AXSETYLABELTHROUGHPUT PREDICTIONSSEC
AXSETTITLEPREDICTION THROUGHPUT FOR DIFFERENT ESTIMATORS D
FEATURES CONFIGURATIONNFEATURES
PLTSHOW

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MAIN CODE
STARTTIME TIMETIME

BENCHMARK BULKATOMIC PREDICTION SPEED FOR VARIOUS REGRESSORS
CONFIGURATION
NTRAIN INT1E3
NTEST INT1E2
NFEATURES INT1E2
ESTIMATORS
NAME LINEAR MODEL
INSTANCE SGDREGRESSORPENALTYELASTICNET ALPHA001
L1RATIO025 FITINTERCEPTTRUE
TOL1E4
COMPLEXITYLABEL NONZERO COEFFICIENTS
COMPLEXITYCOMPUTER LAMBDACLF NPCOUNTNONZEROCLFCOEF
NAME RANDOMFOREST
INSTANCE RANDOMFORESTREGRESSORNESTIMATORS100
COMPLEXITYLABEL ESTIMATORS
COMPLEXITYCOMPUTER LAMBDACLF CLFNESTIMATORS
NAME SVR
INSTANCE SVRKERNELRBF
COMPLEXITYLABEL SUPPORT VECTORS
COMPLEXITYCOMPUTER LAMBDACLF LENCLFSUPPORTVECTORS

BENCHMARKCONFIGURATION
BENCHMARK NFEATURES INFLUENCE ON PREDICTION SPEED
PERCENTILE 90
PERCENTILES NFEATUREINFLUENCERIDGE RIDGE
CONFIGURATIONNTRAIN
CONFIGURATIONNTEST
100 250 500 PERCENTILE
PLOTNFEATURESINFLUENCEPERCENTILES PERCENTILE
BENCHMARK THROUGHPUT
THROUGHPUTS BENCHMARKTHROUGHPUTSCONFIGURATION
PLOTBENCHMARKTHROUGHPUTTHROUGHPUTS CONFIGURATION
STOPTIME TIMETIME
PRINTEXAMPLE RUN IN 2FS STOPTIME STARTTIME
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 9597 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5211 OUTOFCORE CLASSIFICATION OF TEXT DOCUMENTS
THIS IS AN EXAMPLE SHOWING HOW SCIKITLEARN CAN BE USED FOR CLASSIFICATION USING AN OUTOFCORE APPROACH LEARNING FROM DATA THAT DOESN'T FIT INTO MAIN MEMORY WE MAKE USE OF AN ONLINE CLASSIFIER IE ONE THAT SUPPORTS THE PARTIALFIT METHOD THAT WILL BE FED WITH BATCHES OF EXAMPLES TO GUARANTEE THAT THE FEATURES SPACE REMAINS THE SAME OVER TIME
52 EXAMPLES BASED ON REAL WORLD DATASETS 763

WE LEVERAGE A HASHINGVECTORIZER THAT WILL PROJECT EACH EXAMPLE INTO THE SAME FEATURE SPACE THIS IS ESPECIALLY USEFUL
IN THE CASE OF TEXT CLASSIFICATION WHERE NEW FEATURES WORDS MAY APPEAR IN EACH BATCH
THE DATASET USED IN THIS EXAMPLE IS REUTERS21578 AS PROVIDED BY THE UCI ML REPOSITORY IT WILL BE AUTOMATICALLY
DOWNLOADED AND UNCOMPRESSED ON FIRST RUN
THE PLOT REPRESENTS THE LEARNING CURVE OF THE CLASSIFIER THE EVOLUTION OF CLASSIFICATION ACCURACY OVER THE COURSE OF THE
MINIBATCHES ACCURACY IS MEASURED ON THE FIRST 1000 SAMPLES HELD OUT AS A VALIDATION SET
TO LIMIT THE MEMORY CONSUMPTION WE QUEUE EXAMPLES UP TO A FIXED AMOUNT BEFORE FEEDING THEM TO THE LEARNER
 AUTHORS EUSTACHE DIEMERT EUSTACHEDIEMERTFR
 FEDERICOV HTTPSGITHUBCOMFEDERICOV
 LICENSE BSD 3 CLAUSE
FROM GLOB IMPORT GLOB
IMPORT ITERTOOLS
IMPORT OSPATH
IMPORT RE
IMPORT TARFILE
IMPORT TIME
IMPORT SYS
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIB IMPORT RCPARAMS
FROM HTMLPARSER IMPORT HTMLPARSER
FROM URLLIBREQUEST IMPORT URLRETRIEVE
FROM SKLEARNDATASETS IMPORT GETDATAHOME
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT HASHINGVECTORIZER
FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
FROM SKLEARNLINEARMODEL IMPORT PASSIVEAGGRESSIVECLASSIFIER
FROM SKLEARNLINEARMODEL IMPORT PERCEPTRON
FROM SKLEARNNAIVEBAYES IMPORT MULTINOMIALNB
DEFNOTINSPHINX
 HACK TO DETECT WHETHER WE ARE RUNNING BY THE SPHINX BUILDER
RETURNFILE INGLOBALS
REUTERS DATASET RELATED ROUTINES
CLASS REUTERSPARSER HTMLPARSER
UTILITY CLASS TO PARSE A SGML FILE AND YIELD DOCUMENTS ONE AT A TIME
DEFINITSELF ENCODINGLATIN1
HTMLPARSERINITSELF
SELFRESET
SELFENCODING ENCODING
DEFHANDLESTARTTAGSELF TAG ATTRS
METHOD START TAG
GETATTRSELF METHOD LAMBDAX NONEATTRS
DEFHANDLEENDTAGSELF TAG
METHOD END TAG
GETATTRSELF METHOD LAMBDA NONE

```
DEFRESETSELF
SELFINTITLE  0
SELFINBODY  0
SELFINTOPICS  0
SELFINTOPICD  0
SELFTITLE
SELFBODY
SELFTOPICS
SELFTOPICD
DEFPARSESELF FD
SELFDOCS
FORCHUNKINFD
SELFFEEDCHUNKDECODESELFENCODING
FORDOCINSELFDOCS
YIELDDOC
SELFDOCS
SELFCLOSE
DEFHANDLEDATASELF DATA
IFSELFINBODY
SELFBODY  DATA
ELIFSELFINTITLE
SELFTITLE  DATA
ELIFSELFINTOPICD
SELFTOPICD  DATA
DEFSTARTREUTERSSELF ATTRIBUTES
PASS
DEFENDREUTERSSELF
SELFBODY  RESUBRS R  SELFBODY
SELFDOCSAPPENDTITLE SELFTITLE
BODY SELFBODY
TOPICS SELFTOPICS
SELFRESET
DEFSTARTTITLESELF ATTRIBUTES
SELFINTITLE  1
DEFENDTITLESELF
SELFINTITLE  0
DEFSTARTBODYSELF ATTRIBUTES
SELFINBODY  1
DEFENDBODYSELF
SELFINBODY  0
DEFSTARTTOPICSSELF ATTRIBUTES
SELFINTOPICS  1
DEFENDTOPICSSELF
SELFINTOPICS  0
DEFSTARTDSELF ATTRIBUTES
SELFINTOPICD  1
```

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DEFENDDSELF
SELFINTOPICD 0
SELFTOPICSAPPENDSELFTOPICD
SELFTOPICD
DEFSTREAMREUTERSDOCUMENTSDATAPATHNONE
ITERATE OVER DOCUMENTS OF THE REUTERS DATASET
THE REUTERS ARCHIVE WILL AUTOMATICALLY BE DOWNLOADED AND UNCOMPRESSED IF
THE DATAPATH DIRECTORY DOES NOT EXIST
DOCUMENTS ARE REPRESENTED AS DICTIONARIES WITH BODY STR
TITLE STR TOPICS LISTSTR KEYS

DOWNLOADURL HTTPARCHIVEICSUCIEDUMLMACHINELEARNINGDATABASES
REUTERS21578MLDREUTERS21578TARGZ
ARCHIVEFILENAME REUTERS21578TARGZ
IFDATAPATH ISNONE
DATAPATH OSPATHJOINGETDATAHOME REUTERS
IF NOTOSPATHEXISTSDATAPATH
DOWNLOAD THE DATASET
PRINTDOWNLOADING DATASET ONCE AND FOR ALL INTO S
DATAPATH
OSMKDIRDATAPATH
DEFPROGRESSBLOCKNUM BS SIZE
TOTALSZMB   2FMB SIZE 1E6
CURRENTSZMB   2FMB BLOCKNUM BS 1E6
IFNOTINSPHINX
SYSSTDOUTWRITE
RDOWNLOADED SS CURRENTSZMB TOTALSZMB
ARCHIVEPATH OSPATHJOINDATAPATH ARCHIVEFILENAME
URLRETRIEVEDOWNLOADURL FILENAMEARCHIVEPATH
REPORTHOOKPROGRESS
IFNOTINSPHINX
SYSSTDOUTWRITE R
PRINTUNTARRING REUTERS DATASET
TARFILEOPENARCHIVEPATH RGZEXTRACTALLDATAPATH
PRINTDONE
PARSER REUTERSPARSER
FORFILENAME INGLOBOSPATHJOINDATAPATH SGM
FORDOCINPARSERPARSEOPENFILENAME RB
YIELDDOC
MAIN
CREATE THE VECTORIZER AND LIMIT THE NUMBER OF FEATURES TO A REASONABLE MAXIMUM
VECTORIZER HASHINGVECTORIZERDECODEERRORIGNORE NFEATURES2 18
ALTERNATESIGNFALSE

```
SCIKITLEARN USER GUIDE RELEASE 0213
 ITERATOR OVER PARSED REUTERS SGML FILES
DATASTREAM  STREAMREUTERSDOCUMENTS
 WE LEARN A BINARY CLASSIFICATION BETWEEN THE ACQ CLASS AND ALL THE OTHERS
 ACQ WAS CHOSEN AS IT IS MORE OR LESS EVENLY DISTRIBUTED IN THE REUTERS
 FILES FOR OTHER DATASETS ONE SHOULD TAKE CARE OF CREATING A TEST SET WITH
 A REALISTIC PORTION OF POSITIVE INSTANCES
ALLCLASSES  NPARRAY0 1
POSITIVECLASS  ACQ
 HERE ARE SOME CLASSIFIERS THAT SUPPORT THE PARTIALFIT METHOD
PARTIALFITCLASSIFIERS
SGD SGDCLASSIFIERMAXITER5 TOL1E3
PERCEPTRON PERCEPTRONTOL1E3
NB MULTINOMIAL MULTINOMIALNBALPHA001
PASSIVEAGGRESSIVE PASSIVEAGGRESSIVECLASSIFIERTOL1E3

DEFGETMINIBATCHDOCITER SIZE POSCLASSPOSITIVECLASS
EXTRACT A MINIBATCH OF EXAMPLES RETURN A TUPLE XTEXT Y
NOTE SIZE IS BEFORE EXCLUDING INVALID DOCS WITH NO TOPICS ASSIGNED

DATA  TITLE NNBODYFORMAT DOC POSCLASS INDOCTOPICS
FORDOCINITERTOOLSISLICEDOCITER SIZE
IFDOCTOPICS
IF NOTLENDATA
RETURNNPASARRAY DTYPEINT NPASARRAY DTYPEINT
XTEXT Y  ZIP DATA
RETURNXTEXT NPASARRAYY DTYPEINT
DEFITERMINIBATCHESDOCITER MINIBATCHSIZE
GENERATOR OF MINIBATCHES
XTEXT Y  GETMINIBATCHDOCITER MINIBATCHSIZE
WHILELENXTEXT
YIELDXTEXT Y
XTEXT Y  GETMINIBATCHDOCITER MINIBATCHSIZE
 TEST DATA STATISTICS
TESTSTATS  NTEST 0 NTESTPOS 0
 FIRST WE HOLD OUT A NUMBER OF EXAMPLES TO ESTIMATE ACCURACY
NTESTDOCUMENTS  1000
TICK  TIMETIME
XTESTTEXT YTEST  GETMINIBATCHDATASTREAM 1000
PARSINGTIME  TIMETIME  TICK
TICK  TIMETIME
XTEST  VECTORIZERTRANSFORMXTESTTEXT
VECTORIZINGTIME  TIMETIME  TICK
TESTSTATSNTEST  LENYTEST
TESTSTATSNTESTPOS  SUMYTEST
PRINTTEST SET IS DDOCUMENTS  DPOSITIVE  LENYTEST SUMYTEST
52 EXAMPLES BASED ON REAL WORLD DATASETS 767
```

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DEFPROGRESSCLSNAME STATS
REPORT PROGRESS INFORMATION RETURN A STRING
DURATION TIMETIME STATST0
S 20SCLASSIFIER T CLSNAME
S NTRAIN6D TRAIN DOCS NTRAINPOS6D POSITIVE   STATS
S NTEST6D TEST DOCS NTESTPOS6D POSITIVE   TESTSTATS
S ACCURACY ACCURACY3F   STATS
S IN 2FS 5DDOCSS DURATION STATSNTRAIN DURATION
RETURNS
CLSSTATS
FORCLSNAME INPARTIALFITCLASSIFIERS
STATS NTRAIN 0 NTRAINPOS 0
ACCURACY 00 ACCURACYHISTORY 0 0 T0 TIMETIME
RUNTIMEHISTORY 0 0 TOTALFITTIME 00
CLSSTATSCLSNAME STATS
GETMINIBATCHDATASTREAM NTESTDOCUMENTS
 DISCARD TEST SET
 WE WILL FEED THE CLASSIFIER WITH MINIBATCHES OF 1000 DOCUMENTS THIS MEANS
 WE HAVE AT MOST 1000 DOCS IN MEMORY AT ANY TIME THE SMALLER THE DOCUMENT
 BATCH THE BIGGER THE RELATIVE OVERHEAD OF THE PARTIAL FIT METHODS
MINIBATCHSIZE 1000
 CREATE THE DATASTREAM THAT PARSES REUTERS SGML FILES AND ITERATES ON
 DOCUMENTS AS A STREAM
MINIBATCHITERATORS ITERMINIBATCHESDATASTREAM MINIBATCHSIZE
TOTALVECTTIME 00
 MAIN LOOP ITERATE ON MINIBATCHES OF EXAMPLES
FORI XTRAINTEXT YTRAIN INENUMERATEMINIBATCHITERATORS
TICK TIMETIME
XTRAIN VECTORIZERTRANSFORMXTRAINTEXT
TOTALVECTTIME TIMETIME TICK
FORCLSNAME CLS INPARTIALFITCLASSIFIERSITEMS
TICK TIMETIME
 UPDATE ESTIMATOR WITH EXAMPLES IN THE CURRENT MINIBATCH
CLSPARTIALFITXTRAIN YTRAIN CLASSESALLCLASSES
 ACCUMULATE TEST ACCURACY STATS
CLSSTATSCLSNAMETOTALFITTIME TIMETIME TICK
CLSSTATSCLSNAMENTRAIN XTRAINSHAPE0
CLSSTATSCLSNAMENTRAINPOS SUMYTRAIN
TICK TIMETIME
CLSSTATSCLSNAMEACCURACY CLSSCOREXTEST YTEST
CLSSTATSCLSNAMEPREDICTIONTIME TIMETIME TICK
ACCHISTORY CLSSTATSCLSNAMEACCURACY
CLSSTATSCLSNAMENTRAIN
CLSSTATSCLSNAMEACCURACYHISTORYAPPENDACCHISTORY
RUNHISTORY CLSSTATSCLSNAMEACCURACY
TOTALVECTTIME CLSSTATSCLSNAMETOTALFITTIME

SCIKITLEARN USER GUIDE RELEASE 0213
CLSSTATSCLSNAMERUNTIMEHISTORYAPPENDRUNHISTORY
IFI 3 0
PRINTPROGRESSCLSNAME CLSSTATSCLSNAME
IFI 3 0
PRINTN
OUT
DOWNLOADING DATASET ONCE AND FOR ALL INTO HOMECIRCLECISCIKITLEARNDATAREUTERS
UNTARRING REUTERS DATASET
DONE
TEST SET IS 966 DOCUMENTS 88 POSITIVE
SGD CLASSIFIER 994 TRAIN DOCS 121 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0907 IN 074S 1342 DOCSS
PERCEPTRON CLASSIFIER 994 TRAIN DOCS 121 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0922 IN 074S 1338 DOCSS
NB MULTINOMIAL CLASSIFIER 994 TRAIN DOCS 121 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0909 IN 075S 1327 DOCSS
PASSIVEAGGRESSIVE CLASSIFIER 994 TRAIN DOCS 121 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0944 IN 075S 1323 DOCSS
SGD CLASSIFIER 3924 TRAIN DOCS 496 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0957 IN 220S 1784 DOCSS
PERCEPTRON CLASSIFIER 3924 TRAIN DOCS 496 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0952 IN 220S 1782 DOCSS
NB MULTINOMIAL CLASSIFIER 3924 TRAIN DOCS 496 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0917 IN 221S 1778 DOCSS
PASSIVEAGGRESSIVE CLASSIFIER 3924 TRAIN DOCS 496 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0967 IN 221S 1776 DOCSS
SGD CLASSIFIER 6836 TRAIN DOCS 793 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0967 IN 382S 1791 DOCSS
PERCEPTRON CLASSIFIER 6836 TRAIN DOCS 793 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0950 IN 382S 1790 DOCSS
NB MULTINOMIAL CLASSIFIER 6836 TRAIN DOCS 793 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0921 IN 382S 1787 DOCSS
PASSIVEAGGRESSIVE CLASSIFIER 6836 TRAIN DOCS 793 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0967 IN 383S 1786 DOCSS
SGD CLASSIFIER 9597 TRAIN DOCS 1139 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0963 IN 539S 1779 DOCSS
PERCEPTRON CLASSIFIER 9597 TRAIN DOCS 1139 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0955 IN 540S 1778 DOCSS
NB MULTINOMIAL CLASSIFIER 9597 TRAIN DOCS 1139 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0930 IN 540S 1776 DOCSS
PASSIVEAGGRESSIVE CLASSIFIER 9597 TRAIN DOCS 1139 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0965 IN 541S 1775 DOCSS
SGD CLASSIFIER 12513 TRAIN DOCS 1558 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0969 IN 702S 1783 DOCSS
PERCEPTRON CLASSIFIER 12513 TRAIN DOCS 1558 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0843 IN 702S 1783 DOCSS
NB MULTINOMIAL CLASSIFIER 12513 TRAIN DOCS 1558 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0936 IN 702S 1781 DOCSS

SCIKITLEARN USER GUIDE RELEASE 0213
PASSIVEAGGRESSIVE CLASSIFIER 12513 TRAIN DOCS 1558 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0965 IN 703S 1781 DOCSS
SGD CLASSIFIER 14935 TRAIN DOCS 1863 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0966 IN 852S 1752 DOCSS
PERCEPTRON CLASSIFIER 14935 TRAIN DOCS 1863 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0958 IN 853S 1751 DOCSS
NB MULTINOMIAL CLASSIFIER 14935 TRAIN DOCS 1863 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0938 IN 853S 1750 DOCSS
PASSIVEAGGRESSIVE CLASSIFIER 14935 TRAIN DOCS 1863 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0955 IN 854S 1749 DOCSS
SGD CLASSIFIER 17417 TRAIN DOCS 2171 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0960 IN 998S 1745 DOCSS
PERCEPTRON CLASSIFIER 17417 TRAIN DOCS 2171 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0964 IN 998S 1744 DOCSS
NB MULTINOMIAL CLASSIFIER 17417 TRAIN DOCS 2171 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0943 IN 999S 1743 DOCSS
PASSIVEAGGRESSIVE CLASSIFIER 17417 TRAIN DOCS 2171 POSITIVE 966
‹→TEST DOCS 88 POSITIVE ACCURACY 0960 IN 999S 1743 DOCSS
PLOT RESULTS
DEFPLOTACCURACYX Y XLEGEND
PLOT ACCURACY AS A FUNCTION OF X
X NPARRAYX
Y NPARRAYY
PLTTITLECLASSIFICATION ACCURACY AS A FUNCTION OF S XLEGEND
PLTXLABEL S XLEGEND
PLTYLABELACCURACY
PLTGRIDTRUE
PLTPLOTX Y
RCPARAMSLEGENDFONTSIZE 10
CLSNAMES LISTSORTEDCLSSTATSKEYS
 PLOT ACCURACY EVOLUTION
PLTFIGURE
FOR STATS INSORTEDCLSSTATSITEMS
 PLOT ACCURACY EVOLUTION WITH EXAMPLES
ACCURACY NEXAMPLES ZIP STATSACCURACYHISTORY
PLOTACCURACYNEXAMPLES ACCURACY TRAINING EXAMPLES
AX PLTGCA
AXSETYLIM08 1
PLTLEGENDCLSNAMES LOCBEST
PLTFIGURE
FOR STATS INSORTEDCLSSTATSITEMS
 PLOT ACCURACY EVOLUTION WITH RUNTIME
ACCURACY RUNTIME ZIP STATSRUNTIMEHISTORY
PLOTACCURACYRUNTIME ACCURACY RUNTIME S
AX PLTGCA
AXSETYLIM08 1

SCIKITLEARN USER GUIDE RELEASE 0213
PLTLEGENDCLSNAMES LOCBEST
 PLOT FITTING TIMES
PLTFIGURE
FIG PLTGCF
CLSRUNTIME STATSTOTALFITTIME
FORCLSNAME STATS INSORTEDCLSSTATSITEMS
CLSRUNTIMEAPPENDTOTALVECTTIME
CLSNAMESAPPENDVECTORIZATION
BARCOLORS B G R C M Y
AX PLTSUBPLOT111
RECTANGLES PLTBARRANGELENCLSNAMES CLSRUNTIME WIDTH05
COLORBARCOLORS
AXSETXTICKSNPLINSPACE0 LENCLSNAMES 1 LENCLSNAMES
AXSETXTICKLABELSCLSNAMES FONTSIZE10
YMAX MAXCLSRUNTIME 12
AXSETYLIM0 YMAX
AXSETYLABELRUNTIME S
AXSETTITLETRAINING TIMES
DEFAUTOLABELRECTANGLES
ATTACH SOME TEXT VI AUTOLABEL ON RECTANGLES
FORRECTINRECTANGLES
HEIGHT RECTGETHEIGHT
AXTEXTRECTGETX RECTGETWIDTH 2
105HEIGHT 4F HEIGHT
HACENTER VABOTTOM
PLTSETPPLTXTICKS1 ROTATION30
AUTOLABELRECTANGLES
PLTTIGHTLAYOUT
PLTSHOW
 PLOT PREDICTION TIMES
PLTFIGURE
CLSRUNTIME
CLSNAMES LISTSORTEDCLSSTATSKEYS
FORCLSNAME STATS INSORTEDCLSSTATSITEMS
CLSRUNTIMEAPPENDSTATSPREDICTIONTIME
CLSRUNTIMEAPPENDPARSINGTIME
CLSNAMESAPPENDREADPARSE NFEATEXTR
CLSRUNTIMEAPPENDVECTORIZINGTIME
CLSNAMESAPPENDHASHING NVECT
AX PLTSUBPLOT111
RECTANGLES PLTBARRANGELENCLSNAMES CLSRUNTIME WIDTH05
COLORBARCOLORS
AXSETXTICKSNPLINSPACE0 LENCLSNAMES 1 LENCLSNAMES
AXSETXTICKLABELSCLSNAMES FONTSIZE8
PLTSETPPLTXTICKS1 ROTATION30
YMAX MAXCLSRUNTIME 12
AXSETYLIM0 YMAX

SCIKITLEARN USER GUIDE RELEASE 0213
AXSETYLABELRUNTIME S
AXSETTITLEPREDICTION TIMES DINSTANCES NTESTDOCUMENTS
AUTOLABELRECTANGLES
PLTTIGHTLAYOUT
PLTSHOW
•

•

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 12190 SECONDS

53 BICLUSTERING

EXAMPLES CONCERNING THE SKLEARNCLUSTERBICLUSTER MODULE

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

531 A DEMO OF THE SPECTRAL COCLUSTERING ALGORITHM

THIS EXAMPLE DEMONSTRATES HOW TO GENERATE A DATASET AND BICLUSTER IT USING THE SPECTRAL COCLUSTERING ALGORITHM

THE DATASET IS GENERATED USING THE MAKEBICLUSTERS FUNCTION WHICH CREATES A MATRIX OF SMALL VALUES AND IM

PLANTS BICLUSTER WITH LARGE VALUES THE ROWS AND COLUMNS ARE THEN SHUFFLED AND PASSED TO THE SPECTRAL COCLUSTERING ALGORITHM REARRANGING THE SHUFFLED MATRIX TO MAKE BICLUSTERS CONTIGUOUS SHOWS HOW ACCURATELY THE ALGORITHM FOUND THE BICLUSTERS

•

•
OUT
CONSENSUS SCORE 1000
PRINTDOC
 AUTHOR KEMAL EREN KEMALKEMALERENCOM
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM SKLEARNDATASETS IMPORT MAKEBICLUSTERS
FROM SKLEARNDATASETS IMPORT SAMPLESGENERATOR ASSG
FROM SKLEARNCLUSTERBICLUSTER IMPORT SPECTRALCOCLUSTERING
FROM SKLEARNMETRICS IMPORT CONSENSUSSCORE
DATA ROWS COLUMNS MAKEBICLUSTERS
SHAPE300 300 NCLUSTERS5 NOISE5
SHUFFLEFALSE RANDOMSTATE0

SCIKITLEARN USER GUIDE RELEASE 0213
PLTMATSHOWDATA CMAPPLTCMBLUES
PLTTITLEORIGINAL DATASET
DATA ROWIDX COLIDX SGSHUFFLEDATA RANDOMSTATE0
PLTMATSHOWDATA CMAPPLTCMBLUES
PLTTITLESHUFFLED DATASET
MODEL SPECTRALCOCLUSTERINGNCLUSTERS5 RANDOMSTATE0
MODELFITDATA
SCORE CONSENSUSSCOREMODELBICLUSTERS
ROWS ROWIDX COLUMNS COLIDX
PRINTCONSENSUS SCORE 3FFORMATSCORE
FITDATA DATANPARGSORTMODELROWLABELS
FITDATA FITDATA NPARGSORTMODELCOLUMNLABELS
PLTMATSHOWFITDATA CMAPPLTCMBLUES
PLTTITLEAFTER BICLUSTERING REARRANGED TO SHOW BICLUSTERS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0061 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
532 A DEMO OF THE SPECTRAL BICLUSTERING ALGORITHM
THIS EXAMPLE DEMONSTRATES HOW TO GENERATE A CHECKERBOARD DATASET AND BICLUSTER IT USING THE SPECTRAL BICLUSTERING ALGORITHM
THE DATA IS GENERATED WITH THE MAKECHECKERBOARD FUNCTION THEN SHUFFLED AND PASSED TO THE SPECTRAL BICLUSTERING ALGORITHM THE ROWS AND COLUMNS OF THE SHUFFLED MATRIX ARE REARRANGED TO SHOW THE BICLUSTERS FOUND BY THE ALGORITHM
THE OUTER PRODUCT OF THE ROW AND COLUMN LABEL VECTORS SHOWS A REPRESENTATION OF THE CHECKERBOARD STRUCTURE

SCIKITLEARN USER GUIDE RELEASE 0213
•
OUT
CONSENSUS SCORE 10
PRINTDOC
 AUTHOR KEMAL EREN KEMALKEMALERENCOM
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM SKLEARNDATASETS IMPORT MAKECHECKERBOARD
FROM SKLEARNDATASETS IMPORT SAMPLESGENERATOR ASSG
FROM SKLEARNCLUSTERBICLUSTER IMPORT SPECTRALBICLUSTERING
FROM SKLEARNMETRICS IMPORT CONSENSUSSCORE
NCLUSTERS 4 3
DATA ROWS COLUMNS MAKECHECKERBOARD
SHAPE300 300 NCLUSTERSNCLUSTERS NOISE10
SHUFFLEFALSE RANDOMSTATE0
53 BICLUSTERING 783

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PLTMATSHOWDATA CMAPPLTCMBLUES
PLTTITLEORIGINAL DATASET
DATA ROWIDX COLIDX SGSHUFFLEDATA RANDOMSTATE0
PLTMATSHOWDATA CMAPPLTCMBLUES
PLTTITLESHUFFLED DATASET
MODEL SPECTRALBICLUSTERINGNCLUSTERSNCLUSTERS METHODLOG
RANDOMSTATE0
MODELFITDATA
SCORE CONSENSUSSCOREMODELBICLUSTERS
ROWS ROWIDX COLUMNS COLIDX
PRINTCONSENSUS SCORE 1FFORMATSCORE
FITDATA DATANPARGSORTMODELROWLABELS
FITDATA FITDATA NPARGSORTMODELCOLUMNLABELS
PLTMATSHOWFITDATA CMAPPLTCMBLUES
PLTTITLEAFTER BICLUSTERING REARRANGED TO SHOW BICLUSTERS
PLTMATSHOWNPOUTERNPSORTMODELROWLABELS 1
NPSORTMODELCOLUMNLABELS 1
CMAPPLTCMBLUES
PLTTITLECHECKERBOARD STRUCTURE OF REARRANGED DATA
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0447 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
533 BICLUSTERING DOCUMENTS WITH THE SPECTRAL COCLUSTERING ALGORITHM
THIS EXAMPLE DEMONSTRATES THE SPECTRAL COCLUSTERING ALGORITHM ON THE TWENTY NEWSGROUPS DATASET THE ‘COMPOSMS WINDOWSMISC’ CATEGORY IS EXCLUDED BECAUSE IT CONTAINS MANY POSTS CONTAINING NOTHING BUT DATA
THE TFIDF VECTORIZED POSTS FORM A WORD FREQUENCY MATRIX WHICH IS THEN BICLUSTERED USING DHILLON’S SPECTRAL CO CLUSTERING ALGORITHM THE RESULTING DOCUMENTWORD BICLUSTERS INDICATE SUBSETS WORDS USED MORE OFTEN IN THOSE SUBSETS DOCUMENTS
FOR A FEW OF THE BEST BICLUSTERS ITS MOST COMMON DOCUMENT CATEGORIES AND ITS TEN MOST IMPORTANT WORDS GET PRINTED THE BEST BICLUSTERS ARE DETERMINED BY THEIR NORMALIZED CUT THE BEST WORDS ARE DETERMINED BY COMPARING THEIR SUMS INSIDE AND OUTSIDE THE BICLUSTER
FOR COMPARISON THE DOCUMENTS ARE ALSO CLUSTERED USING MINIBATCHKMEANS THE DOCUMENT CLUSTERS DERIVED FROM THE BICLUSTERS ACHIEVE A BETTER VMEASURE THAN CLUSTERS FOUND BY MINIBATCHKMEANS
OUT
VECTORIZING
COCLUSTERING
DONE IN 410S VMEASURE 04435
MINIBATCHKMEANS
DONE IN 636S VMEASURE 03344

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BEST BICLUSTERS

BICLUSTER 0 1957 DOCUMENTS 4363 WORDS
CATEGORIES 23 TALKPOLITICSGUNS 18 TALKPOLITICSMISC 17 SCIMED
WORDS GUN GUNS GEB BANKS GORDON CLINTON PITT CDT SURRENDER VEAL
BICLUSTER 1 1263 DOCUMENTS 3551 WORDS
CATEGORIES 27 SOCRELIGIONCHRISTIAN 25 TALKPOLITICSMIDEAST 24 ALTATHEISM
WORDS GOD JESUS CHRISTIANS SIN OBJECTIVE KENT BELIEF CHRIST FAITH
‹→MORAL
BICLUSTER 2 2212 DOCUMENTS 2774 WORDS
CATEGORIES 18 COMPSYSMACHARDWARE 17 COMPSYSIBMPCHARDWARE 15 COMP
‹→GRAPHICS
WORDS VOLTAGE BOARD DSP STEREO RECEIVER PACKAGES SHIPPING CIRCUIT
‹→PACKAGE COMPRESSION
BICLUSTER 3 1774 DOCUMENTS 2629 WORDS
CATEGORIES 27 RECMOTORCYCLES 23 RECAUTOS 13 MISCFORSALE
WORDS BIKE CAR DOD ENGINE MOTORCYCLE RIDE HONDA BIKES HELMET BMW
BICLUSTER 4 200 DOCUMENTS 1167 WORDS
CATEGORIES 81 TALKPOLITICSMIDEAST 10 ALTATHEISM 8 SOCRELIGIONCHRISTIAN
WORDS TURKISH ARMENIA ARMENIAN ARMENIANS TURKS PETCH SERA ZUMA ARGIC
‹→GVG47
FROM COLLECTIONS IMPORT DEFAULTDICT
IMPORT OPERATOR
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
FROM SKLEARNCLUSTERBICLUSTER IMPORT SPECTRALCOCLUSTERING
FROM SKLEARNCLUSTER IMPORT MINIBATCHKMEANS
FROM SKLEARNDATASETSTWENTYNEWSGROUPS IMPORT FETCH20NEWSGROUPS
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFVECTORIZER
FROM SKLEARNMETRICSCLUSTER IMPORT VMEASURESCORE
PRINTDOC
DEFNUMBERNORMALIZERTOKENS
 MAP ALL NUMERIC TOKENS TO A PLACEHOLDER
FOR MANY APPLICATIONS TOKENS THAT BEGIN WITH A NUMBER ARE NOT DIRECTLY
USEFUL BUT THE FACT THAT SUCH A TOKEN EXISTS CAN BE RELEVANT BY APPLYING
THIS FORM OF DIMENSIONALITY REDUCTION SOME METHODS MAY PERFORM BETTER

RETURNNUMBER IFTOKEN0ISDIGIT ELSETOKENFORTOKENINTOKENS
CLASS NUMBERNORMALIZINGVECTORIZER TFIDFVECTORIZER

```
SCIKITLEARN USER GUIDE RELEASE 0213
DEFBUILDTOKENIZERSELF
TOKENIZE  SUPERBUILDTOKENIZER
RETURN LAMBDA DOC LISTNUMBERNORMALIZERTOKENIZEDOC
 EXCLUDE COMPOSMSWINDOWSMISC
CATEGORIES  ALTATHEISM COMPGRAPHICS
COMPSYSIBMPCHARDWARE COMPSYSMACHARDWARE
COMPWINDOWSX MISCFORSALE RECAUTOS
RECMOTORCYCLES RECSPORTBASEBALL
RECSPORTHOCKEY SCICRYPT SCIELECTRONICS
SCIMED SCISPACE SOCRELIGIONCHRISTIAN
TALKPOLITICSGUNS TALKPOLITICSMIDEAST
TALKPOLITICSMISC TALKRELIGIONMISC
NEWSGROUPS  FETCH20NEWSGROUPSCATEGORIESCATEGORIES
YTRUE  NEWSGROUPSTARGET
VECTORIZER  NUMBERNORMALIZINGVECTORIZERSTOPWORDSENGLISH MINDF5
COCLUSTER  SPECTRALCOCLUSTERINGNCLUSTERSLENCATEGORIES
SVDMETHODARPACK RANDOMSTATE0
KMEANS  MINIBATCHKMEANSNCLUSTERSLENCATEGORIES BATCHSIZE20000
RANDOMSTATE0
PRINTVECTORIZING
X  VECTORIZERFITTRANSFORMNEWSGROUPSDATA
PRINTCOCLUSTERING
STARTTIME  TIME
COCLUSTERFITX
YCOCLUSTER  COCLUSTERROWLABELS
PRINTDONE IN 2FS VMEASURE 4FFORMAT
TIME  STARTTIME
VMEASURESCOREYCOCLUSTER YTRUE
PRINTMINIBATCHKMEANS
STARTTIME  TIME
YKMEANS  KMEANSFITPREDICTX
PRINTDONE IN 2FS VMEASURE 4FFORMAT
TIME  STARTTIME
VMEASURESCOREYKMEANS YTRUE
FEATURENAMES  VECTORIZERGETFEATURENAMES
DOCUMENTNAMES  LISTNEWSGROUPSTARGETNAMESI FORIINNEWSGROUPSTARGET
DEFBICLUSTERNCUTI
ROWS COLS  COCLUSTERGETINDICESI
IF NOTNPANYROWS ANDNPANYCOLS
IMPORT SYS
RETURNSYSFLOATINFOMAX
ROWCOMPLEMENT  NPNONZERONPLOGICALNOTCOCLUSTERROWSI0
COLCOMPLEMENT  NPNONZERONPLOGICALNOTCOCLUSTERCOLUMNSI0
 NOTE THE FOLLOWING IS IDENTICAL TO XROWS NPNEWAXIS
 COLSSUM BUT MUCH FASTER IN SCIPY  016
WEIGHT  XROWS COLSSUM
CUT  XROWCOMPLEMENT COLSSUM
XROWS COLCOMPLEMENTSUM
RETURNCUT  WEIGHT
```

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DEFMOSTCOMMOND
ITEMS OF A DEFAULTDICTINT WITH THE HIGHEST VALUES
LIKE COUNTERMOSTCOMMON IN PYTHON 27

RETURNSORTEDDITEMS KEYOPERATORITEMGETTER1 REVERSETRUE
BICLUSTERNCUTS LISTBICLUSTERNCUTI
FORIINRANGELENNEWSGROUPSTARGETNAMES
BESTIDX NPARGSORTBICLUSTERNCUTS5
PRINT
PRINTBEST BICLUSTERS
PRINT
FORIDX CLUSTER INENUMERATEBESTIDX
NROWS NCOLS COCLUSTERGETSHAPECLUSTER
CLUSTERDOCS CLUSTERWORDS COCLUSTERGETINDICESCLUSTER
IF NOTLENCLUSTERDOCS OR NOTLENCLUSTERWORDS
CONTINUE
 CATEGORIES
COUNTER DEFAULTDICTINT
FORIINCLUSTERDOCS
COUNTERDOCUMENTNAMESI 1
CATSTRING   JOIN0F FORMATFLOATC NROWS 100 NAME
FORNAME C INMOSTCOMMONCOUNTER3
 WORDS
OUTOFCLUSTERDOCS COCLUSTERROWLABELS CLUSTER
OUTOFCLUSTERDOCS NPWHEREOUTOFCLUSTERDOCS0
WORDCOL X CLUSTERWORDS
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WORDSCORES WORDSCORESRAVEL
IMPORTANTWORDS LISTFEATURENAMESCLUSTERWORDSI
FORIINWORDSCORESARGSORT111
PRINTBICLUSTER   DOCUMENTS WORDSFORMAT
IDX NROWS NCOLS
PRINTCATEGORIES FORMATCATSTRING
PRINTWORDS   NFORMAT JOINIMPORTANTWORDS
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 13291 SECONDS
54 CALIBRATION
EXAMPLES ILLUSTRATING THE CALIBRATION OF PREDICTED PROBABILITIES OF CLASSIFIERS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
54 CALIBRATION 787

541 COMPARISON OF CALIBRATION OF CLASSIFIERS

WELL CALIBRATED CLASSIFIERS ARE PROBABILISTIC CLASSIFIERS FOR WHICH THE OUTPUT OF THE PREDICTPROBA METHOD CAN BE DIRECTLY INTERPRETED AS A CONFIDENCE LEVEL FOR INSTANCE A WELL CALIBRATED BINARY CLASSIFIER SHOULD CLASSIFY THE SAMPLES SUCH THAT AMONG THE SAMPLES TO WHICH IT GAVE A PREDICTPROBA VALUE CLOSE TO 08 APPROX 80 ACTUALLY BELONG TO THE POSITIVE CLASS

LOGISTICREGRESSION RETURNS WELL CALIBRATED PREDICTIONS AS IT DIRECTLY OPTIMIZES LOGLOSS IN CONTRAST THE OTHER METHODS RETURN BIASED PROBABILITIES WITH DIFFERENT BIASES PER METHOD

- GAUSSIANNAIVEBAYES TENDS TO PUSH PROBABILITIES TO 0 OR 1 NOTE THE COUNTS IN THE HISTOGRAMS THIS IS MAINLY BECAUSE IT MAKES THE ASSUMPTION THAT FEATURES ARE CONDITIONALLY INDEPENDENT GIVEN THE CLASS WHICH IS NOT THE CASE IN THIS DATASET WHICH CONTAINS 2 REDUNDANT FEATURES
- RANDOMFORESTCLASSIFIER SHOWS THE OPPOSITE BEHAVIOR THE HISTOGRAMS SHOW PEAKS AT APPROX 02 AND 09 PROBABILITY WHILE PROBABILITIES CLOSE TO 0 OR 1 ARE VERY RARE AN EXPLANATION FOR THIS IS GIVEN BY NICULESCUMIZIL AND CARUANA1 “METHODS SUCH AS BAGGING AND RANDOM FORESTS THAT AVERAGE PREDICTIONS FROM A BASE SET OF MODELS CAN HAVE DIFFICULTY MAKING PREDICTIONS NEAR 0 AND 1 BECAUSE VARIANCE IN THE UNDERLYING BASE MODELS WILL BIAS PREDICTIONS THAT SHOULD BE NEAR ZERO OR ONE AWAY FROM THESE VALUES BECAUSE PREDICTIONS ARE RESTRICTED TO THE INTERVAL 01 ERRORS CAUSED BY VARIANCE TEND TO BE ONE SIDED NEAR ZERO AND ONE FOR EXAMPLE IF A MODEL SHOULD PREDICT P 0 FOR A CASE THE ONLY WAY BAGGING CAN ACHIEVE THIS IS IF ALL BAGGED TREES PREDICT ZERO IF WE ADD NOISE TO THE TREES THAT BAGGING IS AVERAGING OVER THIS NOISE WILL CAUSE SOME TREES TO PREDICT VALUES LARGER THAN 0 FOR THIS CASE THUS MOVING THE AVERAGE PREDICTION OF THE BAGGED ENSEMBLE AWAY FROM 0 WE OBSERVE THIS EFFECT MOST STRONGLY WITH RANDOM FORESTS BECAUSE THE BASELEVEL TREES TRAINED WITH RANDOM FORESTS HAVE RELATIVELY HIGH VARIANCE DUE TO FEATURE SUBSETTING” AS A RESULT THE CALIBRATION CURVE SHOWS A CHARACTERISTIC SIGMOID SHAPE INDICATING THAT THE CLASSIFIER COULD TRUST ITS “INTUITION” MORE AND RETURN PROBABILITIES CLOSER TO 0 OR 1 TYPICALLY
- SUPPORT VECTOR CLASSIFICATION SVC SHOWS AN EVEN MORE SIGMOID CURVE AS THE RANDOMFORESTCLASSIFIER WHICH IS TYPICAL FOR MAXIMUMMARGIN METHODS COMPARE NICULESCUMIZIL AND CARUANA1 WHICH FOCUS ON HARD SAMPLES THAT ARE CLOSE TO THE DECISION BOUNDARY THE SUPPORT VECTORS

REFERENCES

1PREDICTING GOOD PROBABILITIES WITH SUPERVISED LEARNING A NICULESCUMIZIL R CARUANA ICML 2005

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
 AUTHOR JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDE
 LICENSE BSD STYLE
IMPORT NUMPY AS NP
NPRANDOMSEED0
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
FROM SKLEARNSVM IMPORT LINEARSVC
54 CALIBRATION 789

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FROM SKLEARNCALIBRATION IMPORT CALIBRATIONCURVE
X Y DATASETSMAKECLASSIFICATIONNSAMPLES100000 NFEATURES20
NINFORMATIVE2 NREDUNDANT2
TRAINSAMPLES 100 SAMPLES USED FOR TRAINING THE MODELS
XTRAIN XTRAINSAMPLES
XTEST XTRAINSAMPLES
YTRAIN YTRAINSAMPLES
YTEST YTRAINSAMPLES
 CREATE CLASSIFIERS
LR LOGISTICREGRESSIONSOLVERLBFGS
GNB GAUSSIANNB
SVC LINEARSVCC10
RFC RANDOMFORESTCLASSIFIERNESTIMATORS100

 PLOT CALIBRATION PLOTS
PLTFIGUREFIGSIZE10 10
AX1 PLTSUBPLOT2GRID3 1 0 0 ROWSPAN2
AX2 PLTSUBPLOT2GRID3 1 2 0
AX1PLOT0 1 0 1 K LABELPERFECTLY CALIBRATED
FORCLF NAME INLR LOGISTIC
GNB NAIVE BAYES
SVC SUPPORT VECTOR CLASSIFICATION
RFC RANDOM FOREST
CLFFITXTRAIN YTRAIN
IFHASATTRCLF PREDICTPROBA
PROBPOS CLFPREDICTPROBAXTEST 1
ELSE USE DECISION FUNCTION
PROBPOS CLFDECISIONFUNCTIONXTEST
PROBPOS
PROBPOS PROBPOSMIN PROBPOSMAX PROBPOSMIN
FRACTIONOFPOSITIVES MEANPREDICTEDVALUE
CALIBRATIONCURVEYTEST PROBPOS NBINS10
AX1PLOTMEANPREDICTEDVALUE FRACTIONOFPOSITIVES S
LABELS NAME
AX2HISTPROBPOS RANGE0 1 BINS10 LABELNAME
HISTTYPESTEP LW2
AX1SETYLABELFRACTION OF POSITIVES
AX1SETYLIM005 105
AX1LEGENDLOCLOWER RIGHT
AX1SETTITLECALIBRATION PLOTS RELIABILITY CURVE
AX2SETXLABELMEAN PREDICTED VALUE
AX2SETYLABELCOUNT
AX2LEGENDLOCUPPER CENTER NCOL2
PLTTIGHTLAYOUT
PLTSHOW

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TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1028 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
542 PROBABILITY CALIBRATION CURVES
WHEN PERFORMING CLASSIFICATION ONE OFTEN WANTS TO PREDICT NOT ONLY THE CLASS LABEL BUT ALSO THE ASSOCIATED PROBABILITY THIS PROBABILITY GIVES SOME KIND OF CONFIDENCE ON THE PREDICTION THIS EXAMPLE DEMONSTRATES HOW TO DISPLAY HOW WELL CALIBRATED THE PREDICTED PROBABILITIES ARE AND HOW TO CALIBRATE AN UNCALIBRATED CLASSIFIER
THE EXPERIMENT IS PERFORMED ON AN ARTIFICIAL DATASET FOR BINARY CLASSIFICATION WITH 100000 SAMPLES 1000 OF THEM ARE USED FOR MODEL FITTING WITH 20 FEATURES OF THE 20 FEATURES ONLY 2 ARE INFORMATIVE AND 10 ARE REDUNDANT THE FIRST FIGURE SHOWS THE ESTIMATED PROBABILITIES OBTAINED WITH LOGISTIC REGRESSION GAUSSIAN NAIVE BAYES AND GAUSSIAN NAIVE BAYES WITH BOTH ISOTONIC CALIBRATION AND SIGMOID CALIBRATION THE CALIBRATION PERFORMANCE IS EVALUATED WITH BRIER SCORE REPORTED IN THE LEGEND THE SMALLER THE BETTER ONE CAN OBSERVE HERE THAT LOGISTIC REGRESSION IS WELL CALIBRATED WHILE RAW GAUSSIAN NAIVE BAYES PERFORMS VERY BADLY THIS IS BECAUSE OF THE REDUNDANT FEATURES WHICH VIOLATE THE ASSUMPTION OF FEATUREINDEPENDENCE AND RESULT IN AN OVERLY CONFIDENT CLASSIFIER WHICH IS INDICATED BY THE TYPICAL TRANSPOSEDSIGMOID CURVE
CALIBRATION OF THE PROBABILITIES OF GAUSSIAN NAIVE BAYES WITH ISOTONIC REGRESSION CAN FIX THIS ISSUE AS CAN BE SEEN FROM THE NEARLY DIAGONAL CALIBRATION CURVE SIGMOID CALIBRATION ALSO IMPROVES THE BRIER SCORE SLIGHTLY ALBEIT NOT AS STRONGLY AS THE NONPARAMETRIC ISOTONIC REGRESSION THIS CAN BE ATTRIBUTED TO THE FACT THAT WE HAVE PLENTY OF CALIBRATION DATA SUCH THAT THE GREATER FLEXIBILITY OF THE NONPARAMETRIC MODEL CAN BE EXPLOITED
THE SECOND FIGURE SHOWS THE CALIBRATION CURVE OF A LINEAR SUPPORTVECTOR CLASSIFIER LINEARSVC LINEARSVC SHOWS THE OPPOSITE BEHAVIOR AS GAUSSIAN NAIVE BAYES THE CALIBRATION CURVE HAS A SIGMOID CURVE WHICH IS TYPICAL FOR AN UNDERCONFIDENT CLASSIFIER IN THE CASE OF LINEARSVC THIS IS CAUSED BY THE MARGIN PROPERTY OF THE HINGE LOSS WHICH LETS THE MODEL FOCUS ON HARD SAMPLES THAT ARE CLOSE TO THE DECISION BOUNDARY THE SUPPORT VECTORS
BOTH KINDS OF CALIBRATION CAN FIX THIS ISSUE AND YIELD NEARLY IDENTICAL RESULTS THIS SHOWS THAT SIGMOID CALIBRATION CAN DEAL WITH SITUATIONS WHERE THE CALIBRATION CURVE OF THE BASE CLASSIFIER IS SIGMOID EG FOR LINEARSVC BUT NOT WHERE IT IS TRANSPOSEDSIGMOID EG GAUSSIAN NAIVE BAYES
54 CALIBRATION 791

•
OUT
LOGISTIC
BRIER 0099
PRECISION 0872
RECALL 0851
F1 0862
NAIVE BAYES
BRIER 0118
PRECISION 0857
RECALL 0876
F1 0867
NAIVE BAYES ISOTONIC
BRIER 0098
PRECISION 0883

RECALL 0836
F1 0859
NAIVE BAYES SIGMOID
BRIER 0109
PRECISION 0861
RECALL 0871
F1 0866
LOGISTIC
BRIER 0099
PRECISION 0872
RECALL 0851
F1 0862
SVC
BRIER 0163
PRECISION 0872
RECALL 0852
F1 0862
SVC ISOTONIC
BRIER 0100
PRECISION 0853
RECALL 0878
F1 0865
SVC SIGMOID
BRIER 0099
PRECISION 0874
RECALL 0849
F1 0861
PRINTDOC
 AUTHOR ALEXANDRE GRAMFORT ALEXANDREGRAMFORTTELECOMPARISTECHFR
 JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDE
 LICENSE BSD STYLE
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
FROM SKLEARNSVM IMPORT LINEARSVC
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARNMETRICS IMPORT BRIERSCORELOSS PRECISIONSCORE RECALLSCORE
F1SCORE
FROM SKLEARNCALIBRATION IMPORT CALIBRATEDCLASSIFIERCV CALIBRATIONCURVE
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
 CREATE DATASET OF CLASSIFICATION TASK WITH MANY REDUNDANT AND FEW
 INFORMATIVE FEATURES

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X Y DATASETSMAKECLASSIFICATIONNSAMPLES100000 NFEATURES20
NINFORMATIVE2 NREDUNDANT10
RANDOMSTATE42
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y TESTSIZE099
RANDOMSTATE42
DEFPLOTCALIBRATIONCURVEEST NAME FIGINDEX
PLOT CALIBRATION CURVE FOR EST WO AND WITH CALIBRATION
 CALIBRATED WITH ISOTONIC CALIBRATION
ISOTONIC CALIBRATEDCLASSIFIERCVEST CV2 METHODISOTONIC
 CALIBRATED WITH SIGMOID CALIBRATION
SIGMOID CALIBRATEDCLASSIFIERCVEST CV2 METHODSIGMOID
 LOGISTIC REGRESSION WITH NO CALIBRATION AS BASELINE
LR LOGISTICREGRESSIONC1 SOLVERLBFGS
FIG PLTFIGUREFIGINDEX FIGSIZE10 10
AX1 PLTSUBPLOT2GRID3 1 0 0 ROWSPAN2
AX2 PLTSUBPLOT2GRID3 1 2 0
AX1PLOT0 1 0 1 K LABELPERFECTLY CALIBRATED
FORCLF NAME INLR LOGISTIC
EST NAME
ISOTONIC NAME   ISOTONIC
SIGMOID NAME   SIGMOID
CLFFITXTRAIN YTRAIN
YPRED CLFPREDICTXTEST
IFHASATTRCLF PREDICTPROBA
PROBPOS CLFPREDICTPROBAXTEST 1
ELSE USE DECISION FUNCTION
PROBPOS CLFDECISIONFUNCTIONXTEST
PROBPOS
PROBPOS PROBPOSMIN PROBPOSMAX PROBPOSMIN
CLFSCORE BRIERSCORELOSSYTEST PROBPOS POSLABELYMAX
PRINTS NAME
PRINTTBRIER13F CLFSCORE
PRINTTPRECISION 13F PRECISIONSCOREYTEST YPRED
PRINTTRECALL 13F RECALLSCOREYTEST YPRED
PRINTTF113FN F1SCOREYTEST YPRED
FRACTIONOFPOSITIVES MEANPREDICTEDVALUE
CALIBRATIONCURVEYTEST PROBPOS NBINS10
AX1PLOTMEANPREDICTEDVALUE FRACTIONOFPOSITIVES S
LABELS13F NAME CLFSCORE
AX2HISTPROBPOS RANGE0 1 BINS10 LABELNAME
HISTTYPESTEP LW2
AX1SETYLABELFRACTION OF POSITIVES
AX1SETYLIM005 105
AX1LEGENDLOCLOWER RIGHT
AX1SETTITLECALIBRATION PLOTS RELIABILITY CURVE

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AX2SETXLABELMEAN PREDICTED VALUE
AX2SETYLABELCOUNT
AX2LEGENDLOCUPPER CENTER NCOL2
PLTTIGHTLAYOUT
PLOT CALIBRATION CURVE FOR GAUSSIAN NAIVE BAYES
PLOTCALIBRATIONCURVEGAUSSIANNB NAIVE BAYES 1
PLOT CALIBRATION CURVE FOR LINEAR SVC
PLOTCALIBRATIONCURVELINEARSVCMAXITER10000 SVC 2
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1993 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
543 PROBABILITY CALIBRATION OF CLASSIFIERS
WHEN PERFORMING CLASSIFICATION YOU OFTEN WANT TO PREDICT NOT ONLY THE CLASS LABEL BUT ALSO THE ASSOCIATED PROBABILITY THIS PROBABILITY GIVES YOU SOME KIND OF CONFIDENCE ON THE PREDICTION HOWEVER NOT ALL CLASSIFIERS PROVIDE WELL CALIBRATED PROBABILITIES SOME BEING OVERCONFIDENT WHILE OTHERS BEING UNDERCONFIDENT THUS A SEPARATE CALIBRATION OF PREDICTED PROBABILITIES IS OFTEN DESIRABLE AS A POSTPROCESSING THIS EXAMPLE ILLUSTRATES TWO DIFFERENT METHODS FOR THIS CALIBRATION AND EVALUATES THE QUALITY OF THE RETURNED PROBABILITIES USING BRIER'S SCORE SEE HTTPSENWIKIPEDIAORG WIKIBRIERSCORE
COMPARED ARE THE ESTIMATED PROBABILITY USING A GAUSSIAN NAIVE BAYES CLASSIFIER WITHOUT CALIBRATION WITH A SIGMOID CALIBRATION AND WITH A NONPARAMETRIC ISOTONIC CALIBRATION ONE CAN OBSERVE THAT ONLY THE NONPARAMETRIC MODEL IS ABLE TO PROVIDE A PROBABILITY CALIBRATION THAT RETURNS PROBABILITIES CLOSE TO THE EXPECTED 05 FOR MOST OF THE SAMPLES BELONGING TO THE MIDDLE CLUSTER WITH HETEROGENEOUS LABELS THIS RESULTS IN A SIGNIFICANTLY IMPROVED BRIER SCORE
796 CHAPTER 5 EXAMPLES

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54 CALIBRATION 797

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OUT
BRIER SCORES THE SMALLER THE BETTER
NO CALIBRATION 0104
WITH ISOTONIC CALIBRATION 0084
WITH SIGMOID CALIBRATION 0109
PRINTDOC
 AUTHOR MATHIEU BLONDEL MATHIEUMBLONDELORG
 ALEXANDRE GRAMFORT ALEXANDREGRAMFORTTELECOMPARISTECHFR
 BALAZS KEGL BALAZSKEGLGMAILCOM
 JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDE
 LICENSE BSD STYLE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIB IMPORT CM
FROM SKLEARNDATASETS IMPORT MAKEBLOBS
FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
FROM SKLEARNMETRICS IMPORT BRIERSCORELOSS

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FROM SKLEARNCALIBRATION IMPORT CALIBRATEDCLASSIFIERCV
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
NSAMPLES 50000
NBINS 3 USE 3 BINS FOR CALIBRATIONCURVE AS WE HAVE 3 CLUSTERS HERE
 GENERATE 3 BLOBS WITH 2 CLASSES WHERE THE SECOND BLOB CONTAINS
 HALF POSITIVE SAMPLES AND HALF NEGATIVE SAMPLES PROBABILITY IN THIS
 BLOB IS THEREFORE 05
CENTERS 5 5 0 0 5 5
X Y MAKEBLOBSNSAMPLESNSAMPLES NFEATURES2 CLUSTERSTD10
CENTERSCENTERS SHUFFLEFALSE RANDOMSTATE42
YNSAMPLES 2 0
YNSAMPLES 2 1
SAMPLEWEIGHT NPRANDOMRANDOMSTATE42RANDYSHAPE0
 SPLIT TRAIN TEST FOR CALIBRATION
XTRAIN XTEST YTRAIN YTEST SWTRAIN SWTEST
TRAINTESTSPLITX Y SAMPLEWEIGHT TESTSIZE09 RANDOMSTATE42
 GAUSSIAN NAIVEBAYES WITH NO CALIBRATION
CLF GAUSSIANNB
CLFFITXTRAIN YTRAIN GAUSSIANNB ITSELF DOES NOT SUPPORT SAMPLEWEIGHTS
PROBPOSCLF CLFPREDICTPROBAXTEST 1
 GAUSSIAN NAIVEBAYES WITH ISOTONIC CALIBRATION
CLFISOTONIC CALIBRATEDCLASSIFIERCVCLF CV2 METHODISOTONIC
CLFISOTONICFITXTRAIN YTRAIN SWTRAIN
PROBPOSISOTONIC CLFISOTONICPREDICTPROBAXTEST 1
 GAUSSIAN NAIVEBAYES WITH SIGMOID CALIBRATION
CLFSIGMOID CALIBRATEDCLASSIFIERCVCLF CV2 METHODSIGMOID
CLFSIGMOIDFITXTRAIN YTRAIN SWTRAIN
PROBPOSSIGMOID CLFSIGMOIDPREDICTPROBAXTEST 1
PRINTBRIER SCORES THE SMALLER THE BETTER
CLFSCORE BRIERSCORELOSSYTEST PROBPOSCLF SWTEST
PRINTNO CALIBRATION 13F CLFSCORE
CLFISOTONICSCORE BRIERSCORELOSSYTEST PROBPOSISOTONIC SWTEST
PRINTWITH ISOTONIC CALIBRATION 13F CLFISOTONICSCORE
CLFSIGMOIDSCORE BRIERSCORELOSSYTEST PROBPOSSIGMOID SWTEST
PRINTWITH SIGMOID CALIBRATION 13F CLFSIGMOIDSCORE

 PLOT THE DATA AND THE PREDICTED PROBABILITIES
PLTFIGURE
YUNIQUE NPUNIQUEY
COLORS CMRAINBOWNPLINSPACE00 10 YUNIQUESIZE
FORTHISY COLOR INZIPYUNIQUE COLORS
THISX XTRAINYTRAIN THISY
THISSW SWTRAINYTRAIN THISY
PLTSCATTERTHISX 0 THISX 1 STHISSW 50
CCOLORNPNEWAXIS

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ALPHA05 EDGECOLORK
LABELCLASS S THISY
PLTLEGENDLOCBEST
PLTTITLEDATA
PLTFIGURE
ORDER NPLEXSORTPROBPOSCLF
PLTPLOTPROBPOSCLFORDER R LABELNO CALIBRATION 13F CLFSCORE
PLTPLOTPROBPOSISOTONICORDER G LINEWIDTH3
LABELISOTONIC CALIBRATION 13F CLFISOTONICSCORE
PLTPLOTPROBPOSSIGMOIDORDER B LINEWIDTH3
LABELSIGMOID CALIBRATION 13F CLFSIGMOIDSCORE
PLTPLOTNPLINSPACE0 YTESTSIZE 5112
YTESTORDERRESHAPE25 1MEAN1
K LINEWIDTH3 LABELREMPIRICAL
PLTYLIM005 105
PLTXLABELINSTANCES SORTED ACCORDING TO PREDICTED PROBABILITY
UNCALIBRATED GNB
PLTYLABELPY1
PLTLEGENDLOCUPPER LEFT
PLTTITLEGAUSSIAN NAIVE BAYES PROBABILITIES
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0108 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
544 PROBABILITY CALIBRATION FOR 3CLASS CLASSIFICATION
THIS EXAMPLE ILLUSTRATES HOW SIGMOID CALIBRATION CHANGES PREDICTED PROBABILITIES FOR A 3CLASS CLASSIFICATION PROBLEM ILLUSTRATED IS THE STANDARD 2SIMPLEX WHERE THE THREE CORNERS CORRESPOND TO THE THREE CLASSES ARROWS POINT FROM THE PROBABILITY VECTORS PREDICTED BY AN UNCALIBRATED CLASSIFIER TO THE PROBABILITY VECTORS PREDICTED BY THE SAME CLASSIFIER AFTER SIGMOID CALIBRATION ON A HOLDOUT VALIDATION SET COLORS INDICATE THE TRUE CLASS OF AN INSTANCE RED CLASS 1 GREEN CLASS 2 BLUE CLASS 3
THE BASE CLASSIFIER IS A RANDOM FOREST CLASSIFIER WITH 25 BASE ESTIMATORS TREES IF THIS CLASSIFIER IS TRAINED ON ALL 800 TRAINING DATAPOINTS IT IS OVERLY CONFIDENT IN ITS PREDICTIONS AND THUS INCURS A LARGE LOGLOSS CALIBRATING AN IDENTICAL CLASSIFIER WHICH WAS TRAINED ON 600 DATAPOINTS WITH METHOD’SIGMOID’ ON THE REMAINING 200 DATAPOINTS REDUCES THE CONFIDENCE OF THE PREDICTIONS IE MOVES THE PROBABILITY VECTORS FROM THE EDGES OF THE SIMPLEX TOWARDS THE CENTER THIS CALIBRATION RESULTS IN A LOWER LOGLOSS NOTE THAT AN ALTERNATIVE WOULD HAVE BEEN TO INCREASE THE NUMBER OF BASE ESTIMATORS WHICH WOULD HAVE RESULTED IN A SIMILAR DECREASE IN LOGLOSS

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54 CALIBRATION 801

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OUT
LOGLOSS OF
UNCALIBRATED CLASSIFIER TRAINED ON 800 DATAPOINTS 1280
CLASSIFIER TRAINED ON 600 DATAPOINTS AND CALIBRATED ON 200 DATAPOINT 0534
PRINTDOC
AUTHOR JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDE
LICENSE BSD STYLE
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNDATASETS IMPORT MAKEBLOBS
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
FROM SKLEARNCALIBRATION IMPORT CALIBRATEDCLASSIFIERCV
FROM SKLEARNMETRICS IMPORT LOGLOSS
NPRANDOMSEED0

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 GENERATE DATA
X Y  MAKEBLOBSNSAMPLES1000 NFEATURES2 RANDOMSTATE42
CLUSTERSTD50
XTRAIN YTRAIN  X600 Y600
XVALID YVALID  X600800 Y600800
XTRAINVALID YTRAINVALID  X800 Y800
XTEST YTEST  X800 Y800
 TRAIN UNCALIBRATED RANDOM FOREST CLASSIFIER ON WHOLE TRAIN AND VALIDATION
 DATA AND EVALUATE ON TEST DATA
CLF  RANDOMFORESTCLASSIFIERNESTIMATORS25
CLFFITXTRAINVALID YTRAINVALID
CLFPROBS  CLFPREDICTPROBAXTEST
SCORE  LOGLOSSYTEST CLFPROBS
 TRAIN RANDOM FOREST CLASSIFIER CALIBRATE ON VALIDATION DATA AND EVALUATE
 ON TEST DATA
CLF  RANDOMFORESTCLASSIFIERNESTIMATORS25
CLFFITXTRAIN YTRAIN
CLFPROBS  CLFPREDICTPROBAXTEST
SIGCLF  CALIBRATEDCLASSIFIERCVCLF METHODSIGMOID CVPREFIT
SIGCLFFITXVALID YVALID
SIGCLFPROBS  SIGCLFPREDICTPROBAXTEST
SIGSCORE  LOGLOSSYTEST SIGCLFPROBS
 PLOT CHANGES IN PREDICTED PROBABILITIES VIA ARROWS
PLTFIGURE
COLORS  R G B
FORIINRANGECLFPROBSSHAPE0
PLTARROWCLFPROBSI 0 CLFPROBSI 1
SIGCLFPROBSI 0  CLFPROBSI 0
SIGCLFPROBSI 1  CLFPROBSI 1
COLORCOLORSYTESTI HEADWIDTH1E2
 PLOT PERFECT PREDICTIONS
PLTPLOT10 00 RO MS20 LABELCLASS 1
PLTPLOT00 10 GO MS20 LABELCLASS 2
PLTPLOT00 00 BO MS20 LABELCLASS 3
 PLOT BOUNDARIES OF UNIT SIMPLEX
PLTPLOT00 10 00 00 00 00 10 00 K LABELSIMPLEX
 ANNOTATE POINTS ON THE SIMPLEX
PLTANNOTATERFRAC13 FRAC13 FRAC13
XY103 103 XYTEXT103 23 XYCOORDSDATA
ARROWPROPSDICTFACECOLORBLACK SHRINK005
HORIZONTALALIGNMENTCENTER VERTICALALIGNMENTCENTER
PLTPLOT103 103 KO MS5
PLTANNOTATERFRAC12 0 FRAC12
XY5 0 XYTEXT5 1 XYCOORDSDATA
ARROWPROPSDICTFACECOLORBLACK SHRINK005
HORIZONTALALIGNMENTCENTER VERTICALALIGNMENTCENTER
PLTANNOTATER0 FRAC12 FRAC12
XY0 5 XYTEXT1 5 XYCOORDSDATA
ARROWPROPSDICTFACECOLORBLACK SHRINK005
HORIZONTALALIGNMENTCENTER VERTICALALIGNMENTCENTER
PLTANNOTATERFRAC12 FRAC12 0
54 CALIBRATION 803
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XY5 5 XYTEXT6 6 XYCOORDSDATA
ARROWPROPSDICTFACECOLORBLACK SHRINK005
HORIZONTALALIGNMENTCENTER VERTICALALIGNMENTCENTER
PLTANNOTATER0 0 1
XY0 0 XYTEXT1 1 XYCOORDSDATA
ARROWPROPSDICTFACECOLORBLACK SHRINK005
HORIZONTALALIGNMENTCENTER VERTICALALIGNMENTCENTER
PLTANNOTATER1 0 0
XY1 0 XYTEXT1 1 XYCOORDSDATA
ARROWPROPSDICTFACECOLORBLACK SHRINK005
HORIZONTALALIGNMENTCENTER VERTICALALIGNMENTCENTER
PLTANNOTATER0 1 0
XY0 1 XYTEXT1 1 XYCOORDSDATA
ARROWPROPSDICTFACECOLORBLACK SHRINK005
HORIZONTALALIGNMENTCENTER VERTICALALIGNMENTCENTER
ADD GRID
PLTGRIDFALSE
FORXIN00 01 02 03 04 05 06 07 08 09 10
PLTPLOT0 X X 0 K ALPHA02
PLTPLOT0 0 1X2 X X 1X2 K ALPHA02
PLTPLOTX X 1X2 0 0 1X2 K ALPHA02
PLTTITLECHANGE OF PREDICTED PROBABILITIES AFTER SIGMOID CALIBRATION
PLTXLABELPROBABILITY CLASS 1
PLTYLABELPROBABILITY CLASS 2
PLTXLIM005 105
PLTYLIM005 105
PLTLEGENDLOCBEST
PRINTLOGLOSS OF
PRINTUNCALIBRATED CLASSIFIER TRAINED ON 800 DATAPOINTS 3F
SCORE
PRINTCLASSIFIER TRAINED ON 600 DATAPOINTS AND CALIBRATED ON
200 DATAPOINT 3F SIGSCORE
ILLUSTRATE CALIBRATOR
PLTFIGURE
GENERATE GRID OVER 2SIMPLEX
P1D NPLINSPACE0 1 20
P0 P1 NPMESHGRIDP1D P1D
P2 1 P0 P1
P NPCP0RAVEL P1RAVEL P2RAVEL
P PP 2 0
CALIBRATEDCLASSIFIER SIGCLFCALIBRATEDCLASSIFIERS0
PREDICTION NPVSTACKCALIBRATORPREDICTTHISP
FORCALIBRATOR THISP IN
ZIPCALIBRATEDCLASSIFIERCALIBRATORS PTT
PREDICTION PREDICTIONSUMAXIS1 NONE
PLOT MODIFICATIONS OF CALIBRATOR
FORIIINRANGEPREDICTIONSHAPE0
PLTARROWPI 0 PI 1
PREDICTIONI 0 PI 0 PREDICTIONI 1 PI 1
HEADWIDTH1E2 COLORCOLORSNPARGMAXPI
PLOT BOUNDARIES OF UNIT SIMPLEX
PLTPLOT00 10 00 00 00 00 10 00 K LABELSIMPLEX

SCIKITLEARN USER GUIDE RELEASE 0213
PLTGRIDFALSE
FORXIN00 01 02 03 04 05 06 07 08 09 10
PLTPLOT0 X X 0 K ALPHA02
PLTPLOT0 0 1X2 X X 1X2 K ALPHA02
PLTPLOTX X 1X2 0 0 1X2 K ALPHA02
PLTTITLEILLUSTRATION OF SIGMOID CALIBRATOR
PLTXLABELPROBABILITY CLASS 1
PLTYLABELPROBABILITY CLASS 2
PLTXLIM005 105
PLTYLIM005 105
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0318 SECONDS
55 CLASSIFICATION
GENERAL EXAMPLES ABOUT CLASSIFICATION ALGORITHMS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
551 RECOGNIZING HANDWRITTEN DIGITS
AN EXAMPLE SHOWING HOW THE SCIKITLEARN CAN BE USED TO RECOGNIZE IMAGES OF HANDWRITTEN DIGITS
THIS EXAMPLE IS COMMENTED IN THE TUTORIAL SECTION OF THE USER MANUAL

OUT
CLASSIFICATION REPORT FOR CLASSIFIER SVCGAMMA0001
PRECISION RECALL F1SCORE SUPPORT
0 100 099 099 88
1 099 097 098 91
2 099 099 099 86
3 098 087 092 91
4 099 096 097 92
5 095 097 096 91
6 099 099 099 91
7 096 099 097 89
8 094 100 097 88
9 093 098 095 92
ACCURACY 097 899
MACRO AVG 097 097 097 899
WEIGHTED AVG 097 097 097 899
CONFUSION MATRIX
87 0 0 0 1 0 0 0 0 0
0 88 1 0 0 0 0 0 1 1
0 0 85 1 0 0 0 0 0 0
0 0 0 79 0 3 0 4 5 0

```
SCIKITLEARN USER GUIDE RELEASE 0213
 0 0 0 0 88 0 0 0 0 4
 0 0 0 0 0 88 1 0 0 2
 0 1 0 0 0 0 90 0 0 0
 0 0 0 0 0 1 0 88 0 0
 0 0 0 0 0 0 0 0 88 0
 0 0 0 1 0 1 0 0 0 90
PRINTDOC
 AUTHOR GAEL VAROQUAUX GAEL DOT VAROQUAUX AT NORMALESUP DOT ORG
 LICENSE BSD 3 CLAUSE
 STANDARD SCIENTIFIC PYTHON IMPORTS
IMPORT MATPLOTLIBPYPLOT AS PLT
 IMPORT DATASETS CLASSIFIERS AND PERFORMANCE METRICS
FROM SKLEARN IMPORT DATASETS SVM METRICS
 THE DIGITS DATASET
DIGITS  DATASETSLOADDIGITS
 THE DATA THAT WE ARE INTERESTED IN IS MADE OF 8X8 IMAGES OF DIGITS LETS
 HAVE A LOOK AT THE FIRST 4 IMAGES STORED IN THE IMAGES ATTRIBUTE OF THE
 DATASET IF WE WERE WORKING FROM IMAGE FILES WE COULD LOAD THEM USING
 MATPLOTLIBPYPLOTIMREAD NOTE THAT EACH IMAGE MUST HAVE THE SAME SIZE FOR THESE
 IMAGES WE KNOW WHICH DIGIT THEY REPRESENT IT IS GIVEN IN THE TARGET OF
 THE DATASET
IMAGESANDLABELS  LISTZIPDIGITSIMAGES DIGITSTARGET
FORINDEX IMAGE LABEL INENUMERATEIMAGESANDLABELS4
PLTSUBPLOT2 4 INDEX  1
PLTAXISOFF
PLTIMSHOWIMAGE CMAPPLTCMGRAYR INTERPOLATIONNEAREST
PLTTITLETRAINING I  LABEL
 TO APPLY A CLASSIFIER ON THIS DATA WE NEED TO FLATTEN THE IMAGE TO
 TURN THE DATA IN A SAMPLES FEATURE MATRIX
NSAMPLES  LENDIGITSIMAGES
DATA  DIGITSIMAGESRESHAPENSAMPLES 1
 CREATE A CLASSIFIER A SUPPORT VECTOR CLASSIFIER
CLASSIFIER  SVMSVCGAMMA0001
 WE LEARN THE DIGITS ON THE FIRST HALF OF THE DIGITS
CLASSIFIERFITDATANSAMPLES  2 DIGITSTARGETNSAMPLES  2
 NOW PREDICT THE VALUE OF THE DIGIT ON THE SECOND HALF
EXPECTED  DIGITSTARGETNSAMPLES  2
PREDICTED  CLASSIFIERPREDICTDATANSAMPLES  2
PRINTCLASSIFICATION REPORT FOR CLASSIFIER SNSN
 CLASSIFIER METRICSCLASSIFICATIONREPORTEXPECTED PREDICTED
PRINTCONFUSION MATRIX NS  METRICSCONFUSIONMATRIXEXPECTED PREDICTED
55 CLASSIFICATION 807
```

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IMAGESANDPREDICTIONS LISTZIPDIGITSIMAGESNSAMPLES 2 PREDICTED
FORINDEX IMAGE PREDICTION INENUMERATEIMAGESANDPREDICTIONS4
PLTSUBPLOT2 4 INDEX 5
PLTAXISOFF
PLTIMSHOWIMAGE CMAPPLTCMGRAYR INTERPOLATIONNEAREST
PLTTITLEPREDICTION I PREDICTION
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0237 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
552 NORMAL AND SHRINKAGE LINEAR DISCRIMINANT ANALYSIS FOR CLASSIFICATION
SHOWS HOW SHRINKAGE IMPROVES CLASSIFICATION
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKEBLOBS
FROM SKLEARNDISCRIMINANTANALYSIS IMPORT LINEARDISCRIMINANTANALYSIS

SCIKITLEARN USER GUIDE RELEASE 0213
NTRAIN 20 SAMPLES FOR TRAINING
NTEST 200 SAMPLES FOR TESTING
NAVERAGES 50 HOW OFTEN TO REPEAT CLASSIFICATION
NFEATURESMAX 75 MAXIMUM NUMBER OF FEATURES
STEP 4 STEP SIZE FOR THE CALCULATION
DEFGENERATEDATANSAMPLES NFEATURES
GENERATE RANDOM BLOBISH DATA WITH NOISY FEATURES
THIS RETURNS AN ARRAY OF INPUT DATA WITH SHAPE NSAMPLES NFEATURES
AND AN ARRAY OF NSAMPLES TARGET LABELS
ONLY ONE FEATURE CONTAINS DISCRIMINATIVE INFORMATION THE OTHER FEATURES
CONTAIN ONLY NOISE

X Y MAKEBLOBSNSAMPLESNSAMPLES NFEATURES1 CENTERS2 2
 ADD NONDISCRIMINATIVE FEATURES
IFNFEATURES 1
X NPHSTACKX NPRANDOMRANDNNSAMPLES NFEATURES 1
RETURNX Y
ACCCLF1 ACCCLF2
NFEATURESRANGE RANGE1 NFEATURESMAX 1 STEP
FORNFEATURES INNFEATURESRANGE
SCORECLF1 SCORECLF2 0 0
FORINRANGENAVERAGES
X Y GENERATEDATANTRAIN NFEATURES
CLF1 LINEARDISCRIMINANTANALYSISSOLVERLSQR SHRINKAGEAUTOFITX Y
CLF2 LINEARDISCRIMINANTANALYSISSOLVERLSQR SHRINKAGENONEFITX Y
X Y GENERATEDATANTEST NFEATURES
SCORECLF1 CLF1SCOREX Y
SCORECLF2 CLF2SCOREX Y
ACCCLF1APPENDSCORECLF1 NAVERAGES
ACCCLF2APPENDSCORECLF2 NAVERAGES
FEATURESSAMPLESRATIO NPARRAYNFEATURESRANGE NTRAIN
PLTPLOTFEATURESSAMPLESRATIO ACCCLF1 LINEWIDTH2
LABELLINEAR DISCRIMINANT ANALYSIS WITH SHRINKAGE COLORNAVY
PLTPLOTFEATURESSAMPLESRATIO ACCCLF2 LINEWIDTH2
LABELLINEAR DISCRIMINANT ANALYSIS COLORGOLD
PLTXLABELNFEATURES NSAMPLES
PLTYLABELCLASSIFICATION ACCURACY
PLTLEGENDLOC1 PROPSIZE 12
PLTSUPTITLELINEAR DISCRIMINANT ANALYSIS VS
SHRINKAGE LINEAR DISCRIMINANT ANALYSIS 1 DISCRIMINATIVE FEATURE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 6160 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
553 PLOT CLASSIFICATION PROBABILITY
PLOT THE CLASSIFICATION PROBABILITY FOR DIFFERENT CLASSIFIERS WE USE A 3 CLASS DATASET AND WE CLASSIFY IT WITH A SUP PORT VECTOR CLASSIFIER L1 AND L2 PENALIZED LOGISTIC REGRESSION WITH EITHER A ONEVSREST OR MULTINOMIAL SETTING AND GAUSSIAN PROCESS CLASSIFICATION
LINEAR SVC IS NOT A PROBABILISTIC CLASSIFIER BY DEFAULT BUT IT HAS A BUILTIN CALIBRATION OPTION ENABLED IN THIS EXAMPLE PROBABILITYTRUE
THE LOGISTIC REGRESSION WITH ONEVSREST IS NOT A MULTICLASS CLASSIFIER OUT OF THE BOX AS A RESULT IT HAS MORE TROUBLE IN SEPARATING CLASS 2 AND 3 THAN THE OTHER ESTIMATORS

OUT
ACCURACY TRAIN FOR L1 LOGISTIC 833
ACCURACY TRAIN FOR L2 LOGISTIC MULTINOMIAL 827
ACCURACY TRAIN FOR L2 LOGISTIC OVR 793
ACCURACY TRAIN FOR LINEAR SVC 820
ACCURACY TRAIN FOR GPC 827
PRINTDOC
 AUTHOR ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
 LICENSE BSD 3 CLAUSE
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNMETRICS IMPORT ACCURACYSCORE
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSCLASSIFIER
FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT RBF
FROM SKLEARN IMPORT DATASETS
IRIS DATASETSLOADIRIS
X IRISDATA 02 WE ONLY TAKE THE FIRST TWO FEATURES FOR VISUALIZATION
Y IRISTARGET
NFEATURES XSHAPE1
C 10
KERNEL 10 RBF10 10 FOR GPC
 CREATE DIFFERENT CLASSIFIERS
CLASSIFIERS
L1 LOGISTIC LOGISTICREGRESSIONCC PENALTYL1
SOLVERSAGA
MULTICLASSMULTINOMIAL
MAXITER10000
L2 LOGISTIC MULTINOMIAL LOGISTICREGRESSIONCC PENALTYL2
SOLVERSAGA
MULTICLASSMULTINOMIAL
MAXITER10000
L2 LOGISTIC OVR LOGISTICREGRESSIONCC PENALTYL2
SOLVERSAGA
MULTICLASSOVR
MAXITER10000
LINEAR SVC SVCKERNELLINEAR CC PROBABILITYTRUE
RANDOMSTATE0
GPC GAUSSIANPROCESSCLASSIFIERKERNEL

NCLASSIFIERS LENCLASSIFIERS

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PLTFIGUREFIGSIZE3 2 NCLASSIFIERS 2
PLTSUBPLOTSADJUSTBOTTOM2 TOP95
XX NPLINSPACE3 9 100
YY NPLINSPACE1 5 100T
XX YY NPMESHGRIDXX YY
XFULL NPCXXRAVEL YYRAVEL
FORINDEX NAME CLASSIFIER INENUMERATECLASSIFIERSITEMS
CLASSIFIERFITX Y
YPRED CLASSIFIERPREDICTX
ACCURACY ACCURACYSCOREY YPRED
PRINTACCURACY TRAIN FOR S01F   NAME ACCURACY 100
 VIEW PROBABILITIES
PROBAS CLASSIFIERPREDICTPROBAXFULL
NCLASSES NPUNIQUEYPREDSIZE
FORKINRANGENCLASSES
PLTSUBPLOTNCLASSIFIERS NCLASSES INDEX NCLASSES K 1
PLTTITLECLASS D K
IFK 0
PLTYLABELNAME
IMSHOWHANDLE PLTIMSHOWPROBAS KRESHAPE100 100
EXTENT3 9 1 5 ORIGINLOWER
PLTXTICKS
PLTYTICKS
IDX YPRED K
IFIDXANY
PLTSCATTERXIDX 0 XIDX 1 MARKERO CW EDGECOLORK
AX PLTAXES015 004 07 005
PLTTITLEPROBABILITY
PLTCOLORBARIMSHOWHANDLE CAXAX ORIENTATIONHORIZONTAL
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1409 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
554 CLASSIFIER COMPARISON
A COMPARISON OF A SEVERAL CLASSIFIERS IN SCIKITLEARN ON SYNTHETIC DATASETS THE POINT OF THIS EXAMPLE IS TO ILLUSTRATE THE NATURE OF DECISION BOUNDARIES OF DIFFERENT CLASSIFIERS THIS SHOULD BE TAKEN WITH A GRAIN OF SALT AS THE INTUITION CONVEYED BY THESE EXAMPLES DOES NOT NECESSARILY CARRY OVER TO REAL DATASETS
PARTICULARLY IN HIGHDIMENSIONAL SPACES DATA CAN MORE EASILY BE SEPARATED LINEARLY AND THE SIMPLICITY OF CLASSIFIERS SUCH AS NAIVE BAYES AND LINEAR SVMS MIGHT LEAD TO BETTER GENERALIZATION THAN IS ACHIEVED BY OTHER CLASSIFIERS
THE PLOTS SHOW TRAINING POINTS IN SOLID COLORS AND TESTING POINTS SEMITRANSPARENT THE LOWER RIGHT SHOWS THE CLASSIFI CATION ACCURACY ON THE TEST SET
55 CLASSIFICATION 813

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PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 ANDREAS MÜLLER
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBCOLORS IMPORT LISTEDCOLORMAP
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM SKLEARNDATASETS IMPORT MAKEMOONS MAKECIRCLES MAKECLASSIFICATION
FROM SKLEARNNEURALNETWORK IMPORT MLPCLASSIFIER
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSCLASSIFIER
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSCLASSIFIER
FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT RBF
FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER ADABOOSTCLASSIFIER
FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
FROM SKLEARNDISCRIMINANTANALYSIS IMPORT QUADRATICDISCRIMINANTANALYSIS
H 02 STEP SIZE IN THE MESH
NAMES NEAREST NEIGHBORS LINEAR SVM RBF SVM GAUSSIAN PROCESS
DECISION TREE RANDOM FOREST NEURAL NET ADABOOST
NAIVE BAYES QDA
CLASSIFIERS
KNEIGHBORSCLASSIFIER3
SVCKERNELLINEAR C0025
SVCGAMMA2 C1
GAUSSIANPROCESSCLASSIFIER10 RBF10
DECISIONTREECLASSIFIERMAXDEPTH5
RANDOMFORESTCLASSIFIERMAXDEPTH5 NESTIMATORS10 MAXFEATURES1
MLPCLASSIFIERALPHA1 MAXITER1000
ADABOOSTCLASSIFIER
GAUSSIANNB
QUADRATICDISCRIMINANTANALYSIS
X Y MAKECLASSIFICATIONNFEATURES2 NREDUNDANT0 NINFORMATIVE2

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RANDOMSTATE1 NCLUSTERSPERCLASS1
RNG NPRANDOMRANDOMSTATE2
X 2RNGUNIFORMSIZEXSHAPE
LINEARLYSEPARABLE X Y
DATASETS MAKEMOONSNOISE03 RANDOMSTATE0
MAKECIRCLESNOISE02 FACTOR05 RANDOMSTATE1
LINEARLYSEPARABLE

FIGURE PLTFIGUREFIGSIZE27 9
I 1
 ITERATE OVER DATASETS
FORDSCNT DS INENUMERATEDATASETS
 PREPROCESS DATASET SPLIT INTO TRAINING AND TEST PART
X Y DS
X STANDARDSCALERFITTRANSFORMX
XTRAIN XTEST YTRAIN YTEST
TRAINTESTSPLITX Y TESTSIZE4 RANDOMSTATE42
XMIN XMAX X 0MIN 5 X 0MAX 5
YMIN YMAX X 1MIN 5 X 1MAX 5
XX YY NPMESHGRIDNPARANGEXMIN XMAX H
NPARANGEYMIN YMAX H
 JUST PLOT THE DATASET FIRST
CM PLTCMRDBU
CMBRIGHT LISTEDCOLORMAPFF0000 0000FF
AX PLTSUBPLOTLENDATASETS LENCLASSIFIERS 1 I
IFDSCNT 0
AXSETTITLEINPUT DATA
 PLOT THE TRAINING POINTS
AXSCATTERXTRAIN 0 XTRAIN 1 CYTRAIN CMAPCMBRIGHT
EDGECOLORSK
 PLOT THE TESTING POINTS
AXSCATTERXTEST 0 XTEST 1 CYTEST CMAPCMBRIGHT ALPHA06
EDGECOLORSK
AXSETXLIMXXMIN XXMAX
AXSETYLIMYYMIN YYMAX
AXSETXTICKS
AXSETYTICKS
I 1
 ITERATE OVER CLASSIFIERS
FORNAME CLF INZIPNAMES CLASSIFIERS
AX PLTSUBPLOTLENDATASETS LENCLASSIFIERS 1 I
CLFFITXTRAIN YTRAIN
SCORE CLFSCOREXTEST YTEST
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
IFHASATTRCLF DECISIONFUNCTION
Z CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
ELSE
Z CLFPREDICTPROBANPCXXRAVEL YYRAVEL 1
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
55 CLASSIFICATION 815

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AXCONTOURFXX YY Z CMAPCM ALPHA8
 PLOT THE TRAINING POINTS
AXSCATTERXTRAIN 0 XTRAIN 1 CYTRAIN CMAPCMBRIGHT
EDGECOLORSK
 PLOT THE TESTING POINTS
AXSCATTERXTEST 0 XTEST 1 CYTEST CMAPCMBRIGHT
EDGECOLORSK ALPHA06
AXSETXLIMXXMIN XXMAX
AXSETYLIMYYMIN YYMAX
AXSETXTICKS
AXSETYTICKS
IFDSCNT 0
AXSETTITLENAME
AXTEXTXXMAX 3 YYMIN 3 2F SCORELSTRIP0
SIZE15 HORIZONTALALIGNMENTRIGHT
I 1
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 5178 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
555 LINEAR AND QUADRATIC DISCRIMINANT ANALYSIS WITH COVARIANCE ELLIPSOID
THIS EXAMPLE PLOTS THE COVARIANCE ELLIPSOIDS OF EACH CLASS AND DECISION BOUNDARY LEARNED BY LDA AND QDA THE ELLIPSOIDS DISPLAY THE DOUBLE STANDARD DEVIATION FOR EACH CLASS WITH LDA THE STANDARD DEVIATION IS THE SAME FOR ALL THE CLASSES WHILE EACH CLASS HAS ITS OWN STANDARD DEVIATION WITH QDA
816 CHAPTER 5 EXAMPLES

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PRINTDOC
FROM SCIPY IMPORT LINALG
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIB AS MPL
FROM MATPLOTLIB IMPORT COLORS
FROM SKLEARNDISCRIMINANTANALYSIS IMPORT LINEARDISCRIMINANTANALYSIS
FROM SKLEARNDISCRIMINANTANALYSIS IMPORT QUADRATICDISCRIMINANTANALYSIS

COLORMAP
CMAP COLORSLINEARSEGMENTEDCOLORMAP
REDBLUECLASSES
RED 0 1 1 1 07 07
GREEN 0 07 07 1 07 07
BLUE 0 07 07 1 1 1
PLTCMREGISTERCMAPCMAPCMAP

GENERATE DATASETS
55 CLASSIFICATION 817

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DEFDATASETFIXEDCOV
GENERATE 2 GAUSSIANS SAMPLES WITH THE SAME COVARIANCE MATRIX
N DIM 300 2
NPRANDOMSEED0
C NPARRAY0 023 083 23
X NPRNPDOTNPRANDOMRANDNN DIM C
NPDOTNPRANDOMRANDNN DIM C NPARRAY1 1
Y NPHSTACKNPZEROSN NPONESN
RETURNX Y
DEFDATASETCOV
GENERATE 2 GAUSSIANS SAMPLES WITH DIFFERENT COVARIANCE MATRICES
N DIM 300 2
NPRANDOMSEED0
C NPARRAY0 1 25 7 2
X NPRNPDOTNPRANDOMRANDNN DIM C
NPDOTNPRANDOMRANDNN DIM CT NPARRAY1 4
Y NPHSTACKNPZEROSN NPONESN
RETURNX Y

 PLOT FUNCTIONS
DEFPLOTDATALDA X Y YPRED FIGINDEX
SPLOT PLTSUBPLOT2 2 FIGINDEX
IFFIGINDEX 1
PLTTITLELINEAR DISCRIMINANT ANALYSIS
PLTYLABELDATA WITH NFIXED COVARIANCE
ELIFFIGINDEX 2
PLTTITLEQUADRATIC DISCRIMINANT ANALYSIS
ELIFFIGINDEX 3
PLTYLABELDATA WITH NVARYING COVARIANCES
TP Y YPRED TRUE POSITIVE
TP0 TP1 TPY 0 TPY 1
X0 X1 XY 0 XY 1
X0TP X0FP X0TP0 X0TP0
X1TP X1FP X1TP1 X1TP1
 CLASS 0 DOTS
PLTSCATTERX0TP 0 X0TP 1 MARKER COLORRED
PLTSCATTERX0FP 0 X0FP 1 MARKERX
S20 COLOR990000 DARK RED
 CLASS 1 DOTS
PLTSCATTERX1TP 0 X1TP 1 MARKER COLORBLUE
PLTSCATTERX1FP 0 X1FP 1 MARKERX
S20 COLOR000099 DARK BLUE
 CLASS 0 AND 1 AREAS
NX NY 200 100
XMIN XMAX PLTXLIM
YMIN YMAX PLTYLIM
XX YY NPMESHGRIDNPLINSPACEXMIN XMAX NX
NPLINSPACEYMIN YMAX NY
Z LDAPREDICTPROBANPCXXRAVEL YYRAVEL
Z Z 1RESHAPEXXSHAPE

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PLTPCOLORMESHXX YY Z CMAPREDBLUECLASSES
NORMCOLORSNORMALIZE0 1 ZORDER0
PLTCONTOURXX YY Z 05 LINEWIDTHS2 COLORSWHITE
 MEANS
PLTPLOTLDAMEANS00 LDAMEANS01
 COLORYELLOW MARKERSIZE15 MARKEREDGECOLORGREY
PLTPLOTLDAMEANS10 LDAMEANS11
 COLORYELLOW MARKERSIZE15 MARKEREDGECOLORGREY
RETURNSPLOT
DEFPLOTELLIPSESPLOT MEAN COV COLOR
V W LINALGEIGHCOV
U W0 LINALGNORMW0
ANGLE NPARCTANU1 U0
ANGLE 180 ANGLE NPPI CONVERT TO DEGREES
 FILLED GAUSSIAN AT 2 STANDARD DEVIATION
ELL MPLPATCHESELLIPSEMEAN 2 V005 2V105
180 ANGLE FACECOLORCOLOR
EDGECOLORBLACK LINEWIDTH2
ELLSETCLIPBOXSPLOTBBOX
ELLSETALPHA02
SPLOTADDARTISTELL
SPLOTSETXTICKS
SPLOTSETYTICKS
DEFPLOTLDACOVLDA SPLOT
PLOTELLIPSESPLOT LDAMEANS0 LDACOVARIANCE RED
PLOTELLIPSESPLOT LDAMEANS1 LDACOVARIANCE BLUE
DEFPLOTQDACOVQDA SPLOT
PLOTELLIPSESPLOT QDAMEANS0 QDACOVARIANCE0 RED
PLOTELLIPSESPLOT QDAMEANS1 QDACOVARIANCE1 BLUE
PLTFIGUREFIGSIZE10 8 FACECOLORWHITE
PLTSUPTITLELINEAR DISCRIMINANT ANALYSIS VS QUADRATIC DISCRIMINANT ANALYSIS
Y098 FONTSIZE15
FORI X Y INENUMERATEDATASETFIXEDCOV DATASETCOV
 LINEAR DISCRIMINANT ANALYSIS
LDA LINEARDISCRIMINANTANALYSISSOLVERSVD STORECOVARIANCETRUE
YPRED LDAFITX YPREDICTX
SPLOT PLOTDATALDA X Y YPRED FIGINDEX2 I 1
PLOTLDACOVLDA SPLOT
PLTAXISTIGHT
 QUADRATIC DISCRIMINANT ANALYSIS
QDA QUADRATICDISCRIMINANTANALYSISSTORECOVARIANCETRUE
YPRED QDAFITX YPREDICTX
SPLOT PLOTDATAQDA X Y YPRED FIGINDEX2 I 2
PLOTQDACOVQDA SPLOT
PLTAXISTIGHT
PLTTIGHTLAYOUT
PLTSUBPLOTSADJUSTTOP092

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PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0231 SECONDS
56 CLUSTERING
EXAMPLES CONCERNING THE SKLEARNCLUSTER MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
561 FEATURE AGGLOMERATION
THESE IMAGES HOW SIMILAR FEATURES ARE MERGED TOGETHER USING FEATURE AGGLOMERATION
PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS CLUSTER
FROM SKLEARNFEATUREEXTRACTIONIMAGE IMPORT GRIDTOGRAPH
DIGITS DATASETSLOADDIGITS
IMAGES DIGITSIMAGES
X NPRESHAPEIMAGES LENIMAGES 1

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CONNECTIVITY GRIDTOGRAPH IMAGES0SHAPE
AGGLO CLUSTERFEATUREAGGLOMERATIONCONNECTIVITYCONNECTIVITY
NCLUSTERS32
AGGLOFITX
XREDUCED AGGLOTRANSFORMX
XRESTORED AGGLOINVERSETRANSFORMXREDUCED
IMAGESRESTORED NPRESHAPEXRESTORED IMAGESSHAPE
PLTFIGURE1 FIGSIZE4 35
PLTCLF
PLTSUBPLOTSADJUSTLEFT01 RIGHT99 BOTTOM01 TOP91
FORIINRANGE4
PLTSUBPLOT3 4 I 1
PLTIMSHOWIMAGESI CMAPPLTCMGRAY VMAX16 INTERPOLATIONNEAREST
PLTXTICKS
PLTYTICKS
IFI 1
PLTTITLEORIGINAL DATA
PLTSUBPLOT3 4 4 I 1
PLTIMSHOWIMAGESRESTOREDI CMAPPLTCMGRAY VMAX16
INTERPOLATIONNEAREST
IFI 1
PLTTITLEAGGLOMERATED DATA
PLTXTICKS
PLTYTICKS
PLTSUBPLOT3 4 10
PLTIMSHOWNPRESHAPEAGGLOLABELS IMAGES0SHAPE
INTERPOLATIONNEAREST CMAPPLTCMNIPYSPECTRAL
PLTXTICKS
PLTYTICKS
PLTTITLELABELS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0174 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
562 A DEMO OF THE MEANSHIFT CLUSTERING ALGORITHM
REFERENCE
DORIN COMANICIU AND PETER MEER “MEAN SHIFT A ROBUST APPROACH TOWARD FEATURE SPACE ANALYSIS” IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE 2002 PP 603619

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OUT
NUMBER OF ESTIMATED CLUSTERS 3
PRINTDOC
IMPORT NUMPY AS NP
FROM SKLEARNCLUSTER IMPORT MEANSHIFT ESTIMATEBANDWIDTH
FROM SKLEARNDATASETSSAMPLESGENERATOR IMPORT MAKEBLOBS

 GENERATE SAMPLE DATA
CENTERS 1 1 1 1 1 1
X   MAKEBLOBSNSAMPLES10000 CENTERSCENTERS CLUSTERSTD06

 COMPUTE CLUSTERING WITH MEANSHIFT
 THE FOLLOWING BANDWIDTH CAN BE AUTOMATICALLY DETECTED USING
BANDWIDTH ESTIMATEBANDWIDTHX QUANTILE02 NSAMPLES500

SCIKITLEARN USER GUIDE RELEASE 0213
MS MEANSHIFTBANDWIDTHBANDWIDTH BINSEEDINGTRUE
MSFITX
LABELS MSLABELS
CLUSTERCENTERS MSCLUSTERCENTERS
LABELSUNIQUE NPUNIQUELABELS
NCLUSTERS LENLABELSUNIQUE
PRINTNUMBER OF ESTIMATED CLUSTERS D NCLUSTERS

 PLOT RESULT
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM ITERTOOLS IMPORT CYCLE
PLTFIGURE1
PLTCLF
COLORS CYCLEBGRCMYKBGRCMYKBGRCMYKBGRCMYK
FORK COLINZIPRANGENCLUSTERS COLORS
MYMEMBERS LABELS K
CLUSTERCENTER CLUSTERCENTERSK
PLTPLOTXMYMEMBERS 0 XMYMEMBERS 1 COL
PLTPLOTCLUSTERCENTER0 CLUSTERCENTER1 O MARKERFACECOLORCOL
MARKEREDGECOLORK MARKERSIZE14
PLTTITLEESTIMATED NUMBER OF CLUSTERS D NCLUSTERS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0397 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
563 DEMONSTRATION OF KMEANS ASSUMPTIONS
THIS EXAMPLE IS MEANT TO ILLUSTRATE SITUATIONS WHERE KMEANS WILL PRODUCE UNINTUITIVE AND POSSIBLY UNEXPECTED CLUSTERS IN THE FIRST THREE PLOTS THE INPUT DATA DOES NOT CONFORM TO SOME IMPLICIT ASSUMPTION THAT KMEANS MAKES AND UNDESIRABLE CLUSTERS ARE PRODUCED AS A RESULT IN THE LAST PLOT KMEANS RETURNS INTUITIVE CLUSTERS DESPITE UNEVENLY SIZED BLOBS

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
 AUTHOR PHIL ROTH MRPHILROTHGMAILCOM
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNCLUSTER IMPORT KMEANS
FROM SKLEARNDATASETS IMPORT MAKEBLOBS
PLTFIGUREFIGSIZE12 12
NSAMPLES 1500
RANDOMSTATE 170

SCIKITLEARN USER GUIDE RELEASE 0213
X Y MAKEBLOBSNSAMPLESNSAMPLES RANDOMSTATERANDOMSTATE
 INCORRECT NUMBER OF CLUSTERS
YPRED KMEANSNCLUSTERS2 RANDOMSTATERANDOMSTATEFITPREDICTX
PLTSUBPLOT221
PLTSCATTERX 0 X 1 CYPRED
PLTTITLEINCORRECT NUMBER OF BLOBS
 ANISOTROPICLY DISTRIBUTED DATA
TRANSFORMATION 060834549 063667341 040887718 085253229
XANISO NPDOTX TRANSFORMATION
YPRED KMEANSNCLUSTERS3 RANDOMSTATERANDOMSTATEFITPREDICTXANISO
PLTSUBPLOT222
PLTSCATTERXANISO 0 XANISO 1 CYPRED
PLTTITLEANISOTROPICLY DISTRIBUTED BLOBS
 DIFFERENT VARIANCE
XVARIED YVARIED MAKEBLOBSNSAMPLESNSAMPLES
CLUSTERSTD10 25 05
RANDOMSTATERANDOMSTATE
YPRED KMEANSNCLUSTERS3 RANDOMSTATERANDOMSTATEFITPREDICTXVARIED
PLTSUBPLOT223
PLTSCATTERXVARIED 0 XVARIED 1 CYPRED
PLTTITLEUNEQUAL VARIANCE
 UNEVENLY SIZED BLOBS
XFILTERED NPVSTACKXY 0500 XY 1100 XY 210
YPRED KMEANSNCLUSTERS3
RANDOMSTATERANDOMSTATEFITPREDICTXFILTERED
PLTSUBPLOT224
PLTSCATTERXFILTERED 0 XFILTERED 1 CYPRED
PLTTITLEUNEVENLY SIZED BLOBS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0163 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
564 ONLINE LEARNING OF A DICTIONARY OF PARTS OF FACES
THIS EXAMPLE USES A LARGE DATASET OF FACES TO LEARN A SET OF 20 X 20 IMAGES PATCHES THAT CONSTITUTE FACES
FROM THE PROGRAMMING STANDPOINT IT IS INTERESTING BECAUSE IT SHOWS HOW TO USE THE ONLINE API OF THE SCIKITLEARN
TO PROCESS A VERY LARGE DATASET BY CHUNKS THE WAY WE PROCEED IS THAT WE LOAD AN IMAGE AT A TIME AND EXTRACT
RANDOMLY 50 PATCHES FROM THIS IMAGE ONCE WE HAVE ACCUMULATED 500 OF THESE PATCHES USING 10 IMAGES WE RUN THE
PARTIALFIT METHOD OF THE ONLINE KMEANS OBJECT MINIBATCHKMEANS
THE VERBOSE SETTING ON THE MINIBATCHKMEANS ENABLES US TO SEE THAT SOME CLUSTERS ARE REASSIGNED DURING THE SUCCESSIVE
CALLS TO PARTIALFIT THIS IS BECAUSE THE NUMBER OF PATCHES THAT THEY REPRESENT HAS BECOME TOO LOW AND IT IS BETTER TO
CHOOSE A RANDOM NEW CLUSTER

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OUT
LEARNING THE DICTIONARY
PARTIAL FIT OF 100 OUT OF 2400
PARTIAL FIT OF 200 OUT OF 2400
MINIBATCHKMEANS REASSIGNING 16 CLUSTER CENTERS
PARTIAL FIT OF 300 OUT OF 2400
PARTIAL FIT OF 400 OUT OF 2400
PARTIAL FIT OF 500 OUT OF 2400
PARTIAL FIT OF 600 OUT OF 2400
PARTIAL FIT OF 700 OUT OF 2400
PARTIAL FIT OF 800 OUT OF 2400
PARTIAL FIT OF 900 OUT OF 2400
PARTIAL FIT OF 1000 OUT OF 2400
PARTIAL FIT OF 1100 OUT OF 2400
PARTIAL FIT OF 1200 OUT OF 2400
PARTIAL FIT OF 1300 OUT OF 2400
PARTIAL FIT OF 1400 OUT OF 2400
PARTIAL FIT OF 1500 OUT OF 2400
PARTIAL FIT OF 1600 OUT OF 2400
PARTIAL FIT OF 1700 OUT OF 2400
PARTIAL FIT OF 1800 OUT OF 2400
PARTIAL FIT OF 1900 OUT OF 2400
PARTIAL FIT OF 2000 OUT OF 2400
PARTIAL FIT OF 2100 OUT OF 2400
PARTIAL FIT OF 2200 OUT OF 2400
PARTIAL FIT OF 2300 OUT OF 2400
PARTIAL FIT OF 2400 OUT OF 2400
DONE IN 506S

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
IMPORT TIME
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNCLUSTER IMPORT MINIBATCHKMEANS
FROM SKLEARNFEATUREEXTRACTIONIMAGE IMPORT EXTRACTPATCHES2D
FACES DATASETSFETCHOLIVETTIFACES

 LEARN THE DICTIONARY OF IMAGES
PRINTLEARNING THE DICTIONARY
RNG NPRANDOMRANDOMSTATE0
KMEANS MINIBATCHKMEANSNCLUSTERS81 RANDOMSTATERNG VERBOSETRUE
PATCHSIZE 20 20
BUFFER
T0 TIMETIME
 THE ONLINE LEARNING PART CYCLE OVER THE WHOLE DATASET 6 TIMES
INDEX 0
FORINRANGE6
FORIMGINFACESIMAGES
DATA EXTRACTPATCHES2DIMG PATCHSIZE MAXPATCHES50
RANDOMSTATERNG
DATA NPRESHAPEDATA LENDATA 1
BUFFERAPPENDDATA
INDEX 1
IFINDEX 10 0
DATA NPCONCATENATEBUFFER AXIS0
DATA NPMEANDATA AXIS0
DATA NPSTDDATA AXIS0
KMEANSPARTIALFITDATA
BUFFER
IFINDEX 100 0
PRINTPARTIAL FIT OF 4IOUT OFI
 INDEX 6 LENFACESIMAGES
DT TIMETIME T0
PRINTDONE IN 2FS DT

 PLOT THE RESULTS
PLTFIGUREFIGSIZE42 4
FORI PATCH INENUMERATEKMEANSCLUSTERCENTERS
PLTSUBPLOT9 9 I 1
PLTIMSHOWPATCHRESHAPEPATCHSIZE CMAPPLTCMGRAY
INTERPOLATIONNEAREST
PLTXTICKS

SCIKITLEARN USER GUIDE RELEASE 0213
PLTYTICKS
PLTSUPTITLEPATCHES OF FACES NTRAIN TIME 1FS ONDPATCHES
DT 8LENFACESIMAGES FONTSIZE16
PLTSUBPLOTSADJUST008 002 092 085 008 023
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 6148 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
565 VECTOR QUANTIZATION EXAMPLE
FACE A 1024 X 768 SIZE IMAGE OF A RACCOON FACE IS USED HERE TO ILLUSTRATE HOW KMEANS IS USED FOR VECTOR QUANTIZATION
•
•

•
•
PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT SCIPY AS SP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT CLUSTER
TRY SCIPY 016 HAVE FACE IN MISC
FROM SCIPYMISC IMPORT FACE
FACE FACEGRAYTRUE
EXCEPTIMPORTERROR
FACE SPFACEGRAYTRUE
NCLUSTERS 5
NPRANDOMSEED0
X FACERESHAPE1 1 WE NEED AN NSAMPLE NFEATURE ARRAY
KMEANS CLUSTERKMEANSNCLUSTERSNCLUSTERS NINIT4
KMEANSFITX
VALUES KMEANSCLUSTERCENTERSSQUEEZE
LABELS KMEANSLABELS

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CREATE AN ARRAY FROM LABELS AND VALUES
FACECOMPRESSED NPCHOOSELABELS VALUES
FACECOMPRESSEDSHAPE FACESHAPE
VMIN FACEMIN
VMAX FACEMAX
ORIGINAL FACE
PLTFIGURE1 FIGSIZE3 22
PLTIMSHOWFACE CMAPPLTCMGRAY VMINVMIN VMAX256
COMPRESSED FACE
PLTFIGURE2 FIGSIZE3 22
PLTIMSHOWFACECOMPRESSED CMAPPLTCMGRAY VMINVMIN VMAXVMAX
EQUAL BINS FACE
REGULARVALUES NPLINSPACE0 256 NCLUSTERS 1
REGULARLABELS NPSEARCHSORTEDREGULARVALUES FACE 1
REGULARVALUES 5 REGULARVALUES1 REGULARVALUES1 MEAN
REGULARFACE NPCHOOSEREGULARLABELSRAVEL REGULARVALUES MODECLIP
REGULARFACESHAPE FACESHAPE
PLTFIGURE3 FIGSIZE3 22
PLTIMSHOWREGULARFACE CMAPPLTCMGRAY VMINVMIN VMAXVMAX
HISTOGRAM
PLTFIGURE4 FIGSIZE3 22
PLTCLF
PLTAXES01 01 98 98
PLTHISTX BINS256 COLOR5 EDGECOLOR5
PLTYTICKS
PLTXTICKSREGULARVALUES
VALUES NPSORTVALUES
FORCENTER1 CENTER2 INZIPVALUES1 VALUES1
PLTAXVLINE5 CENTER1 CENTER2 COLORB
FORCENTER1 CENTER2 INZIPREGULARVALUES1 REGULARVALUES1
PLTAXVLINE5 CENTER1 CENTER2 COLORB LINESTYLE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3752 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
566 AGGLOMERATIVE CLUSTERING WITH AND WITHOUT STRUCTURE
THIS EXAMPLE SHOWS THE EFFECT OF IMPOSING A CONNECTIVITY GRAPH TO CAPTURE LOCAL STRUCTURE IN THE DATA THE GRAPH IS SIMPLY THE GRAPH OF 20 NEAREST NEIGHBORS
TWO CONSEQUENCES OF IMPOSING A CONNECTIVITY CAN BE SEEN FIRST CLUSTERING WITH A CONNECTIVITY MATRIX IS MUCH FASTER SECOND WHEN USING A CONNECTIVITY MATRIX SINGLE AVERAGE AND COMPLETE LINKAGE ARE UNSTABLE AND TEND TO CREATE A FEW CLUSTERS THAT GROW VERY QUICKLY INDEED AVERAGE AND COMPLETE LINKAGE FIGHT THIS PERCOLATION BEHAVIOR BY CONSIDERING ALL THE DISTANCES BETWEEN TWO CLUSTERS WHEN MERGING THEM WHILE SINGLE LINKAGE EXAGGERATES THE BEHAVIOUR BY CONSIDERING

ONLY THE SHORTEST DISTANCE BETWEEN CLUSTERS THE CONNECTIVITY GRAPH BREAKS THIS MECHANISM FOR AVERAGE AND COMPLETE LINKAGE MAKING THEM RESEMBLE THE MORE BRITTLE SINGLE LINKAGE THIS EFFECT IS MORE PRONOUNCED FOR VERY SPARSE GRAPHS TRY DECREASING THE NUMBER OF NEIGHBORS IN KNEIGHBORSGRAPH AND WITH COMPLETE LINKAGE IN PARTICULAR HAVING A VERY SMALL NUMBER OF NEIGHBORS IN THE GRAPH IMPOSES A GEOMETRY THAT IS CLOSE TO THAT OF SINGLE LINKAGE WHICH IS WELL KNOWN TO HAVE THIS PERCOLATION INSTABILITY

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•
 AUTHORS GAEL VAROQUAUX NELLE VAROQUAUX
 LICENSE BSD 3 CLAUSE
IMPORT TIME
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNCLUSTER IMPORT AGGLOMERATIVECLUSTERING
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSGRAPH
 GENERATE SAMPLE DATA
NSAMPLES  1500
NPRANDOMSEED0
T  15 NPPI1  3NPRANDOMRAND1 NSAMPLES
X  TNPCOST
Y  TNPSINT
X  NPCONCATENATEX Y
X  7 NPRANDOMRANDN2 NSAMPLES
X  XT
 CREATE A GRAPH CAPTURING LOCAL CONNECTIVITY LARGER NUMBER OF NEIGHBORS
 WILL GIVE MORE HOMOGENEOUS CLUSTERS TO THE COST OF COMPUTATION
 TIME A VERY LARGE NUMBER OF NEIGHBORS GIVES MORE EVENLY DISTRIBUTED
 CLUSTER SIZES BUT MAY NOT IMPOSE THE LOCAL MANIFOLD STRUCTURE OF
 THE DATA
KNNGRAPH  KNEIGHBORSGRAPHX 30 INCLUDESELFFALSE
FORCONNECTIVITY INNONE KNNGRAPH
FORNCLUSTERS IN30 3
PLTFIGUREFIGSIZE10 4
FORINDEX LINKAGE INENUMERATEAVERAGE
COMPLETE
WARD
SINGLE
PLTSUBPLOT1 4 INDEX  1
MODEL  AGGLOMERATIVECLUSTERINGLINKAGELINKAGE
CONNECTIVITYCONNECTIVITY
NCLUSTERSNCLUSTERS
T0  TIMETIME
```

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MODELFITX
ELAPSEDTIME TIMETIME T0
PLTSCATTERX 0 X 1 CMODELLABELS
CMAPPLTCMNIPYSPECTRAL
PLTTITLELINKAGE SNTIME2FS LINKAGE ELAPSEDTIME
FONTDICTDICTVERTICALALIGNMENTTOP
PLTAXISEQUAL
PLTAXISOFF
PLTSUBPLOTSADJUSTBOTTOM0 TOP89 WSPACE0
LEFT0 RIGHT1
PLTSUPTITLENCLUSTER I CONNECTIVITY R
NCLUSTERS CONNECTIVITY IS NOTNONE SIZE17
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1743 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
567 DEMO OF AFFINITY PROPAGATION CLUSTERING ALGORITHM
REFERENCE BRENDAN J FREY AND DELBERT DUECK “CLUSTERING BY PASSING MESSAGES BETWEEN DATA POINTS” SCIENCE FEB 2007

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OUT
ESTIMATED NUMBER OF CLUSTERS 3
HOMOGENEITY 0872
COMPLETENESS 0872
VMEASURE 0872
ADJUSTED RAND INDEX 0912
ADJUSTED MUTUAL INFORMATION 0871
SILHOUETTE COEFFICIENT 0753
PRINTDOC
FROM SKLEARNCLUSTER IMPORT AFFINITYPROPAGATION
FROM SKLEARN IMPORT METRICS
FROM SKLEARNDATASETSSAMPLESGENERATOR IMPORT MAKEBLOBS

GENERATE SAMPLE DATA
CENTERS 1 1 1 1 1 1
X LABELSTRUE MAKEBLOBSNSAMPLES300 CENTERSCENTERS CLUSTERSTD05
RANDOMSTATE0

```
 COMPUTE AFFINITY PROPAGATION
AF  AFFINITYPROPAGATIONPREFERENCE50FITX
CLUSTERCENTERSINDICES  AFCLUSTERCENTERSINDICES
LABELS  AFLABELS
NCLUSTERS  LENCLUSTERCENTERSINDICES
PRINTESTIMATED NUMBER OF CLUSTERS D  NCLUSTERS
PRINTHOMOGENEITY 03F  METRICSHOMOGENEITYSCORELABELSTRUE LABELS
PRINTCOMPLETENESS 03F  METRICSCOMPLETENESSSCORELABELSTRUE LABELS
PRINTVMEASURE 03F  METRICSVMEASURESCORELABELSTRUE LABELS
PRINTADJUSTED RAND INDEX 03F
 METRICSADJUSTEDRANDSCORELABELSTRUE LABELS
PRINTADJUSTED MUTUAL INFORMATION 03F
 METRICSADJUSTEDMUTUALINFOSCORELABELSTRUE LABELS
AVERAGEMETHODARITHMETIC
PRINTSILHOUETTE COEFFICIENT 03F
 METRICSSILHOUETTESCOREX LABELS METRICSQEUCLIDEAN

 PLOT RESULT
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM ITERTOOLS IMPORT CYCLE
PLTCLOSEALL
PLTFIGURE1
PLTCLF
COLORS  CYCLEBGRCMYKBGRCMYKBGRCMYKBGRCMYK
FORK COLINZIPRANGENCLUSTERS COLORS
CLASSMEMBERS  LABELS  K
CLUSTERCENTER  XCLUSTERCENTERSINDICESK
PLTPLOTXCLASSMEMBERS 0 XCLASSMEMBERS 1 COL
PLTPLOTCLUSTERCENTER0 CLUSTERCENTER1 O MARKERFACECOLORCOL
MARKEREDGECOLORK MARKERSIZE14
FORXINXCLASSMEMBERS
PLTPLOTCLUSTERCENTER0 X0 CLUSTERCENTER1 X1 COL
PLTTITLEESTIMATED NUMBER OF CLUSTERS D  NCLUSTERS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT  0 MINUTES 0569 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
568 SEGMENTING THE PICTURE OF GREEK COINS IN REGIONS
THIS EXAMPLE USES SPECTRAL CLUSTERING ON A GRAPH CREATED FROM VOXELTOVOXEL DIFFERENCE ON AN IMAGE TO BREAK THIS
IMAGE INTO MULTIPLE PARTLYHOMOGENEOUS REGIONS
THIS PROCEDURE SPECTRAL CLUSTERING ON AN IMAGE IS AN EFFICIENT APPROXIMATE SOLUTION FOR FINDING NORMALIZED GRAPH CUTS
THERE ARE TWO OPTIONS TO ASSIGN LABELS
```

• WITH ‘KMEANS’ SPECTRAL CLUSTERING WILL CLUSTER SAMPLES IN THE EMBEDDING SPACE USING A KMEANS ALGORITHM
• WHEREAS ‘DISCRETE’ WILL ITERATIVELY SEARCH FOR THE CLOSEST PARTITION SPACE TO THE EMBEDDING SPACE

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PRINTDOC
 AUTHOR GAEL VAROQUAUX GAELVAROQUAUXNORMALESUPORG BRIAN CHEUNG
 LICENSE BSD 3 CLAUSE
IMPORT TIME
IMPORT NUMPY AS NP
FROM DISTUTILSVERSION IMPORT LOOSEVERSION
FROM SCIPYNDIMAGEFILTERS IMPORT GAUSSIANFILTER
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT SKIMAGE
FROM SKIMAGEDATA IMPORT COINS
FROM SKIMAGETRANSFORM IMPORT RESCALE
FROM SKLEARNFEATUREEXTRACTION IMPORT IMAGE
FROM SKLEARNCLUSTER IMPORT SPECTRALCLUSTERING
 THESE WERE INTRODUCED IN SKIMAGE014
IFLOOSEVERSIONSKIMAGEVERSION  014
RESCALEPARAMS  ANTIALIASING FALSE MULTICHANNEL FALSE
ELSE
RESCALEPARAMS
 LOAD THE COINS AS A NUMPY ARRAY
ORIGCOINS  COINS
 RESIZE IT TO 20 OF THE ORIGINAL SIZE TO SPEED UP THE PROCESSING
 APPLYING A GAUSSIAN FILTER FOR SMOOTHING PRIOR TO DOWNSCALING
 REDUCES ALIASING ARTIFACTS
SMOOTHENEDCOINS  GAUSSIANFILTERORIGCOINS SIGMA2
RESCALEDCOINS  RESCALESMOOTHENEDCOINS 02 MODEREFLECT
RESCALEPARAMS
 CONVERT THE IMAGE INTO A GRAPH WITH THE VALUE OF THE GRADIENT ON THE
 EDGES
GRAPH  IMAGEIMGTOGRAPHRESCALEDCOINS
 TAKE A DECREASING FUNCTION OF THE GRADIENT AN EXPONENTIAL
 THE SMALLER BETA IS THE MORE INDEPENDENT THE SEGMENTATION IS OF THE
 ACTUAL IMAGE FOR BETA1 THE SEGMENTATION IS CLOSE TO A VORONOI
BETA  10
EPS  1E6
GRAPHDATA  NPEXPBETA GRAPHDATA  GRAPHDATASTD  EPS
 APPLY SPECTRAL CLUSTERING THIS STEP GOES MUCH FASTER IF YOU HAVE PYAMG
 INSTALLED
NREGIONS  25
VISUALIZE THE RESULTING REGIONS
FORASSIGNLABELS INKMEANS DISCRETIZE
T0  TIMETIME
LABELS  SPECTRALCLUSTERINGGRAPH NCLUSTERSNREGIONS
ASSIGNLABELSASSIGNLABELS RANDOMSTATE42
```

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T1 TIMETIME
LABELS LABELSRESHAPERESCALEDCOINSSHAPE
PLTFIGUREFIGSIZE5 5
PLTIMSHOWRESCALEDCOINS CMAPPLTCMGRAY
FORLINRANGENREGIONS
PLTCONTOURLABELS L
COLORSPLTCMNIPYSPECTRALL FLOATNREGIONS
PLTXTICKS
PLTYTICKS
TITLE SPECTRAL CLUSTERING S2FS ASSIGNLABELS T1 T0
PRINTTITLE
PLTTITLETITLE
PLTSHOW
•

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OUT

SPECTRAL CLUSTERING KMEANS 515S

SPECTRAL CLUSTERING DISCRETIZE 598S

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 11961 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

569 KMEANS CLUSTERING

THE PLOTS DISPLAY FIRSTLY WHAT A KMEANS ALGORITHM WOULD YIELD USING THREE CLUSTERS IT IS THEN SHOWN WHAT THE EFFECT OF A BAD INITIALIZATION IS ON THE CLASSIFICATION PROCESS BY SETTING NINIT TO ONLY 1 DEFAULT IS 10 THE AMOUNT OF TIMES THAT THE ALGORITHM WILL BE RUN WITH DIFFERENT CENTROID SEEDS IS REDUCED THE NEXT PLOT DISPLAYS WHAT USING EIGHT CLUSTERS WOULD DELIVER AND FINALLY THE GROUND TRUTH

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PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
 THOUGH THE FOLLOWING IMPORT IS NOT DIRECTLY BEING USED IT IS REQUIRED
 FOR 3D PROJECTION TO WORK
FROM MPLTOOLKITSMPLOT3D IMPORT AXES3D
FROM SKLEARNCLUSTER IMPORT KMEANS
FROM SKLEARN IMPORT DATASETS
NPRANDOMSEED5

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IRIS DATASETSLOADIRIS
X IRISDATA
Y IRISTARGET
ESTIMATORS KMEANSIRIS8 KMEANSNCLUSTERS8
KMEANSIRIS3 KMEANSNCLUSTERS3
KMEANSIRISBADINIT KMEANSNCLUSTERS3 NINIT1
INITRANDOM
FIGNUM 1
TITLES 8 CLUSTERS 3 CLUSTERS 3 CLUSTERS BAD INITIALIZATION
FORNAME EST INESTIMATORS
FIG PLTFIGUREFIGNUM FIGSIZE4 3
AX AXES3DFIG RECT0 0 95 1 ELEV48 AZIM134
ESTFITX
LABELS ESTLABELS
AXSCATTERX 3 X 0 X 2
CLABELSASTYPENPFLOAT EDGECOLORK
AXWXAXISSETTICKLABELS
AXWYAXISSETTICKLABELS
AXWZAXISSETTICKLABELS
AXSETXLABELPETAL WIDTH
AXSETYLABELSEPAL LENGTH
AXSETZLABELPETAL LENGTH
AXSETTITLETITLESFIGNUM 1
AXDIST 12
FIGNUM FIGNUM 1
 PLOT THE GROUND TRUTH
FIG PLTFIGUREFIGNUM FIGSIZE4 3
AX AXES3DFIG RECT0 0 95 1 ELEV48 AZIM134
FORNAME LABEL INSETOSA 0
VERSICOLOUR 1
VIRGINICA 2
AXTEXT3DXY LABEL 3MEAN
XY LABEL 0MEAN
XY LABEL 2MEAN 2 NAME
HORIZONTALALIGNMENTCENTER
BBOXDICTALPHA2 EDGECOLORW FACECOLORW
 REORDER THE LABELS TO HAVE COLORS MATCHING THE CLUSTER RESULTS
Y NPCHOOSEY 1 2 0ASTYPENPFLOAT
AXSCATTERX 3 X 0 X 2 CY EDGECOLORK
AXWXAXISSETTICKLABELS
AXWYAXISSETTICKLABELS
AXWZAXISSETTICKLABELS
AXSETXLABELPETAL WIDTH
AXSETYLABELSEPAL LENGTH
AXSETZLABELPETAL LENGTH
AXSETTITLEGROUND TRUTH
AXDIST 12
FIGSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0241 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5610 VARIOUS AGGLOMERATIVE CLUSTERING ON A 2D EMBEDDING OF DIGITS
AN ILLUSTRATION OF VARIOUS LINKAGE OPTION FOR AGGLOMERATIVE CLUSTERING ON A 2D EMBEDDING OF THE DIGITS DATASET
THE GOAL OF THIS EXAMPLE IS TO SHOW INTUITIVELY HOW THE METRICS BEHAVE AND NOT TO FIND GOOD CLUSTERS FOR THE DIGITS
THIS IS WHY THE EXAMPLE WORKS ON A 2D EMBEDDING
WHAT THIS EXAMPLE SHOWS US IS THE BEHAVIOR “RICH GETTING RICHER” OF AGGLOMERATIVE CLUSTERING THAT TENDS TO CREATE UNEVEN CLUSTER SIZES THIS BEHAVIOR IS PRONOUNCED FOR THE AVERAGE LINKAGE STRATEGY THAT ENDS UP WITH A COUPLE OF SINGLETON CLUSTERS WHILE IN THE CASE OF SINGLE LINKAGE WE GET A SINGLE CENTRAL CLUSTER WITH ALL OTHER CLUSTERS BEING DRAWN FROM NOISE POINTS AROUND THE FRINGES
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OUT
COMPUTING EMBEDDING
DONE
WARD 046S
AVERAGE 036S
COMPLETE 038S
SINGLE 017S
 AUTHORS GAEL VAROQUAUX
 LICENSE BSD 3 CLAUSE C INRIA 2014
PRINTDOC
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
FROM SCIPY IMPORT NDIMAGE
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM SKLEARN IMPORT MANIFOLD DATASETS
DIGITS DATASETSLOADDIGITSNCLASS10
X DIGITSDATA
Y DIGITSTARGET
NSAMPLES NFEATURES XSHAPE

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NPRANDOMSEED0
DEFNUDGEIMAGESX Y
 HAVING A LARGER DATASET SHOWS MORE CLEARLY THE BEHAVIOR OF THE
 METHODS BUT WE MULTIPLY THE SIZE OF THE DATASET ONLY BY 2 AS THE
 COST OF THE HIERARCHICAL CLUSTERING METHODS ARE STRONGLY
 SUPERLINEAR IN NSAMPLES
SHIFT LAMBDAX NDIMAGESHIFTXRESHAPE8 8
3NPRANDOMNORMALSIZE2
MODECONSTANT
RAVEL
X NPCONCATENATEX NPAPPLYALONGAXISSHIFT 1 X
Y NPCONCATENATEY Y AXIS0
RETURNX Y
X Y NUDGEIMAGESX Y

 VISUALIZE THE CLUSTERING
DEFPLOTCLUSTERINGXRED LABELS TITLENONE
XMIN XMAX NPMINXRED AXIS0 NPMAXXRED AXIS0
XRED XRED XMIN XMAX XMIN
PLTFIGUREFIGSIZE6 4
FORIINRANGEXREDSHAPE0
PLTTEXTXREDI 0 XREDI 1 STRYI
COLORPLTCMNIPYSPECTRALLABELSI 10
FONTDICTWEIGHT BOLD SIZE 9
PLTXTICKS
PLTYTICKS
IFTITLEIS NOTNONE
PLTTITLETITLE SIZE17
PLTAXISOFF
PLTTIGHTLAYOUTRECT0 003 1 095

 2D EMBEDDING OF THE DIGITS DATASET
PRINTCOMPUTING EMBEDDING
XRED MANIFOLDSPECTRALEMBEDDINGNCOMPONENTS2FITTRANSFORMX
PRINTDONE
FROM SKLEARNCLUSTER IMPORT AGGLOMERATIVECLUSTERING
FORLINKAGE INWARD AVERAGE COMPLETE SINGLE
CLUSTERING AGGLOMERATIVECLUSTERINGLINKAGELINKAGE NCLUSTERS10
T0 TIME
CLUSTERINGFITXRED
PRINTST2FS LINKAGE TIME T0
PLOTCLUSTERINGXRED CLUSTERINGLABELS SLINKAGE LINKAGE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 26873 SECONDS
56 CLUSTERING 845

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5611 SPECTRAL CLUSTERING FOR IMAGE SEGMENTATION
IN THIS EXAMPLE AN IMAGE WITH CONNECTED CIRCLES IS GENERATED AND SPECTRAL CLUSTERING IS USED TO SEPARATE THE CIRCLES
IN THESE SETTINGS THE SPECTRAL CLUSTERING APPROACH SOLVES THE PROBLEM KNOW AS ‘NORMALIZED GRAPH CUTS’ THE IMAGE IS SEEN AS A GRAPH OF CONNECTED VOXELS AND THE SPECTRAL CLUSTERING ALGORITHM AMOUNTS TO CHOOSING GRAPH CUTS DEFINING REGIONS WHILE MINIMIZING THE RATIO OF THE GRADIENT ALONG THE CUT AND THE VOLUME OF THE REGION
AS THE ALGORITHM TRIES TO BALANCE THE VOLUME IE BALANCE THE REGION SIZES IF WE TAKE CIRCLES WITH DIFFERENT SIZES THE SEGMENTATION FAILS
IN ADDITION AS THERE IS NO USEFUL INFORMATION IN THE INTENSITY OF THE IMAGE OR ITS GRADIENT WE CHOOSE TO PERFORM THE SPECTRAL CLUSTERING ON A GRAPH THAT IS ONLY WEAKLY INFORMED BY THE GRADIENT THIS IS CLOSE TO PERFORMING A V ORONOI PARTITION OF THE GRAPH
IN ADDITION WE USE THE MASK OF THE OBJECTS TO RESTRICT THE GRAPH TO THE OUTLINE OF THE OBJECTS IN THIS EXAMPLE WE ARE INTERESTED IN SEPARATING THE OBJECTS ONE FROM THE OTHER AND NOT FROM THE BACKGROUND
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56 CLUSTERING 847

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PRINTDOC
 AUTHORS EMMANUELLE GOUILLART EMMANUELLEGOUILLARTNORMALESUPORG
 GAEL VAROQUAUX GAELVAROQUAUXNORMALESUPORG
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNFEATUREEXTRACTION IMPORT IMAGE
FROM SKLEARNCLUSTER IMPORT SPECTRALCLUSTERING
L  100
X Y  NPINDICESL L
CENTER1  28 24
CENTER2  40 50
CENTER3  67 58
CENTER4  24 70
RADIUS1 RADIUS2 RADIUS3 RADIUS4  16 14 15 14
CIRCLE1  X  CENTER10 2  Y  CENTER11 2  RADIUS1 2
CIRCLE2  X  CENTER20 2  Y  CENTER21 2  RADIUS2 2
CIRCLE3  X  CENTER30 2  Y  CENTER31 2  RADIUS3 2
CIRCLE4  X  CENTER40 2  Y  CENTER41 2  RADIUS4 2
```

```
 4 CIRCLES
IMG  CIRCLE1  CIRCLE2  CIRCLE3  CIRCLE4
 WE USE A MASK THAT LIMITS TO THE FOREGROUND THE PROBLEM THAT WE ARE
 INTERESTED IN HERE IS NOT SEPARATING THE OBJECTS FROM THE BACKGROUND
 BUT SEPARATING THEM ONE FROM THE OTHER
MASK  IMGASTYPEBOOL
IMG  IMGASTYPEFLOAT
IMG  1  02 NPRANDOMRANDN IMGSHAPE
 CONVERT THE IMAGE INTO A GRAPH WITH THE VALUE OF THE GRADIENT ON THE
 EDGES
GRAPH  IMAGEIMGTOGRAPHIMG MASKMASK
 TAKE A DECREASING FUNCTION OF THE GRADIENT WE TAKE IT WEAKLY
 DEPENDENT FROM THE GRADIENT THE SEGMENTATION IS CLOSE TO A VORONOI
GRAPHDATA  NPEXPGRAPHDATA  GRAPHDATASTD
 FORCE THE SOLVER TO BE ARPACK SINCE AMG IS NUMERICALLY
 UNSTABLE ON THIS EXAMPLE
LABELS  SPECTRALCLUSTERINGGRAPH NCLUSTERS4 EIGENSOLVERARPACK
LABELIM  NPFULLMASKSHAPE 1
LABELIMMASK  LABELS
PLTMATSHOWIMG
PLTMATSHOWLABELIM

 2 CIRCLES
IMG  CIRCLE1  CIRCLE2
MASK  IMGASTYPEBOOL
IMG  IMGASTYPEFLOAT
IMG  1  02 NPRANDOMRANDN IMGSHAPE
GRAPH  IMAGEIMGTOGRAPHIMG MASKMASK
GRAPHDATA  NPEXPGRAPHDATA  GRAPHDATASTD
LABELS  SPECTRALCLUSTERINGGRAPH NCLUSTERS2 EIGENSOLVERARPACK
LABELIM  NPFULLMASKSHAPE 1
LABELIMMASK  LABELS
PLTMATSHOWIMG
PLTMATSHOWLABELIM
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT  0 MINUTES 0675 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
```

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5612 A DEMO OF STRUCTURED WARD HIERARCHICAL CLUSTERING ON AN IMAGE OF COINS
COMPUTE THE SEGMENTATION OF A 2D IMAGE WITH WARD HIERARCHICAL CLUSTERING THE CLUSTERING IS SPATIALLY CONSTRAINED IN ORDER FOR EACH SEGMENTED REGION TO BE IN ONE PIECE
OUT
COMPUTE STRUCTURED HIERARCHICAL CLUSTERING
ELAPSED TIME 02273859977722168
NUMBER OF PIXELS 4697
NUMBER OF CLUSTERS 27
AUTHOR VINCENT MICHEL 2010
ALEXANDRE GRAMFORT 2011
LICENSE BSD 3 CLAUSE
PRINTDOC
IMPORT TIME AS TIME
56 CLUSTERING 851

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IMPORT NUMPY AS NP
FROM DISTUTILSVERSION IMPORT LOOSEVERSION
FROM SCIPYNDIMAGEFILTERS IMPORT GAUSSIANFILTER
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT SKIMAGE
FROM SKIMAGEDATA IMPORT COINS
FROM SKIMAGETRANSFORM IMPORT RESCALE
FROM SKLEARNFEATUREEXTRACTIONIMAGE IMPORT GRIDTOGRAPH
FROM SKLEARNCLUSTER IMPORT AGGLOMERATIVECLUSTERING
 THESE WERE INTRODUCED IN SKIMAGE014
IFLOOSEVERSIONSKIMAGEVERSION 014
RESCALEPARAMS ANTIALIASING FALSE MULTICHANNEL FALSE
ELSE
RESCALEPARAMS

 GENERATE DATA
ORIGCOINS COINS
 RESIZE IT TO 20 OF THE ORIGINAL SIZE TO SPEED UP THE PROCESSING
 APPLYING A GAUSSIAN FILTER FOR SMOOTHING PRIOR TO DOWNSCALING
 REDUCES ALIASING ARTIFACTS
SMOOTHENEDCOINS GAUSSIANFILTERORIGCOINS SIGMA2
RESCALEDCOINS RESCALESMOOTHENEDCOINS 02 MODEREFLECT
RESCALEPARAMS
X NPRESHAPERESCALEDCOINS 1 1

 DEFINE THE STRUCTURE A OF THE DATA PIXELS CONNECTED TO THEIR NEIGHBORS
CONNECTIVITY GRIDTOGRAPH RESCALEDCOINSSHAPE

 COMPUTE CLUSTERING
PRINTCOMPUTE STRUCTURED HIERARCHICAL CLUSTERING
ST TIMETIME
NCLUSTERS 27 NUMBER OF REGIONS
WARD AGGLOMERATIVECLUSTERINGNCLUSTERSNCLUSTERS LINKAGEWARD
CONNECTIVITYCONNECTIVITY
WARDFITX
LABEL NPRESHAPEWARDLABELS RESCALEDCOINSSHAPE
PRINTELAPSED TIME TIMETIME ST
PRINTNUMBER OF PIXELS LABELSIZE
PRINTNUMBER OF CLUSTERS NPUNIQUELABELSIZE

 PLOT THE RESULTS ON AN IMAGE
PLTFIGUREFIGSIZE5 5
PLTIMSHOWRESCALEDCOINS CMAPPLTCMGRAY
FORLINRANGENCLUSTERS
PLTCONTOURLABEL L
COLORSPLTCMNIPYSPECTRALL FLOATNCLUSTERS
PLTXTICKS
PLTYTICKS

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PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0897 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5613 DEMO OF DBSCAN CLUSTERING ALGORITHM
FINDS CORE SAMPLES OF HIGH DENSITY AND EXPANDS CLUSTERS FROM THEM
OUT
ESTIMATED NUMBER OF CLUSTERS 3
ESTIMATED NUMBER OF NOISE POINTS 18
HOMOGENEITY 0953
COMPLETENESS 0883
VMEASURE 0917
ADJUSTED RAND INDEX 0952
ADJUSTED MUTUAL INFORMATION 0916
SILHOUETTE COEFFICIENT 0626
56 CLUSTERING 853

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PRINTDOC
IMPORT NUMPY AS NP
FROM SKLEARNCLUSTER IMPORT DBSCAN
FROM SKLEARN IMPORT METRICS
FROM SKLEARNDATASETSSAMPLESGENERATOR IMPORT MAKEBLOBS
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER

GENERATE SAMPLE DATA
CENTERS 1 1 1 1 1 1
X LABELSTRUE MAKEBLOBSNSAMPLES750 CENTERSCENTERS CLUSTERSTD04
RANDOMSTATE0
X STANDARDSCALERFITTRANSFORMX

COMPUTE DBSCAN
DB DBSCANEPS03 MINSAMPLES10FITX
CORESAMPLESMASK NPZEROSLIKEDBLABELS DTYPEBOOL
CORESAMPLESMASKDBCORESAMPLEINDICES TRUE
LABELS DBLABELS
NUMBER OF CLUSTERS IN LABELS IGNORING NOISE IF PRESENT
NCLUSTERS LENSETLABELS 1 IF1INLABELSELSE0
NNOISE LISTLABELSCOUNT1
PRINTESTIMATED NUMBER OF CLUSTERS D NCLUSTERS
PRINTESTIMATED NUMBER OF NOISE POINTS D NNOISE
PRINTHOMOGENEITY 03F METRICSHOMOGENEITYSCORELABELSTRUE LABELS
PRINTCOMPLETENESS 03F METRICSCOMPLETENESSSCORELABELSTRUE LABELS
PRINTVMEASURE 03F METRICSVMEASURESCORELABELSTRUE LABELS
PRINTADJUSTED RAND INDEX 03F
METRICSADJUSTEDRANDSCORELABELSTRUE LABELS
PRINTADJUSTED MUTUAL INFORMATION 03F
METRICSADJUSTEDMUTUALINFOSCORELABELSTRUE LABELS
AVERAGEMETHODARITHMETIC
PRINTSILHOUETTE COEFFICIENT 03F
METRICSSILHOUETTESCOREX LABELS

PLOT RESULT
IMPORT MATPLOTLIBPYPLOT AS PLT
BLACK REMOVED AND IS USED FOR NOISE INSTEAD
UNIQUELABELS SETLABELS
COLORS PLTCMSPECTRALEACH
FOREACHINNPLINSPACE0 1 LENUNIQUELABELS
FORK COLINZIPUNIQUELABELS COLORS
IFK 1
BLACK USED FOR NOISE
COL 0 0 0 1

CLASSMEMBERMASK LABELS K
XY XCLASSMEMBERMASK CORESAMPLESMASK
PLTPLOTXY 0 XY 1 O MARKERFACECOLORTUPLECOL
MARKEREDGECOLORK MARKERSIZE14
XY XCLASSMEMBERMASK CORESAMPLESMASK
PLTPLOTXY 0 XY 1 O MARKERFACECOLORTUPLECOL
MARKEREDGECOLORK MARKERSIZE6
PLTTITLEESTIMATED NUMBER OF CLUSTERS D NCLUSTERS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0043 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5614 COLOR QUANTIZATION USING KMEANS
PERFORMS A PIXELWISE VECTOR QUANTIZATION VQ OF AN IMAGE OF THE SUMMER PALACE CHINA REDUCING THE NUMBER OF COLORS REQUIRED TO SHOW THE IMAGE FROM 96615 UNIQUE COLORS TO 64 WHILE PRESERVING THE OVERALL APPEARANCE QUALITY IN THIS EXAMPLE PIXELS ARE REPRESENTED IN A 3DSPACE AND KMEANS IS USED TO FIND 64 COLOR CLUSTERS IN THE IMAGE PROCESSING LITERATURE THE CODEBOOK OBTAINED FROM KMEANS THE CLUSTER CENTERS IS CALLED THE COLOR PALETTE USING A SINGLE BYTE UP TO 256 COLORS CAN BE ADDRESSED WHEREAS AN RGB ENCODING REQUIRES 3 BYTES PER PIXEL THE GIF FILE FORMAT FOR EXAMPLE USES SUCH A PALETTE
FOR COMPARISON A QUANTIZED IMAGE USING A RANDOM CODEBOOK COLORS PICKED UP RANDOMLY IS ALSO SHOWN

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56 CLUSTERING 857

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```
OUT
FITTING MODEL ON A SMALL SUBSAMPLE OF THE DATA
DONE IN 0264S
PREDICTING COLOR INDICES ON THE FULL IMAGE KMEANS
DONE IN 0216S
PREDICTING COLOR INDICES ON THE FULL IMAGE RANDOM
DONE IN 0310S
```

AUTHORS ROBERT LAYTON ROBERTLAYTONGMAILCOM
OLIVIER GRISEL OLIVIERGRISELENSTAORG
MATHIEU BLONDEL MATHIEUMBLONDELORG


```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNCLUSTER IMPORT KMEANS
FROM SKLEARNMETRICS IMPORT PAIRWISEDISTANCESARGMIN
FROM SKLEARNDATASETS IMPORT LOADSAMPLEIMAGE
FROM SKLEARNUTILS IMPORT SHUFFLE
```

```
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FROM TIME IMPORT TIME
NCOLORS  64
 LOAD THE SUMMER PALACE PHOTO
CHINA  LOADSAMPLEIMAGECHINAJPG
 CONVERT TO FLOATS INSTEAD OF THE DEFAULT 8 BITS INTEGER CODING DIVIDING BY
 255 IS IMPORTANT SO THAT PLTIMSHOW BEHAVES WORKS WELL ON FLOAT DATA NEED TO
 BE IN THE RANGE 01
CHINA  NPARRAYCHINA DTYPENPFLOAT64  255
 LOAD IMAGE AND TRANSFORM TO A 2D NUMPY ARRAY
W H D  ORIGINALSHAPE  TUPLECHINASHAPE
ASSERTD  3
IMAGEARRAY  NPRESHAPECHINA W H D
PRINTFITTING MODEL ON A SMALL SUBSAMPLE OF THE DATA
T0  TIME
IMAGEARRAYSAMPLE  SHUFFLEIMAGEARRAY RANDOMSTATE01000
KMEANS  KMEANSNCLUSTERSNCOLORS RANDOMSTATE0FITIMAGEARRAYSAMPLE
PRINTDONE IN 03FS  TIME  T0
 GET LABELS FOR ALL POINTS
PRINTPREDICTING COLOR INDICES ON THE FULL IMAGE KMEANS
T0  TIME
LABELS  KMEANSPREDICTIMAGEARRAY
PRINTDONE IN 03FS  TIME  T0
CODEBOOKRANDOM  SHUFFLEIMAGEARRAY RANDOMSTATE0NCOLORS
PRINTPREDICTING COLOR INDICES ON THE FULL IMAGE RANDOM
T0  TIME
LABELSRANDOM  PAIRWISEDISTANCESARGMINCODEBOOKRANDOM
IMAGEARRAY
AXIS0
PRINTDONE IN 03FS  TIME  T0
DEFRECREATEIMAGECODEBOOK LABELS W H
RECREATE THE COMPRESSED IMAGE FROM THE CODE BOOK  LABELS
D  CODEBOOKSHAPE1
IMAGE  NPZEROSW H D
LABELIDX  0
FORIINRANGEW
FORJINRANGEH
IMAGEIJ  CODEBOOKLABELSLABELIDX
LABELIDX  1
RETURNIMAGE
 DISPLAY ALL RESULTS ALONGSIDE ORIGINAL IMAGE
PLTFIGURE1
PLTCLF
PLTAXISOFF
PLTTITLEORIGINAL IMAGE 96615 COLORS
PLTIMSHOWCHINA
PLTFIGURE2
```

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PLTCLF
PLTAXISOFF
PLTTITLEQUANTIZED IMAGE 64 COLORS KMEANS
PLTIMSHOWRECREATEIMAGEKMEANSCLUSTERCENTERS LABELS W H
PLTFIGURE3
PLTCLF
PLTAXISOFF
PLTTITLEQUANTIZED IMAGE 64 COLORS RANDOM
PLTIMSHOWRECREATEIMAGECODEBOOKRANDOM LABELSRANDOM W H
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1400 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5615 HIERARCHICAL CLUSTERING STRUCTURED VS UNSTRUCTURED WARD
EXAMPLE BUILDS A SWISS ROLL DATASET AND RUNS HIERARCHICAL CLUSTERING ON THEIR POSITION
FOR MORE INFORMATION SEE HIERARCHICAL CLUSTERING
IN A FIRST STEP THE HIERARCHICAL CLUSTERING IS PERFORMED WITHOUT CONNECTIVITY CONSTRAINTS ON THE STRUCTURE AND IS SOLELY BASED ON DISTANCE WHEREAS IN A SECOND STEP THE CLUSTERING IS RESTRICTED TO THE KNEAREST NEIGHBORS GRAPH IT'S A HIERARCHICAL CLUSTERING WITH STRUCTURE PRIOR
SOME OF THE CLUSTERS LEARNED WITHOUT CONNECTIVITY CONSTRAINTS DO NOT RESPECT THE STRUCTURE OF THE SWISS ROLL AND EXTEND ACROSS DIFFERENT FOLDS OF THE MANIFOLDS ON THE OPPOSITE WHEN OPPOSING CONNECTIVITY CONSTRAINTS THE CLUSTERS FORM A NICE PARCELLATION OF THE SWISS ROLL

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56 CLUSTERING 861

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OUT
COMPUTE UNSTRUCTURED HIERARCHICAL CLUSTERING
ELAPSED TIME 008S
NUMBER OF POINTS 1500
COMPUTE STRUCTURED HIERARCHICAL CLUSTERING
ELAPSED TIME 007S
NUMBER OF POINTS 1500
AUTHORS VINCENT MICHEL 2010
ALEXANDRE GRAMFORT 2010
GAEL VAROQUAUX 2010
LICENSE BSD 3 CLAUSE
PRINTDOC
IMPORT TIME AS TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MPLTOOLKITSMPLOT3DAXES3D AS P3
FROM SKLEARNCLUSTER IMPORT AGGLOMERATIVECLUSTERING
FROM SKLEARNDATASETSSAMPLESGENERATOR IMPORT MAKESWISSROLL

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```
 GENERATE DATA SWISS ROLL DATASET
NSAMPLES  1500
NOISE  005
X   MAKESWISSROLLNSAMPLES NOISE
 MAKE IT THINNER
X 1  5

 COMPUTE CLUSTERING
PRINTCOMPUTE UNSTRUCTURED HIERARCHICAL CLUSTERING
ST  TIMETIME
WARD  AGGLOMERATIVECLUSTERINGNCLUSTERS6 LINKAGEWARDFITX
ELAPSEDTIME  TIMETIME  ST
LABEL  WARDLABELS
PRINTELAPSED TIME 2FS  ELAPSEDTIME
PRINTNUMBER OF POINTS I  LABELSIZE

 PLOT RESULT
FIG  PLTFIGURE
AX  P3AXES3DFIG
AXVIEWINIT7 80
FORLINNPUNIQUELABEL
AXSCATTERXLABEL  L 0 XLABEL  L 1 XLABEL  L 2
COLORPLTCMJETNPFLOATL  NPMAXLABEL  1
S20 EDGECOLORK
PLTTITLEWITHOUT CONNECTIVITY CONSTRAINTS TIME 2FS  ELAPSEDTIME

 DEFINE THE STRUCTURE A OF THE DATA HERE A 10 NEAREST NEIGHBORS
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSGRAPH
CONNECTIVITY  KNEIGHBORSGRAPHX NNEIGHBORS10 INCLUDESELFFALSE

 COMPUTE CLUSTERING
PRINTCOMPUTE STRUCTURED HIERARCHICAL CLUSTERING
ST  TIMETIME
WARD  AGGLOMERATIVECLUSTERINGNCLUSTERS6 CONNECTIVITYCONNECTIVITY
LINKAGEWARDFITX
ELAPSEDTIME  TIMETIME  ST
LABEL  WARDLABELS
PRINTELAPSED TIME 2FS  ELAPSEDTIME
PRINTNUMBER OF POINTS I  LABELSIZE

 PLOT RESULT
FIG  PLTFIGURE
AX  P3AXES3DFIG
AXVIEWINIT7 80
FORLINNPUNIQUELABEL
AXSCATTERXLABEL  L 0 XLABEL  L 1 XLABEL  L 2
COLORPLTCMJETFLOATL  NPMAXLABEL  1
S20 EDGECOLORK
PLTTITLEWITH CONNECTIVITY CONSTRAINTS TIME 2FS  ELAPSEDTIME
```

PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0202 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5616 AGGLOMERATIVE CLUSTERING WITH DIFFERENT METRICS
DEMONSTRATES THE EFFECT OF DIFFERENT METRICS ON THE HIERARCHICAL CLUSTERING
THE EXAMPLE IS ENGINEERED TO SHOW THE EFFECT OF THE CHOICE OF DIFFERENT METRICS IT IS APPLIED TO WAVEFORMS WHICH CAN BE SEEN AS HIGHDIMENSIONAL VECTOR INDEED THE DIFFERENCE BETWEEN METRICS IS USUALLY MORE PRONOUNCED IN HIGH DIMENSION IN PARTICULAR FOR EUCLIDEAN AND CITYBLOCK
WE GENERATE DATA FROM THREE GROUPS OF WAVEFORMS TWO OF THE WAVEFORMS WAVEFORM 1 AND WAVEFORM 2 ARE PROPOR TIONAL ONE TO THE OTHER THE COSINE DISTANCE IS INVARIANT TO A SCALING OF THE DATA AS A RESULT IT CANNOT DISTINGUISH THESE TWO WAVEFORMS THUS EVEN WITH NO NOISE CLUSTERING USING THIS DISTANCE WILL NOT SEPARATE OUT WAVEFORM 1 AND 2
WE ADD OBSERVATION NOISE TO THESE WAVEFORMS WE GENERATE VERY SPARSE NOISE ONLY 6 OF THE TIME POINTS CONTAIN NOISE AS A RESULT THE L1 NORM OF THIS NOISE IE “CITYBLOCK” DISTANCE IS MUCH SMALLER THAN IT’S L2 NORM “EUCLIDEAN” DISTANCE THIS CAN BE SEEN ON THE INTERCLASS DISTANCE MATRICES THE VALUES ON THE DIAGONAL THAT CHARACTERIZE THE SPREAD OF THE CLASS ARE MUCH BIGGER FOR THE EUCLIDEAN DISTANCE THAN FOR THE CITYBLOCK DISTANCE
WHEN WE APPLY CLUSTERING TO THE DATA WE FIND THAT THE CLUSTERING REFLECTS WHAT WAS IN THE DISTANCE MATRICES INDEED FOR THE EUCLIDEAN DISTANCE THE CLASSES ARE ILLSEPARATED BECAUSE OF THE NOISE AND THUS THE CLUSTERING DOES NOT SEPARATE THE WAVEFORMS FOR THE CITYBLOCK DISTANCE THE SEPARATION IS GOOD AND THE WAVEFORM CLASSES ARE RECOVERED FINALLY THE COSINE DISTANCE DOES NOT SEPARATE AT ALL WAVEFORM 1 AND 2 THUS THE CLUSTERING PUTS THEM IN THE SAME CLUSTER

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56 CLUSTERING 865

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56 CLUSTERING 867

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56 CLUSTERING 869

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•
 AUTHOR GAEL VAROQUAUX
 LICENSE BSD 3CLAUSE OR CC0
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNCLUSTER IMPORT AGGLOMERATIVECLUSTERING
FROM SKLEARNMETRICS IMPORT PAIRWISEDISTANCES
NPRANDOMSEED0
 GENERATE WAVEFORM DATA
NFEATURES  2000
T  NPPI NPLINSPACE0 1 NFEATURES
DEFSQRX
RETURNNPSIGNNPCOSX
X  LIST
Y  LIST
FORI PHI A INENUMERATE5 15 5 6 3 2
FORINRANGE30
PHASENOISE  01 NPRANDOMNORMAL
AMPLITUDENOISE  04 NPRANDOMNORMAL
ADDITIONALNOISE  1  2 NPRANDOMRANDNFEATURES
 MAKE THE NOISE SPARSE
```

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ADDITIONALNOISENPABSADDITIONALNOISE  997  0
XAPPEND12 A  AMPLITUDENOISE
SQR6T  PHI  PHASENOISE
 ADDITIONALNOISE
YAPPENDI
X  NPARRAYX
Y  NPARRAYY
NCLUSTERS  3
LABELS  WAVEFORM 1 WAVEFORM 2 WAVEFORM 3
 PLOT THE GROUNDTRUTH LABELLING
PLTFIGURE
PLTAXES0 0 1 1
FORL C N INZIPRANGENCLUSTERS RGB
LABELS
LINES  PLTPLOTXY  LT CC ALPHA5
LINES0SETLABELN
PLTLEGENDLOCBEST
PLTAXISTIGHT
PLTAXISOFF
PLTSUPTITLEGROUND TRUTH SIZE20
 PLOT THE DISTANCES
FORINDEX METRIC INENUMERATECOSINE EUCLIDEAN CITYBLOCK
AVGDIST  NPZEROSNCLUSTERS NCLUSTERS
PLTFIGUREFIGSIZE5 45
FORIINRANGENCLUSTERS
FORJINRANGENCLUSTERS
AVGDISTI J  PAIRWISEDISTANCESXY  I XY  J
METRICMETRICMEAN
AVGDIST  AVGDISTMAX
FORIINRANGENCLUSTERS
FORJINRANGENCLUSTERS
PLTTEXTI J  53F  AVGDISTI J
VERTICALALIGNMENTCENTER
HORIZONTALALIGNMENTCENTER
PLTIMSHOWAVGDIST INTERPOLATIONNEAREST CMAPPLTCMGNUPLOT2
VMIN0
PLTXTICKSRANGENCLUSTERS LABELS ROTATION45
PLTYTICKSRANGENCLUSTERS LABELS
PLTCOLORBAR
PLTSUPTITLEINTERCLASS SDISTANCES  METRIC SIZE18
PLTTIGHTLAYOUT
 PLOT CLUSTERING RESULTS
FORINDEX METRIC INENUMERATECOSINE EUCLIDEAN CITYBLOCK
MODEL  AGGLOMERATIVECLUSTERINGNCLUSTERSNCLUSTERS
LINKAGEAVERAGE AFFINITYMETRIC
MODELFITX
872 CHAPTER 5 EXAMPLES
```

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PLTFIGURE
PLTAXES0 0 1 1
FORL CINZIPNPARANGEMODELNCLUSTERS RGBK
PLTPLOTXMODELLABELS LT CC ALPHA5
PLTAXISTIGHT
PLTAXISOFF
PLTSUPTITLEAGGLOMERATIVECLUSTERINGAFFINITY S METRIC SIZE20
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0584 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5617 INDUCTIVE CLUSTERING
CLUSTERING CAN BE EXPENSIVE ESPECIALLY WHEN OUR DATASET CONTAINS MILLIONS OF DATAPOINTS MANY CLUSTERING ALGORITHMS ARE NOT INDUCTIVE AND SO CANNOT BE DIRECTLY APPLIED TO NEW DATA SAMPLES WITHOUT RECOMPUTING THE CLUSTERING WHICH MAY BE INTRACTABLE INSTEAD WE CAN USE CLUSTERING TO THEN LEARN AN INDUCTIVE MODEL WITH A CLASSIFIER WHICH HAS SEVERAL BENEFITS
• IT ALLOWS THE CLUSTERS TO SCALE AND APPLY TO NEW DATA
• UNLIKE REFITTING THE CLUSTERS TO NEW SAMPLES IT MAKES SURE THE LABELLING PROCEDURE IS CONSISTENT OVER TIME
• IT ALLOWS US TO USE THE INFERENTIAL CAPABILITIES OF THE CLASSIFIER TO DESCRIBE OR EXPLAIN THE CLUSTERS
THIS EXAMPLE ILLUSTRATES A GENERIC IMPLEMENTATION OF A METAESTIMATOR WHICH EXTENDS CLUSTERING BY INDUCING A CLASSIFIER FROM THE CLUSTER LABELS
 AUTHORS CHIRAG NAGPAL
 CHRISTOS ARIDAS
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNBASE IMPORT BASEESTIMATOR CLONE
FROM SKLEARNCLUSTER IMPORT AGGLOMERATIVECLUSTERING
FROM SKLEARNDATASETS IMPORT MAKEBLOBS
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER

```
FROM SKLEARNUTILSMETAESTIMATORS IMPORT IFDELEGATEHASMETHOD
NSAMPLES  5000
RANDOMSTATE  42
CLASS INDUCTIVECLUSTERER BASEESTIMATOR
DEFINITSELF CLUSTERER CLASSIFIER
SELFCLUSTERER  CLUSTERER
SELFCLASSIFIER  CLASSIFIER
DEFFITSELF X YNONE
SELFCLUSTERER  CLONESELFCLUSTERER
SELFCLASSIFIER  CLONESELFCLASSIFIER
Y  SELFCLUSTERERFITPREDICTX
SELFCLASSIFIERFITX Y
RETURNSELF
IFDELEGATEHASMETHOD DELEGATECLASSIFIER
DEFPREDICTSELF X
RETURNSELFCLASSIFIERPREDICTX
IFDELEGATEHASMETHOD DELEGATECLASSIFIER
DEFDECISIONFUNCTIONSELF X
RETURNSELFCLASSIFIERDECISIONFUNCTIONX
DEFPLOTSCATTERX COLOR ALPHA05
RETURNPLTSCATTERX 0
X 1
CCOLOR
ALPHAALPHA
EDGECOLORK
 GENERATE SOME TRAINING DATA FROM CLUSTERING
X Y  MAKEBLOBSNSAMPLESNSAMPLES
CLUSTERSTD10 10 05
CENTERS5 5 0 0 5 5
RANDOMSTATERANDOMSTATE
 TRAIN A CLUSTERING ALGORITHM ON THE TRAINING DATA AND GET THE CLUSTER LABELS
CLUSTERER  AGGLOMERATIVECLUSTERINGNCLUSTERS3
CLUSTERLABELS  CLUSTERERFITPREDICTX
PLTFIGUREFIGSIZE12 4
PLTSUBPLOT131
PLOTSCATTERX CLUSTERLABELS
PLTTITLEWARD LINKAGE
 GENERATE NEW SAMPLES AND PLOT THEM ALONG WITH THE ORIGINAL DATASET
XNEW YNEW  MAKEBLOBSNSAMPLES10
CENTERS7 1 2 4 3 6
RANDOMSTATERANDOMSTATE
```

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PLTSUBPLOT132
PLOTSCATTERX CLUSTERLABELS
PLOTSCATTERXNEW BLACK 1
PLTTITLEUNKNOWN INSTANCES
 DECLARE THE INDUCTIVE LEARNING MODEL THAT IT WILL BE USED TO
 PREDICT CLUSTER MEMBERSHIP FOR UNKNOWN INSTANCES
CLASSIFIER RANDOMFORESTCLASSIFIERRANDOMSTATERANDOMSTATE
INDUCTIVELEARNER INDUCTIVECLUSTERERCLUSTERER CLASSIFIERFITX
PROBABLECLUSTERS INDUCTIVELEARNERPREDICTXNEW
PLTSUBPLOT133
PLOTSCATTERX CLUSTERLABELS
PLOTSCATTERXNEW PROBABLECLUSTERS
 PLOTTING DECISION REGIONS
XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX 01
NPARANGEYMIN YMAX 01
Z INDUCTIVELEARNERPREDICTNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
PLTCONTOURFXX YY Z ALPHA04
PLTTITLECLASSIFY UNKNOWN INSTANCES
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1436 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5618 DEMO OF OPTICS CLUSTERING ALGORITHM
FINDS CORE SAMPLES OF HIGH DENSITY AND EXPANDS CLUSTERS FROM THEM THIS EXAMPLE USES DATA THAT IS GENERATED SO
THAT THE CLUSTERS HAVE DIFFERENT DENSITIES THE SKLEARNCLUSTEROPTICS IS FIRST USED WITH ITS XI CLUSTER DETEC
TION METHOD AND THEN SETTING SPECIFIC THRESHOLDS ON THE REACHABILITY WHICH CORRESPONDS TO SKLEARNCLUSTER
DBSCAN WE CAN SEE THAT THE DIFFERENT CLUSTERS OF OPTICS’S XI METHOD CAN BE RECOVERED WITH DIFFERENT CHOICES OF
THRESHOLDS IN DBSCAN

```
SCIKITLEARN USER GUIDE RELEASE 0213
 AUTHORS SHANE GRIGSBY REFUGEROCKTALUSCOM
 ADRIN JALALI ADRINJALALIGMAILCOM
 LICENSE BSD 3 CLAUSE
FROM SKLEARNCLUSTER IMPORT OPTICS CLUSTEROPTICSDBSCAN
IMPORT MATPLOTLIBGRIDSPEC AS GRIDSPEC
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
 GENERATE SAMPLE DATA
NPRANDOMSEED0
NPOINTSPERCLUSTER  250
C1  5 2  8 NPRANDOMRANDNNPOINTSPERCLUSTER 2
C2  4 1  1 NPRANDOMRANDNNPOINTSPERCLUSTER 2
C3  1 2  2 NPRANDOMRANDNNPOINTSPERCLUSTER 2
C4  2 3  3 NPRANDOMRANDNNPOINTSPERCLUSTER 2
C5  3 2  16 NPRANDOMRANDNNPOINTSPERCLUSTER 2
C6  5 6  2 NPRANDOMRANDNNPOINTSPERCLUSTER 2
X  NPVSTACKC1 C2 C3 C4 C5 C6
CLUST  OPTICSMINSAMPLES50 XI05 MINCLUSTERSIZE05
 RUN THE FIT
CLUSTFITX
```

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LABELS050 CLUSTEROPTICSDBSCANREACHABILITYCLUSTREACHABILITY
COREDISTANCESCLUSTCOREDISTANCES
ORDERINGCLUSTORDERING EPS05
LABELS200 CLUSTEROPTICSDBSCANREACHABILITYCLUSTREACHABILITY
COREDISTANCESCLUSTCOREDISTANCES
ORDERINGCLUSTORDERING EPS2
SPACE NPARANGELENX
REACHABILITY CLUSTREACHABILITYCLUSTORDERING
LABELS CLUSTLABELSCLUSTORDERING
PLTFIGUREFIGSIZE10 7
G GRIDSPECGRIDSPEC2 3
AX1 PLTSUBPLOTG0
AX2 PLTSUBPLOTG1 0
AX3 PLTSUBPLOTG1 1
AX4 PLTSUBPLOTG1 2
 REACHABILITY PLOT
COLORS G R B Y C
FORKLASS COLOR INZIPRANGE0 5 COLORS
XK SPACELABELS KLASS
RK REACHABILITYLABELS KLASS
AX1PLOTXK RK COLOR ALPHA03
AX1PLOTSPACELABELS 1 REACHABILITYLABELS 1 K ALPHA03
AX1PLOTSPACE NPFULLLIKESPACE 2 DTYPEFLOAT K ALPHA05
AX1PLOTSPACE NPFULLLIKESPACE 05 DTYPEFLOAT K ALPHA05
AX1SETYLABELREACHABILITY EPSILON DISTANCE
AX1SETTITLEREACHABILITY PLOT
 OPTICS
COLORS G R B Y C
FORKLASS COLOR INZIPRANGE0 5 COLORS
XK XCLUSTLABELS KLASS
AX2PLOTXK 0 XK 1 COLOR ALPHA03
AX2PLOTXCLUSTLABELS 1 0 XCLUSTLABELS 1 1 K ALPHA01
AX2SETTITLEAUTOMATIC CLUSTERING NOPTICS
 DBSCAN AT 05
COLORS G GREENYELLOW OLIVE R B C
FORKLASS COLOR INZIPRANGE0 6 COLORS
XK XLABELS050 KLASS
AX3PLOTXK 0 XK 1 COLOR ALPHA03 MARKER
AX3PLOTXLABELS050 1 0 XLABELS050 1 1 K ALPHA01
AX3SETTITLECLUSTERING AT 05 EPSILON CUT NDBSCAN
 DBSCAN AT 2
COLORS G M Y C
FORKLASS COLOR INZIPRANGE0 4 COLORS
XK XLABELS200 KLASS
AX4PLOTXK 0 XK 1 COLOR ALPHA03
AX4PLOTXLABELS200 1 0 XLABELS200 1 1 K ALPHA01
AX4SETTITLECLUSTERING AT 20 EPSILON CUT NDBSCAN
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0935 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5619 COMPARE BIRCH AND MINIBATCHKMEANS
THIS EXAMPLE COMPARES THE TIMING OF BIRCH WITH AND WITHOUT THE GLOBAL CLUSTERING STEP AND MINIBATCHKMEANS ON A SYNTHETIC DATASET HAVING 100000 SAMPLES AND 2 FEATURES GENERATED USING MAKEBLOBS
IFNCLUSTERS IS SET TO NONE THE DATA IS REDUCED FROM 100000 SAMPLES TO A SET OF 158 CLUSTERS THIS CAN BE VIEWED AS A PREPROCESSING STEP BEFORE THE FINAL GLOBAL CLUSTERING STEP THAT FURTHER REDUCES THESE 158 CLUSTERS TO 100 CLUSTERS
OUT
BIRCH WITHOUT GLOBAL CLUSTERING AS THE FINAL STEP TOOK 247 SECONDS
NCLUSTERS 158
BIRCH WITH GLOBAL CLUSTERING AS THE FINAL STEP TOOK 290 SECONDS
NCLUSTERS 100
TIME TAKEN TO RUN MINIBATCHKMEANS 360 SECONDS
 AUTHORS MANOJ KUMAR MANOJKUMARSIVARAJ334GMAILCOM
 ALEXANDRE GRAMFORT ALEXANDREGRAMFORTTELECOMPARISTECHFR
 LICENSE BSD 3 CLAUSE
PRINTDOC
FROM ITERTOOLS IMPORT CYCLE
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIBCOLORS AS COLORS
FROM SKLEARNCLUSTER IMPORT BIRCH MINIBATCHKMEANS
FROM SKLEARNDATASETSSAMPLESGENERATOR IMPORT MAKEBLOBS
 GENERATE CENTERS FOR THE BLOBS SO THAT IT FORMS A 10 X 10 GRID

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XX NPLINSPACE22 22 10
YY NPLINSPACE22 22 10
XX YY NPMESHGRIDXX YY
NCENTRES NPHSTACKNPRAVELXX NPNEWAXIS
NPRAVELYY NPNEWAXIS
 GENERATE BLOBS TO DO A COMPARISON BETWEEN MINIBATCHKMEANS AND BIRCH
X Y MAKEBLOBSNSAMPLES100000 CENTERSNCENTRES RANDOMSTATE0
 USE ALL COLORS THAT MATPLOTLIB PROVIDES BY DEFAULT
COLORS CYCLECOLORSCNAMESKEYS
FIG PLTFIGUREFIGSIZE12 4
FIGSUBPLOTSADJUSTLEFT004 RIGHT098 BOTTOM01 TOP09
 COMPUTE CLUSTERING WITH BIRCH WITH AND WITHOUT THE FINAL CLUSTERING STEP
 AND PLOT
BIRCHMODELS BIRCHTHRESHOLD17 NCLUSTERSNONE
BIRCHTHRESHOLD17 NCLUSTERS100
FINALSTEP WITHOUT GLOBAL CLUSTERING WITH GLOBAL CLUSTERING
FORIND BIRCHMODEL INFO INENUMERATEZIPBIRCHMODELS FINALSTEP
T TIME
BIRCHMODELFITX
TIME TIME T
PRINTBIRCH SAS THE FINAL STEP TOOK 02FSECONDS
INFO TIME T
 PLOT RESULT
LABELS BIRCHMODELLABELS
CENTROIDS BIRCHMODELSUBCLUSTERCENTERS
NCLUSTERS NPUNIQUELABELSSIZE
PRINTNCLUSTERS D NCLUSTERS
AX FIGADDSUBPLOT1 3 IND 1
FORTHISCENTROID K COL INZIPCENTROIDS RANGENCLUSTERS COLORS
MASK LABELS K
AXSCATTERXMASK 0 XMASK 1
CW EDGECOLORCOL MARKER ALPHA05
IFBIRCHMODELNCLUSTERS ISNONE
AXSCATTERTHISCENTROID0 THISCENTROID1 MARKER
CK S25
AXSETYLIM25 25
AXSETXLIM25 25
AXSETAUTOSCALEYONFALSE
AXSETTITLEBIRCH S INFO
 COMPUTE CLUSTERING WITH MINIBATCHKMEANS
MBK MINIBATCHKMEANSINITKMEANS NCLUSTERS100 BATCHSIZE100
NINIT10 MAXNOIMPROVEMENT10 VERBOSE0
RANDOMSTATE0
T0 TIME
MBKFITX
TMINIBATCH TIME T0
PRINTTIME TAKEN TO RUN MINIBATCHKMEANS 02FSECONDS TMINIBATCH
MBKMEANSLABELSUNIQUE NPUNIQUEMBKLABELS
AX FIGADDSUBPLOT1 3 3

SCIKITLEARN USER GUIDE RELEASE 0213
FORTHISCENTROID K COL INZIPMBKCLUSTERCENTERS
RANGENCLUSTERS COLORS
MASK MBKLABELS K
AXSCATTERXMASK 0 XMASK 1 MARKER
CW EDGECOLORCOL ALPHA05
AXSCATTERTHISCENTROID0 THISCENTROID1 MARKER
CK S25
AXSETXLIM25 25
AXSETYLIM25 25
AXSETTITLEMINIBATCHKMEANS
AXSETAUTOSCALEYONFALSE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 10943 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5620 EMPIRICAL EVALUATION OF THE IMPACT OF KMEANS INITIALIZATION
EVALUATE THE ABILITY OF KMEANS INITIALIZATIONS STRATEGIES TO MAKE THE ALGORITHM CONVERGENCE ROBUST AS MEASURED BY THE RELATIVE STANDARD DEVIATION OF THE INERTIA OF THE CLUSTERING IE THE SUM OF SQUARED DISTANCES TO THE NEAREST CLUSTER CENTER
THE FIRST PLOT SHOWS THE BEST INERTIA REACHED FOR EACH COMBINATION OF THE MODEL KMEANS ORMINIBATCHKMEANS AND THE INIT METHOD INITRANDOM ORINITKMEANS FOR INCREASING VALUES OF THE NINIT PARAMETER THAT CONTROLS THE NUMBER OF INITIALIZATIONS
THE SECOND PLOT DEMONSTRATE ONE SINGLE RUN OF THE MINIBATCHKMEANS ESTIMATOR USING A INITRANDOM AND NINIT1 THIS RUN LEADS TO A BAD CONVERGENCE LOCAL OPTIMUM WITH ESTIMATED CENTERS STUCK BETWEEN GROUND TRUTH CLUSTERS
THE DATASET USED FOR EVALUATION IS A 2D GRID OF ISOTROPIC GAUSSIAN CLUSTERS WIDELY SPACED

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56 CLUSTERING 881

•
OUT
EVALUATION OF KMEANS WITH KMEANS INIT
EVALUATION OF KMEANS WITH RANDOM INIT
EVALUATION OF MINIBATCHKMEANS WITH KMEANS INIT
EVALUATION OF MINIBATCHKMEANS WITH RANDOM INIT
PRINTDOC
 AUTHOR OLIVIER GRISEL OLIVIERGRISELENSTAORG
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIBCM AS CM
FROM SKLEARNUTILS IMPORT SHUFFLE
FROM SKLEARNUTILS IMPORT CHECKRANDOMSTATE
FROM SKLEARNCLUSTER IMPORT MINIBATCHKMEANS
FROM SKLEARNCLUSTER IMPORT KMEANS
RANDOMSTATE NPRANDOMRANDOMSTATE0

```
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 NUMBER OF RUN WITH RANDOMLY GENERATED DATASET FOR EACH STRATEGY SO AS
 TO BE ABLE TO COMPUTE AN ESTIMATE OF THE STANDARD DEVIATION
NRUNS  5
 KMEANS MODELS CAN DO SEVERAL RANDOM INITS SO AS TO BE ABLE TO TRADE
 CPU TIME FOR CONVERGENCE ROBUSTNESS
NINITRANGE  NPARRAY1 5 10 15 20
 DATASETS GENERATION PARAMETERS
NSAMPLESPERCENTER  100
GRIDSIZE  3
SCALE  01
NCLUSTERS  GRIDSIZE 2
DEFMAKEDATARANDOMSTATE NSAMPLESPERCENTER GRIDSIZE SCALE
RANDOMSTATE  CHECKRANDOMSTATERANDOMSTATE
CENTERS  NPARRAYI J
FORIINRANGEGRIDSIZE
FORJINRANGEGRIDSIZE
NCLUSTERSTRUE NFEATURES  CENTERSSHAPE
NOISE  RANDOMSTATENORMAL
SCALESCALE SIZENSAMPLESPERCENTER CENTERSSHAPE1
X  NPCONCATENATEC  NOISE FORCINCENTERS
Y  NPCONCATENATEI NSAMPLESPERCENTER
FORIINRANGENCLUSTERSTRUE
RETURNSHUFFLEX Y RANDOMSTATERANDOMSTATE
 PART 1 QUANTITATIVE EVALUATION OF VARIOUS INIT METHODS
PLTFIGURE
PLOTS
LEGENDS
CASES
KMEANS KMEANS
KMEANS RANDOM
MINIBATCHKMEANS KMEANS MAXNOIMPROVEMENT 3
MINIBATCHKMEANS RANDOM MAXNOIMPROVEMENT 3 INITSIZE 500

FORFACTORY INIT PARAMS INCASES
PRINTEVALUATION OF SWITHSINIT  FACTORYNAME INIT
INERTIA  NPEMPTYLENNINITRANGE NRUNS
FORRUNIDINRANGENRUNS
X Y  MAKEDATARUNID NSAMPLESPERCENTER GRIDSIZE SCALE
FORI NINIT INENUMERATENINITRANGE
KM  FACTORYNCLUSTERSNCLUSTERS INITINIT RANDOMSTATERUNID
NINITNINIT PARAMSFITX
INERTIAI RUNID  KMINERTIA
P  PLTERRORBARNINITRANGE INERTIAMEANAXIS1 INERTIASTDAXIS1
PLOTSAPPENDP0
LEGENDSAPPEND SWITHSINIT  FACTORYNAME INIT
56 CLUSTERING 883
```

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PLTXLABELNINIT
PLTYLABELINERTIA
PLTLEGENDPLOTS LEGENDS
PLTTITLEMEAN INERTIA FOR VARIOUS KMEANS INIT ACROSS DRUNS NRUNS
 PART 2 QUALITATIVE VISUAL INSPECTION OF THE CONVERGENCE
X Y MAKEDATARANDOMSTATE NSAMPLESPERCENTER GRIDSIZE SCALE
KM MINIBATCHKMEANSNCLUSTERSNCLUSTERS INITRANDOM NINIT1
RANDOMSTATERANDOMSTATEFITX
PLTFIGURE
FORKINRANGENCLUSTERS
MYMEMBERS KMLABELS K
COLOR CMNIPYSPECTRALFLOATK NCLUSTERS 1
PLTPLOTXMYMEMBERS 0 XMYMEMBERS 1 O MARKER CCOLOR
CLUSTERCENTER KMCLUSTERCENTERSK
PLTPLOTCLUSTERCENTER0 CLUSTERCENTER1 O
MARKERFACECOLORCOLOR MARKEREDGECOLORK MARKERSIZE6
PLTTITLEEXAMPLE CLUSTER ALLOCATION WITH A SINGLE RANDOM INIT N
WITH MINIBATCHKMEANS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2695 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5621 ADJUSTMENT FOR CHANCE IN CLUSTERING PERFORMANCE EVALUATION
THE FOLLOWING PLOTS DEMONSTRATE THE IMPACT OF THE NUMBER OF CLUSTERS AND NUMBER OF SAMPLES ON VARIOUS CLUSTERING PERFORMANCE EVALUATION METRICS
NONADJUSTED MEASURES SUCH AS THE VMEASURE SHOW A DEPENDENCY BETWEEN THE NUMBER OF CLUSTERS AND THE NUMBER OF SAMPLES THE MEAN VMEASURE OF RANDOM LABELING INCREASES SIGNIFICANTLY AS THE NUMBER OF CLUSTERS IS CLOSER TO THE TOTAL NUMBER OF SAMPLES USED TO COMPUTE THE MEASURE
ADJUSTED FOR CHANCE MEASURE SUCH AS ARI DISPLAY SOME RANDOM VARIATIONS CENTERED AROUND A MEAN SCORE OF 00 FOR ANY NUMBER OF SAMPLES AND CLUSTERS
ONLY ADJUSTED MEASURES CAN HENCE SAFELY BE USED AS A CONSENSUS INDEX TO EVALUATE THE AVERAGE STABILITY OF CLUSTERING ALGORITHMS FOR A GIVEN VALUE OF K ON VARIOUS OVERLAPPING SUBSAMPLES OF THE DATASET

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56 CLUSTERING 885

•

OUT

COMPUTING ADJUSTEDRANDSCORE FOR 10 VALUES OF NCLUSTERS AND NSAMPLES100
DONE IN 0026S
COMPUTING VMEASURESCORE FOR 10 VALUES OF NCLUSTERS AND NSAMPLES100
DONE IN 0040S
COMPUTING AMISCORE FOR 10 VALUES OF NCLUSTERS AND NSAMPLES100
DONE IN 0349S
COMPUTING MUTUALINFOSCORE FOR 10 VALUES OF NCLUSTERS AND NSAMPLES100
DONE IN 0033S
COMPUTING ADJUSTEDRANDSCORE FOR 10 VALUES OF NCLUSTERS AND NSAMPLES1000
DONE IN 0041S
COMPUTING VMEASURESCORE FOR 10 VALUES OF NCLUSTERS AND NSAMPLES1000
DONE IN 0053S
COMPUTING AMISCORE FOR 10 VALUES OF NCLUSTERS AND NSAMPLES1000
DONE IN 0208S
COMPUTING MUTUALINFOSCORE FOR 10 VALUES OF NCLUSTERS AND NSAMPLES1000
DONE IN 0043S
PRINTDOC
AUTHOR OLIVIER GRISEL OLIVIERGRISELENSTAORG

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LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM TIME IMPORT TIME
FROM SKLEARN IMPORT METRICS
DEFUNIFORMLABELINGSSCORESSCOREFUNC NSAMPLES NCLUSTERSRANGE
FIXEDNCLASSESNONE NRUNS5 SEED42
COMPUTE SCORE FOR 2 RANDOM UNIFORM CLUSTER LABELINGS
BOTH RANDOM LABELINGS HAVE THE SAME NUMBER OF CLUSTERS FOR EACH VALUE
POSSIBLE VALUE IN NCLUSTERSRANGE
WHEN FIXEDNCLASSES IS NOT NONE THE FIRST LABELING IS CONSIDERED A GROUND
TRUTH CLASS ASSIGNMENT WITH FIXED NUMBER OF CLASSES

RANDOMLABELS NPRANDOMRANDOMSTATESEEDRANDINT
SCORES NPZEROSLENNCLUSTERSRANGE NRUNS
IFFIXEDNCLASSES IS NOTNONE
LABELSA RANDOMLABELSLOW0 HIGHFIXEDNCLASSES SIZENSAMPLES
FORI KINENUMERATENCLUSTERSRANGE
FORJINRANGENRUNS
IFFIXEDNCLASSES ISNONE
LABELSA RANDOMLABELSLOW0 HIGHK SIZENSAMPLES
LABELSB RANDOMLABELSLOW0 HIGHK SIZENSAMPLES
SCORESI J SCOREFUNCLABELSA LABELSB
RETURNSCORES
DEFAMISCOREU V
RETURNMETRICSADJUSTEDMUTUALINFOSCOREU V
AVERAGEMETHODARITHMETIC
SCOREFUNCS
METRICSADJUSTEDRANDSCORE
METRICSVMEASURESCORE
AMISCORE
METRICSMUTUALINFOSCORE

2 INDEPENDENT RANDOM CLUSTERINGS WITH EQUAL CLUSTER NUMBER
NSAMPLES 100
NCLUSTERSRANGE NPLINSPACE2 NSAMPLES 10ASTYPENPINT
PLTFIGURE1
PLOTS
NAMES
FORSCOREFUNC INSCOREFUNCS
PRINTCOMPUTING SFORDVALUES OF NCLUSTERS AND NSAMPLES D
SCOREFUNCNAME LENNCLUSTERSRANGE NSAMPLES
T0 TIME
SCORES UNIFORMLABELINGSSCORESSCOREFUNC NSAMPLES NCLUSTERSRANGE

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PRINTDONE IN 03FS TIME T0
PLOTSAPPENDPLTERRORBAR
NCLUSTERSRANGE NPMEDIANSCORES AXIS1 SCORESSTDAXIS10
NAMESAPPENDSCOREFUNCNAME
PLTTITLECLUSTERING MEASURES FOR 2 RANDOM UNIFORM LABELINGS N
WITH EQUAL NUMBER OF CLUSTERS
PLTXLABELNUMBER OF CLUSTERS NUMBER OF SAMPLES IS FIXED TO D NSAMPLES
PLTYLABELSCORE VALUE
PLTLEGENDPLOTS NAMES
PLTYLIMBOTTOM005 TOP105
 RANDOM LABELING WITH VARYING NCLUSTERS AGAINST GROUND CLASS LABELS
 WITH FIXED NUMBER OF CLUSTERS
NSAMPLES 1000
NCLUSTERSRANGE NPLINSPACE2 100 10ASTYPENPINT
NCLASSES 10
PLTFIGURE2
PLOTS
NAMES
FORSCOREFUNC INSCOREFUNCS
PRINTCOMPUTING SFORDVALUES OF NCLUSTERS AND NSAMPLES D
 SCOREFUNCNAME LENNCLUSTERSRANGE NSAMPLES
T0 TIME
SCORES UNIFORMLABELINGSSCORESSCOREFUNC NSAMPLES NCLUSTERSRANGE
FIXEDNCLASSESNCLASSES
PRINTDONE IN 03FS TIME T0
PLOTSAPPENDPLTERRORBAR
NCLUSTERSRANGE SCORESMEANAXIS1 SCORESSTDAXIS10
NAMESAPPENDSCOREFUNCNAME
PLTTITLECLUSTERING MEASURES FOR RANDOM UNIFORM LABELING N
AGAINST REFERENCE ASSIGNMENT WITH DCLASSES NCLASSES
PLTXLABELNUMBER OF CLUSTERS NUMBER OF SAMPLES IS FIXED TO D NSAMPLES
PLTYLABELSCORE VALUE
PLTYLIMBOTTOM005 TOP105
PLTLEGENDPLOTS NAMES
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0835 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5622 FEATURE AGGLOMERATION VS UNIVARIATE SELECTION
THIS EXAMPLE COMPARES 2 DIMENSIONALITY REDUCTION STRATEGIES
• UNIVARIATE FEATURE SELECTION WITH ANOVA
• FEATURE AGGLOMERATION WITH WARD HIERARCHICAL CLUSTERING

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BOTH METHODS ARE COMPARED IN A REGRESSION PROBLEM USING A BAYESIANRIDGE AS SUPERVISED ESTIMATOR
OUT

MEMORY CALLING SKLEARNCLUSTERHIERARCHICALWARDTREE
WARDTREEARRAY0451933 0675318

 0275706 1085711
1600X1600 SPARSE MATRIX OF TYPE CLASS NUMPYINT64
WITH 7840 STORED ELEMENTS IN COORDINATE FORMAT NCLUSTERSNONE RETURN
‘→DISTANCEFALSE
WARDTREE 01S 00MIN

MEMORY CALLING SKLEARNCLUSTERHIERARCHICALWARDTREE
WARDTREEARRAY 0905206 0161245

0849835 1091621
1600X1600 SPARSE MATRIX OF TYPE CLASS NUMPYINT64
WITH 7840 STORED ELEMENTS IN COORDINATE FORMAT NCLUSTERSNONE RETURN
‘→DISTANCEFALSE
WARDTREE 01S 00MIN

MEMORY CALLING SKLEARNCLUSTERHIERARCHICALWARDTREE
WARDTREEARRAY 0905206 0675318

0849835 1085711
1600X1600 SPARSE MATRIX OF TYPE CLASS NUMPYINT64
WITH 7840 STORED ELEMENTS IN COORDINATE FORMAT NCLUSTERSNONE RETURN
‘→DISTANCEFALSE
WARDTREE 01S 00MIN

MEMORY CALLING SKLEARNFEATURESELECTIONUNIVARIATESELECTIONFREGRESSION
FREGRESSIONARRAY0451933 0275706

0675318 1085711
ARRAY 25267703 25026711
FREGRESSION 00S 00MIN

MEMORY CALLING SKLEARNFEATURESELECTIONUNIVARIATESELECTIONFREGRESSION
FREGRESSIONARRAY 0905206 0849835

SCIKITLEARN USER GUIDE RELEASE 0213
0161245 1091621
ARRAY 27447268 112638768
FREGRESSION 00S 00MIN

MEMORY CALLING SKLEARNFEATURESELECTIONUNIVARIATESELECTIONFREGRESSION
FREGRESSIONARRAY 0905206 0849835

0675318 1085711
ARRAY27447268 25026711
FREGRESSION 00S 00MIN
AUTHOR ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
LICENSE BSD 3 CLAUSE
PRINTDOC
IMPORT SHUTIL
IMPORT TEMPFILE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPY IMPORT LINALG NDIMAGE
FROM JOBLIB IMPORT MEMORY
FROM SKLEARNFEATUREEXTRACTIONIMAGE IMPORT GRIDTOGRAPH
FROM SKLEARN IMPORT FEATURESELECTION
FROM SKLEARNCLUSTER IMPORT FEATUREAGGLOMERATION
FROM SKLEARNLINEARMODEL IMPORT BAYESIANRIDGE
FROM SKLEARNPIPELINE IMPORT PIPELINE
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNMODELSELECTION IMPORT KFOLD

GENERATE DATA
NSAMPLES 200
SIZE 40 IMAGE SIZE
ROISIZE 15
SNR 5
NPRANDOMSEED0
MASK NPONESSIZE SIZE DTYPENPBOOL
COEF NPZEROSSIZE SIZE
COEF0ROISIZE 0ROISIZE 1
COEFROISIZE ROISIZE 1
X NPRANDOMRANDNNSAMPLES SIZE 2
FORXINX SMOOTH DATA
X NDIMAGEGAUSSIANFILTERXRESHAPESIZE SIZE SIGMA10RAVEL
X XMEANAXIS0
X XSTDAXIS0
Y NPDOTX COEFRAVEL
NOISE NPRANDOMRANDNYSHAPE0

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NOISECOEF LINALGNORMY 2 NPEXPSNR 20 LINALGNORMNOISE 2
Y NOISECOEF NOISE ADD NOISE

 COMPUTE THE COEFS OF A BAYESIAN RIDGE WITH GRIDSEARCH
CV KFOLD2 CROSSVALIDATION GENERATOR FOR MODEL SELECTION
RIDGE BAYESIANRIDGE
CACHEDIR TEMPFILEMKDTEMP
MEM MEMORYLOCATIONCACHEDIR VERBOSE1
 WARD AGGLOMERATION FOLLOWED BY BAYESIANRIDGE
CONNECTIVITY GRIDTOGRAPHNXSIZE NYSIZE
WARD FEATUREAGGLOMERATIONNCLUSTERS10 CONNECTIVITYCONNECTIVITY
MEMORYMEM
CLF PIPELINEWARD WARD RIDGE RIDGE
 SELECT THE OPTIMAL NUMBER OF PARCELS WITH GRID SEARCH
CLF GRIDSEARCHCVCLF WARDNCLUSTERS 10 20 30 NJOBS1 CVCV
CLFFITX Y SET THE BEST PARAMETERS
COEF CLFBESTESTIMATORSTEPS11COEF
COEF CLFBESTESTIMATORSTEPS01INVERSETRANSFORMCOEF
COEFAGGLOMERATION COEFRESHAPESIZE SIZE
 ANOVA UNIVARIATE FEATURE SELECTION FOLLOWED BY BAYESIANRIDGE
FREGRESSION MEMCACHEFEATURESELECTIONFREGRESSION CACHING FUNCTION
ANOVA FEATURESELECTIONSELECTPERCENTILEFREGRESSION
CLF PIPELINEANOVA ANOVA RIDGE RIDGE
 SELECT THE OPTIMAL PERCENTAGE OF FEATURES WITH GRID SEARCH
CLF GRIDSEARCHCVCLF ANOVAPERCENTILE 5 10 20 CVCV
CLFFITX Y SET THE BEST PARAMETERS
COEF CLFBESTESTIMATORSTEPS11COEF
COEF CLFBESTESTIMATORSTEPS01INVERSETRANSFORMCOEFRESHAPE1 1
COEFSELECTION COEFRESHAPESIZE SIZE

 INVERSE THE TRANSFORMATION TO PLOT THE RESULTS ON AN IMAGE
PLTCLOSEALL
PLTFIGUREFIGSIZE73 27
PLTSUBPLOT1 3 1
PLTIMSHOWCOEF INTERPOLATIONNEAREST CMAPPLTCMRDBUR
PLTTITLETRUE WEIGHTS
PLTSUBPLOT1 3 2
PLTIMSHOWCOEFSELECTION INTERPOLATIONNEAREST CMAPPLTCMRDBUR
PLTTITLEFEATURE SELECTION
PLTSUBPLOT1 3 3
PLTIMSHOWCOEFAGGLOMERATION INTERPOLATIONNEAREST CMAPPLTCMRDBUR
PLTTITLEFEATURE AGGLOMERATION
PLTSUBPLOTSADJUST004 00 098 094 016 026
PLTSHOW
 ATTEMPT TO REMOVE THE TEMPORARY CACHEDIR BUT DONT WORRY IF IT FAILS
SHUTILRMTREECACHEDIR IGNOREERRORSTRUE
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0623 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5623 COMPARISON OF THE KMEANS AND MINIBATCHKMEANS CLUSTERING ALGORITHMS

WE WANT TO COMPARE THE PERFORMANCE OF THE MINIBATCHKMEANS AND KMEANS THE MINIBATCHKMEANS IS FASTER BUT GIVES SLIGHTLY DIFFERENT RESULTS SEE MINI BATCH KMEANS

WE WILL CLUSTER A SET OF DATA FIRST WITH KMEANS AND THEN WITH MINIBATCHKMEANS AND PLOT THE RESULTS WE WILL ALSO PLOT THE POINTS THAT ARE LABELLED DIFFERENTLY BETWEEN THE TWO ALGORITHMS

```
PRINTDOC
IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNCLUSTER IMPORT MINIBATCHKMEANS KMEANS
FROM SKLEARNMETRICSPAIRWISE IMPORT PAIRWISEDISTANCESARGMIN
FROM SKLEARNDATASETSSAMPLESGENERATOR IMPORT MAKEBLOBS

 GENERATE SAMPLE DATA
NPRANDOMSEED0
BATCHSIZE  45
CENTERS  1 1 1 1 1 1
NCLUSTERS  LENCENTERS
X LABELSTRUE  MAKEBLOBSNSAMPLES3000 CENTERSCENTERS CLUSTERSTD07

 COMPUTE CLUSTERING WITH MEANS
KMEANS  KMEANSINITKMEANS NCLUSTERS3 NINIT10
T0  TIMETIME
KMEANSFITX
TBATCH  TIMETIME  T0

 COMPUTE CLUSTERING WITH MINIBATCHKMEANS
MBK  MINIBATCHKMEANSINITKMEANS NCLUSTERS3 BATCHSIZEBATCHSIZE
NINIT10 MAXNOIMPROVEMENT10 VERBOSE0
T0  TIMETIME
```

SCIKITLEARN USER GUIDE RELEASE 0213
MBKFITX
TMINIBATCH TIMETIME T0

 PLOT RESULT
FIG PLTFIGUREFIGSIZE8 3
FIGSUBPLOTSADJUSTLEFT002 RIGHT098 BOTTOM005 TOP09
COLORS 4EACC5 FF9C34 4E9A06
 WE WANT TO HAVE THE SAME COLORS FOR THE SAME CLUSTER FROM THE
 MINIBATCHKMEANS AND THE KMEANS ALGORITHM LETS PAIR THE CLUSTER CENTERS PER
 CLOSEST ONE
KMEANSCLUSTERCENTERS NPSORTKMEANSCLUSTERCENTERS AXIS0
MBKMEANSCLUSTERCENTERS NPSORTMBKCLUSTERCENTERS AXIS0
KMEANSLABELS PAIRWISEDISTANCESARGMINX KMEANSCLUSTERCENTERS
MBKMEANSLABELS PAIRWISEDISTANCESARGMINX MBKMEANSCLUSTERCENTERS
ORDER PAIRWISEDISTANCESARGMINKMEANSCLUSTERCENTERS
MBKMEANSCLUSTERCENTERS
 KMEANS
AX FIGADDSUBPLOT1 3 1
FORK COLINZIPRANGENCLUSTERS COLORS
MYMEMBERS KMEANSLABELS K
CLUSTERCENTER KMEANSCLUSTERCENTERSK
AXPLOTXMYMEMBERS 0 XMYMEMBERS 1 W
MARKERFACECOLORCOL MARKER
AXPLOTCLUSTERCENTER0 CLUSTERCENTER1 O MARKERFACECOLORCOL
MARKEREDGECOLORK MARKERSIZE6
AXSETTITLEKMEANS
AXSETXTICKS
AXSETYTICKS
PLTTEXT35 18 TRAIN TIME 2FSNINERTIA F
TBATCH KMEANSINERTIA
 MINIBATCHKMEANS
AX FIGADDSUBPLOT1 3 2
FORK COLINZIPRANGENCLUSTERS COLORS
MYMEMBERS MBKMEANSLABELS ORDERK
CLUSTERCENTER MBKMEANSCLUSTERCENTERSORDERK
AXPLOTXMYMEMBERS 0 XMYMEMBERS 1 W
MARKERFACECOLORCOL MARKER
AXPLOTCLUSTERCENTER0 CLUSTERCENTER1 O MARKERFACECOLORCOL
MARKEREDGECOLORK MARKERSIZE6
AXSETTITLEMINIBATCHKMEANS
AXSETXTICKS
AXSETYTICKS
PLTTEXT35 18 TRAIN TIME 2FSNINERTIA F
TMINIBATCH MBKINERTIA
 INITIALISE THE DIFFERENT ARRAY TO ALL FALSE
DIFFERENT MBKMEANSLABELS 4
AX FIGADDSUBPLOT1 3 3
FORKINRANGENCLUSTERS
DIFFERENT KMEANSLABELS K MBKMEANSLABELS ORDERK
IDENTIC NPLOGICALNOTDIFFERENT

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AXPLOTXIDENTIC 0 XIDENTIC 1 W
MARKERFACECOLORBBBBBB MARKER
AXPLOTXDIFFERENT 0 XDIFFERENT 1 W
MARKERFACECOLORM MARKER
AXSETTITLEDIFFERENCE
AXSETXTICKS
AXSETYTICKS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0127 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5624 A DEMO OF KMEANS CLUSTERING ON THE HANDWRITTEN DIGITS DATA
IN THIS EXAMPLE WE COMPARE THE VARIOUS INITIALIZATION STRATEGIES FOR KMEANS IN TERMS OF RUNTIME AND QUALITY OF THE RESULTS
AS THE GROUND TRUTH IS KNOWN HERE WE ALSO APPLY DIFFERENT CLUSTER QUALITY METRICS TO JUDGE THE GOODNESS OF FIT OF THE CLUSTER LABELS TO THE GROUND TRUTH
CLUSTER QUALITY METRICS EVALUATED SEE CLUSTERING PERFORMANCE EVALUATION FOR DEFINITIONS AND DISCUSSIONS OF THE MET RICS
SHORTHAND FULL NAME
HOMO HOMOGENEITY SCORE
COMPL COMPLETENESS SCORE
VMEAS V MEASURE
ARI ADJUSTED RAND INDEX
AMI ADJUSTED MUTUAL INFORMATION
SILHOUETTE SILHOUETTE COEFFICIENT

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OUT
NDIGITS 10 NSAMPLES 1797 NFEATURES 64

INIT TIME INERTIA HOMO COMPL VMEAS ARI AMI SILHOUETTE
KMEANS 037S 69432 0602 0650 0625 0465 0621 0146
RANDOM 027S 69694 0669 0710 0689 0553 0686 0147
PCABASED 003S 70804 0671 0698 0684 0561 0681 0118

PRINTDOC
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT METRICS
FROM SKLEARNCLUSTER IMPORT KMEANS
FROM SKLEARNDATASETS IMPORT LOADDIGITS
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNPREPROCESSING IMPORT SCALE

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NPRANDOMSEED42
DIGITS LOADDIGITS
DATA SCALEDIGITSDATA
NSAMPLES NFEATURES DATASHAPE
NDIGITS LENNPUNIQUEDIGITSTARGET
LABELS DIGITSTARGET
SAMPLESIZE 300
PRINTNDIGITS DTNSAMPLES DTNFEATURES D
 NDIGITS NSAMPLES NFEATURES
PRINT82
PRINTINITTTTIMETINERTIATHOMOTCOMPLTVMEASTARITAMITSILHOUETTE
DEFBENCHKMEANSESTIMATOR NAME DATA
T0 TIME
ESTIMATORFITDATA
PRINT9ST2FSTIT3FT3FT3FT3FT3F
 NAME TIME T0 ESTIMATORINERTIA
METRICSHOMOGENEITYSCORELABELS ESTIMATORLABELS
METRICSCOMPLETENESSSCORELABELS ESTIMATORLABELS
METRICSVMEASURESCORELABELS ESTIMATORLABELS
METRICSADJUSTEDRANDSCORELABELS ESTIMATORLABELS
METRICSADJUSTEDMUTUALINFOSCORELABELS ESTIMATORLABELS
AVERAGEMETHODARITHMETIC
METRICSSILHOUETTESCOREDATA ESTIMATORLABELS
METRICEUCLIDEAN
SAMPLESIZESAMPLESIZE
BENCHKMEANSKMEANSINITKMEANS NCLUSTERSNDIGITS NINIT10
NAMEKMEANS DATADATA
BENCHKMEANSKMEANSINITRANDOM NCLUSTERSNDIGITS NINIT10
NAMERANDOM DATADATA
 IN THIS CASE THE SEEDING OF THE CENTERS IS DETERMINISTIC HENCE WE RUN THE
 KMEANS ALGORITHM ONLY ONCE WITH NINIT1
PCA PCANCOMPONENTSNDIGITSFITDATA
BENCHKMEANSKMEANSINITPCACOMPONENTS NCLUSTERSNDIGITS NINIT1
NAMEPCABASED
DATADATA
PRINT82

 VISUALIZE THE RESULTS ON PCAREDUCED DATA
REDUCEDDATA PCANCOMPONENTS2FITTRANSFORMDATA
KMEANS KMEANSINITKMEANS NCLUSTERSNDIGITS NINIT10
KMEANSFITREDUCEDDATA
 STEP SIZE OF THE MESH DECREASE TO INCREASE THE QUALITY OF THE VQ
H 02 POINT IN THE MESH XMIN XMAXXYMIN YMAX

```
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
XMIN XMAX  REDUCEDDATA 0MIN  1 REDUCEDDATA 0MAX  1
YMIN YMAX  REDUCEDDATA 1MIN  1 REDUCEDDATA 1MAX  1
XX YY  NPMESHGRIDNPARANGEXMIN XMAX H NPARANGEYMIN YMAX H
 OBTAIN LABELS FOR EACH POINT IN MESH USE LAST TRAINED MODEL
Z  KMEANSPREDICTNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z  ZRESHAPEXXSHAPE
PLTFIGURE1
PLTCLF
PLTIMSHOWZ INTERPOLATIONNEAREST
EXTENTXXMIN XXMAX YYMIN YYMAX
CMAPPLTCMPAIRED
ASPECTAUTO ORIGINLOWER
PLTPLOTREDUCEDDATA 0 REDUCEDDATA 1 K MARKERSIZE2
 PLOT THE CENTROIDS AS A WHITE X
CENTROIDS  KMEANSCLUSTERCENTERS
PLTSCATTERCENTROIDS 0 CENTROIDS 1
MARKERX S169 LINEWIDTHS3
COLORW ZORDER10
PLTTITLEKMEANS CLUSTERING ON THE DIGITS DATASET PCAREDUCED DATA N
CENTROIDS ARE MARKED WITH WHITE CROSS
PLTXLIMXMIN XMAX
PLTYLIMYMIN YMAX
PLTXTICKS
PLTYTICKS
PLTSHOW
```
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1230 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5625 COMPARING DIFFERENT HIERARCHICAL LINKAGE METHODS ON TOY DATASETS
THIS EXAMPLE SHOWS CHARACTERISTICS OF DIFFERENT LINKAGE METHODS FOR HIERARCHICAL CLUSTERING ON DATASETS THAT ARE “INTER ESTING” BUT STILL IN 2D
THE MAIN OBSERVATIONS TO MAKE ARE
• SINGLE LINKAGE IS FAST AND CAN PERFORM WELL ON NONGLOBULAR DATA BUT IT PERFORMS POORLY IN THE PRESENCE OF NOISE
• AVERAGE AND COMPLETE LINKAGE PERFORM WELL ON CLEANLY SEPARATED GLOBULAR CLUSTERS BUT HAVE MIXED RESULTS OTHER WISE
• WARD IS THE MOST EFFECTIVE METHOD FOR NOISY DATA
WHILE THESE EXAMPLES GIVE SOME INTUITION ABOUT THE ALGORITHMS THIS INTUITION MIGHT NOT APPLY TO VERY HIGH DIMENSIONAL DATA
```
PRINTDOC
IMPORT TIME
```

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IMPORT WARNINGS
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT CLUSTER DATASETS
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM ITERTOOLS IMPORT CYCLE ISLICE
NPRANDOMSEED0
GENERATE DATASETS WE CHOOSE THE SIZE BIG ENOUGH TO SEE THE SCALABILITY OF THE ALGORITHMS BUT NOT TOO BIG TO AVOID TOO LONG RUNNING TIMES
NSAMPLES 1500
NOISYCIRCLES DATASETSMAKECIRCLESNSAMPLESNSAMPLES FACTOR5
NOISE05
NOISYMOONS DATASETSMAKEMOONSNSAMPLESNSAMPLES NOISE05
BLOBS DATASETSMAKEBLOBSNSAMPLESNSAMPLES RANDOMSTATE8
NOSTRUCTURE NPRANDOMRANDNSAMPLES 2 NONE
 ANISOTROPICLY DISTRIBUTED DATA
RANDOMSTATE 170
X Y DATASETSMAKEBLOBSNSAMPLESNSAMPLES RANDOMSTATERANDOMSTATE
TRANSFORMATION 06 06 04 08
XANISO NPDOTX TRANSFORMATION
ANISO XANISO Y
 BLOBS WITH VARIED VARIANCES
VARIED DATASETSMAKEBLOBSNSAMPLESNSAMPLES
CLUSTERSTD10 25 05
RANDOMSTATERANDOMSTATE
RUN THE CLUSTERING AND PLOT
 SET UP CLUSTER PARAMETERS
PLTFIGUREFIGSIZE9 13 2 145
PLTSUBPLOTSADJUSTLEFT02 RIGHT98 BOTTOM001 TOP96 WSPACE05
HSPACE01
PLOTNUM 1
DEFAULTBASE NNEIGHBORS 10
NCLUSTERS 3
DATASETS
NOISYCIRCLES NCLUSTERS 2
NOISYMOONS NCLUSTERS 2
VARIED NNEIGHBORS 2
ANISO NNEIGHBORS 2
BLOBS
NOSTRUCTURE
FORIDATASET DATASET ALGOPARAMS INENUMERATEDATASETS
 UPDATE PARAMETERS WITH DATASETSPECIFIC VALUES
PARAMS DEFAULTBASECOPY
PARAMSUPDATEALGOPARAMS

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X Y DATASET
 NORMALIZE DATASET FOR EASIER PARAMETER SELECTION
X STANDARDSCALERFITTRANSFORMX

 CREATE CLUSTER OBJECTS

WARD CLUSTERAGGLOMERATIVECLUSTERING
NCLUSTERSPARAMSNCLUSTERS LINKAGEWARD
COMPLETE CLUSTERAGGLOMERATIVECLUSTERING
NCLUSTERSPARAMSNCLUSTERS LINKAGECOMPLETE
AVERAGE CLUSTERAGGLOMERATIVECLUSTERING
NCLUSTERSPARAMSNCLUSTERS LINKAGEAVERAGE
SINGLE CLUSTERAGGLOMERATIVECLUSTERING
NCLUSTERSPARAMSNCLUSTERS LINKAGESINGLE
CLUSTERINGALGORITHMS
SINGLE LINKAGE SINGLE
AVERAGE LINKAGE AVERAGE
COMPLETE LINKAGE COMPLETE
WARD LINKAGE WARD

FORNAME ALGORITHM INCLUSTERINGALGORITHMS
T0 TIMETIME
 CATCH WARNINGS RELATED TO KNEIGHBORSGRAPH
WITHWARNINGSCATCHWARNINGS
WARNINGSFILTERWARNINGS
IGNORE
MESSAGETHE NUMBER OF CONNECTED COMPONENTS OF THE
CONNECTIVITY MATRIX IS 0912
  1 COMPLETING IT TO AVOID STOPPING THE TREE EARLY
CATEGORYUSERWARNING
ALGORITHMFITX
T1 TIMETIME
IFHASATTRALGORITHM LABELS
YPRED ALGORITHMLABELSASTYPENPINT
ELSE
YPRED ALGORITHMPREDICTX
PLTSUBPLOTLENDATASETS LENCLUSTERINGALGORITHMS PLOTNUM
IFIDATASET 0
PLTTITLENAME SIZE18
COLORS NPARRAYLISTISLICECYCLE377EB8 FF7F00 4DAF4A
F781BF A65628 984EA3
999999 E41A1C DEDE00
INTMAXYPRED 1
PLTSCATTERX 0 X 1 S10 COLORCOLORSYPRED
PLTXLIM25 25
PLTYLIM25 25
PLTXTICKS
PLTYTICKS
PLTTEXT99 01 2FS T1 T0LSTRIP0
56 CLUSTERING 899

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TRANSFORMPLTGCATRANSAXES SIZE15
HORIZONTALALIGNMENTRIGHT
PLOTNUM 1
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1577 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
900 CHAPTER 5 EXAMPLES

5626 SELECTING THE NUMBER OF CLUSTERS WITH SILHOUETTE ANALYSIS ON KMEANS CLUS
TERING
SILHOUETTE ANALYSIS CAN BE USED TO STUDY THE SEPARATION DISTANCE BETWEEN THE RESULTING CLUSTERS THE SILHOUETTE PLOT DISPLAYS A MEASURE OF HOW CLOSE EACH POINT IN ONE CLUSTER IS TO POINTS IN THE NEIGHBORING CLUSTERS AND THUS PROVIDES A WAY TO ASSESS PARAMETERS LIKE NUMBER OF CLUSTERS VISUALLY THIS MEASURE HAS A RANGE OF 1 1
SILHOUETTE COEFFICIENTS AS THESE VALUES ARE REFERRED TO AS NEAR 1 INDICATE THAT THE SAMPLE IS FAR AWAY FROM THE NEIGH BORING CLUSTERS A VALUE OF 0 INDICATES THAT THE SAMPLE IS ON OR VERY CLOSE TO THE DECISION BOUNDARY BETWEEN TWO NEIGHBORING CLUSTERS AND NEGATIVE VALUES INDICATE THAT THOSE SAMPLES MIGHT HAVE BEEN ASSIGNED TO THE WRONG CLUSTER
IN THIS EXAMPLE THE SILHOUETTE ANALYSIS IS USED TO CHOOSE AN OPTIMAL VALUE FOR NCLUSTERS THE SILHOUETTE PLOT SHOWS THAT THENCLUSTERS VALUE OF 3 5 AND 6 ARE A BAD PICK FOR THE GIVEN DATA DUE TO THE PRESENCE OF CLUSTERS WITH BELOW AVERAGE SILHOUETTE SCORES AND ALSO DUE TO WIDE FLUCTUATIONS IN THE SIZE OF THE SILHOUETTE PLOTS SILHOUETTE ANALYSIS IS MORE AMBIVALENT IN DECIDING BETWEEN 2 AND 4
ALSO FROM THE THICKNESS OF THE SILHOUETTE PLOT THE CLUSTER SIZE CAN BE VISUALIZED THE SILHOUETTE PLOT FOR CLUSTER 0 WHEN NCLUSTERS IS EQUAL TO 2 IS BIGGER IN SIZE OWING TO THE GROUPING OF THE 3 SUB CLUSTERS INTO ONE BIG CLUSTER HOWEVER WHEN THENCLUSTERS IS EQUAL TO 4 ALL THE PLOTS ARE MORE OR LESS OF SIMILAR THICKNESS AND HENCE ARE OF SIMILAR SIZES AS CAN BE ALSO VERIFIED FROM THE LABELLED SCATTER PLOT ON THE RIGHT
•
•

•
•
•
OUT
FOR NCLUSTERS 2 THE AVERAGE SILHOUETTESCORE IS 07049787496083262
FOR NCLUSTERS 3 THE AVERAGE SILHOUETTESCORE IS 05882004012129721
FOR NCLUSTERS 4 THE AVERAGE SILHOUETTESCORE IS 06505186632729437
FOR NCLUSTERS 5 THE AVERAGE SILHOUETTESCORE IS 056376469026194
FOR NCLUSTERS 6 THE AVERAGE SILHOUETTESCORE IS 04504666294372765

```
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FROM SKLEARNDATASETS IMPORT MAKEBLOBS
FROM SKLEARNCLUSTER IMPORT KMEANS
FROM SKLEARNMETRICS IMPORT SILHOUETTESAMPLES SILHOUETTESCORE
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIBCM AS CM
IMPORT NUMPY AS NP
PRINTDOC
 GENERATING THE SAMPLE DATA FROM MAKEBLOBS
 THIS PARTICULAR SETTING HAS ONE DISTINCT CLUSTER AND 3 CLUSTERS PLACED CLOSE
 TOGETHER
X Y  MAKEBLOBSNSAMPLES500
NFEATURES2
CENTERS4
CLUSTERSTD1
CENTERBOX100 100
SHUFFLETRUE
RANDOMSTATE1  FOR REPRODUCIBILITY
RANGENCLUSTERS  2 3 4 5 6
FORNCLUSTERS INRANGENCLUSTERS
 CREATE A SUBPLOT WITH 1 ROW AND 2 COLUMNS
FIG AX1 AX2  PLTSUBPLOTS1 2
FIGSETSIZEINCHES18 7
 THE 1ST SUBPLOT IS THE SILHOUETTE PLOT
 THE SILHOUETTE COEFFICIENT CAN RANGE FROM 1 1 BUT IN THIS EXAMPLE ALL
 LIE WITHIN 01 1
AX1SETXLIM01 1
 THE NCLUSTERS1 10 IS FOR INSERTING BLANK SPACE BETWEEN SILHOUETTE
 PLOTS OF INDIVIDUAL CLUSTERS TO DEMARCATE THEM CLEARLY
AX1SETYLIM0 LENX  NCLUSTERS  1 10
 INITIALIZE THE CLUSTERER WITH NCLUSTERS VALUE AND A RANDOM GENERATOR
 SEED OF 10 FOR REPRODUCIBILITY
CLUSTERER  KMEANSNCLUSTERSNCLUSTERS RANDOMSTATE10
CLUSTERLABELS  CLUSTERERFITPREDICTX
 THE SILHOUETTESCORE GIVES THE AVERAGE VALUE FOR ALL THE SAMPLES
 THIS GIVES A PERSPECTIVE INTO THE DENSITY AND SEPARATION OF THE FORMED
 CLUSTERS
SILHOUETTEAVG  SILHOUETTESCOREX CLUSTERLABELS
PRINTFOR NCLUSTERS  NCLUSTERS
THE AVERAGE SILHOUETTESCORE IS  SILHOUETTEAVG
 COMPUTE THE SILHOUETTE SCORES FOR EACH SAMPLE
SAMPLESILHOUETTEVALUES  SILHOUETTESAMPLESX CLUSTERLABELS
YLOWER  10
FORIINRANGENCLUSTERS
 AGGREGATE THE SILHOUETTE SCORES FOR SAMPLES BELONGING TO
 CLUSTER I AND SORT THEM
```

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ITHCLUSTERSILHOUETTEVALUES
SAMPLESILHOUETTEVALUESCLUSTERLABELS I
ITHCLUSTERSILHOUETTEVALUESSORT
SIZECLUSTERI ITHCLUSTERSILHOUETTEVALUESSHAPE0
YUPPER YLOWER SIZECLUSTERI
COLOR CMNIPYSPECTRALFLOATI NCLUSTERS
AX1FILLBETWEENXNPARANGEYLOWER YUPPER
0 ITHCLUSTERSILHOUETTEVALUES
FACECOLORCOLOR EDGECOLORCOLOR ALPHA07
 LABEL THE SILHOUETTE PLOTS WITH THEIR CLUSTER NUMBERS AT THE MIDDLE
AX1TEXT005 YLOWER 05 SIZECLUSTERI STRI
 COMPUTE THE NEW YLOWER FOR NEXT PLOT
YLOWER YUPPER 10 10 FOR THE 0 SAMPLES
AX1SETTITLETHE SILHOUETTE PLOT FOR THE VARIOUS CLUSTERS
AX1SETXLABELTHE SILHOUETTE COEFFICIENT VALUES
AX1SETYLABELCLUSTER LABEL
 THE VERTICAL LINE FOR AVERAGE SILHOUETTE SCORE OF ALL THE VALUES
AX1AXVLINEXSILHOUETTEAVG COLORRED LINESTYLE
AX1SETYTICKS CLEAR THE YAXIS LABELS TICKS
AX1SETXTICKS01 0 02 04 06 08 1
 2ND PLOT SHOWING THE ACTUAL CLUSTERS FORMED
COLORS CMNIPYSPECTRALCLUSTERLABELSASTYPEFLOAT NCLUSTERS
AX2SCATTERX 0 X 1 MARKER S30 LW0 ALPHA07
CCOLORS EDGECOLORK
 LABELING THE CLUSTERS
CENTERS CLUSTERERCLUSTERCENTERS
 DRAW WHITE CIRCLES AT CLUSTER CENTERS
AX2SCATTERCENTERS 0 CENTERS 1 MARKERO
CWHITE ALPHA1 S200 EDGECOLORK
FORI CINENUMERATECENTERS
AX2SCATTERC0 C1 MARKER D I ALPHA1
S50 EDGECOLORK
AX2SETTITLETHE VISUALIZATION OF THE CLUSTERED DATA
AX2SETXLABELFEATURE SPACE FOR THE 1ST FEATURE
AX2SETYLABELFEATURE SPACE FOR THE 2ND FEATURE
PLTSUPTITLESILHOUETTE ANALYSIS FOR KMEANS CLUSTERING ON SAMPLE DATA
WITH NCLUSTERS D NCLUSTERS
FONTSIZE14 FONTWEIGHTBOLD
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0629 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5627 COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
THIS EXAMPLE SHOWS CHARACTERISTICS OF DIFFERENT CLUSTERING ALGORITHMS ON DATASETS THAT ARE “INTERESTING” BUT STILL IN 2D WITH THE EXCEPTION OF THE LAST DATASET THE PARAMETERS OF EACH OF THESE DATASETALGORITHM PAIRS HAS BEEN TUNED TO PRODUCE GOOD CLUSTERING RESULTS SOME ALGORITHMS ARE MORE SENSITIVE TO PARAMETER VALUES THAN OTHERS
THE LAST DATASET IS AN EXAMPLE OF A ‘NULL’ SITUATION FOR CLUSTERING THE DATA IS HOMOGENEOUS AND THERE IS NO GOOD CLUSTERING FOR THIS EXAMPLE THE NULL DATASET USES THE SAME PARAMETERS AS THE DATASET IN THE ROW ABOVE IT WHICH REPRESENTS A MISMATCH IN THE PARAMETER VALUES AND THE DATA STRUCTURE
WHILE THESE EXAMPLES GIVE SOME INTUITION ABOUT THE ALGORITHMS THIS INTUITION MIGHT NOT APPLY TO VERY HIGH DIMENSIONAL DATA
PRINTDOC
IMPORT TIME
IMPORT WARNINGS
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT CLUSTER DATASETS MIXTURE
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSGRAPH
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM ITERTOOLS IMPORT CYCLE ISLICE
NPRANDOMSEED0

```
 GENERATE DATASETS WE CHOOSE THE SIZE BIG ENOUGH TO SEE THE SCALABILITY
 OF THE ALGORITHMS BUT NOT TOO BIG TO AVOID TOO LONG RUNNING TIMES

NSAMPLES  1500
NOISYCIRCLES  DATASETSMAKECIRCLESNSAMPLESNSAMPLES FACTOR5
NOISE05
NOISYMOONS  DATASETSMAKEMOONSNSAMPLESNSAMPLES NOISE05
BLOBS  DATASETSMAKEBLOBSNSAMPLESNSAMPLES RANDOMSTATE8
NOSTRUCTURE  NPRANDOMRANDNSAMPLES 2 NONE
 ANISOTROPICLY DISTRIBUTED DATA
RANDOMSTATE  170
X Y  DATASETSMAKEBLOBSNSAMPLESNSAMPLES RANDOMSTATERANDOMSTATE
TRANSFORMATION  06 06 04 08
XANISO  NPDOTX TRANSFORMATION
ANISO  XANISO Y
 BLOBS WITH VARIED VARIANCES
VARIED  DATASETSMAKEBLOBSNSAMPLESNSAMPLES
CLUSTERSTD10 25 05
RANDOMSTATERANDOMSTATE

 SET UP CLUSTER PARAMETERS

PLTFIGUREFIGSIZE9 2  3 125
PLTSUBPLOTSADJUSTLEFT02 RIGHT98 BOTTOM001 TOP96 WSPACE05
HSPACE01
PLOTNUM  1
DEFAULTBASE  QUANTILE 3
EPS 3
DAMPING 9
PREFERENCE 200
NNEIGHBORS 10
NCLUSTERS 3
MINSAMPLES 20
XI 005
MINCLUSTERSIZE 01
DATASETS
NOISYCIRCLES DAMPING 77 PREFERENCE 240
QUANTILE 2 NCLUSTERS 2
MINSAMPLES 20 XI 025
NOISYMOONS DAMPING 75 PREFERENCE 220 NCLUSTERS 2
VARIED EPS 18 NNEIGHBORS 2
MINSAMPLES 5 XI 0035 MINCLUSTERSIZE 2
ANISO EPS 15 NNEIGHBORS 2
MINSAMPLES 20 XI 01 MINCLUSTERSIZE 2
BLOBS
NOSTRUCTURE
FORIDATASET DATASET ALGOPARAMS INENUMERATEDATASETS
 UPDATE PARAMETERS WITH DATASETSPECIFIC VALUES
PARAMS  DEFAULTBASECOPY
```

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PARAMSUPDATEALGOPARAMS
X Y DATASET
 NORMALIZE DATASET FOR EASIER PARAMETER SELECTION
X STANDARDSCALERFITTRANSFORMX
 ESTIMATE BANDWIDTH FOR MEAN SHIFT
BANDWIDTH CLUSTERESTIMATEBANDWIDTHX QUANTILEPARAMSQUANTILE
 CONNECTIVITY MATRIX FOR STRUCTURED WARD
CONNECTIVITY KNEIGHBORSGRAPH
X NNEIGHBORSPARAMSNNEIGHBORS INCLUDESELFFALSE
 MAKE CONNECTIVITY SYMMETRIC
CONNECTIVITY 05 CONNECTIVITY CONNECTIVITYT

 CREATE CLUSTER OBJECTS

MS CLUSTERMEANSHIFTBANDWIDTHBANDWIDTH BINSEEDINGTRUE
TWOMEANS CLUSTERMINIBATCHKMEANSNCLUSTERSPARAMSNCLUSTERS
WARD CLUSTERAGGLOMERATIVECLUSTERING
NCLUSTERSPARAMSNCLUSTERS LINKAGEWARD
CONNECTIVITYCONNECTIVITY
SPECTRAL CLUSTERSPECTRALCLUSTERING
NCLUSTERSPARAMSNCLUSTERS EIGENSOLVERARPACK
AFFINITYNEARESTNEIGHBORS
DBSCAN CLUSTERDBSCANEPSPARAMSEPS
OPTICS CLUSTEROPTICSMINSAMPLESPARAMSMINSAMPLES
XIPARAMSXI
MINCLUSTERSIZEPARAMSMINCLUSTERSIZE
AFFINITYPROPAGATION CLUSTERAFFINITYPROPAGATION
DAMPINGPARAMSDAMPING PREFERENCEPARAMSPREFERENCE
AVERAGELINKAGE CLUSTERAGGLOMERATIVECLUSTERING
LINKAGEAVERAGE AFFINITYCITYBLOCK
NCLUSTERSPARAMSNCLUSTERS CONNECTIVITYCONNECTIVITY
BIRCH CLUSTERBIRCHNCLUSTERSPARAMSNCLUSTERS
GMM MIXTUREGAUSSIANMIXTURE
NCOMPONENTSPARAMSNCLUSTERS COVARIANCETYPEFULL
CLUSTERINGALGORITHMS
MINIBATCHKMEANS TWOMEANS
AFFINITYPROPAGATION AFFINITYPROPAGATION
MEANSHIFT MS
SPECTRALCLUSTERING SPECTRAL
WARD WARD
AGGLOMERATIVECLUSTERING AVERAGELINKAGE
DBSCAN DBSCAN
OPTICS OPTICS
BIRCH BIRCH
GAUSSIANMIXTURE GMM

FORNAME ALGORITHM INCLUSTERINGALGORITHMS
T0 TIMETIME
 CATCH WARNINGS RELATED TO KNEIGHBORSGRAPH
WITHWARNINGSCATCHWARNINGS

SCIKITLEARN USER GUIDE RELEASE 0213
WARNINGSFILTERWARNINGS
IGNORE
MESSAGETHE NUMBER OF CONNECTED COMPONENTS OF THE
CONNECTIVITY MATRIX IS 0912
  1 COMPLETING IT TO AVOID STOPPING THE TREE EARLY
CATEGORYUSERWARNING
WARNINGSFILTERWARNINGS
IGNORE
MESSAGEGRAPH IS NOT FULLY CONNECTED SPECTRAL EMBEDDING
 MAY NOT WORK AS EXPECTED
CATEGORYUSERWARNING
ALGORITHMFITX
T1 TIMETIME
IFHASATTRALGORITHM LABELS
YPRED ALGORITHMLABELSASTYPENPINT
ELSE
YPRED ALGORITHMPREDICTX
PLTSUBPLOTLENDATASETS LENCLUSTERINGALGORITHMS PLOTNUM
IFIDATASET 0
PLTTITLENAME SIZE18
COLORS NPARRAYLISTISLICECYCLE377EB8 FF7F00 4DAF4A
F781BF A65628 984EA3
999999 E41A1C DEDE00
INTMAXYPRED 1
 ADD BLACK COLOR FOR OUTLIERS IF ANY
COLORS NPAPPENDCOLORS 000000
PLTSCATTERX 0 X 1 S10 COLORCOLORSYPRED
PLTXLIM25 25
PLTYLIM25 25
PLTXTICKS
PLTYTICKS
PLTTEXT99 01 2FS T1 T0LSTRIP0
TRANSFORMPLTGCATRANSAXES SIZE15
HORIZONTALALIGNMENTRIGHT
PLOTNUM 1
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 39530 SECONDS
57 PIPELINES AND COMPOSITE ESTIMATORS
EXAMPLES OF HOW TO COMPOSE TRANSFORMERS AND PIPELINES FROM OTHER ESTIMATORS SEE THE USER GUIDE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

571 CONCATENATING MULTIPLE FEATURE EXTRACTION METHODS
IN MANY REALWORLD EXAMPLES THERE ARE MANY WAYS TO EXTRACT FEATURES FROM A DATASET OFTEN IT IS BENEFICIAL TO COMBINE SEVERAL METHODS TO OBTAIN GOOD PERFORMANCE THIS EXAMPLE SHOWS HOW TO USE FEATUREUNION TO COMBINE FEATURES OBTAINED BY PCA AND UNIVARIATE SELECTION
COMBINING FEATURES USING THIS TRANSFORMER HAS THE BENEFIT THAT IT ALLOWS CROSS VALIDATION AND GRID SEARCHES OVER THE WHOLE PROCESS
THE COMBINATION USED IN THIS EXAMPLE IS NOT PARTICULARLY HELPFUL ON THIS DATASET AND IS ONLY USED TO ILLUSTRATE THE USAGE OF FEATUREUNION
OUT
COMBINED SPACE HAS 3 FEATURES
FITTING 5 FOLDS FOR EACH OF 18 CANDIDATES TOTALLING 90 FITS
CV FEATURESPCANCOMPONENTS1 FEATURESUNIVSELECTK1 SVMC01
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PIPELINESTEPSFEATURES
FEATUREUNIONTRANSFORMERLISTPCA PCANCOMPONENTS3
UNIVSELECT
SELECTKBESTK1
SVM SVCC10 KERNELLINEAR
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AUTHOR ANDREAS MUELLER AMUELLERAISUNIBONNDE

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```
FROM SKLEARNPIPELINE IMPORT PIPELINE FEATUREUNION
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNDATASETS IMPORT LOADIRIS
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNFEATURESELECTION IMPORT SELECTKBEST
IRIS  LOADIRIS
X Y  IRISDATA IRISTARGET
 THIS DATASET IS WAY TOO HIGHDIMENSIONAL BETTER DO PCA
PCA  PCANCOMPONENTS2
 MAYBE SOME ORIGINAL FEATURES WHERE GOOD TOO
SELECTION  SELECTKBESTK1
 BUILD ESTIMATOR FROM PCA AND UNIVARIATE SELECTION
COMBINEDFEATURES  FEATUREUNIONPCA PCA UNIVSELECT SELECTION
 USE COMBINED FEATURES TO TRANSFORM DATASET
XFEATURES  COMBINEDFEATURESFITX YTRANSFORMX
PRINTCOMBINED SPACE HAS XFEATURESSHAPE1 FEATURES
SVM  SVCKERNELLINEAR
 DO GRID SEARCH OVER K NCOMPONENTS AND C
PIPELINE  PIPELINEFEATURES COMBINEDFEATURES SVM SVM
PARAMGRID  DICTFEATURESPCANCOMPONENTS1 2 3
FEATURESUNIVSELECTK1 2
SVMC01 1 10
GRIDSEARCH  GRIDSEARCHCVPIPELINE PARAMGRIDPARAMGRID CV5 VERBOSE10
GRIDSEARCHFITX Y
PRINTGRIDSEARCHBESTESTIMATOR
```

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0865 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
572 PIPELINING CHAINING A PCA AND A LOGISTIC REGRESSION
THE PCA DOES AN UNSUPERVISED DIMENSIONALITY REDUCTION WHILE THE LOGISTIC REGRESSION DOES THE PREDICTION
WE USE A GRIDSEARCHCV TO SET THE DIMENSIONALITY OF THE PCA
914 CHAPTER 5 EXAMPLES

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OUT
BEST PARAMETER CV SCORE0917
LOGISTICALPHA 001 PCANCOMPONENTS 64
PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
57 PIPELINES AND COMPOSITE ESTIMATORS 915

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IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT PANDAS AS PD
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
FROM SKLEARNPIPELINE IMPORT PIPELINE
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
DEFINE A PIPELINE TO SEARCH FOR THE BEST COMBINATION OF PCA TRUNCATION
AND CLASSIFIER REGULARIZATION
LOGISTIC SGDCLASSIFIERLOSSLOG PENALTYL2 EARLYSTOPPINGTRUE
MAXITER10000 TOL1E5 RANDOMSTATE0
PCA PCA
PIPE PIPELINESTEPSPCA PCA LOGISTIC LOGISTIC
DIGITS DATASETSLOADDIGITS
XDIGITS DIGITSDATA
YDIGITS DIGITSTARGET
PARAMETERS OF PIPELINES CAN BE SET USING ‘’ SEPARATED PARAMETER NAMES
PARAMGRID
PCANCOMPONENTS 5 20 30 40 50 64
LOGISTICALPHA NPLOGSPACE4 4 5

SEARCH GRIDSEARCHCVPIPE PARAMGRID IIDFALSE CV5
SEARCHFITXDIGITS YDIGITS
PRINTBEST PARAMETER CV SCORE 03F SEARCHBESTSCORE
PRINTSEARCHBESTPARAMS
PLOT THE PCA SPECTRUM
PCAFITXDIGITS
FIG AX0 AX1 PLTSUBPLOTSNROWS2 SHAREXTRUE FIGSIZE6 6
AX0PLOTPCAEXPLAINEDVARIANCERATIO LINEWIDTH2
AX0SETYLABELPCA EXPLAINED VARIANCE
AX0AXVLINESEARCHBESTESTIMATORNAMEDSTEPSPCANCOMPONENTS
LINESTYLE LABELNCOMPONENTS CHOSEN
AX0LEGENDPROPDICTSIZE12
FOR EACH NUMBER OF COMPONENTS FIND THE BEST CLASSIFIER RESULTS
RESULTS PDDATAFRAMESEARCHCVRESULTS
COMPONENTSCOL PARAMPCANCOMPONENTS
BESTCLFS RESULTSGROUPBYCOMPONENTSCOLAPPLY
LAMBDAG GNLARGEST1 MEANTESTSCORE
BESTCLFSPLOTXCOMPONENTSCOL YMEANTESTSCORE YERRSTDTESTSCORE
LEGENDFALSE AXAX1
AX1SETYLABELCLASSIFICATION ACCURACY VAL
AX1SETXLABELNCOMPONENTS
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 20748 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
573 COLUMN TRANSFORMER WITH MIXED TYPES
THIS EXAMPLE ILLUSTRATES HOW TO APPLY DIFFERENT PREPROCESSING AND FEATURE EXTRACTION PIPELINES TO DIFFERENT SUBSETS OF FEATURES USING SKLEARNCOMPOSECOLUMNTRANSFORMER THIS IS PARTICULARLY HANDY FOR THE CASE OF DATASETS THAT CONTAIN HETEROGENEOUS DATA TYPES SINCE WE MAY WANT TO SCALE THE NUMERIC FEATURES AND ONEHOT ENCODE THE CATEGORICAL ONES
IN THIS EXAMPLE THE NUMERIC DATA IS STANDARDSCALED AFTER MEANIMPUTATION WHILE THE CATEGORICAL DATA IS ONEHOT ENCODED AFTER IMPUTING MISSING VALUES WITH A NEW CATEGORY MISSING
FINALLY THE PREPROCESSING PIPELINE IS INTEGRATED IN A FULL PREDICTION PIPELINE USING SKLEARNPIPELINE PIPELINE TOGETHER WITH A SIMPLE CLASSIFICATION MODEL
 AUTHOR PEDRO MORALES PARTMORALESGMAILCOM

 LICENSE BSD 3 CLAUSE
```
IMPORT PANDAS AS PD
IMPORT NUMPY AS NP
FROM SKLEARNCOMPOSE IMPORT COLUMNTRANSFORMER
FROM SKLEARNPIPELINE IMPORT PIPELINE
FROM SKLEARNIMPUTE IMPORT SIMPLEIMPUTER
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER ONEHOTENCODER
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT GRIDSEARCHCV
NPRANDOMSEED0
 READ DATA FROM TITANIC DATASET
TITANICURL  HTTPSRAWGITHUBUSERCONTENTCOMAMUELLER
SCIPY2017SKLEARN091D371NOTEBOOKSDATASETSTITANIC3CSV
DATA  PDREADCSVTITANICURL
 WE WILL TRAIN OUR CLASSIFIER WITH THE FOLLOWING FEATURES
 NUMERIC FEATURES
  AGE FLOAT
  FARE FLOAT
 CATEGORICAL FEATURES
  EMBARKED CATEGORIES ENCODED AS STRINGS C S Q
  SEX CATEGORIES ENCODED AS STRINGS FEMALE MALE
  PCLASS ORDINAL INTEGERS 1 2 3
 WE CREATE THE PREPROCESSING PIPELINES FOR BOTH NUMERIC AND CATEGORICAL DATA
NUMERICFEATURES  AGE FARE
NUMERICTRANSFORMER  PIPELINESTEPS
IMPUTER SIMPLEIMPUTERSTRATEGYMEDIAN
SCALER STANDARDSCALER
CATEGORICALFEATURES  EMBARKED SEX PCLASS
CATEGORICALTRANSFORMER  PIPELINESTEPS
IMPUTER SIMPLEIMPUTERSTRATEGYCONSTANT FILLVALUEMISSING
ONEHOT ONEHOTENCODERHANDLEUNKNOWNIGNORE
```

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PREPROCESSOR COLUMNTRANSFORMER
TRANSFORMERS
NUM NUMERICTRANSFORMER NUMERICFEATURES
CAT CATEGORICALTRANSFORMER CATEGORICALFEATURES
 APPEND CLASSIFIER TO PREPROCESSING PIPELINE
 NOW WE HAVE A FULL PREDICTION PIPELINE
CLF PIPELINESTEPSPREPROCESSOR PREPROCESSOR
CLASSIFIER LOGISTICREGRESSIONSOLVERLBFGS
X DATADROPSURVIVED AXIS1
Y DATASURVIVED
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y TESTSIZE02
CLFFITXTRAIN YTRAIN
PRINTMODEL SCORE 3F CLFSCOREXTEST YTEST
OUT
MODEL SCORE 0790
USING THE PREDICTION PIPELINE IN A GRID SEARCH
GRID SEARCH CAN ALSO BE PERFORMED ON THE DIFFERENT PREPROCESSING STEPS DEFINED IN THE
COLUMNTRANSFORMER OBJECT TOGETHER WITH THE CLASSIFIER'S HYPERPARAMETERS AS PART OF THE PIPELINE
WE WILL SEARCH FOR BOTH THE IMPUTER STRATEGY OF THE NUMERIC PREPROCESSING AND THE REGULARIZATION PARAMETER
OF THE LOGISTIC REGRESSION USING SKLEARNMODELSELECTIONGRIDSEARCHCV
PARAMGRID
PREPROCESSORNUMIMPUTERSTRATEGY MEAN MEDIAN
CLASSIFIERC 01 10 10 100

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BEST LOGISTIC REGRESSION FROM GRID SEARCH 0798
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2103 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
574 SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV
THIS EXAMPLE CONSTRUCTS A PIPELINE THAT DOES DIMENSIONALITY REDUCTION FOLLOWED BY PREDICTION WITH A SUPPORT VECTOR
CLASSIFIER IT DEMONSTRATES THE USE OF GRIDSEARCHCV ANDPIPELINE TO OPTIMIZE OVER DIFFERENT CLASSES OF ESTIMATORS

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IN A SINGLE CV RUN – UNSUPERVISED PCA ANDNMF DIMENSIONALITY REDUCTIONS ARE COMPARED TO UNIVARIATE FEATURE SELECTION DURING THE GRID SEARCH
ADDITIONALLY PIPELINE CAN BE INSTANTIATED WITH THE MEMORY ARGUMENT TO MEMOIZE THE TRANSFORMERS WITHIN THE PIPELINE AVOIDING TO FIT AGAIN THE SAME TRANSFORMERS OVER AND OVER
NOTE THAT THE USE OF MEMORY TO ENABLE CACHING BECOMES INTERESTING WHEN THE FITTING OF A TRANSFORMER IS COSTLY
ILLUSTRATION OF PIPELINE ANDGRIDSEARCHCV
THIS SECTION ILLUSTRATES THE USE OF A PIPELINE WITHGRIDSEARCHCV
AUTHORS ROBERT MCGIBBON JOEL NOTHMAN GUILLAUME LEMAITRE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT LOADDIGITS
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNPIPELINE IMPORT PIPELINE
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CACHING TRANSFORMERS WITHIN A PIPELINE
IT IS SOMETIMES WORTHWHILE STORING THE STATE OF A SPECIFIC TRANSFORMER SINCE IT COULD BE USED AGAIN USING A PIPELINE INGRIDSEARCHCV TRIGGERS SUCH SITUATIONS THEREFORE WE USE THE ARGUMENT MEMORY TO ENABLE CACHING

WARNING NOTE THAT THIS EXAMPLE IS HOWEVER ONLY AN ILLUSTRATION SINCE FOR THIS SPECIFIC CASE FITTING PCA IS NOT NECESSARILY SLOWER THAN LOADING THE CACHE HENCE USE THE MEMORY CONSTRUCTOR PARAMETER WHEN THE FITTING OF A TRANSFORMER IS COSTLY

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FROM TEMPFILE IMPORT MKDTEMP
FROM SHUTIL IMPORT RMTREE
FROM JOBLIB IMPORT MEMORY
 CREATE A TEMPORARY FOLDER TO STORE THE TRANSFORMERS OF THE PIPELINE
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MEMORYMEMORY
 THIS TIME A CACHED PIPELINE WILL BE USED WITHIN THE GRID SEARCH
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‹→SKLEARNPIPELINEFITTRANSFORMONE591ACAE8E60C9632AA990E4FA0962A67
FITTRANSFORMONE CACHE LOADED 00S 00MIN
MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
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‹→SKLEARNPIPELINEFITTRANSFORMONE997E4CE30BA5143E90330DB664BF61C5
FITTRANSFORMONE CACHE LOADED 00S 00MIN
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FITTRANSFORMONE CACHE LOADED 00S 00MIN
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‹→SKLEARNPIPELINEFITTRANSFORMONE26CD3A8242ACB986F98CF38291EF5BAA
FITTRANSFORMONE CACHE LOADED 00S 00MIN
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‹→SKLEARNPIPELINEFITTRANSFORMONEB72F745822A406F2191B6EBFD8CA9DF9
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MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
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MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
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MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
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MEMORY CALLING SKLEARNPIPELINEFITTRANSFORMONE
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FITTRANSFORMONESELECTKBESTK2 SCOREFUNCFUNCTION CHI2 AT 0X7EFE30BB2268
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FITTRANSFORMONESELECTKBESTK4 SCOREFUNCFUNCTION CHI2 AT 0X7EFE30BB2268
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MEMORY CALLING SKLEARNPIPELINEFITTRANSFORMONE
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MEMORY00S 00MIN  LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
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FITTRANSFORMONE CACHE LOADED 00S 00MIN
MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
‹→SKLEARNPIPELINEFITTRANSFORMONED27C6056FC9AB1F3FB4327FD17346312
FITTRANSFORMONE CACHE LOADED 00S 00MIN
MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
‹→SKLEARNPIPELINEFITTRANSFORMONED649C35672F6E2731789F5C6A9B03066
FITTRANSFORMONE CACHE LOADED 00S 00MIN
MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
‹→SKLEARNPIPELINEFITTRANSFORMONE4906C4AFA619398FB77288E086D5DD82
FITTRANSFORMONE CACHE LOADED 00S 00MIN
MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
‹→SKLEARNPIPELINEFITTRANSFORMONE7DC3C29273FD5C57E2913F82C9185294
FITTRANSFORMONE CACHE LOADED 00S 00MIN
MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
‹→SKLEARNPIPELINEFITTRANSFORMONE63C1C1AF7115994B5CD17A1189691D5B
FITTRANSFORMONE CACHE LOADED 00S 00MIN
MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
‹→SKLEARNPIPELINEFITTRANSFORMONE670746700924677F7A550FA4CAE5C9BB
FITTRANSFORMONE CACHE LOADED 00S 00MIN
MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
‹→SKLEARNPIPELINEFITTRANSFORMONEF9617292C7B763D23B3F6C9D96697C29
FITTRANSFORMONE CACHE LOADED 00S 00MIN

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MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
‹→SKLEARNPIPELINEFITTRANSFORMONE9A2BCB4639D1B192E5525C2BF0DCA317
FITTRANSFORMONE CACHE LOADED 00S 00MIN
MEMORY00S 00MIN LOADING FITTRANSFORMONE FROM TMPTMPL5RIBDVUJOBLIB
‹→SKLEARNPIPELINEFITTRANSFORMONE87C7C41885D63769A203E26B244FD823
FITTRANSFORMONE CACHE LOADED 00S 00MIN

MEMORY CALLING SKLEARNPIPELINEFITTRANSFORMONE
FITTRANSFORMONEPCAITERATEDPOWER7 NCOMPONENTS8 ARRAY0 0

0 0 ARRAY0 8 NONE MESSAGECLSNAMEPIPELINE
‹→MESSAGENONE
FITTRANSFORMONE 00S 00MIN
THEPCA FITTING IS ONLY COMPUTED AT THE EVALUATION OF THE FIRST CONFIGURATION OF THE CPARAMETER OF THE LINEARSVC CLASSIFIER THE OTHER CONFIGURATIONS OF CWILL TRIGGER THE LOADING OF THE CACHED PCA ESTIMATOR DATA LEADING TO SAVE PROCESSING TIME THEREFORE THE USE OF CACHING THE PIPELINE USING MEMORY IS HIGHLY BENEFICIAL WHEN FITTING A TRANSFORMER IS COSTLY
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 20695 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
575 COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
DATASETS CAN OFTEN CONTAIN COMPONENTS OF THAT REQUIRE DIFFERENT FEATURE EXTRACTION AND PROCESSING PIPELINES THIS SCENARIO MIGHT OCCUR WHEN
1 YOUR DATASET CONSISTS OF HETEROGENEOUS DATA TYPES EG RASTER IMAGES AND TEXT CAPTIONS
2 YOUR DATASET IS STORED IN A PANDAS DATAFRAME AND DIFFERENT COLUMNS REQUIRE DIFFERENT PROCESSING PIPELINES
THIS EXAMPLE DEMONSTRATES HOW TO USE SKLEARNCOMPOSECOLUMNTRANSFORMER ON A DATASET CONTAINING DIFFERENT TYPES OF FEATURES WE USE THE 20NEWSGROUPS DATASET AND COMPUTE STANDARD BAGOFWORDS FEATURES FOR THE SUBJECT LINE AND BODY IN SEPARATE PIPELINES AS WELL AS AD HOC FEATURES ON THE BODY WE COMBINE THEM WITH WEIGHTS USING A COLUMNTRANSFORMER AND FINALLY TRAIN A CLASSIFIER ON THE COMBINED SET OF FEATURES
THE CHOICE OF FEATURES IS NOT PARTICULARLY HELPFUL BUT SERVES TO ILLUSTRATE THE TECHNIQUE
OUT
PIPELINE STEP 1 OF 3 PROCESSING SUBJECTBODY TOTAL 01S
PIPELINE STEP 2 OF 3 PROCESSING UNION TOTAL 03S
PIPELINE STEP 3 OF 3 PROCESSING SVC TOTAL 03S
PRECISION RECALL F1SCORE SUPPORT
0 096 062 076 494
1 025 084 039 76
ACCURACY 065 570
MACRO AVG 061 073 057 570
WEIGHTED AVG 087 065 071 570

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AUTHOR MATT TERRY MATTTERRYGMAILCOM

LICENSE BSD 3 CLAUSE

```
IMPORT NUMPY AS NP
FROM SKLEARNBASE IMPORT BASEESTIMATOR TRANSFORMERMIXIN
FROM SKLEARNDATASETS IMPORT FETCH20NEWSGROUPS
FROM SKLEARNDATASETSTWENTYNEWSGROUPS IMPORT STRIPNEWSGROUPFOOTER
FROM SKLEARNDATASETSTWENTYNEWSGROUPS IMPORT STRIPNEWSGROUPQUOTING
FROM SKLEARNDECOMPOSITION IMPORT TRUNCATEDSVD
FROM SKLEARNFEATUREEXTRACTION IMPORT DICTVECTORIZER
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFVECTORIZER
FROM SKLEARNMETRICS IMPORT CLASSIFICATIONREPORT
FROM SKLEARNPIPELINE IMPORT PIPELINE
FROM SKLEARNCOMPOSE IMPORT COLUMNTRANSFORMER
FROM SKLEARNSVM IMPORT LINEARSVC
CLASS TEXTSTATS BASEESTIMATOR TRANSFORMERMIXIN
EXTRACT FEATURES FROM EACH DOCUMENT FOR DICTVECTORIZER
DEFFITSELF X YNONE
RETURNSELF
DEFTRANSFORMSELF POSTS
RETURNLENGTH LENTEXT
NUMSENTENCES TEXTCOUNT
FORTEXTINPOSTS
CLASS SUBJECTBODYEXTRACTOR BASEESTIMATOR TRANSFORMERMIXIN
EXTRACT THE SUBJECT  BODY FROM A USENET POST IN A SINGLE PASS
TAKES A SEQUENCE OF STRINGS AND PRODUCES A DICT OF SEQUENCES KEYS ARE
SUBJECT AND BODY

DEFFITSELF X YNONE
RETURNSELF
DEFTRANSFORMSELF POSTS
 CONSTRUCT OBJECT DTYPE ARRAY WITH TWO COLUMNS
 FIRST COLUMN  SUBJECT AND SECOND COLUMN  BODY
FEATURES  NPEMPTYSHAPELENPOSTS 2 DTYPEOBJECT
FORI TEXT INENUMERATEPOSTS
HEADERS  BOD  TEXTPARTITION NN
BOD  STRIPNEWSGROUPFOOTERBOD
BOD  STRIPNEWSGROUPQUOTINGBOD
FEATURESI 1  BOD
PREFIX  SUBJECT
SUB
FORLINEINHEADERSSPLIT N
IFLINESTARTSWITHPREFIX
SUB  LINELENPREFIX
BREAK
FEATURESI 0  SUB
```

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RETURNFEATURES
PIPELINE PIPELINE
 EXTRACT THE SUBJECT BODY
SUBJECTBODY SUBJECTBODYEXTRACTOR
 USE COLUMNTRANSFORMER TO COMBINE THE FEATURES FROM SUBJECT AND BODY
UNION COLUMNTRANSFORMER

 PULLING FEATURES FROM THE POSTS SUBJECT LINE FIRST COLUMN
SUBJECT TFIDFVECTORIZERMINDF50 0
 PIPELINE FOR STANDARD BAGOFWORDS MODEL FOR BODY SECOND COLUMN
BODYBOW PIPELINE
TFIDF TFIDFVECTORIZER
BEST TRUNCATEDSVDNCOMPONENTS50
 1
 PIPELINE FOR PULLING AD HOC FEATURES FROM POSTS BODY
BODYSTATS PIPELINE
STATS TEXTSTATS RETURNS A LIST OF DICTS
VECT DICTVECTORIZER LIST OF DICTS FEATURE MATRIX
 1

 WEIGHT COMPONENTS IN COLUMNTRANSFORMER
TRANSFORMERWEIGHTS
SUBJECT 08
BODYBOW 05
BODYSTATS 10

 USE A SVC CLASSIFIER ON THE COMBINED FEATURES
SVC LINEARSVC
 VERBOSETRUE
 LIMIT THE LIST OF CATEGORIES TO MAKE RUNNING THIS EXAMPLE FASTER
CATEGORIES ALTATHEISM TALKRELIGIONMISC
TRAIN FETCH20NEWSGROUPSRANDOMSTATE1
SUBSETTRAIN
CATEGORIESCATEGORIES

TEST FETCH20NEWSGROUPSRANDOMSTATE1
SUBSETTEST
CATEGORIESCATEGORIES

PIPELINEFITTRAINDATA TRAINTARGET
Y PIPELINEPREDICTTESTDATA
PRINTCLASSIFICATIONREPORTY TESTTARGET
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1258 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

576 EFFECT OF TRANSFORMING THE TARGETS IN REGRESSION MODEL
IN THIS EXAMPLE WE GIVE AN OVERVIEW OF THE SKLEARNCOMPOSETRANSFORMEDTARGETREGRESSOR TWO
EXAMPLES ILLUSTRATE THE BENEFIT OF TRANSFORMING THE TARGETS BEFORE LEARNING A LINEAR REGRESSION MODEL THE FIRST EXAMPLE
USES SYNTHETIC DATA WHILE THE SECOND EXAMPLE IS BASED ON THE BOSTON HOUSING DATA SET
 AUTHOR GUILLAUME LEMAITRE GUILLAUMELEMAITREINRIAFR
 LICENSE BSD 3 CLAUSE
```
IMPORT NUMPY AS NP
IMPORT MATPLOTLIB
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM DISTUTILSVERSION IMPORT LOOSEVERSION
PRINTDOC
SYNTHETIC EXAMPLE
FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNLINEARMODEL IMPORT RIDGECV
FROM SKLEARNCOMPOSE IMPORT TRANSFORMEDTARGETREGRESSOR
FROM SKLEARNMETRICS IMPORT MEDIANABSOLUTEERROR R2SCORE
 NORMED IS BEING DEPRECATED IN FAVOR OF DENSITY IN HISTOGRAMS
IFLOOSEVERSIONMATPLOTLIBVERSION  21
DENSITYPARAM  DENSITY TRUE
ELSE
DENSITYPARAM  NORMED TRUE
```
A SYNTHETIC RANDOM REGRESSION PROBLEM IS GENERATED THE TARGETS YARE MODIFIED BY I TRANSLATING ALL TARGETS SUCH
THAT ALL ENTRIES ARE NONNEGATIVE AND II APPLYING AN EXPONENTIAL FUNCTION TO OBTAIN NONLINEAR TARGETS WHICH CANNOT BE
FITTED USING A SIMPLE LINEAR MODEL
THEREFORE A LOGARITHMIC NPLOG1P AND AN EXPONENTIAL FUNCTION NPEXPM1 WILL BE USED TO TRANSFORM THE TARGETS
BEFORE TRAINING A LINEAR REGRESSION MODEL AND USING IT FOR PREDICTION
```
X Y  MAKEREGRESSIONNSAMPLES10000 NOISE100 RANDOMSTATE0
Y  NPEXPY  ABSYMIN  200
YTRANS  NPLOG1PY
```
THE FOLLOWING ILLUSTRATE THE PROBABILITY DENSITY FUNCTIONS OF THE TARGET BEFORE AND AFTER APPLYING THE LOGARITHMIC FUNC
TIONS
```
F AX0 AX1  PLTSUBPLOTS1 2
AX0HISTY BINS100 DENSITYPARAM
AX0SETXLIM0 2000
AX0SETYLABELPROBABILITY
AX0SETXLABELTARGET
AX0SETTITLETARGET DISTRIBUTION
AX1HISTYTRANS BINS100 DENSITYPARAM
AX1SETYLABELPROBABILITY
```

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AX1SETXLABELTARGET
AX1SETTITLETRANSFORMED TARGET DISTRIBUTION
FSUPTITLESYNTHETIC DATA Y0035
FTIGHTLAYOUTRECT005 005 095 095
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y RANDOMSTATE0
AT FIRST A LINEAR MODEL WILL BE APPLIED ON THE ORIGINAL TARGETS DUE TO THE NONLINEARITY THE MODEL TRAINED WILL NOT BE PRECISE DURING THE PREDICTION SUBSEQUENTLY A LOGARITHMIC FUNCTION IS USED TO LINEARIZE THE TARGETS ALLOWING BETTER PREDICTION EVEN WITH A SIMILAR LINEAR MODEL AS REPORTED BY THE MEDIAN ABSOLUTE ERROR MAE
F AX0 AX1 PLTSUBPLOTS1 2 SHAREYTRUE
REGR RIDGECV
REGRFITXTRAIN YTRAIN
YPRED REGRPREDICTXTEST
AX0SCATTERYTEST YPRED
AX0PLOT0 2000 0 2000 K
AX0SETYLABELTARGET PREDICTED
AX0SETXLABELTRUE TARGET
AX0SETTITLERIDGE REGRESSION NWITHOUT TARGET TRANSFORMATION
AX0TEXT100 1750 RR2 2F MAE2F
R2SCOREYTEST YPRED MEDIANABSOLUTEERRORYTEST YPRED
AX0SETXLIM0 2000

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AX0SETYLIM0 2000
REGRTRANS TRANSFORMEDTARGETREGRESSORREGRESSORRIDGECV
FUNCNPLOG1P
INVERSEFUNCNPEXPM1
REGRTRANSFITXTRAIN YTRAIN
YPRED REGRTRANSPREDICTXTEST
AX1SCATTERYTEST YPRED
AX1PLOT0 2000 0 2000 K
AX1SETYLABELTARGET PREDICTED
AX1SETXLABELTRUE TARGET
AX1SETTITLERIDGE REGRESSION NWITH TARGET TRANSFORMATION
AX1TEXT100 1750 RR2 2F MAE2F
R2SCOREYTEST YPRED MEDIANABSOLUTEERRORYTEST YPRED
AX1SETXLIM0 2000
AX1SETYLIM0 2000
FSUPTITLESYNTHETIC DATA Y0035
FTIGHTLAYOUTRECT005 005 095 095

REALWORLD DATA SET
IN A SIMILAR MANNER THE BOSTON HOUSING DATA SET IS USED TO SHOW THE IMPACT OF TRANSFORMING THE TARGETS BEFORE LEARNING A MODEL IN THIS EXAMPLE THE TARGETS TO BE PREDICTED CORRESPONDS TO THE WEIGHTED DISTANCES TO THE FIVE BOSTON EMPLOYMENT CENTERS

```
FROM SKLEARNDATASETS IMPORT LOADBOSTON
FROM SKLEARNPREPROCESSING IMPORT QUANTILETRANSFORMER QUANTILETRANSFORM
DATASET  LOADBOSTON
TARGET  NPARRAYDATASETFEATURENAMES  DIS
X  DATASETDATA NPLOGICALNOTTARGET
Y  DATASETDATA TARGETSQUEEZE
YTRANS  QUANTILETRANSFORMDATASETDATA TARGET
NQUANTILES300
OUTPUTDISTRIBUTIONNORMAL
COPYTRUESQUEEZE
ASKLEARNPREPROCESSINGQUANTILETRANSFORMER IS USED SUCH THAT THE TARGETS FOLLOWS A NORMAL DISTRI
BUTION BEFORE APPLYING A SKLEARNLINEARMODELRIDGECV MODEL
F AX0 AX1  PLTSUBPLOTS1 2
AX0HISTY BINS100 DENSITYPARAM
AX0SETYLABELPROBABILITY
AX0SETXLABELTARGET
AX0SETTITLETARGET DISTRIBUTION
AX1HISTYTRANS BINS100 DENSITYPARAM
AX1SETYLABELPROBABILITY
AX1SETXLABELTARGET
AX1SETTITLETRANSFORMED TARGET DISTRIBUTION
FSUPTITLEBOSTON HOUSING DATA DISTANCE TO EMPLOYMENT CENTERS Y0035
FTIGHTLAYOUTRECT005 005 095 095
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLITX Y RANDOMSTATE1
```

THE EFFECT OF THE TRANSFORMER IS WEAKER THAN ON THE SYNTHETIC DATA HOWEVER THE TRANSFORM INDUCES A DECREASE OF THE MAE

```
F AX0 AX1  PLTSUBPLOTS1 2 SHAREYTRUE
REGR  RIDGECV
REGRFITXTRAIN YTRAIN
YPRED  REGRPREDICTXTEST
AX0SCATTERYTEST YPRED
AX0PLOT0 10 0 10 K
AX0SETYLABELTARGET PREDICTED
AX0SETXLABELTRUE TARGET
AX0SETTITLERIDGE REGRESSION NWITHOUT TARGET TRANSFORMATION
AX0TEXT1 9 RR2 2F MAE2F
R2SCOREYTEST YPRED MEDIANABSOLUTEERRORYTEST YPRED
AX0SETXLIM0 10
AX0SETYLIM0 10
REGRTRANS  TRANSFORMEDTARGETREGRESSOR
REGRESSORRIDGECV
TRANSFORMERQUANTILETRANSFORMERNQUANTILES300
OUTPUTDISTRIBUTIONNORMAL
REGRTRANSFITXTRAIN YTRAIN
YPRED  REGRTRANSPREDICTXTEST
```

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AX1SCATTERYTEST YPRED
AX1PLOT0 10 0 10 K
AX1SETYLABELTARGET PREDICTED
AX1SETXLABELTRUE TARGET
AX1SETTITLERIDGE REGRESSION NWITH TARGET TRANSFORMATION
AX1TEXT1 9 RR2 2F MAE2F
R2SCOREYTEST YPRED MEDIANABSOLUTEERRORYTEST YPRED
AX1SETXLIM0 10
AX1SETYLIM0 10
FSUPTITLEBOSTON HOUSING DATA DISTANCE TO EMPLOYMENT CENTERS Y0035
FTIGHTLAYOUTRECT005 005 095 095
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1682 SECONDS
58 COVARIANCE ESTIMATION
EXAMPLES CONCERNING THE SKLEARNCOVARIANCE MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
942 CHAPTER 5 EXAMPLES

581 LEDOITWOLF VS OAS ESTIMATION

THE USUAL COVARIANCE MAXIMUM LIKELIHOOD ESTIMATE CAN BE REGULARIZED USING SHRINKAGE LEDOIT AND WOLF PROPOSED A CLOSE FORMULA TO COMPUTE THE ASYMPTOTICALLY OPTIMAL SHRINKAGE PARAMETER MINIMIZING A MSE CRITERION YIELDING THE LEDOITWOLF COVARIANCE ESTIMATE

CHEN ET AL PROPOSED AN IMPROVEMENT OF THE LEDOITWOLF SHRINKAGE PARAMETER THE OAS COEFFICIENT WHOSE CONVERGENCE IS SIGNIFICANTLY BETTER UNDER THE ASSUMPTION THAT THE DATA ARE GAUSSIAN

THIS EXAMPLE INSPIRED FROM CHEN'S PUBLICATION 1 SHOWS A COMPARISON OF THE ESTIMATED MSE OF THE LW AND OAS METHODS USING GAUSSIAN DISTRIBUTED DATA

1 "SHRINKAGE ALGORITHMS FOR MMSE COVARIANCE ESTIMATION" CHEN ET AL IEEE TRANS ON SIGN PROC V OLUME 58 ISSUE 10 OCTOBER 2010

```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPYLINALG IMPORT TOEPLITZ CHOLESKY
FROM SKLEARNCOVARIANCE IMPORT LEDOITWOLF OAS
NPRANDOMSEED0
NFEATURES  100
 SIMULATION COVARIANCE MATRIX AR1 PROCESS
R  01
REALCOV  TOEPLITZR NPARANGENFEATURES
COLORINGMATRIX  CHOLESKYREALCOV
NSAMPLESRANGE  NPARANGE6 31 1
REPEAT  100
LWMSE  NPZEROSNSAMPLESRANGESIZE REPEAT
OAMSE  NPZEROSNSAMPLESRANGESIZE REPEAT
LWSHRINKAGE  NPZEROSNSAMPLESRANGESIZE REPEAT
OASHRINKAGE  NPZEROSNSAMPLESRANGESIZE REPEAT
FORI NSAMPLES INENUMERATENSAMPLESRANGE
FORJINRANGEREPEAT
X  NPDOT
NPRANDOMNORMALSIZENSAMPLES NFEATURES COLORINGMATRIXT
LW  LEDOITWOLFSTOREPRECISIONFALSE ASSUMECENTEREDTRUE
LWFITX
LWMSEI J  LWERRORNORMREALCOV SCALINGFALSE
LWSHRINKAGEI J  LWSHRINKAGE
OA  OASSTOREPRECISIONFALSE ASSUMECENTEREDTRUE
OAFITX
OAMSEI J  OAERRORNORMREALCOV SCALINGFALSE
OASHRINKAGEI J  OASHRINKAGE
 PLOT MSE
PLTSUBPLOT2 1 1
PLTERRORBARNSAMPLESRANGE LWMSEMEAN1 YERRLWMSESTD1
LABELLEDOITWOLF COLORNAVY LW2
PLTERRORBARNSAMPLESRANGE OAMSEMEAN1 YERROAMSESTD1
LABELOAS COLORDARKORANGE LW2
PLTYLABELSQUARED ERROR
```

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PLTLEGENDLOCUPPER RIGHT
PLTTITLECOMPARISON OF COVARIANCE ESTIMATORS
PLTXLIM5 31
 PLOT SHRINKAGE COEFFICIENT
PLTSUBPLOT2 1 2
PLTERRORBARNSAMPLESRANGE LWSHRINKAGEMEAN1 YERRLWSHRINKAGESTD1
LABELLEDOITWOLF COLORNAVY LW2
PLTERRORBARNSAMPLESRANGE OASHRINKAGEMEAN1 YERROASHRINKAGESTD1
LABELOAS COLORDARKORANGE LW2
PLTXLABELNSAMPLES
PLTYLABELSHRINKAGE
PLTLEGENDLOCLOWER RIGHT
PLTYLIMPLTYLIM0 1 PLTYLIM1 PLTYLIM0 10
PLTXLIM5 31
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3818 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

582 SPARSE INVERSE COVARIANCE ESTIMATION

USING THE GRAPHICALLASSO ESTIMATOR TO LEARN A COVARIANCE AND SPARSE PRECISION FROM A SMALL NUMBER OF SAMPLES

TO ESTIMATE A PROBABILISTIC MODEL EG A GAUSSIAN MODEL ESTIMATING THE PRECISION MATRIX THAT IS THE INVERSE COVARIANCE MATRIX IS AS IMPORTANT AS ESTIMATING THE COVARIANCE MATRIX INDEED A GAUSSIAN MODEL IS PARAMETRIZED BY THE PRECISION MATRIX

TO BE IN FAVORABLE RECOVERY CONDITIONS WE SAMPLE THE DATA FROM A MODEL WITH A SPARSE INVERSE COVARIANCE MATRIX IN ADDITION WE ENSURE THAT THE DATA IS NOT TOO MUCH CORRELATED LIMITING THE LARGEST COEFFICIENT OF THE PRECISION MATRIX AND THAT THERE A NO SMALL COEFFICIENTS IN THE PRECISION MATRIX THAT CANNOT BE RECOVERED IN ADDITION WITH A SMALL NUMBER OF OBSERVATIONS IT IS EASIER TO RECOVER A CORRELATION MATRIX RATHER THAN A COVARIANCE THUS WE SCALE THE TIME SERIES

HERE THE NUMBER OF SAMPLES IS SLIGHTLY LARGER THAN THE NUMBER OF DIMENSIONS THUS THE EMPIRICAL COVARIANCE IS STILL INVERTIBLE HOWEVER AS THE OBSERVATIONS ARE STRONGLY CORRELATED THE EMPIRICAL COVARIANCE MATRIX IS ILLCONDITIONED AND AS A RESULT ITS INVERSE –THE EMPIRICAL PRECISION MATRIX– IS VERY FAR FROM THE GROUND TRUTH

IF WE USE L2 SHRINKAGE AS WITH THE LEDOITWOLF ESTIMATOR AS THE NUMBER OF SAMPLES IS SMALL WE NEED TO SHRINK A LOT AS A RESULT THE LEDOITWOLF PRECISION IS FAIRLY CLOSE TO THE GROUND TRUTH PRECISION THAT IS NOT FAR FROM BEING DIAGONAL BUT THE OFFDIAGONAL STRUCTURE IS LOST

THE L1PENALIZED ESTIMATOR CAN RECOVER PART OF THIS OFFDIAGONAL STRUCTURE IT LEARNS A SPARSE PRECISION IT IS NOT ABLE TO RECOVER THE EXACT SPARSITY PATTERN IT DETECTS TOO MANY NONZERO COEFFICIENTS HOWEVER THE HIGHEST NONZERO COEFFICIENTS OF THE L1 ESTIMATED CORRESPOND TO THE NONZERO COEFFICIENTS IN THE GROUND TRUTH FINALLY THE COEFFICIENTS OF THE L1 PRECISION ESTIMATE ARE BIASED TOWARD ZERO BECAUSE OF THE PENALTY THEY ARE ALL SMALLER THAN THE CORRESPONDING GROUND TRUTH VALUE AS CAN BE SEEN ON THE FIGURE

NOTE THAT THE COLOR RANGE OF THE PRECISION MATRICES IS TWEAKED TO IMPROVE READABILITY OF THE FIGURE THE FULL RANGE OF VALUES OF THE EMPIRICAL PRECISION IS NOT DISPLAYED

THE ALPHA PARAMETER OF THE GRAPHICALLASSO SETTING THE SPARSITY OF THE MODEL IS SET BY INTERNAL CROSSVALIDATION IN THE GRAPHICALLASSOCV AS CAN BE SEEN ON FIGURE 2 THE GRID TO COMPUTE THE CROSSVALIDATION SCORE IS ITERATIVELY REFINED IN THE NEIGHBORHOOD OF THE MAXIMUM

•

•

```
PRINTDOC
 AUTHOR GAEL VAROQUAUX GAELVAROQUAUXINRIAFR
 LICENSE BSD 3 CLAUSE
 COPYRIGHT INRIA
IMPORT NUMPY AS NP
FROM SCIPY IMPORT LINALG
FROM SKLEARNDATASETS IMPORT MAKESPARSESPDMATRIX
FROM SKLEARNCOVARIANCE IMPORT GRAPHICALLASSOCV LEDOITWOLF
IMPORT MATPLOTLIBPYPLOT AS PLT

 GENERATE THE DATA
NSAMPLES  60
NFEATURES  20
PRNG  NPRANDOMRANDOMSTATE1
PREC  MAKESPARSESPDMATRIXNFEATURES ALPHA98
SMALLESTCOEF4
LARGESTCOEF7
RANDOMSTATEPRNG
COV  LINALGINVPREC
D  NPSQRTNPDIAGCOV
COV  D
COV  D NPNEWAXIS
PREC D
PREC D NPNEWAXIS
X  PRNGMULTIVARIATENORMALNPZEROSNFEATURES COV SIZENSAMPLES
X  XMEANAXIS0
X  XSTDAXIS0

 ESTIMATE THE COVARIANCE
EMPCOV  NPDOTXT X  NSAMPLES
MODEL  GRAPHICALLASSOCVCV5
MODELFITX
COV  MODELCOVARIANCE
```

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PREC MODELPRECISION
LWCOV   LEDOITWOLFX
LWPREC LINALGINVLWCOV

 PLOT THE RESULTS
PLTFIGUREFIGSIZE10 6
PLTSUBPLOTSADJUSTLEFT002 RIGHT098
 PLOT THE COVARIANCES
COVS EMPIRICAL EMPCOV LEDOITWOLF LWCOV
GRAPHICALLASSOCV COV TRUE COV
VMAX COVMAX
FORI NAME THISCOV INENUMERATECOVS
PLTSUBPLOT2 4 I 1
PLTIMSHOWTHISCOV INTERPOLATIONNEAREST VMINVMAX VMAXVMAX
CMAPPLTCMRDBUR
PLTXTICKS
PLTYTICKS
PLTTITLE SCOVARIANCE NAME
 PLOT THE PRECISIONS
PRECS EMPIRICAL LINALGINVEMPCOV LEDOITWOLF LWPREC
GRAPHICALLASSO PREC TRUE PREC
VMAX 9 PRECMAX
FORI NAME THISPREC INENUMERATEPRECS
AX PLTSUBPLOT2 4 I 5
PLTIMSHOWNPMAMASKEDEQUALTHISPREC 0
INTERPOLATIONNEAREST VMINVMAX VMAXVMAX
CMAPPLTCMRDBUR
PLTXTICKS
PLTYTICKS
PLTTITLE SPRECISION NAME
IFHASATTRAX SETFACECOLOR
AXSETFACECOLOR7
ELSE
AXSETAXISBGCOLOR7
 PLOT THE MODEL SELECTION METRIC
PLTFIGUREFIGSIZE4 3
PLTAXES2 15 75 7
PLTPLOTMODELCVALPHAS NPMEANMODELGRIDSCORES AXIS1 O
PLTAXVLINEMODELALPHA COLOR5
PLTTITLEMODEL SELECTION
PLTYLABELCROSSVALIDATION SCORE
PLTXLABELALPHA
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0501 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

583 SHRINKAGE COVARIANCE ESTIMATION LEDOITWOLF VS OAS AND MAXLIKELIHOOD
WHEN WORKING WITH COVARIANCE ESTIMATION THE USUAL APPROACH IS TO USE A MAXIMUM LIKELIHOOD ESTIMATOR SUCH AS THESKLEARNCOVARIANCEEMPIRICALCOVARIANCE IT IS UNBIASED IE IT CONVERGES TO THE TRUE POPULATION COVARIANCE WHEN GIVEN MANY OBSERVATIONS HOWEVER IT CAN ALSO BE BENEFICIAL TO REGULARIZE IT IN ORDER TO REDUCE ITS VARIANCE THIS IN TURN INTRODUCES SOME BIAS THIS EXAMPLE ILLUSTRATES THE SIMPLE REGULARIZATION USED IN SHRUNK COVARIANCE ESTIMATORS IN PARTICULAR IT FOCUSES ON HOW TO SET THE AMOUNT OF REGULARIZATION IE HOW TO CHOOSE THE BIASVARIANCE TRADEOFF
HERE WE COMPARE 3 APPROACHES
• SETTING THE PARAMETER BY CROSSVALIDATING THE LIKELIHOOD ON THREE FOLDS ACCORDING TO A GRID OF POTENTIAL SHRINKAGE PARAMETERS
• A CLOSE FORMULA PROPOSED BY LEDOIT AND WOLF TO COMPUTE THE ASYMPTOTICALLY OPTIMAL REGULARIZATION PARAMETER MINIMIZING A MSE CRITERION YIELDING THE SKLEARNCOVARIANCELEDOITWOLF COVARIANCE ESTIMATE
• AN IMPROVEMENT OF THE LEDOITWOLF SHRINKAGE THE SKLEARNCOVARIANCEOAS PROPOSED BY CHEN ET AL
ITS CONVERGENCE IS SIGNIFICANTLY BETTER UNDER THE ASSUMPTION THAT THE DATA ARE GAUSSIAN IN PARTICULAR FOR SMALL SAMPLES
TO QUANTIFY ESTIMATION ERROR WE PLOT THE LIKELIHOOD OF UNSEEN DATA FOR DIFFERENT VALUES OF THE SHRINKAGE PARAMETER WE ALSO SHOW THE CHOICES BY CROSSVALIDATION OR WITH THE LEDOITWOLF AND OAS ESTIMATES
NOTE THAT THE MAXIMUM LIKELIHOOD ESTIMATE CORRESPONDS TO NO SHRINKAGE AND THUS PERFORMS POORLY THE LEDOITWOLF ESTIMATE PERFORMS REALLY WELL AS IT IS CLOSE TO THE OPTIMAL AND IS COMPUTATIONAL NOT COSTLY IN THIS EXAMPLE THE OAS ESTIMATE IS A BIT FURTHER AWAY INTERESTINGLY BOTH APPROACHES OUTPERFORM CROSSVALIDATION WHICH IS SIGNIFICANTLY MOST COMPUTATIONALLY COSTLY

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPY IMPORT LINALG
FROM SKLEARNCOVARIANCE IMPORT LEDOITWOLF OAS SHRUNKCOVARIANCE
LOGLIKELIHOOD EMPIRICALCOVARIANCE
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV

GENERATE SAMPLE DATA
NFEATURES NSAMPLES 40 20
NPRANDOMSEED42
BASEXTRAIN NPRANDOMNORMALSIZENSAMPLES NFEATURES
BASEXTEST NPRANDOMNORMALSIZENSAMPLES NFEATURES
COLOR SAMPLES
COLORINGMATRIX NPRANDOMNORMALSIZENFEATURES NFEATURES
XTRAIN NPDOTBASEXTRAIN COLORINGMATRIX
XTEST NPDOTBASEXTEST COLORINGMATRIX

COMPUTE THE LIKELIHOOD ON TEST DATA

```
 SPANNING A RANGE OF POSSIBLE SHRINKAGE COEFFICIENT VALUES
SHRINKAGES  NPLOGSPACE2 0 30
NEGATIVELOGLIKS  SHRUNKCOVARIANCESHRINKAGESFITXTRAINSCOREXTEST
FORSINSHRINKAGES
 UNDER THE GROUNDTRUTH MODEL WHICH WE WOULD NOT HAVE ACCESS TO IN REAL
 SETTINGS
REALCOV  NPDOTCOLORINGMATRIXT COLORINGMATRIX
EMPCOV  EMPIRICALCOVARIANCEXTRAIN
LOGLIKREAL  LOGLIKELIHOODEMPCOV LINALGINVREALCOV

 COMPARE DIFFERENT APPROACHES TO SETTING THE PARAMETER
 GRIDSEARCH FOR AN OPTIMAL SHRINKAGE COEFFICIENT
TUNEDPARAMETERS  SHRINKAGE SHRINKAGES
CV  GRIDSEARCHCVSHRUNKCOVARIANCE TUNEDPARAMETERS CV5
CVFITXTRAIN
 LEDOITWOLF OPTIMAL SHRINKAGE COEFFICIENT ESTIMATE
LW  LEDOITWOLF
LOGLIKLW  LWFITXTRAINSCOREXTEST
 OAS COEFFICIENT ESTIMATE
OA  OAS
LOGLIKOA  OAFITXTRAINSCOREXTEST

 PLOT RESULTS
FIG  PLTFIGURE
PLTTITLEREGULARIZED COVARIANCE LIKELIHOOD AND SHRINKAGE COEFFICIENT
PLTXLABELREGULARIZATION PARAMETER SHRINKAGE COEFFICIENT
PLTYLABELERROR NEGATIVE LOGLIKELIHOOD ON TEST DATA
 RANGE SHRINKAGE CURVE
PLTLOGLOGSHRINKAGES NEGATIVELOGLIKS LABELNEGATIVE LOGLIKELIHOOD
PLTPLOTPLTXLIM 2 LOGLIKREAL R
LABELREAL COVARIANCE LIKELIHOOD
 ADJUST VIEW
LIKMAX  NPAMAXNEGATIVELOGLIKS
LIKMIN  NPAMINNEGATIVELOGLIKS
YMIN  LIKMIN  6 NPLOGPLTYLIM1  PLTYLIM0
YMAX  LIKMAX  10 NPLOGLIKMAX  LIKMIN
XMIN  SHRINKAGES0
XMAX  SHRINKAGES1
 LW LIKELIHOOD
PLTVLINESLWSHRINKAGE YMIN LOGLIKLW COLORMAGENTA
LINEWIDTH3 LABELLEDOITWOLF ESTIMATE
 OAS LIKELIHOOD
PLTVLINESOASHRINKAGE YMIN LOGLIKOA COLORPURPLE
LINEWIDTH3 LABELOAS ESTIMATE
 BEST CV ESTIMATOR LIKELIHOOD
PLTVLINESCVBESTESTIMATORSHRINKAGE YMIN
CVBESTESTIMATORSCOREXTEST COLORCYAN
LINEWIDTH3 LABELCROSSVALIDATION BEST ESTIMATE
PLTYLIMYMIN YMAX
```

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PLTXLIMXMIN XMAX
PLTLEGEND
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0183 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
584 ROBUST COVARIANCE ESTIMATION AND MAHALANOBIS DISTANCES RELEVANCE
AN EXAMPLE TO SHOW COVARIANCE ESTIMATION WITH THE MAHALANOBIS DISTANCES ON GAUSSIAN DISTRIBUTED DATA
FOR GAUSSIAN DISTRIBUTED DATA THE DISTANCE OF AN OBSERVATION □□TO THE MODE OF THE DISTRIBUTION CAN BE COMPUTED USING ITS MAHALANOBIS DISTANCE □□Σ□□2 □□−□′□−1□□−□WHERE □AND□ARE THE LOCATION AND THE COVARIANCE OF THE UNDERLYING GAUSSIAN DISTRIBUTION
IN PRACTICE □AND□ARE REPLACED BY SOME ESTIMATES THE USUAL COVARIANCE MAXIMUM LIKELIHOOD ESTIMATE IS VERY SENSITIVE TO THE PRESENCE OF OUTLIERS IN THE DATA SET AND THEREFOR THE CORRESPONDING MAHALANOBIS DISTANCES ARE ONE WOULD BETTER HAVE TO USE A ROBUST ESTIMATOR OF COVARIANCE TO GUARANTEE THAT THE ESTIMATION IS RESISTANT TO “ERRONEOUS” OBSERVATIONS IN THE DATA SET AND THAT THE ASSOCIATED MAHALANOBIS DISTANCES ACCURATELY REFLECT THE TRUE ORGANISATION OF THE OBSERVATIONS
THE MINIMUM COVARIANCE DETERMINANT ESTIMATOR IS A ROBUST HIGHBREAKDOWN POINT IE IT CAN BE USED TO ESTIMATE THE COVARIANCE MATRIX OF HIGHLY CONTAMINATED DATASETS UP TO□SAMPLES−□FEATURES−1
2OUTLIERS ESTIMATOR OF COVARIANCE THE IDEA IS
TO FIND□SAMPLES□FEATURES1
2OBSERVATIONS WHOSE EMPIRICAL COVARIANCE HAS THE SMALLEST DETERMINANT YIELDING A “PURE” SUBSET
OF OBSERVATIONS FROM WHICH TO COMPUTE STANDARDS ESTIMATES OF LOCATION AND COVARIANCE
THE MINIMUM COVARIANCE DETERMINANT ESTIMATOR MCD HAS BEEN INTRODUCED BY PJROUSSEUW IN 1
THIS EXAMPLE ILLUSTRATES HOW THE MAHALANOBIS DISTANCES ARE AFFECTED BY OUTLYING DATA OBSERVATIONS DRAWN FROM A CONTAMINATING DISTRIBUTION ARE NOT DISTINGUISHABLE FROM THE OBSERVATIONS COMING FROM THE REAL GAUSSIAN DISTRIBUTION THAT ONE MAY WANT TO WORK WITH USING MCDBASED MAHALANOBIS DISTANCES THE TWO POPULATIONS BECOME DISTINGUISH ABLE ASSOCIATED APPLICATIONS ARE OUTLIERS DETECTION OBSERVATIONS RANKING CLUSTERING FOR VISUALIZATION PURPOSE THE CUBIC ROOT OF THE MAHALANOBIS DISTANCES ARE REPRESENTED IN THE BOXPLOT AS WILSON AND HILFERTY SUGGEST 2
1 P J ROUSSEEUW LEAST MEDIAN OF SQUARES REGRESSION J AM STAT ASS 79871 1984
2 WILSON E B HILFERTY M M 1931 THE DISTRIBUTION OF CHISQUARE PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA 17 684688
58 COVARIANCE ESTIMATION 951

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNCOVARIANCE IMPORT EMPIRICALCOVARIANCE MINCOVDET
NSAMPLES 125
NOUTLIERS 25
NFEATURES 2
 GENERATE DATA
GENCOV NPEYENFEATURES
GENCOV0 0 2
X NPDOTNPRANDOMRANDNNSAMPLES NFEATURES GENCOV
 ADD SOME OUTLIERS
OUTLIERSCOV NPEYENFEATURES
OUTLIERSCOVNPARANGE1 NFEATURES NPARANGE1 NFEATURES 7
XNOUTLIERS NPDOTNPRANDOMRANDNNOUTLIERS NFEATURES OUTLIERSCOV
 FIT A MINIMUM COVARIANCE DETERMINANT MCD ROBUST ESTIMATOR TO DATA
ROBUSTCOV MINCOVDETFITX
 COMPARE ESTIMATORS LEARNT FROM THE FULL DATA SET WITH TRUE PARAMETERS
EMPCOV EMPIRICALCOVARIANCEFITX

```
 DISPLAY RESULTS
FIG  PLTFIGURE
PLTSUBPLOTSADJUSTHSPACE1 WSPACE4 TOP95 BOTTOM05
 SHOW DATA SET
SUBFIG1  PLTSUBPLOT3 1 1
INLIERPLOT  SUBFIG1SCATTERX 0 X 1
COLORBLACK LABELINLIERS
OUTLIERPLOT  SUBFIG1SCATTERX 0NOUTLIERS X 1NOUTLIERS
COLORRED LABELOUTLIERS
SUBFIG1SETXLIMSUBFIG1GETXLIM0 11
SUBFIG1SETTITLEMAHALANOBIS DISTANCES OF A CONTAMINATED DATA SET
 SHOW CONTOURS OF THE DISTANCE FUNCTIONS
XX YY  NPMESHGRIDNPLINSPACEPLTXLIM0 PLTXLIM1 100
NPLINSPACEPLTYLIM0 PLTYLIM1 100
ZZ  NPCXXRAVEL YYRAVEL
MAHALEMPCOV  EMPCOVMAHALANOBISZZ
MAHALEMPCOV  MAHALEMPCOVRESHAPEXXSHAPE
EMPCOVCONTOUR  SUBFIG1CONTOURXX YY NPSQRTMAHALEMPCOV
CMAPPLTCMPUBUR
LINESTYLESDASHED
MAHALROBUSTCOV  ROBUSTCOVMAHALANOBISZZ
MAHALROBUSTCOV  MAHALROBUSTCOVRESHAPEXXSHAPE
ROBUSTCONTOUR  SUBFIG1CONTOURXX YY NPSQRTMAHALROBUSTCOV
CMAPPLTCMYLORBRR LINESTYLESDOTTED
SUBFIG1LEGENDEMPCOVCONTOURCOLLECTIONS1 ROBUSTCONTOURCOLLECTIONS1
INLIERPLOT OUTLIERPLOT
MLE DIST ROBUST DIST INLIERS OUTLIERS
LOCUPPER RIGHT BORDERAXESPAD0
PLTXTICKS
PLTYTICKS
 PLOT THE SCORES FOR EACH POINT
EMPMAHAL  EMPCOVMAHALANOBISX  NPMEANX 0 033
SUBFIG2  PLTSUBPLOT2 2 3
SUBFIG2BOXPLOTEMPMAHALNOUTLIERS EMPMAHALNOUTLIERS WIDTHS25
SUBFIG2PLOTNPFULLNSAMPLES  NOUTLIERS 126
EMPMAHALNOUTLIERS K MARKEREDGEWIDTH1
SUBFIG2PLOTNPFULLNOUTLIERS 226
EMPMAHALNOUTLIERS K MARKEREDGEWIDTH1
SUBFIG2AXESSETXTICKLABELSINLIERS OUTLIERS SIZE15
SUBFIG2SETYLABELRSQRT3RMMAHAL DIST SIZE16
SUBFIG2SETTITLE1 FROM NONROBUST ESTIMATES NMAXIMUM LIKELIHOOD
PLTYTICKS
ROBUSTMAHAL  ROBUSTCOVMAHALANOBISX  ROBUSTCOVLOCATION 033
SUBFIG3  PLTSUBPLOT2 2 4
SUBFIG3BOXPLOTROBUSTMAHALNOUTLIERS ROBUSTMAHALNOUTLIERS
WIDTHS25
SUBFIG3PLOTNPFULLNSAMPLES  NOUTLIERS 126
ROBUSTMAHALNOUTLIERS K MARKEREDGEWIDTH1
SUBFIG3PLOTNPFULLNOUTLIERS 226
ROBUSTMAHALNOUTLIERS K MARKEREDGEWIDTH1
```

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SUBFIG3AXESSETXTICKLABELSINLIERS OUTLIERS SIZE15
SUBFIG3SETYLABELRSQRT3RMMAHAL DIST SIZE16
SUBFIG3SETTITLE2 FROM ROBUST ESTIMATES NMINIMUM COVARIANCE DETERMINANT
PLTYTICKS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0298 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
585 ROBUST VS EMPIRICAL COVARIANCE ESTIMATE
THE USUAL COVARIANCE MAXIMUM LIKELIHOOD ESTIMATE IS VERY SENSITIVE TO THE PRESENCE OF OUTLIERS IN THE DATA SET IN SUCH A CASE IT WOULD BE BETTER TO USE A ROBUST ESTIMATOR OF COVARIANCE TO GUARANTEE THAT THE ESTIMATION IS RESISTANT TO “ERRONEOUS” OBSERVATIONS IN THE DATA SET12
MINIMUM COVARIANCE DETERMINANT ESTIMATOR
THE MINIMUM COVARIANCE DETERMINANT ESTIMATOR IS A ROBUST HIGHBREAKDOWN POINT IE IT CAN BE USED TO ESTIMATE THE COVARIANCE MATRIX OF HIGHLY CONTAMINATED DATASETS UP TO□SAMPLES−□FEATURES−1
2OUTLIERS ESTIMATOR OF COVARIANCE THE IDEA IS
TO FIND□SAMPLES□FEATURES1
2OBSERVATIONS WHOSE EMPIRICAL COVARIANCE HAS THE SMALLEST DETERMINANT YIELDING A “PURE” SUBSET OF OBSERVATIONS FROM WHICH TO COMPUTE STANDARDS ESTIMATES OF LOCATION AND COVARIANCE AFTER A CORRECTION STEP AIMING AT COMPENSATING THE FACT THAT THE ESTIMATES WERE LEARNED FROM ONLY A PORTION OF THE INITIAL DATA WE END UP WITH ROBUST ESTIMATES OF THE DATA SET LOCATION AND COVARIANCE
THE MINIMUM COVARIANCE DETERMINANT ESTIMATOR MCD HAS BEEN INTRODUCED BY PJROUSSEUW IN3
EVALUATION
IN THIS EXAMPLE WE COMPARE THE ESTIMATION ERRORS THAT ARE MADE WHEN USING VARIOUS TYPES OF LOCATION AND COVARIANCE ESTIMATES ON CONTAMINATED GAUSSIAN DISTRIBUTED DATA SETS
• THE MEAN AND THE EMPIRICAL COVARIANCE OF THE FULL DATASET WHICH BREAK DOWN AS SOON AS THERE ARE OUTLIERS IN THE DATA SET
• THE ROBUST MCD THAT HAS A LOW ERROR PROVIDED □SAMPLES 5□FEATURES
• THE MEAN AND THE EMPIRICAL COVARIANCE OF THE OBSERVATIONS THAT ARE KNOWN TO BE GOOD ONES THIS CAN BE CONSID
ERED AS A “PERFECT” MCD ESTIMATION SO ONE CAN TRUST OUR IMPLEMENTATION BY COMPARING TO THIS CASE
1JOHANNA HARDIN DAVID M ROCKE THE DISTRIBUTION OF ROBUST DISTANCES JOURNAL OF COMPUTATIONAL AND GRAPHICAL STATISTICS DECEM
144 928946
2ZOUBIR A KOIVUNEN V CHAKHCHOUKH Y AND MUMA M 2012 ROBUST ESTIMATION IN SIGNAL PROCESSING A TUTORIALSTYLE TREATMENT OF FU
MENTAL CONCEPTS IEEE SIGNAL PROCESSING MAGAZINE 294 6180
3P J ROUSSEEUW LEAST MEDIAN OF SQUARES REGRESSION JOURNAL OF AMERICAN STATISTICAL ASS 79871 1984
954 CHAPTER 5 EXAMPLES

REFERENCES
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIBFONTMANAGER
FROM SKLEARNCOVARIANCE IMPORT EMPIRICALCOVARIANCE MINCOVDET
EXAMPLE SETTINGS
NSAMPLES 80
NFEATURES 5
REPEAT 10
RANGENOUTLIERS NPCONCATENATE
NPLINSPACE0 NSAMPLES 8 5
NPLINSPACENSAMPLES 8 NSAMPLES 2 511ASTYPENPINT
DEFINITION OF ARRAYS TO STORE RESULTS
ERRLOCMCD NPZEROSRANGENOUTLIERSSIZE REPEAT
ERRCOVMCD NPZEROSRANGENOUTLIERSSIZE REPEAT
ERRLOCEMPFULL NPZEROSRANGENOUTLIERSSIZE REPEAT
ERRCOVEMPFULL NPZEROSRANGENOUTLIERSSIZE REPEAT
ERRLOCEMPPURE NPZEROSRANGENOUTLIERSSIZE REPEAT
ERRCOVEMPPURE NPZEROSRANGENOUTLIERSSIZE REPEAT

```
 COMPUTATION
FORI NOUTLIERS INENUMERATERANGENOUTLIERS
FORJINRANGEREPEAT
RNG  NPRANDOMRANDOMSTATEI J
 GENERATE DATA
X  RNGRANDNNSAMPLES NFEATURES
 ADD SOME OUTLIERS
OUTLIERSINDEX  RNGPERMUTATIONNSAMPLESNOUTLIERS
OUTLIERSOFFSET  10
NPRANDOMRANDINT2 SIZENOUTLIERS NFEATURES  05
XOUTLIERSINDEX  OUTLIERSOFFSET
INLIERSMASK  NPONESNSAMPLESASTYPEBOOL
INLIERSMASKOUTLIERSINDEX  FALSE
 FIT A MINIMUM COVARIANCE DETERMINANT MCD ROBUST ESTIMATOR TO DATA
MCD  MINCOVDETFITX
 COMPARE RAW ROBUST ESTIMATES WITH THE TRUE LOCATION AND COVARIANCE
ERRLOCMCDI J  NPSUMMCDLOCATION 2
ERRCOVMCDI J  MCDERRORNORMNPEYENFEATURES
 COMPARE ESTIMATORS LEARNED FROM THE FULL DATA SET WITH TRUE
 PARAMETERS
ERRLOCEMPFULLI J  NPSUMXMEAN0 2
ERRCOVEMPFULLI J  EMPIRICALCOVARIANCEFITXERRORNORM
NPEYENFEATURES
 COMPARE WITH AN EMPIRICAL COVARIANCE LEARNED FROM A PURE DATA SET
 IE PERFECT MCD
PUREX  XINLIERSMASK
PURELOCATION  PUREXMEAN0
PUREEMPCOV  EMPIRICALCOVARIANCEFITPUREX
ERRLOCEMPPUREI J  NPSUMPURELOCATION 2
ERRCOVEMPPUREI J  PUREEMPCOVERRORNORMNPEYENFEATURES
 DISPLAY RESULTS
FONTPROP  MATPLOTLIBFONTMANAGERFONTPROPERTIESSIZE11
PLTSUBPLOT2 1 1
LW  2
PLTERRORBARRANGENOUTLIERS ERRLOCMCDMEAN1
YERRERRLOCMCDSTD1  NPSQRTREPEAT
LABELROBUST LOCATION LWLW COLORM
PLTERRORBARRANGENOUTLIERS ERRLOCEMPFULLMEAN1
YERRERRLOCEMPFULLSTD1  NPSQRTREPEAT
LABELFULL DATA SET MEAN LWLW COLORGREEN
PLTERRORBARRANGENOUTLIERS ERRLOCEMPPUREMEAN1
YERRERRLOCEMPPURESTD1  NPSQRTREPEAT
LABELPURE DATA SET MEAN LWLW COLORBLACK
PLTTITLEINFLUENCE OF OUTLIERS ON THE LOCATION ESTIMATION
PLTYLABELRERROR MU  HATMU22
PLTLEGENDLOCUPPER LEFT PROPFONTPROP
PLTSUBPLOT2 1 2
XSIZE  RANGENOUTLIERSSIZE
PLTERRORBARRANGENOUTLIERS ERRCOVMCDMEAN1
YERRERRCOVMCDSTD1
```

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LABELROBUST COVARIANCE MCD COLORM
PLTERRORBARRANGENOUTLIERSXSIZE 5 1
ERRCOVEMPFULLMEAN1XSIZE 5 1
YERRERRCOVEMPFULLSTD1XSIZE 5 1
LABELFULL DATA SET EMPIRICAL COVARIANCE COLORGREEN
PLTPLOTRANGENOUTLIERSXSIZE 5XSIZE 2 1
ERRCOVEMPFULLMEAN1XSIZE 5XSIZE 2 1
COLORGREEN LS
PLTERRORBARRANGENOUTLIERS ERRCOVEMPPUREMEAN1
YERRERRCOVEMPPURESTD1
LABELPURE DATA SET EMPIRICAL COVARIANCE COLORBLACK
PLTTITLEINFLUENCE OF OUTLIERS ON THE COVARIANCE ESTIMATION
PLTXLABELAMOUNT OF CONTAMINATION
PLTYLABELRMSE
PLTLEGENDLOCUPPER CENTER PROPFONTPROP
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2985 SECONDS
59 CROSS DECOMPOSITION
EXAMPLES CONCERNING THE SKLEARNCROSSDECOMPOSITION MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
591 COMPARE CROSS DECOMPOSITION METHODS
SIMPLE USAGE OF VARIOUS CROSS DECOMPOSITION ALGORITHMS PLSCANONICAL PLSREGRESSION WITH MULTIVARIATE RE
SPONSE AKA PLS2 PLSREGRESSION WITH UNIVARIATE RESPONSE AKA PLS1 CCA
GIVEN 2 MULTIVARIATE COVARYING TWODIMENSIONAL DATASETS X AND Y PLS EXTRACTS THE ‘DIRECTIONS OF COVARIANCE’ IE
THE COMPONENTS OF EACH DATASETS THAT EXPLAIN THE MOST SHARED VARIANCE BETWEEN BOTH DATASETS THIS IS APPARENT ON THE
SCATTERPLOT MATRIX DISPLAY COMPONENTS 1 IN DATASET X AND DATASET Y ARE MAXIMALLY CORRELATED POINTS LIE AROUND THE
FIRST DIAGONAL THIS IS ALSO TRUE FOR COMPONENTS 2 IN BOTH DATASET HOWEVER THE CORRELATION ACROSS DATASETS FOR DIFFERENT
COMPONENTS IS WEAK THE POINT CLOUD IS VERY SPHERICAL

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OUT
CORRX
1 051 007 005
051 1 011 001
007 011 1 049
005 001 049 1
CORRY
1 048 005 003
048 1 004 012
005 004 1 051
003 012 051 1
TRUE B SUCH THAT Y XB ERR
1 1 1
2 2 2
0 0 0
0 0 0
0 0 0
0 0 0
0 0 0
0 0 0
0 0 0
0 0 0
ESTIMATED B
1 1 1
2 2 2
0 0 0
0 0 0
0 0 0

SCIKITLEARN USER GUIDE RELEASE 0213
 0 0 0
0 0 01
0 0 0
 0 0 01
 0 0 0
ESTIMATED BETAS
 1
 21
 0
 0
 0
0
0
 0
0
0
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNCROSSDECOMPOSITION IMPORT PLSCANONICAL PLSREGRESSION CCA

 DATASET BASED LATENT VARIABLES MODEL
N 500
 2 LATENTS VARS
L1 NPRANDOMNORMALSIZEN
L2 NPRANDOMNORMALSIZEN
LATENTS NPARRAYL1 L1 L2 L2T
X LATENTS NPRANDOMNORMALSIZE4 NRESHAPEN 4
Y LATENTS NPRANDOMNORMALSIZE4 NRESHAPEN 4
XTRAIN XN 2
YTRAIN YN 2
XTEST XN 2
YTEST YN 2
PRINTCORRX
PRINTNPROUNDNPCORRCOEFXT 2
PRINTCORRY
PRINTNPROUNDNPCORRCOEFYT 2

 CANONICAL SYMMETRIC PLS
 TRANSFORM DATA

PLSCA PLSCANONICALNCOMPONENTS2
PLSCAFITXTRAIN YTRAIN
XTRAINR YTRAINR PLSCATRANSFORMXTRAIN YTRAIN
59 CROSS DECOMPOSITION 959

SCIKITLEARN USER GUIDE RELEASE 0213
XTESTR YTESTR PLSCATRANSFORMXTEST YTEST
 SCATTER PLOT OF SCORES

 1 ON DIAGONAL PLOT X VS Y SCORES ON EACH COMPONENTS
PLTFIGUREFIGSIZE12 8
PLTSUBPLOT221
PLTSCATTERXTRAINR 0 YTRAINR 0 LABELTRAIN
MARKERO CB S25
PLTSCATTERXTESTR 0 YTESTR 0 LABELTEST
MARKERO CR S25
PLTXLABELX SCORES
PLTYLABELY SCORES
PLTTITLECOMP 1 X VS Y TEST CORR 2F
NPCORRCOEFXTESTR 0 YTESTR 00 1
PLTXTICKS
PLTYTICKS
PLTLEGENDLOCBEST
PLTSUBPLOT224
PLTSCATTERXTRAINR 1 YTRAINR 1 LABELTRAIN
MARKERO CB S25
PLTSCATTERXTESTR 1 YTESTR 1 LABELTEST
MARKERO CR S25
PLTXLABELX SCORES
PLTYLABELY SCORES
PLTTITLECOMP 2 X VS Y TEST CORR 2F
NPCORRCOEFXTESTR 1 YTESTR 10 1
PLTXTICKS
PLTYTICKS
PLTLEGENDLOCBEST
 2 OFF DIAGONAL PLOT COMPONENTS 1 VS 2 FOR X AND Y
PLTSUBPLOT222
PLTSCATTERXTRAINR 0 XTRAINR 1 LABELTRAIN
MARKER CB S50
PLTSCATTERXTESTR 0 XTESTR 1 LABELTEST
MARKER CR S50
PLTXLABELX COMP 1
PLTYLABELX COMP 2
PLTTITLEX COMP 1 VS X COMP 2 TEST CORR 2F
 NPCORRCOEFXTESTR 0 XTESTR 10 1
PLTLEGENDLOCBEST
PLTXTICKS
PLTYTICKS
PLTSUBPLOT223
PLTSCATTERYTRAINR 0 YTRAINR 1 LABELTRAIN
MARKER CB S50
PLTSCATTERYTESTR 0 YTESTR 1 LABELTEST
MARKER CR S50
PLTXLABELY COMP 1
PLTYLABELY COMP 2
PLTTITLEY COMP 1 VS Y COMP 2 TEST CORR 2F
 NPCORRCOEFYTESTR 0 YTESTR 10 1
PLTLEGENDLOCBEST
PLTXTICKS
PLTYTICKS

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PLTSHOW

PLS REGRESSION WITH MULTIVARIATE RESPONSE AKA PLS2
N 1000
Q 3
P 10
X NPRANDOMNORMALSIZEN PRESHAPEN P
B NPARRAY1 2 0 P 2 QT
EACH YJ 1 X1 2X2 NOIZE
Y NPDOTX B NPRANDOMNORMALSIZEN QRESHAPEN Q 5
PLS2 PLSREGRESSIONNCOMPONENTS3
PLS2FITX Y
PRINTTRUE B SUCH THAT Y XB ERR
PRINTB
COMPARE PLS2COEF WITH B
PRINTESTIMATED B
PRINTNPROUNDPLS2COEF 1
PLS2PREDICTX
PLS REGRESSION WITH UNIVARIATE RESPONSE AKA PLS1
N 1000
P 10
X NPRANDOMNORMALSIZEN PRESHAPEN P
Y X 0 2 X 1 NPRANDOMNORMALSIZEN 1 5
PLS1 PLSREGRESSIONNCOMPONENTS3
PLS1FITX Y
NOTE THAT THE NUMBER OF COMPONENTS EXCEEDS 1 THE DIMENSION OF Y
PRINTESTIMATED BETAS
PRINTNPROUNDPLS1COEF 1

CCA PLS MODE B WITH SYMMETRIC DEFLATION
CCA CCANCOMPONENTS2
CCAFITXTRAIN YTRAIN
XTRAINR YTRAINR CCATRANSFORMXTRAIN YTRAIN
XTESTR YTESTR CCATRANSFORMXTEST YTEST
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0099 SECONDS
510 DATASET EXAMPLES
EXAMPLES CONCERNING THE SKLEARNDATASETS MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
510 DATASET EXAMPLES 961

5101 THE DIGIT DATASET
THIS DATASET IS MADE UP OF 1797 8X8 IMAGES EACH IMAGE LIKE THE ONE SHOWN BELOW IS OF A HANDWRITTEN DIGIT IN ORDER TO UTILIZE AN 8X8 FIGURE LIKE THIS WE'D HAVE TO FIRST TRANSFORM IT INTO A FEATURE VECTOR WITH LENGTH 64
SEE HERE FOR MORE INFORMATION ABOUT THIS DATASET

```
PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
FROM SKLEARN IMPORT DATASETS
IMPORT MATPLOTLIBPYPLOT AS PLT
LOAD THE DIGITS DATASET
DIGITS  DATASETSLOADDIGITS
DISPLAY THE FIRST DIGIT
PLTFIGURE1 FIGSIZE3 3
PLTIMSHOWDIGITSIMAGES1 CMAPPLTCMGRAYR INTERPOLATIONNEAREST
PLTSHOW
```

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0113 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5102 THE IRIS DATASET
THIS DATA SETS CONSISTS OF 3 DIFFERENT TYPES OF IRISES' SETOSA VERSICOLOUR AND VIRGINICA PETAL AND SEPAL LENGTH STORED IN A 150X4 NUMPYNDARRAY
THE ROWS BEING THE SAMPLES AND THE COLUMNS BEING SEPAL LENGTH SEPAL WIDTH PETAL LENGTH AND PETAL WIDTH

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THE BELOW PLOT USES THE FIRST TWO FEATURES SEE HERE FOR MORE INFORMATION ON THIS DATASET
•
510 DATASET EXAMPLES 963

•

```
PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MPLTOOLKITSMPLOT3D IMPORT AXES3D
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNDECOMPOSITION IMPORT PCA
 IMPORT SOME DATA TO PLAY WITH
IRIS  DATASETSLOADIRIS
X  IRISDATA 2  WE ONLY TAKE THE FIRST TWO FEATURES
Y  IRISTARGET
XMIN XMAX  X 0MIN  5 X 0MAX  5
YMIN YMAX  X 1MIN  5 X 1MAX  5
PLTFIGURE2 FIGSIZE8 6
PLTCLF
 PLOT THE TRAINING POINTS
PLTSCATTERX 0 X 1 CY CMAPPLTCMSET1
EDGECOLORK
PLTXLABELSEPAL LENGTH
```

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PLTYLABELSEPAL WIDTH
PLTXLIMXMIN XMAX
PLTYLIMYMIN YMAX
PLTXTICKS
PLTYTICKS
 TO GETTER A BETTER UNDERSTANDING OF INTERACTION OF THE DIMENSIONS
 PLOT THE FIRST THREE PCA DIMENSIONS
FIG PLTFIGURE1 FIGSIZE8 6
AX AXES3DFIG ELEV150 AZIM110
XREDUCED PCANCOMPONENTS3FITTRANSFORMIRISDATA
AXSCATTERXREDUCED 0 XREDUCED 1 XREDUCED 2 CY
CMAPPLTCMSET1 EDGECOLORK S40
AXSETTITLEFIRST THREE PCA DIRECTIONS
AXSETXLABEL1ST EIGENVECTOR
AXWXAXISSETTICKLABELS
AXSETYLABEL2ND EIGENVECTOR
AXWYAXISSETTICKLABELS
AXSETZLABEL3RD EIGENVECTOR
AXWZAXISSETTICKLABELS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0059 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5103 PLOT RANDOMLY GENERATED CLASSIFICATION DATASET
PLOT SEVERAL RANDOMLY GENERATED 2D CLASSIFICATION DATASETS THIS EXAMPLE ILLUSTRATES THE DATASETS
MAKECLASSIFICATION DATASETSMAKEBLOBS ANDDATASETSMAKEGAUSSIANQUANTILES FUNC
TIONS
FORMAKECLASSIFICATION THREE BINARY AND TWO MULTICLASS CLASSIFICATION DATASETS ARE GENERATED WITH DIFFERENT
NUMBERS OF INFORMATIVE FEATURES AND CLUSTERS PER CLASS
510 DATASET EXAMPLES 965

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PRINTDOC
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
FROM SKLEARNDATASETS IMPORT MAKEBLOBS
FROM SKLEARNDATASETS IMPORT MAKEGAUSSIANQUANTILES
PLTFIGUREFIGSIZE8 8
PLTSUBPLOTSADJUSTBOTTOM05 TOP9 LEFT05 RIGHT95
PLTSUBPLOT321
PLTTITLEONE INFORMATIVE FEATURE ONE CLUSTER PER CLASS FONTSIZESMALL
X1 Y1 MAKECLASSIFICATIONNFEATURES2 NREDUNDANT0 NINFORMATIVE1
NCLUSTERSPERCLASS1
966 CHAPTER 5 EXAMPLES

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PLTSCATTERX1 0 X1 1 MARKERO CY1
S25 EDGECOLORK
PLTSUBPLOT322
PLTTITLETWO INFORMATIVE FEATURES ONE CLUSTER PER CLASS FONTSIZESMALL
X1 Y1 MAKECLASSIFICATIONNFEATURES2 NREDUNDANT0 NINFORMATIVE2
NCLUSTERSPERCLASS1
PLTSCATTERX1 0 X1 1 MARKERO CY1
S25 EDGECOLORK
PLTSUBPLOT323
PLTTITLETWO INFORMATIVE FEATURES TWO CLUSTERS PER CLASS
FONTSIZESMALL
X2 Y2 MAKECLASSIFICATIONNFEATURES2 NREDUNDANT0 NINFORMATIVE2
PLTSCATTERX2 0 X2 1 MARKERO CY2
S25 EDGECOLORK
PLTSUBPLOT324
PLTTITLEMULTICLASS TWO INFORMATIVE FEATURES ONE CLUSTER
FONTSIZESMALL
X1 Y1 MAKECLASSIFICATIONNFEATURES2 NREDUNDANT0 NINFORMATIVE2
NCLUSTERSPERCLASS1 NCLASSES3
PLTSCATTERX1 0 X1 1 MARKERO CY1
S25 EDGECOLORK
PLTSUBPLOT325
PLTTITLETHREE BLOBS FONTSIZESMALL
X1 Y1 MAKEBLOBSNFEATURES2 CENTERS3
PLTSCATTERX1 0 X1 1 MARKERO CY1
S25 EDGECOLORK
PLTSUBPLOT326
PLTTITLEGAUSSIAN DIVIDED INTO THREE QUANTILES FONTSIZESMALL
X1 Y1 MAKEGAUSSIANQUANTILESNFEATURES2 NCLASSES3
PLTSCATTERX1 0 X1 1 MARKERO CY1
S25 EDGECOLORK
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0097 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5104 PLOT RANDOMLY GENERATED MULTILABEL DATASET
THIS ILLUSTRATES THE DATASETSMAKEMULTILABELCLASSIFICATION DATASET GENERATOR EACH SAMPLE CONSISTS
OF COUNTS OF TWO FEATURES UP TO 50 IN TOTAL WHICH ARE DIFFERENTLY DISTRIBUTED IN EACH OF TWO CLASSES
POINTS ARE LABELED AS FOLLOWS WHERE Y MEANS THE CLASS IS PRESENT
510 DATASET EXAMPLES 967

123COLOR
Y N N RED
N Y N BLUE
N N Y YELLOW
Y Y N PURPLE
Y N Y ORANGE
Y Y N GREEN
Y Y Y BROWN
A STAR MARKS THE EXPECTED SAMPLE FOR EACH CLASS ITS SIZE REFLECTS THE PROBABILITY OF SELECTING THAT CLASS LABEL
THE LEFT AND RIGHT EXAMPLES HIGHLIGHT THE NLABELS PARAMETER MORE OF THE SAMPLES IN THE RIGHT PLOT HAVE 2 OR 3 LABELS
NOTE THAT THIS TWODIMENSIONAL EXAMPLE IS VERY DEGENERATE GENERALLY THE NUMBER OF FEATURES WOULD BE MUCH GREATER THAN THE “DOCUMENT LENGTH” WHILE HERE WE HAVE MUCH LARGER DOCUMENTS THAN VOCABULARY SIMILARLY WITH NCLASSES NFEATURES IT IS MUCH LESS LIKELY THAT A FEATURE DISTINGUISHES A PARTICULAR CLASS
OUT
THE DATA WAS GENERATED FROM RANDOMSTATE1013
CLASS PC PW0C PW1C
RED 064 097 003
BLUE 006 060 040
YELLOW 030 009 091
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKEMULTILABELCLASSIFICATION ASMAKEMLCLF

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
COLORS NPARRAY
FF3333 RED
0198E1 BLUE
BF5FFF PURPLE
FCD116 YELLOW
FF7216 ORANGE
4DBD33 GREEN
87421F BROWN

 USE SAME RANDOM SEED FOR MULTIPLE CALLS TO MAKEMULTILABELCLASSIFICATION TO
 ENSURE SAME DISTRIBUTIONS
RANDOMSEED NPRANDOMRANDINT2 10
DEFPLOT2DAX NLABELS1 NCLASSES3 LENGTH50
X Y PC PWC MAKEMLCLFNSAMPLES150 NFEATURES2
NCLASSESNCLASSES NLABELSNLABELS
LENGTHLENGTH ALLOWUNLABELEDFALSE
RETURNDISTRIBUTIONSTRUE
RANDOMSTATERANDOMSEED
AXSCATTERX 0 X 1 COLORCOLORSTAKEY 1 2 4
SUMAXIS1
MARKER
AXSCATTERPWC0 LENGTH PWC1 LENGTH
MARKER LINEWIDTH5 EDGECOLORBLACK
S20 1500 PC2
COLORCOLORSTAKE1 2 4
AXSETXLABELFEATURE 0 COUNT
RETURNPC PWC
 AX1 AX2 PLTSUBPLOTS1 2 SHAREXROW SHAREYROW FIGSIZE8 4
PLTSUBPLOTSADJUSTBOTTOM15
PC PWC PLOT2DAX1 NLABELS1
AX1SETTITLENLABELS1 LENGTH50
AX1SETYLABELFEATURE 1 COUNT
PLOT2DAX2 NLABELS3
AX2SETTITLENLABELS3 LENGTH50
AX2SETXLIMLEFT0 AUTOTRUE
AX2SETYLIMBOTTOM0 AUTOTRUE
PLTSHOW
PRINTTHE DATA WAS GENERATED FROM RANDOMSTATE D RANDOMSEED
PRINTCLASS PC PW0C PW1C SEP T
FORK P PW INZIPRED BLUE YELLOW PC PWCT
PRINTST02FT02FT02F K P PW0 PW1
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0085 SECONDS
510 DATASET EXAMPLES 969

511 DECOMPOSITION
EXAMPLES CONCERNING THE SKLEARNDECOMPOSITION MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5111 BETADIVERGENCE LOSS FUNCTIONS
A PLOT THAT COMPARES THE VARIOUS BETADIVERGENCE LOSS FUNCTIONS SUPPORTED BY THE MULTIPLICATIVEUPDATE ‘MU’ SOLVER
INSKLEARNDECOMPOSITIONNMF
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDECOMPOSITIONNMF IMPORT BETADIVERGENCE
PRINTDOC
X NPLINSPACE0001 4 1000
Y NPZEROSXSHAPE
COLORS MBGYR
FORJ BETA INENUMERATE0 05 1 15 2

SCIKITLEARN USER GUIDE RELEASE 0213
FORI XIINENUMERATEX
YI BETADIVERGENCE1 XI 1 BETA
NAME BETA 11F BETA
PLTPLOTX Y LABELNAME COLORCOLORSJ
PLTXLABELX
PLTTITLEBETADIVERGENCE1 X
PLTLEGENDLOC0
PLTAXIS0 4 0 3
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0225 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5112 PCA EXAMPLE WITH IRIS DATASET
PRINCIPAL COMPONENT ANALYSIS APPLIED TO THE IRIS DATASET
SEE HERE FOR MORE INFORMATION ON THIS DATASET
PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MPLTOOLKITSMPLOT3D IMPORT AXES3D
FROM SKLEARN IMPORT DECOMPOSITION
FROM SKLEARN IMPORT DATASETS
511 DECOMPOSITION 971

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NPRANDOMSEED5
CENTERS 1 1 1 1 1 1
IRIS DATASETSLOADIRIS
X IRISDATA
Y IRISTARGET
FIG PLTFIGURE1 FIGSIZE4 3
PLTCLF
AX AXES3DFIG RECT0 0 95 1 ELEV48 AZIM134
PLTCLA
PCA DECOMPOSITIONPCANCOMPONENTS3
PCAFITX
X PCATRANSFORMX
FORNAME LABEL INSETOSA 0 VERSICOLOUR 1 VIRGINICA 2
AXTEXT3DXY LABEL 0MEAN
XY LABEL 1MEAN 15
XY LABEL 2MEAN NAME
HORIZONTALALIGNMENTCENTER
BBOXDICTALPHA5 EDGECOLORW FACECOLORW
 REORDER THE LABELS TO HAVE COLORS MATCHING THE CLUSTER RESULTS
Y NPCHOOSEY 1 2 0ASTYPENPFLOAT
AXSCATTERX 0 X 1 X 2 CY CMAPPLTCMNIPYSPECTRAL
EDGECOLORK
AXWXAXISSETTICKLABELS
AXWYAXISSETTICKLABELS
AXWZAXISSETTICKLABELS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0186 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5113 INCREMENTAL PCA
INCREMENTAL PRINCIPAL COMPONENT ANALYSIS IPCA IS TYPICALLY USED AS A REPLACEMENT FOR PRINCIPAL COMPONENT ANALYSIS PCA WHEN THE DATASET TO BE DECOMPOSED IS TOO LARGE TO FIT IN MEMORY IPCA BUILDS A LOWRANK APPROXIMATION FOR THE INPUT DATA USING AN AMOUNT OF MEMORY WHICH IS INDEPENDENT OF THE NUMBER OF INPUT DATA SAMPLES IT IS STILL DEPENDENT ON THE INPUT DATA FEATURES BUT CHANGING THE BATCH SIZE ALLOWS FOR CONTROL OF MEMORY USAGE
THIS EXAMPLE SERVES AS A VISUAL CHECK THAT IPCA IS ABLE TO FIND A SIMILAR PROJECTION OF THE DATA TO PCA TO A SIGN FLIP WHILE ONLY PROCESSING A FEW SAMPLES AT A TIME THIS CAN BE CONSIDERED A “TOY EXAMPLE” AS IPCA IS INTENDED FOR LARGE DATASETS WHICH DO NOT FIT IN MAIN MEMORY REQUIRING INCREMENTAL APPROACHES

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511 DECOMPOSITION 973

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PRINTDOC
 AUTHORS KYLE KASTNER
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT LOADIRIS
FROM SKLEARNDECOMPOSITION IMPORT PCA INCREMENTALPCA
IRIS LOADIRIS
X IRISDATA
Y IRISTARGET
NCOMPONENTS 2
IPCA INCREMENTALPCANCOMPONENTSNCOMPONENTS BATCHSIZE10
974 CHAPTER 5 EXAMPLES

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XIPCA IPCAFITTRANSFORMX
PCA PCANCOMPONENTSNCOMPONENTS
XPCA PCAFITTRANSFORMX
COLORS NAVY TURQUOISE DARKORANGE
FORXTRANSFORMED TITLE INXIPCA INCREMENTAL PCA XPCA PCA
PLTFIGUREFIGSIZE8 8
FORCOLOR I TARGETNAME INZIPCOLORS 0 1 2 IRISTARGETNAMES
PLTSCATTERXTRANSFORMEDY I 0 XTRANSFORMEDY I 1
COLORCOLOR LW2 LABELTARGETNAME
IFINCREMENTAL INTITLE
ERR NPABSNPABSXPCA NPABSXIPCAMEAN
PLTTITLETITLE   OF IRIS DATASET NMEAN ABSOLUTE UNSIGNED ERROR
6F ERR
ELSE
PLTTITLETITLE   OF IRIS DATASET
PLTLEGENDLOCBEST SHADOWFALSE SCATTERPOINTS1
PLTAXIS4 4 15 15
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0143 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5114 COMPARISON OF LDA AND PCA 2D PROJECTION OF IRIS DATASET
THE IRIS DATASET REPRESENTS 3 KIND OF IRIS FLOWERS SETOSA VERSICOLOUR AND VIRGINICA WITH 4 ATTRIBUTES SEPAL LENGTH SEPAL WIDTH PETAL LENGTH AND PETAL WIDTH
PRINCIPAL COMPONENT ANALYSIS PCA APPLIED TO THIS DATA IDENTIFIES THE COMBINATION OF ATTRIBUTES PRINCIPAL COMPONENTS OR DIRECTIONS IN THE FEATURE SPACE THAT ACCOUNT FOR THE MOST VARIANCE IN THE DATA HERE WE PLOT THE DIFFERENT SAMPLES ON THE 2 FIRST PRINCIPAL COMPONENTS
LINEAR DISCRIMINANT ANALYSIS LDA TRIES TO IDENTIFY ATTRIBUTES THAT ACCOUNT FOR THE MOST VARIANCE BETWEEN CLASSES IN PARTICULAR LDA IN CONTRAST TO PCA IS A SUPERVISED METHOD USING KNOWN CLASS LABELS
511 DECOMPOSITION 975

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```
OUT
EXPLAINED VARIANCE RATIO FIRST TWO COMPONENTS 092461872 005306648
PRINTDOC
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNDISCRIMINANTANALYSIS IMPORT LINEARDISCRIMINANTANALYSIS
IRIS  DATASETSLOADIRIS
X  IRISDATA
Y  IRISTARGET
TARGETNAMES  IRISTARGETNAMES
PCA  PCANCOMPONENTS2
XR  PCAFITXTRANSFORMX
LDA  LINEARDISCRIMINANTANALYSISNCOMPONENTS2
```

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XR2 LDAFITX YTRANSFORMX
 PERCENTAGE OF VARIANCE EXPLAINED FOR EACH COMPONENTS
PRINTEXPLAINED VARIANCE RATIO FIRST TWO COMPONENTS S
 STRPCAEXPLAINEDVARIANCERATIO
PLTFIGURE
COLORS NAVY TURQUOISE DARKORANGE
LW 2
FORCOLOR I TARGETNAME INZIPCOLORS 0 1 2 TARGETNAMES
PLTSCATTERXRY I 0 XRY I 1 COLORCOLOR ALPHA8 LWLW
LABELTARGETNAME
PLTLEGENDLOCBEST SHADOWFALSE SCATTERPOINTS1
PLTTITLEPCA OF IRIS DATASET
PLTFIGURE
FORCOLOR I TARGETNAME INZIPCOLORS 0 1 2 TARGETNAMES
PLTSCATTERXR2Y I 0 XR2Y I 1 ALPHA8 COLORCOLOR
LABELTARGETNAME
PLTLEGENDLOCBEST SHADOWFALSE SCATTERPOINTS1
PLTTITLELDA OF IRIS DATASET
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0057 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5115 BLIND SOURCE SEPARATION USING FASTICA
AN EXAMPLE OF ESTIMATING SOURCES FROM NOISY DATA
INDEPENDENT COMPONENT ANALYSIS ICA IS USED TO ESTIMATE SOURCES GIVEN NOISY MEASUREMENTS IMAGINE 3 INSTRUMENTS PLAYING SIMULTANEOUSLY AND 3 MICROPHONES RECORDING THE MIXED SIGNALS ICA IS USED TO RECOVER THE SOURCES IE WHAT IS PLAYED BY EACH INSTRUMENT IMPORTANTLY PCA FAILS AT RECOVERING OUR INSTRUMENTS SINCE THE RELATED SIGNALS REFLECT NONGAUSSIAN PROCESSES
978 CHAPTER 5 EXAMPLES

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPY IMPORT SIGNAL
FROM SKLEARNDECOMPOSITION IMPORT FASTICA PCA

 GENERATE SAMPLE DATA
NPRANDOMSEED0
NSAMPLES  2000
TIME  NPLINSPACE0 8 NSAMPLES
S1  NPSIN2 TIME SIGNAL 1  SINUSOIDAL SIGNAL
S2  NPSIGNNPSIN3 TIME  SIGNAL 2  SQUARE SIGNAL
S3  SIGNALSAWTOOTH2 NPPITIME SIGNAL 3 SAW TOOTH SIGNAL
S  NPCS1 S2 S3
S  02 NPRANDOMNORMALSIZESSHAPE  ADD NOISE
S  SSTDAXIS0  STANDARDIZE DATA
 MIX DATA
A  NPARRAY1 1 1 05 2 10 15 10 20  MIXING MATRIX
X  NPDOTS AT  GENERATE OBSERVATIONS
511 DECOMPOSITION 979
```

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 COMPUTE ICA
ICA FASTICANCOMPONENTS3
S ICAFITTRANSFORMX RECONSTRUCT SIGNALS
A ICAMIXING GET ESTIMATED MIXING MATRIX
 WE CAN PROVE THAT THE ICA MODEL APPLIES BY REVERTING THE UNMIXING
ASSERTNPALLCLOSEX NPDOTS AT ICAMEAN
 FOR COMPARISON COMPUTE PCA
PCA PCANCOMPONENTS3
H PCAFITTRANSFORMX RECONSTRUCT SIGNALS BASED ON ORTHOGONAL COMPONENTS

 PLOT RESULTS
PLTFIGURE
MODELS X S S H
NAMES OBSERVATIONS MIXED SIGNAL
TRUE SOURCES
ICA RECOVERED SIGNALS
PCA RECOVERED SIGNALS
COLORS RED STEELBLUE ORANGE
FORII MODEL NAME INENUMERATEZIPMODELS NAMES 1
PLTSUBPLOT4 1 II
PLTTITLENAME
FORSIG COLOR INZIPMODELT COLORS
PLTPLOTSIG COLORCOLOR
PLTSUBPLOTSADJUST009 004 094 094 026 046
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0089 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5116 PRINCIPAL COMPONENTS ANALYSIS PCA
THESE FIGURES AID IN ILLUSTRATING HOW A POINT CLOUD CAN BE VERY FLAT IN ONE DIRECTION–WHICH IS WHERE PCA COMES IN TO CHOOSE A DIRECTION THAT IS NOT FLAT
980 CHAPTER 5 EXAMPLES

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•
•
PRINTDOC
 AUTHORS GAEL VAROQUAUX
 JAQUES GROBLER
 KEVIN HUGHES
 LICENSE BSD 3 CLAUSE
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM MPLTOOLKITSMPLOT3D IMPORT AXES3D
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPY IMPORT STATS

 CREATE THE DATA
511 DECOMPOSITION 981

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E NPEXP1
NPRANDOMSEED4
DEFPDFX
RETURN05STATSNORMSCALE025 EPDFX
 STATSNORMSCALE4 EPDFX
Y NPRANDOMNORMALSCALE05 SIZE30000
X NPRANDOMNORMALSCALE05 SIZE30000
Z NPRANDOMNORMALSCALE01 SIZELENX
DENSITY PDFX PDFY
PDFZ PDF5 Z
DENSITY PDFZ
A X Y
B 2Y
C A B Z
NORM NPSQRTAVAR BVAR
A NORM
B NORM

 PLOT THE FIGURES
DEFPLOTFIGSFIGNUM ELEV AZIM
FIG PLTFIGUREFIGNUM FIGSIZE4 3
PLTCLF
AX AXES3DFIG RECT0 0 95 1 ELEVELEV AZIMAZIM
AXSCATTERA10 B10 C10 CDENSITY10 MARKER ALPHA4
Y NPCA B C
 USING SCIPYS SVD THIS WOULD BE
  PCASCORE V SCIPYLINALGSVDY FULLMATRICESFALSE
PCA PCANCOMPONENTS3
PCAFITY
PCASCORE PCAEXPLAINEDVARIANCERATIO
V PCACOMPONENTS
XPCAAXIS YPCAAXIS ZPCAAXIS 3 VT
XPCAPLANE NPRXPCAAXIS2 XPCAAXIS11
YPCAPLANE NPRYPCAAXIS2 YPCAAXIS11
ZPCAPLANE NPRZPCAAXIS2 ZPCAAXIS11
XPCAPLANESHAPE 2 2
YPCAPLANESHAPE 2 2
ZPCAPLANESHAPE 2 2
AXPLOTSURFACEXPCAPLANE YPCAPLANE ZPCAPLANE
AXWXAXISSETTICKLABELS
AXWYAXISSETTICKLABELS
AXWZAXISSETTICKLABELS
ELEV 40

AZIM 80
PLOTFIGS1 ELEV AZIM
ELEV 30
AZIM 20
PLOTFIGS2 ELEV AZIM
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0114 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5117 FASTICA ON 2D POINT CLOUDS
THIS EXAMPLE ILLUSTRATES VISUALLY IN THE FEATURE SPACE A COMPARISON BY RESULTS USING TWO DIFFERENT COMPONENT ANALYSIS TECHNIQUES
INDEPENDENT COMPONENT ANALYSIS ICA VSPRINCIPAL COMPONENT ANALYSIS PCA
REPRESENTING ICA IN THE FEATURE SPACE GIVES THE VIEW OF ‘GEOMETRIC ICA’ ICA IS AN ALGORITHM THAT FINDS DIRECTIONS IN THE FEATURE SPACE CORRESPONDING TO PROJECTIONS WITH HIGH NONGAUSSIANITY THESE DIRECTIONS NEED NOT BE ORTHOGONAL IN THE ORIGINAL FEATURE SPACE BUT THEY ARE ORTHOGONAL IN THE WHITENED FEATURE SPACE IN WHICH ALL DIRECTIONS CORRESPOND TO THE SAME VARIANCE
PCA ON THE OTHER HAND FINDS ORTHOGONAL DIRECTIONS IN THE RAW FEATURE SPACE THAT CORRESPOND TO DIRECTIONS ACCOUNTING FOR MAXIMUM VARIANCE
HERE WE SIMULATE INDEPENDENT SOURCES USING A HIGHLY NONGAUSSIAN PROCESS 2 STUDENT T WITH A LOW NUMBER OF DEGREES OF FREEDOM TOP LEFT FIGURE WE MIX THEM TO CREATE OBSERVATIONS TOP RIGHT FIGURE IN THIS RAW OBSERVATION SPACE DIRECTIONS IDENTIFIED BY PCA ARE REPRESENTED BY ORANGE VECTORS WE REPRESENT THE SIGNAL IN THE PCA SPACE AFTER WHITENING BY THE VARIANCE CORRESPONDING TO THE PCA VECTORS LOWER LEFT RUNNING ICA CORRESPONDS TO FINDING A ROTATION IN THIS SPACE TO IDENTIFY THE DIRECTIONS OF LARGEST NONGAUSSIANITY LOWER RIGHT

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PRINTDOC
 AUTHORS ALEXANDRE GRAMFORT GAEL VAROQUAUX
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDECOMPOSITION IMPORT PCA FASTICA

 GENERATE SAMPLE DATA
RNG NPRANDOMRANDOMSTATE42
S RNGSTANDARDT15 SIZE20000 2
S 0 2
 MIX DATA
A NPARRAY1 1 0 2 MIXING MATRIX
X NPDOTS AT GENERATE OBSERVATIONS
PCA PCA
SPCA PCAFITXTRANSFORMX
ICA FASTICARANDOMSTATERNG
SICA ICAFITXTRANSFORMX ESTIMATE THE SOURCES

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SICA SICASTDAXIS0

 PLOT RESULTS
DEFPLOTSAMPLESS AXISLISTNONE
PLTSCATTERS 0 S 1 S2 MARKERO ZORDER10
COLORSTEELBLUE ALPHA05
IFAXISLIST IS NOTNONE
COLORS ORANGE RED
FORCOLOR AXIS INZIPCOLORS AXISLIST
AXIS AXISSTD
XAXIS YAXIS AXIS
 TRICK TO GET LEGEND TO WORK
PLTPLOT01 XAXIS 01 YAXIS LINEWIDTH2 COLORCOLOR
PLTQUIVER0 0 XAXIS YAXIS ZORDER11 WIDTH001 SCALE6
COLORCOLOR
PLTHLINES0 3 3
PLTVLINES0 3 3
PLTXLIM3 3
PLTYLIM3 3
PLTXLABELX
PLTYLABELY
PLTFIGURE
PLTSUBPLOT2 2 1
PLOTSAMPLESS SSTD
PLTTITLETRUE INDEPENDENT SOURCES
AXISLIST PCACOMPONENTST ICAMIXING
PLTSUBPLOT2 2 2
PLOTSAMPLESX NPSTDX AXISLISTAXISLIST
LEGEND PLTLEGENDPCA ICA LOCUPPER RIGHT
LEGENDSETZORDER100
PLTTITLEOBSERVATIONS
PLTSUBPLOT2 2 3
PLOTSAMPLESSPCA NPSTDSPCA AXIS0
PLTTITLEPCA RECOVERED SIGNALS
PLTSUBPLOT2 2 4
PLOTSAMPLESSICA NPSTDSICA
PLTTITLEICA RECOVERED SIGNALS
PLTSUBPLOTSADJUST009 004 094 094 026 036
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0357 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
511 DECOMPOSITION 985

5118 KERNEL PCA
THIS EXAMPLE SHOWS THAT KERNEL PCA IS ABLE TO FIND A PROJECTION OF THE DATA THAT MAKES DATA LINEARLY SEPARABLE
PRINTDOC
 AUTHORS MATHIEU BLONDEL
 ANDREAS MUELLER
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDECOMPOSITION IMPORT PCA KERNELPCA
FROM SKLEARNDATASETS IMPORT MAKECIRCLES
NPRANDOMSEED0
X Y MAKECIRCLESNSAMPLES400 FACTOR3 NOISE05
KPCA KERNELPCAKERNELRBF FITINVERSETRANSFORMTRUE GAMMA10
XKPCA KPCAFITTRANSFORMX
XBACK KPCAINVERSETRANSFORMXKPCA
PCA PCA
XPCA PCAFITTRANSFORMX

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PLOT RESULTS
PLTFIGURE
PLTSUBPLOT2 2 1 ASPECTEQUAL
PLTTITLEORIGINAL SPACE
REDS Y 0
BLUES Y 1
PLTSCATTERXREDS 0 XREDS 1 CRED
S20 EDGECOLORK
PLTSCATTERXBLUES 0 XBLUES 1 CBLUE
S20 EDGECOLORK
PLTXLABELX1
PLTYLABELX2
X1 X2 NPMESHGRIDNPLINSPACE15 15 50 NPLINSPACE15 15 50
XGRID NPARRAYNPRAVELX1 NPRAVELX2T
PROJECTION ON THE FIRST PRINCIPAL COMPONENT IN THE PHI SPACE
ZGRID KPCATRANSFORMXGRID 0RESHAPEX1SHAPE
PLTCONTOURX1 X2 ZGRID COLORSGREY LINEWIDTHS1 ORIGINLOWER
PLTSUBPLOT2 2 2 ASPECTEQUAL
PLTSCATTERXPCAREDS 0 XPCAREDS 1 CRED
S20 EDGECOLORK
PLTSCATTERXPCABLUES 0 XPCABLUES 1 CBLUE
S20 EDGECOLORK
PLTTITLEPROJECTION BY PCA
PLTXLABEL1ST PRINCIPAL COMPONENT
PLTYLABEL2ND COMPONENT
PLTSUBPLOT2 2 3 ASPECTEQUAL
PLTSCATTERXKPCAREDS 0 XKPCAREDS 1 CRED
S20 EDGECOLORK
PLTSCATTERXKPCABLUES 0 XKPCABLUES 1 CBLUE
S20 EDGECOLORK
PLTTITLEPROJECTION BY KPCA
PLTXLABELR1ST PRINCIPAL COMPONENT IN SPACE INDUCED BY PHI
PLTYLABEL2ND COMPONENT
PLTSUBPLOT2 2 4 ASPECTEQUAL
PLTSCATTERXBACKREDS 0 XBACKREDS 1 CRED
S20 EDGECOLORK
PLTSCATTERXBACKBLUES 0 XBACKBLUES 1 CBLUE
S20 EDGECOLORK
PLTTITLEORIGINAL SPACE AFTER INVERSE TRANSFORM
PLTXLABELX1
PLTYLABELX2
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0460 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
511 DECOMPOSITION 987

5119 MODEL SELECTION WITH PROBABILISTIC PCA AND FACTOR ANALYSIS FA
PROBABILISTIC PCA AND FACTOR ANALYSIS ARE PROBABILISTIC MODELS THE CONSEQUENCE IS THAT THE LIKELIHOOD OF NEW DATA CAN BE USED FOR MODEL SELECTION AND COVARIANCE ESTIMATION HERE WE COMPARE PCA AND FA WITH CROSSVALIDATION ON LOW RANK DATA CORRUPTED WITH HOMOSCEDASTIC NOISE NOISE VARIANCE IS THE SAME FOR EACH FEATURE OR HETEROSCEDASTIC NOISE NOISE VARIANCE IS THE DIFFERENT FOR EACH FEATURE IN A SECOND STEP WE COMPARE THE MODEL LIKELIHOOD TO THE LIKELIHOODS OBTAINED FROM SHRINKAGE COVARIANCE ESTIMATORS
ONE CAN OBSERVE THAT WITH HOMOSCEDASTIC NOISE BOTH FA AND PCA SUCCEED IN RECOVERING THE SIZE OF THE LOW RANK SUBSPACE THE LIKELIHOOD WITH PCA IS HIGHER THAN FA IN THIS CASE HOWEVER PCA FAILS AND OVERESTIMATES THE RANK WHEN HETEROSCEDASTIC NOISE IS PRESENT UNDER APPROPRIATE CIRCUMSTANCES THE LOW RANK MODELS ARE MORE LIKELY THAN SHRINKAGE MODELS
THE AUTOMATIC ESTIMATION FROM AUTOMATIC CHOICE OF DIMENSIONALITY FOR PCA NIPS 2000 598604 BY THOMAS P MINKA IS ALSO COMPARED
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OUT
BEST NCOMPONENTS BY PCA CV  10
BEST NCOMPONENTS BY FACTORANALYSIS CV  10
BEST NCOMPONENTS BY PCA MLE  10
BEST NCOMPONENTS BY PCA CV  35
BEST NCOMPONENTS BY FACTORANALYSIS CV  10
BEST NCOMPONENTS BY PCA MLE  38
 AUTHORS ALEXANDRE GRAMFORT
 DENIS A ENGEMANN
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPY IMPORT LINALG
FROM SKLEARNDECOMPOSITION IMPORT PCA FACTORANALYSIS
FROM SKLEARNCOVARIANCE IMPORT SHRUNKCOVARIANCE LEDOITWOLF
FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
```

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PRINTDOC

CREATE THE DATA
NSAMPLES NFEATURES RANK 1000 50 10
SIGMA 1
RNG NPRANDOMRANDOMSTATE42
U   LINALGSVDRNGRANDNNFEATURES NFEATURES
X NPDOTRNGRANDNNSAMPLES RANK U RANKT
ADDING HOMOSCEDASTIC NOISE
XHOMO X SIGMA RNGRANDNNSAMPLES NFEATURES
ADDING HETEROSCEDASTIC NOISE
SIGMAS SIGMA RNGRANDNFEATURES SIGMA 2
XHETERO X RNGRANDNNSAMPLES NFEATURES SIGMAS

FIT THE MODELS
NCOMPONENTS NPARANGE0 NFEATURES 5 OPTIONS FOR NCOMPONENTS
DEFCOMPUTESCORESX
PCA PCASVDSOLVERFULL
FA FACTORANALYSIS
PCASCORES FASCORES
FORNINNCOMPONENTS
PCANCOMPONENTS N
FANCOMPONENTS N
PCASCORESAPPENDNPMEANCROSSVALSCOREPCA X CV5
FASCORESAPPENDNPMEANCROSSVALSCOREFA X CV5
RETURNPCASCORES FASCORES
DEFSHRUNKCOVSCOREX
SHRINKAGES NPLOGSPACE2 0 30
CV GRIDSEARCHCVSHRUNKCOVARIANCE SHRINKAGE SHRINKAGES CV5
RETURNNPMEANCROSSVALSCORECVFITXBESTESTIMATOR X CV5
DEFLWSCOREX
RETURNNPMEANCROSSVALSCORELEDOITWOLF X CV5
FORX TITLE INXHOMO HOMOSCEDASTIC NOISE
XHETERO HETEROSCEDASTIC NOISE
PCASCORES FASCORES COMPUTESCORESX
NCOMPONENTSPCA NCOMPONENTSNPARGMAXPCASCORES
NCOMPONENTSFA NCOMPONENTSNPARGMAXFASCORES
PCA PCASVDSOLVERFULL NCOMPONENTSMLE
PCAFITX
NCOMPONENTSPCAMLE PCANCOMPONENTS

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PRINTBEST NCOMPONENTS BY PCA CV D NCOMPONENTSPCA
PRINTBEST NCOMPONENTS BY FACTORANALYSIS CV D NCOMPONENTSFA
PRINTBEST NCOMPONENTS BY PCA MLE D NCOMPONENTSPCAMLE
PLTFIGURE
PLTPLOTNCOMPONENTS PCASCORES B LABELPCA SCORES
PLTPLOTNCOMPONENTS FASCORES R LABELFA SCORES
PLTAXVLINERANK COLORG LABELTRUTH D RANK LINESTYLE
PLTAXVLINENCOMPONENTSPCA COLORB
LABELPCA CV D NCOMPONENTSPCA LINESTYLE
PLTAXVLINENCOMPONENTSFA COLORR
LABELFACTORANALYSIS CV D NCOMPONENTSFA
LINESTYLE
PLTAXVLINENCOMPONENTSPCAMLE COLORK
LABELPCA MLE D NCOMPONENTSPCAMLE LINESTYLE
 COMPARE WITH OTHER COVARIANCE ESTIMATORS
PLTAXHLINESHRUNKCOVSCOREX COLORVIOLET
LABELSHRUNK COVARIANCE MLE LINESTYLE
PLTAXHLINELWSCOREX COLORORANGE
LABELLEDOITWOLF MLE NCOMPONENTSPCAMLE LINESTYLE
PLTXLABELNB OF COMPONENTS
PLTYLABELCV SCORES
PLTLEGENDLOCLOWER RIGHT
PLTTITLETITLE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 17528 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51110 SPARSE CODING WITH A PRECOMPUTED DICTIONARY
TRANSFORM A SIGNAL AS A SPARSE COMBINATION OF RICKER WAVELETS THIS EXAMPLE VISUALLY COMPARES DIFFERENT SPARSE CODING METHODS USING THE SKLEARNDECOMPOSITIONSPARSECODER ESTIMATOR THE RICKER ALSO KNOWN AS MEXICAN
HAT OR THE SECOND DERIVATIVE OF A GAUSSIAN IS NOT A PARTICULARLY GOOD KERNEL TO REPRESENT PIECEWISE CONSTANT SIGNALS LIKE THIS ONE IT CAN THEREFORE BE SEEN HOW MUCH ADDING DIFFERENT WIDTHS OF ATOMS MATTERS AND IT THEREFORE MOTIVATES LEARNING THE DICTIONARY TO BEST FIT YOUR TYPE OF SIGNALS
THE RICHER DICTIONARY ON THE RIGHT IS NOT LARGER IN SIZE HEAVIER SUBSAMPLING IS PERFORMED IN ORDER TO STAY ON THE SAME ORDER OF MAGNITUDE
511 DECOMPOSITION 991

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PRINTDOC
FROM DISTUTILSVERSION IMPORT LOOSEVERSION
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDECOMPOSITION IMPORT SPARSECODER
DEFRICKERFUNCTIONRESOLUTION CENTER WIDTH
DISCRETE SUBSAMPLED RICKER MEXICAN HAT WAVELET
X NPLINSPACE0 RESOLUTION 1 RESOLUTION
X 2 NPSQRT3 WIDTHNPPI1 4
1 X CENTER 2 WIDTH 2
NPEXPX CENTER 2 2 WIDTH2
RETURNX
DEFRICKERMATRIXWIDTH RESOLUTION NCOMPONENTS
DICTIONARY OF RICKER MEXICAN HAT WAVELETS
CENTERS NPLINSPACE0 RESOLUTION 1 NCOMPONENTS
D NPEMPTYNCOMPONENTS RESOLUTION
FORI CENTER INENUMERATECENTERS
DI RICKERFUNCTIONRESOLUTION CENTER WIDTH
D NPSQRTNPSUMD 2 AXIS1 NPNEWAXIS
RETURND
RESOLUTION 1024
SUBSAMPLING 3 SUBSAMPLING FACTOR
WIDTH 100
NCOMPONENTS RESOLUTION SUBSAMPLING
 COMPUTE A WAVELET DICTIONARY
DFIXED RICKERMATRIXWIDTHWIDTH RESOLUTIONRESOLUTION
NCOMPONENTSNCOMPONENTS
DMULTI NPRTUPLERICKERMATRIXWIDTHW RESOLUTIONRESOLUTION

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NCOMPONENTSNCOMPONENTS 5
FORWIN10 50 100 500 1000
 GENERATE A SIGNAL
Y NPLINSPACE0 RESOLUTION 1 RESOLUTION
FIRSTQUARTER Y RESOLUTION 4
YFIRSTQUARTER 3
YNPLOGICALNOTFIRSTQUARTER 1
 LIST THE DIFFERENT SPARSE CODING METHODS IN THE FOLLOWING FORMAT
 TITLE TRANSFORMALGORITHM TRANSFORMALPHA
 TRANSFORMNNOZEROCOEFS COLOR
ESTIMATORS OMP OMP NONE 15 NAVY
LASSO LASSOLARS 2 NONE TURQUOISE
LW 2
 AVOID FUTUREWARNING ABOUT DEFAULT VALUE CHANGE WHEN NUMPY 114
LSTSQRCOND NONE IFLOOSEVERSIONNPVERSION 114 ELSE1
PLTFIGUREFIGSIZE13 6
FORSUBPLOT D TITLE INENUMERATEZIPDFIXED DMULTI
FIXED WIDTH MULTIPLE WIDTHS
PLTSUBPLOT1 2 SUBPLOT 1
PLTTITLESPARSE CODING AGAINST SDICTIONARY TITLE
PLTPLOTY LWLW LINESTYLE LABELORIGINAL SIGNAL
 DO A WAVELET APPROXIMATION
FORTITLE ALGO ALPHA NNONZERO COLOR INESTIMATORS
CODER SPARSECODERDICTIONARYD TRANSFORMNNONZEROCOEFSNNONZERO
TRANSFORMALPHAALPHA TRANSFORMALGORITHMALGO
X CODERTRANSFORMYRESHAPE1 1
DENSITY LENNPFLATNONZEROX
X NPRAVELNPDOTX D
SQUAREDERROR NPSUMY X 2
PLTPLOTX COLORCOLOR LWLW
LABELSSNONZERO COEFS N2FERROR
 TITLE DENSITY SQUAREDERROR
 SOFT THRESHOLDING DEBIASING
CODER SPARSECODERDICTIONARYD TRANSFORMALGORITHMTHRESHOLD
TRANSFORMALPHA20
X CODERTRANSFORMYRESHAPE1 1
 IDX NPWHEREX 0
X0 IDX   NPLINALGLSTSQDIDX T Y RCONDLSTSQRCOND
X NPRAVELNPDOTX D
SQUAREDERROR NPSUMY X 2
PLTPLOTX COLORDARKORANGE LWLW
LABELTHRESHOLDING W DEBIASING NDNONZERO COEFS 2FERROR
 LENIDX SQUAREDERROR
PLTAXISTIGHT
PLTLEGENDSHADOWFALSE LOCBEST
PLTSUBPLOTSADJUST04 07 97 90 09 2
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0238 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
511 DECOMPOSITION 993

51111 IMAGE DENOISING USING DICTIONARY LEARNING

AN EXAMPLE COMPARING THE EFFECT OF RECONSTRUCTING NOISY FRAGMENTS OF A RACCOON FACE IMAGE USING FIRSTLY ONLINE DICTIONARY LEARNING AND VARIOUS TRANSFORM METHODS

THE DICTIONARY IS FITTED ON THE DISTORTED LEFT HALF OF THE IMAGE AND SUBSEQUENTLY USED TO RECONSTRUCT THE RIGHT HALF NOTE THAT EVEN BETTER PERFORMANCE COULD BE ACHIEVED BY FITTING TO AN UNDISTORTED IE NOISELESS IMAGE BUT HERE WE START FROM THE ASSUMPTION THAT IT IS NOT AVAILABLE

A COMMON PRACTICE FOR EVALUATING THE RESULTS OF IMAGE DENOISING IS BY LOOKING AT THE DIFFERENCE BETWEEN THE RECON STRUCTION AND THE ORIGINAL IMAGE IF THE RECONSTRUCTION IS PERFECT THIS WILL LOOK LIKE GAUSSIAN NOISE

IT CAN BE SEEN FROM THE PLOTS THAT THE RESULTS OF ORTHOGONAL MATCHING PURSUIT OMP WITH TWO NONZERO COEFFICIENTS IS A BIT LESS BIASED THAN WHEN KEEPING ONLY ONE THE EDGES LOOK LESS PROMINENT IT IS IN ADDITION CLOSER FROM THE GROUND TRUTH IN FROBENIUS NORM

THE RESULT OF LEAST ANGLE REGRESSION IS MUCH MORE STRONGLY BIASED THE DIFFERENCE IS REMINISCENT OF THE LOCAL INTENSITY VALUE OF THE ORIGINAL IMAGE

THRESHOLDING IS CLEARLY NOT USEFUL FOR DENOISING BUT IT IS HERE TO SHOW THAT IT CAN PRODUCE A SUGGESTIVE OUTPUT WITH VERY HIGH SPEED AND THUS BE USEFUL FOR OTHER TASKS SUCH AS OBJECT CLASSIFICATION WHERE PERFORMANCE IS NOT NECESSARILY RELATED TO VISUALISATION

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OUT
DISTORTING IMAGE
EXTRACTING REFERENCE PATCHES
DONE IN 001S
LEARNING THE DICTIONARY
DONE IN 722S
EXTRACTING NOISY PATCHES
DONE IN 000S
ORTHOGONAL MATCHING PURSUIT
1 ATOM
DONE IN 119S
ORTHOGONAL MATCHING PURSUIT
2 ATOMS
DONE IN 235S
LEASTANGLE REGRESSION
5 ATOMS
DONE IN 1750S
THRESHOLDING
ALPHA01
DONE IN 025S
PRINTDOC
FROM TIME IMPORT TIME
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
IMPORT SCIPY AS SP
FROM SKLEARNDECOMPOSITION IMPORT MINIBATCHDICTIONARYLEARNING

```
FROM SKLEARNFEATUREEXTRACTIONIMAGE IMPORT EXTRACTPATCHES2D
FROM SKLEARNFEATUREEXTRACTIONIMAGE IMPORT RECONSTRUCTFROMPATCHES2D
TRY SCIPY  016 HAVE FACE IN MISC
FROM SCIPYMISC IMPORT FACE
FACE  FACEGRAYTRUE
EXCEPTIMPORTERROR
FACE  SPFACEGRAYTRUE
 CONVERT FROM UINT8 REPRESENTATION WITH VALUES BETWEEN 0 AND 255 TO
 A FLOATING POINT REPRESENTATION WITH VALUES BETWEEN 0 AND 1
FACE  FACE  255
 DOWNSAMPLE FOR HIGHER SPEED
FACE  FACE4 4  FACE14 4  FACE4 14  FACE14 14
FACE  40
HEIGHT WIDTH  FACESHAPE
 DISTORT THE RIGHT HALF OF THE IMAGE
PRINTDISTORTING IMAGE
DISTORTED  FACECOPY
DISTORTED WIDTH  2  0075 NPRANDOMRANDNHEIGHT WIDTH  2
 EXTRACT ALL REFERENCE PATCHES FROM THE LEFT HALF OF THE IMAGE
PRINTEXTRACTING REFERENCE PATCHES
T0  TIME
PATCHSIZE  7 7
DATA  EXTRACTPATCHES2DDISTORTED WIDTH  2 PATCHSIZE
DATA  DATARESHAPEDATASHAPE0 1
DATA  NPMEANDATA AXIS0
DATA  NPSTDDATA AXIS0
PRINTDONE IN 2FS  TIME  T0

 LEARN THE DICTIONARY FROM REFERENCE PATCHES
PRINTLEARNING THE DICTIONARY
T0  TIME
DICO  MINIBATCHDICTIONARYLEARNINGNCOMPONENTS100 ALPHA1 NITER500
V  DICOFITDATACOMPONENTS
DT  TIME  T0
PRINTDONE IN 2FS  DT
PLTFIGUREFIGSIZE42 4
FORI COMP INENUMERATEV100
PLTSUBPLOT10 10 I  1
PLTIMSHOWCOMPRESHAPEPATCHSIZE CMAPPLTCMGRAYR
INTERPOLATIONNEAREST
PLTXTICKS
PLTYTICKS
PLTSUPTITLEDICTIONARY LEARNED FROM FACE PATCHES N
TRAIN TIME 1FS ONDPATCHES  DT LENDATA
FONTSIZE16
PLTSUBPLOTSADJUST008 002 092 085 008 023
```

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DISPLAY THE DISTORTED IMAGE
DEFSHOWWITHDIFFIMAGE REFERENCE TITLE
HELPER FUNCTION TO DISPLAY DENOISING
PLTFIGUREFIGSIZE5 33
PLTSUBPLOT1 2 1
PLTTITLEIMAGE
PLTIMSHOWIMAGE VMIN0 VMAX1 CMAPPLTCMGRAY
INTERPOLATIONNEAREST
PLTXTICKS
PLTYTICKS
PLTSUBPLOT1 2 2
DIFFERENCE IMAGE REFERENCE
PLTTITLEDIFFERENCE NORM 2F NPSQRTNPSUMDIFFERENCE 2
PLTIMSHOWDIFFERENCE VMIN05 VMAX05 CMAPPLTCMPUOR
INTERPOLATIONNEAREST
PLTXTICKS
PLTYTICKS
PLTSUPTITLETITLE SIZE16
PLTSUBPLOTSADJUST002 002 098 079 002 02
SHOWWITHDIFFDISTORTED FACE DISTORTED IMAGE

EXTRACT NOISY PATCHES AND RECONSTRUCT THEM USING THE DICTIONARY
PRINTEXTRACTING NOISY PATCHES
T0 TIME
DATA EXTRACTPATCHES2DDISTORTED WIDTH 2 PATCHSIZE
DATA DATARESHAPEDATASHAPE0 1
INTERCEPT NPMEANDATA AXIS0
DATA INTERCEPT
PRINTDONE IN 2FS TIME T0
TRANSFORMALGORITHMS
ORTHOGONAL MATCHING PURSUIT N1 ATOM OMP
TRANSFORMNNONZEROCOEFS 1
ORTHOGONAL MATCHING PURSUIT N2 ATOMS OMP
TRANSFORMNNONZEROCOEFS 2
LEASTANGLE REGRESSION N5 ATOMS LARS
TRANSFORMNNONZEROCOEFS 5
THRESHOLDING NALPHA01 THRESHOLD TRANSFORMALPHA 1
RECONSTRUCTIONS
FORTITLE TRANSFORMALGORITHM KWARGS INTRANSFORMALGORITHMS
PRINTTITLE
RECONSTRUCTIONSTITLE FACECOPY
T0 TIME
DICOSETPARAMSTRANSFORMALGORITHMTRANSFORMALGORITHM KWARGS
CODE DICOTRANSFORMDATA
PATCHES NPDOTCODE V
PATCHES INTERCEPT
PATCHES PATCHESRESHAPELENDATA PATCHSIZE
IFTRANSFORMALGORITHM THRESHOLD
PATCHES PATCHESMIN
PATCHES PATCHESMAX
511 DECOMPOSITION 999

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RECONSTRUCTIONSTITLE WIDTH 2 RECONSTRUCTFROMPATCHES2D
PATCHES HEIGHT WIDTH 2
DT TIME T0
PRINTDONE IN 2FS DT
SHOWWITHDIFFRECONSTRUCTIONSTITLE FACE
TITLE   TIME 1FS DT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 30244 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51112 FACES DATASET DECOMPOSITIONS
THIS EXAMPLE APPLIES TO OLIVETTIFACES DIFFERENT UNSUPERVISED MATRIX DECOMPOSITION DIMENSION REDUCTION METHODS
FROM THE MODULE SKLEARNDECOMPOSITION SEE THE DOCUMENTATION CHAPTER DECOMPOSING SIGNALS IN COMPONENTS
MATRIX FACTORIZATION PROBLEMS
•

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511 DECOMPOSITION 1005

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OUT
DATASET CONSISTS OF 400 FACES
EXTRACTING THE TOP 6 EIGENFACES  PCA USING RANDOMIZED SVD
DONE IN 0018S
EXTRACTING THE TOP 6 NONNEGATIVE COMPONENTS  NMF
DONE IN 0109S
EXTRACTING THE TOP 6 INDEPENDENT COMPONENTS  FASTICA
DONE IN 0295S
EXTRACTING THE TOP 6 SPARSE COMP  MINIBATCHSPARSEPCA
DONE IN 1129S
EXTRACTING THE TOP 6 MINIBATCHDICTIONARYLEARNING
DONE IN 0979S
EXTRACTING THE TOP 6 CLUSTER CENTERS  MINIBATCHKMEANS
DONE IN 0221S
EXTRACTING THE TOP 6 FACTOR ANALYSIS COMPONENTS  FA
DONE IN 0206S
EXTRACTING THE TOP 6 DICTIONARY LEARNING
DONE IN 1099S
EXTRACTING THE TOP 6 DICTIONARY LEARNING  POSITIVE DICTIONARY
DONE IN 1213S
EXTRACTING THE TOP 6 DICTIONARY LEARNING  POSITIVE CODE
DONE IN 0688S
EXTRACTING THE TOP 6 DICTIONARY LEARNING  POSITIVE DICTIONARY  CODE
DONE IN 0470S
```

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PRINTDOC
 AUTHORS VLAD NICULAE ALEXANDRE GRAMFORT
 LICENSE BSD 3 CLAUSE
IMPORT LOGGING
FROM TIME IMPORT TIME
FROM NUMPYRANDOM IMPORT RANDOMSTATE
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT FETCHOLIVETTIFACES
FROM SKLEARNCLUSTER IMPORT MINIBATCHKMEANS
FROM SKLEARN IMPORT DECOMPOSITION
 DISPLAY PROGRESS LOGS ON STDOUT
LOGGINGBASICCONFIGLEVELLOGGINGINFO
FORMAT ASCTIMES LEVELNAMES MESSAGES
NROW NCOL  2 3
NCOMPONENTS  NROW NCOL
IMAGESHAPE  64 64
RNG  RANDOMSTATE0

 LOAD FACES DATA
DATASET  FETCHOLIVETTIFACESSHUFFLETRUE RANDOMSTATERNG
FACES  DATASETDATA
NSAMPLES NFEATURES  FACESSHAPE
 GLOBAL CENTERING
FACESCENTERED  FACES  FACESMEANAXIS0
 LOCAL CENTERING
FACESCENTERED  FACESCENTEREDMEANAXIS1RESHAPENSAMPLES 1
PRINTDATASET CONSISTS OF DFACES  NSAMPLES
DEFPLOTGALLERYTITLE IMAGES NCOLNCOL NROWNROW CMAPPLTCMGRAY
PLTFIGUREFIGSIZE2 NCOL 226 NROW
PLTSUPTITLETITLE SIZE16
FORI COMP INENUMERATEIMAGES
PLTSUBPLOTNROW NCOL I  1
VMAX  MAXCOMPMAX COMPMIN
PLTIMSHOWCOMPRESHAPEIMAGESHAPE CMAPCMAP
INTERPOLATIONNEAREST
VMINVMAX VMAXVMAX
PLTXTICKS
PLTYTICKS
PLTSUBPLOTSADJUST001 005 099 093 004 0

 LIST OF THE DIFFERENT ESTIMATORS WHETHER TO CENTER AND TRANSPOSE THE
 PROBLEM AND WHETHER THE TRANSFORMER USES THE CLUSTERING API
ESTIMATORS
EIGENFACES  PCA USING RANDOMIZED SVD
DECOMPOSITIONPCANCOMPONENTSNCOMPONENTS SVDSOLVERRANDOMIZED
511 DECOMPOSITION 1013
```

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WHITENTRUE
TRUE
NONNEGATIVE COMPONENTS NMF
DECOMPOSITIONNMFNCOMPONENTSNCOMPONENTS INITNNDSVDA TOL5E3
FALSE
INDEPENDENT COMPONENTS FASTICA
DECOMPOSITIONFASTICANCOMPONENTSNCOMPONENTS WHITENTRUE
TRUE
SPARSE COMP MINIBATCHSPARSEPCA
DECOMPOSITIONMINIBATCHSPARSEPCANCOMPONENTSNCOMPONENTS ALPHA08
NITER100 BATCHSIZE3
RANDOMSTATERNG
NORMALIZECOMPONENTSTRUE
TRUE
MINIBATCHDICTIONARYLEARNING
DECOMPOSITIONMINIBATCHDICTIONARYLEARNINGNCOMPONENTS15 ALPHA01
NITER50 BATCHSIZE3
RANDOMSTATERNG
TRUE
CLUSTER CENTERS MINIBATCHKMEANS
MINIBATCHKMEANSNCLUSTERSNCOMPONENTS TOL1E3 BATCHSIZE20
MAXITER50 RANDOMSTATERNG
TRUE
FACTOR ANALYSIS COMPONENTS FA
DECOMPOSITIONFACTORANALYSISNCOMPONENTSNCOMPONENTS MAXITER20
TRUE

 PLOT A SAMPLE OF THE INPUT DATA
PLOTGALLERYFIRST CENTERED OLIVETTI FACES FACESCENTEREDNCOMPONENTS

 DO THE ESTIMATION AND PLOT IT
FORNAME ESTIMATOR CENTER INESTIMATORS
PRINTEXTRACTING THE TOP D S NCOMPONENTS NAME
T0 TIME
DATA FACES
IFCENTER
DATA FACESCENTERED
ESTIMATORFITDATA
TRAINTIME TIME T0
PRINTDONE IN 03FS TRAINTIME
IFHASATTRESTIMATOR CLUSTERCENTERS
COMPONENTS ESTIMATORCLUSTERCENTERS
ELSE
COMPONENTS ESTIMATORCOMPONENTS
 PLOT AN IMAGE REPRESENTING THE PIXELWISE VARIANCE PROVIDED BY THE

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 ESTIMATOR EG ITS NOISEVARIANCE ATTRIBUTE THE EIGENFACES ESTIMATOR
 VIA THE PCA DECOMPOSITION ALSO PROVIDES A SCALAR NOISEVARIANCE
 THE MEAN OF PIXELWISE VARIANCE THAT CANNOT BE DISPLAYED AS AN IMAGE
 SO WE SKIP IT
IFHASATTRESTIMATOR NOISEVARIANCE AND
ESTIMATORNOISEVARIANCENDIM 0 SKIP THE EIGENFACES CASE
PLOTGALLERYPIXELWISE VARIANCE
ESTIMATORNOISEVARIANCERESHAPE1 1 NCOL1
NROW1
PLOTGALLERY S TRAIN TIME 1FS NAME TRAINTIME
COMPONENTSNCOMPONENTS
PLTSHOW

 VARIOUS POSITIVITY CONSTRAINTS APPLIED TO DICTIONARY LEARNING
ESTIMATORS
DICTIONARY LEARNING
DECOMPOSITIONMINIBATCHDICTIONARYLEARNINGNCOMPONENTS15 ALPHA01
NITER50 BATCHSIZE3
RANDOMSTATERNG
TRUE
DICTIONARY LEARNING POSITIVE DICTIONARY
DECOMPOSITIONMINIBATCHDICTIONARYLEARNINGNCOMPONENTS15 ALPHA01
NITER50 BATCHSIZE3
RANDOMSTATERNG
POSITIVEDICTTRUE
TRUE
DICTIONARY LEARNING POSITIVE CODE
DECOMPOSITIONMINIBATCHDICTIONARYLEARNINGNCOMPONENTS15 ALPHA01
NITER50 BATCHSIZE3
RANDOMSTATERNG
POSITIVECODETRUE
TRUE
DICTIONARY LEARNING POSITIVE DICTIONARY CODE
DECOMPOSITIONMINIBATCHDICTIONARYLEARNINGNCOMPONENTS15 ALPHA01
NITER50 BATCHSIZE3
RANDOMSTATERNG
POSITIVEDICTTRUE
POSITIVECODETRUE
TRUE

 PLOT A SAMPLE OF THE INPUT DATA
PLOTGALLERYFIRST CENTERED OLIVETTI FACES FACESCENTEREDNCOMPONENTS
CMAPPLTCMRDBU

 DO THE ESTIMATION AND PLOT IT
FORNAME ESTIMATOR CENTER INESTIMATORS
PRINTEXTRACTING THE TOP D S NCOMPONENTS NAME
T0 TIME
DATA FACES
IFCENTER
511 DECOMPOSITION 1015

SCIKITLEARN USER GUIDE RELEASE 0213
DATA FACESCENTERED
ESTIMATORFITDATA
TRAINTIME TIME T0
PRINTDONE IN 03FS TRAINTIME
COMPONENTS ESTIMATORCOMPONENTS
PLOTGALLERYNAME COMPONENTSNCOMPONENTS CMAPPLTCMRDBU
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 8614 SECONDS
512 ENSEMBLE METHODS
EXAMPLES CONCERNING THE SKLEARNENSEMBLE MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5121 DECISION TREE REGRESSION WITH ADABOOST
A DECISION TREE IS BOOSTED USING THE ADABOOSTR21ALGORITHM ON A 1D SINUSOIDAL DATASET WITH A SMALL AMOUNT OF GAUSSIAN NOISE 299 BOOSTS 300 DECISION TREES IS COMPARED WITH A SINGLE DECISION TREE REGRESSOR AS THE NUMBER OF BOOSTS IS INCREASED THE REGRESSOR CAN FIT MORE DETAIL
1
8 DRUCKER “IMPROVING REGRESSORS USING BOOSTING TECHNIQUES” 1997
1016 CHAPTER 5 EXAMPLES

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 AUTHOR NOEL DAWE NOELDAWEGMAILCOM

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 IMPORTING NECESSARY LIBRARIES
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNTREE IMPORT DECISIONTREEREGRESSOR
FROM SKLEARNENSEMBLE IMPORT ADABOOSTREGRESSOR
 CREATE THE DATASET
RNG NPRANDOMRANDOMSTATE1
X NPLINSPACE0 6 100 NPNEWAXIS
Y NPSINXRAVEL NPSIN6 XRAVEL RNGNORMAL0 01 XSHAPE0
 FIT REGRESSION MODEL
REGR1 DECISIONTREEREGRESSORMAXDEPTH4
REGR2 ADABOOSTREGRESSORDECISIONTREEREGRESSORMAXDEPTH4
NESTIMATORS300 RANDOMSTATERNG
REGR1FITX Y
REGR2FITX Y
512 ENSEMBLE METHODS 1017

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 PREDICT
Y1  REGR1PREDICTX
Y2  REGR2PREDICTX
 PLOT THE RESULTS
PLTFIGURE
PLTSCATTERX Y CK LABELTRAINING SAMPLES
PLTPLOTX Y1 CG LABELNESTIMATORS1 LINEWIDTH2
PLTPLOTX Y2 CR LABELNESTIMATORS300 LINEWIDTH2
PLTXLABELDATA
PLTYLABELTARGET
PLTTITLEBOOSTED DECISION TREE REGRESSION
PLTLEGEND
PLTSHOW
```

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0226 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5122 PIXEL IMPORTANCES WITH A PARALLEL FOREST OF TREES

THIS EXAMPLE SHOWS THE USE OF FORESTS OF TREES TO EVALUATE THE IMPORTANCE OF THE PIXELS IN AN IMAGE CLASSIFICATION TASK FACES THE HOTTER THE PIXEL THE MORE IMPORTANT

THE CODE BELOW ALSO ILLUSTRATES HOW THE CONSTRUCTION AND THE COMPUTATION OF THE PREDICTIONS CAN BE PARALLELIZED WITHIN MULTIPLE JOBS

SCIKITLEARN USER GUIDE RELEASE 0213
OUT
FITTING EXTRATREESCLASSIFIER ON FACES DATA WITH 1 CORES
DONE IN 1028S
PRINTDOC
FROM TIME IMPORT TIME
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT FETCHOLIVETTIFACES
FROM SKLEARNENSEMBLE IMPORT EXTRATREESCLASSIFIER
 NUMBER OF CORES TO USE TO PERFORM PARALLEL FITTING OF THE FOREST MODEL
NJOBS 1
 LOAD THE FACES DATASET
DATA FETCHOLIVETTIFACES
X DATAIMAGESRESHAPELENDATAIMAGES 1
Y DATATARGET
512 ENSEMBLE METHODS 1019

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MASK Y 5 LIMIT TO 5 CLASSES
X XMASK
Y YMASK
 BUILD A FOREST AND COMPUTE THE PIXEL IMPORTANCES
PRINTFITTING EXTRATREESCLASSIFIER ON FACES DATA WITH DCORES NJOBS
T0 TIME
FOREST EXTRATREESCLASSIFIERNESTIMATORS1000
MAXFEATURES128
NJOBSNJOBS
RANDOMSTATE0
FORESTFITX Y
PRINTDONE IN 03FS TIME T0
IMPORTANCES FORESTFEATUREIMPORTANCES
IMPORTANCES IMPORTANCESRESHAPEDATAIMAGES0SHAPE
 PLOT PIXEL IMPORTANCES
PLTMATSHOWIMPORTANCES CMAPPLTCMHOT
PLTTITLEPIXEL IMPORTANCES WITH FORESTS OF TREES
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1147 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5123 PLOT INDIVIDUAL AND VOTING REGRESSION PREDICTIONS
PLOT INDIVIDUAL AND AVERAGED REGRESSION PREDICTIONS FOR BOSTON DATASET
FIRST THREE EXEMPLARY REGRESSORS ARE INITIALIZED GRADIENTBOOSTINGREGRESSOR
RANDOMFORESTREGRESSOR ANDLINEARREGRESSION AND USED TO INITIALIZE A VOTINGREGRESSOR
THE RED STARRED DOTS ARE THE AVERAGED PREDICTIONS

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PRINTDOC
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGREGRESSOR
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTREGRESSOR
FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION
FROM SKLEARNENSEMBLE IMPORT VOTINGREGRESSOR
 LOADING SOME EXAMPLE DATA
BOSTON DATASETSLOADBOSTON
X BOSTONDATA
Y BOSTONTARGET
 TRAINING CLASSIFIERS
REG1 GRADIENTBOOSTINGREGRESSORRANDOMSTATE1 NESTIMATORS10
REG2 RANDOMFORESTREGRESSORRANDOMSTATE1 NESTIMATORS10
REG3 LINEARREGRESSION
EREG VOTINGREGRESSORGB REG1 RF REG2 LR REG3
REG1FITX Y
REG2FITX Y
REG3FITX Y
EREGFITX Y
XT X20
512 ENSEMBLE METHODS 1021

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PLTFIGURE
PLTPLOTREG1PREDICTXT GD LABELGRADIENTBOOSTINGREGRESSOR
PLTPLOTREG2PREDICTXT B LABELRANDOMFORESTREGRESSOR
PLTPLOTREG3PREDICTXT YS LABELLINEARREGRESSION
PLTPLOTEREGPREDICTXT R LABELVOTINGREGRESSOR
PLTTICKPARAMSAXISX WHICHBOTH BOTTOMFALSE TOPFALSE
LABELBOTTOMFALSE
PLTYLABELPREDICTED
PLTXLABELTRAINING SAMPLES
PLTLEGENDLOCBEST
PLTTITLECOMPARISON OF INDIVIDUAL PREDICTIONS WITH AVERAGED
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0117 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5124 FEATURE IMPORTANCES WITH FORESTS OF TREES
THIS EXAMPLES SHOWS THE USE OF FORESTS OF TREES TO EVALUATE THE IMPORTANCE OF FEATURES ON AN ARTIFICIAL CLASSIFICATION
TASK THE RED BARS ARE THE FEATURE IMPORTANCES OF THE FOREST ALONG WITH THEIR INTERTREES VARIABILITY
AS EXPECTED THE PLOT SUGGESTS THAT 3 FEATURES ARE INFORMATIVE WHILE THE REMAINING ARE NOT

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OUT
FEATURE RANKING
1 FEATURE 1 0295902
2 FEATURE 2 0208351
3 FEATURE 0 0177632
4 FEATURE 3 0047121
5 FEATURE 6 0046303
6 FEATURE 8 0046013
7 FEATURE 7 0045575
8 FEATURE 4 0044614
9 FEATURE 9 0044577
10 FEATURE 5 0043912
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
FROM SKLEARNENSEMBLE IMPORT EXTRATREESCLASSIFIER

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BUILD A CLASSIFICATION TASK USING 3 INFORMATIVE FEATURES
X Y MAKECLASSIFICATIONNSAMPLES1000
NFEATURES10
NINFORMATIVE3
NREDUNDANT0
NREPEATED0
NCLASSES2
RANDOMSTATE0
SHUFFLEFALSE
BUILD A FOREST AND COMPUTE THE FEATURE IMPORTANCES
FOREST EXTRATREESCLASSIFIERNESTIMATORS250
RANDOMSTATE0
FORESTFITX Y
IMPORTANCES FORESTFEATUREIMPORTANCES
STD NPSTDTREEFEATUREIMPORTANCES FORTREEINFORESTESTIMATORS
AXIS0
INDICES NPARGSORTIMPORTANCES1
PRINT THE FEATURE RANKING
PRINTFEATURE RANKING
FORFINRANGEXSHAPE1
PRINTD FEATURE DF F 1 INDICESF IMPORTANCESINDICESF
PLOT THE FEATURE IMPORTANCES OF THE FOREST
PLTFIGURE
PLTTITLEFEATURE IMPORTANCES
PLTBARRANGEXSHAPE1 IMPORTANCESINDICES
COLORR YERRSTDINDICES ALIGNCENTER
PLTXTICKSRANGEXSHAPE1 INDICES
PLTXLIM1 XSHAPE1
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0343 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5125 ISOLATIONFOREST EXAMPLE
AN EXAMPLE USING SKLEARNENSEMBLEISOLATIONFOREST FOR ANOMALY DETECTION
THE ISOLATIONFOREST ‘ISOLATES’ OBSERVATIONS BY RANDOMLY SELECTING A FEATURE AND THEN RANDOMLY SELECTING A SPLIT VALUE BETWEEN THE MAXIMUM AND MINIMUM VALUES OF THE SELECTED FEATURE
SINCE RECURSIVE PARTITIONING CAN BE REPRESENTED BY A TREE STRUCTURE THE NUMBER OF SPLITTINGS REQUIRED TO ISOLATE A SAMPLE IS EQUIVALENT TO THE PATH LENGTH FROM THE ROOT NODE TO THE TERMINATING NODE
THIS PATH LENGTH AVERAGED OVER A FOREST OF SUCH RANDOM TREES IS A MEASURE OF NORMALITY AND OUR DECISION FUNCTION
RANDOM PARTITIONING PRODUCES NOTICEABLE SHORTER PATHS FOR ANOMALIES HENCE WHEN A FOREST OF RANDOM TREES COLLEC TIVELY PRODUCE SHORTER PATH LENGTHS FOR PARTICULAR SAMPLES THEY ARE HIGHLY LIKELY TO BE ANOMALIES

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNENSEMBLE IMPORT ISOLATIONFOREST
RNG NPRANDOMRANDOMSTATE42
 GENERATE TRAIN DATA
X 03 RNGRANDN100 2
XTRAIN NPRX 2 X 2
 GENERATE SOME REGULAR NOVEL OBSERVATIONS
X 03 RNGRANDN20 2
XTEST NPRX 2 X 2
 GENERATE SOME ABNORMAL NOVEL OBSERVATIONS
XOUTLIERS RNGUNIFORMLOW4 HIGH4 SIZE20 2
 FIT THE MODEL
CLF ISOLATIONFORESTBEHAVIOURNEW MAXSAMPLES100
RANDOMSTATERNG CONTAMINATIONAUTO
CLFFITXTRAIN
YPREDTRAIN CLFPREDICTXTRAIN
YPREDTEST CLFPREDICTXTEST
YPREDOUTLIERS CLFPREDICTXOUTLIERS
 PLOT THE LINE THE SAMPLES AND THE NEAREST VECTORS TO THE PLANE

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XX YY NPMESHGRIDNPLINSPACE5 5 50 NPLINSPACE5 5 50
Z CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
PLTTITLEISOLATIONFOREST
PLTCONTOURFXX YY Z CMAPPLTCMBLUESR
B1 PLTSCATTERXTRAIN 0 XTRAIN 1 CWHITE
S20 EDGECOLORK
B2 PLTSCATTERXTEST 0 XTEST 1 CGREEN
S20 EDGECOLORK
C PLTSCATTERXOUTLIERS 0 XOUTLIERS 1 CRED
S20 EDGECOLORK
PLTAXISTIGHT
PLTXLIM5 5
PLTYLIM5 5
PLTLEGENDB1 B2 C
TRAINING OBSERVATIONS
NEW REGULAR OBSERVATIONS NEW ABNORMAL OBSERVATIONS
LOCUPPER LEFT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0237 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5126 PLOT THE DECISION BOUNDARIES OF A VOTINGCLASSIFIER
PLOT THE DECISION BOUNDARIES OF A VOTINGCLASSIFIER FOR TWO FEATURES OF THE IRIS DATASET
PLOT THE CLASS PROBABILITIES OF THE FIRST SAMPLE IN A TOY DATASET PREDICTED BY THREE DIFFERENT CLASSIFIERS AND AVERAGED BY THEVOTINGCLASSIFIER
FIRST THREE EXEMPLARY CLASSIFIERS ARE INITIALIZED DECISIONTREECLASSIFIER KNEIGHBORSCLASSIFIER AND
SVC AND USED TO INITIALIZE A SOFTVOTING VOTINGCLASSIFIER WITH WEIGHTS 2 1 2 WHICH MEANS THAT THE
PREDICTED PROBABILITIES OF THE DECISIONTREECLASSIFIER ANDSVC COUNT 5 TIMES AS MUCH AS THE WEIGHTS OF THE
KNEIGHBORSCLASSIFIER CLASSIFIER WHEN THE AVERAGED PROBABILITY IS CALCULATED

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PRINTDOC
FROM ITERTOOLS IMPORT PRODUCT
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSCLASSIFIER
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNENSEMBLE IMPORT VOTINGCLASSIFIER
 LOADING SOME EXAMPLE DATA
IRIS DATASETSLOADIRIS
X IRISDATA 0 2
Y IRISTARGET
 TRAINING CLASSIFIERS
CLF1 DECISIONTREECLASSIFIERMAXDEPTH4
CLF2 KNEIGHBORSCLASSIFIERNNEIGHBORS7
CLF3 SVCGAMMA1 KERNELRBF PROBABILITYTRUE
ECLF VOTINGCLASSIFIERESTIMATORSDT CLF1 KNN CLF2
512 ENSEMBLE METHODS 1027

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SVC CLF3
VOTINGSOFT WEIGHTS2 1 2
CLF1FITX Y
CLF2FITX Y
CLF3FITX Y
ECLFFITX Y
 PLOTTING DECISION REGIONS
XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX 01
NPARANGEYMIN YMAX 01
F AXARR PLTSUBPLOTS2 2 SHAREXCOL SHAREYROW FIGSIZE10 8
FORIDX CLF TT INZIPPRODUCT0 1 0 1
CLF1 CLF2 CLF3 ECLF
DECISION TREE DEPTH4 KNN K7
KERNEL SVM SOFT VOTING
Z CLFPREDICTNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
AXARRIDX0 IDX1CONTOURFXX YY Z ALPHA04
AXARRIDX0 IDX1SCATTERX 0 X 1 CY
S20 EDGECOLORK
AXARRIDX0 IDX1SETTITLETT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0202 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5127 COMPARING RANDOM FORESTS AND THE MULTIOUTPUT META ESTIMATOR
AN EXAMPLE TO COMPARE MULTIOUTPUT REGRESSION WITH RANDOM FOREST AND THE MULTIOUTPUTMULTIOUTPUTREGRESSOR META ESTIMATOR
THIS EXAMPLE ILLUSTRATES THE USE OF THE MULTIOUTPUTMULTIOUTPUTREGRESSOR METAESTIMATOR TO PERFORM MULTIOUTPUT RE GRESSION A RANDOM FOREST REGRESSOR IS USED WHICH SUPPORTS MULTIOUTPUT REGRESSION NATIVELY SO THE RESULTS CAN BE COMPARED
THE RANDOM FOREST REGRESSOR WILL ONLY EVER PREDICT VALUES WITHIN THE RANGE OF OBSERVATIONS OR CLOSER TO ZERO FOR EACH OF THE TARGETS AS A RESULT THE PREDICTIONS ARE BIASED TOWARDS THE CENTRE OF THE CIRCLE
USING A SINGLE UNDERLYING FEATURE THE MODEL LEARNS BOTH THE X AND Y COORDINATE AS OUTPUT

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PRINTDOC
 AUTHOR TIM HEAD BETATIMGMAILCOM

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IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTREGRESSOR
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNMULTIOUTPUT IMPORT MULTIOUTPUTREGRESSOR
 CREATE A RANDOM DATASET
RNG NPRANDOMRANDOMSTATE1
X NPSORT200 RNGRAND600 1 100 AXIS0
Y NPARRAYNPPI NPSINXRAVEL NPPI NPCOSXRAVELT
Y 05 RNGRAND YSHAPE
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLIT
X Y TRAINSIZE400 TESTSIZE200 RANDOMSTATE4
MAXDEPTH 30
REGRMULTIRF MULTIOUTPUTREGRESSORRANDOMFORESTREGRESSORNESTIMATORS100
MAXDEPTHMAXDEPTH
RANDOMSTATE0
512 ENSEMBLE METHODS 1029

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REGRMULTIRFFITXTRAIN YTRAIN
REGRRF RANDOMFORESTREGRESSORNESTIMATORS100 MAXDEPTHMAXDEPTH
RANDOMSTATE2
REGRRFFITXTRAIN YTRAIN
 PREDICT ON NEW DATA
YMULTIRF REGRMULTIRFPREDICTXTEST
YRF REGRRFPREDICTXTEST
 PLOT THE RESULTS
PLTFIGURE
S 50
A 04
PLTSCATTERYTEST 0 YTEST 1 EDGECOLORK
CNAVY SS MARKERS ALPHAA LABELDATA
PLTSCATTERYMULTIRF 0 YMULTIRF 1 EDGECOLORK
CCORNFLOWERBLUE SS ALPHAA
LABELMULTI RF SCORE 2F REGRMULTIRFSCOREXTEST YTEST
PLTSCATTERYRF 0 YRF 1 EDGECOLORK
CC SS MARKER ALPHAA
LABELRF SCORE 2F REGRRFSCOREXTEST YTEST
PLTXLIM6 6
PLTYLIM6 6
PLTXLABELTARGET 1
PLTYLABELTARGET 2
PLTTITLECOMPARING RANDOM FORESTS AND THE MULTIOUTPUT META ESTIMATOR
PLTLEGEND
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0299 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5128 PREDICTION INTERVALS FOR GRADIENT BOOSTING REGRESSION
THIS EXAMPLE SHOWS HOW QUANTILE REGRESSION CAN BE USED TO CREATE PREDICTION INTERVALS
1030 CHAPTER 5 EXAMPLES

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IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGREGRESSOR
NPRANDOMSEED1
DEFFX
THE FUNCTION TO PREDICT
RETURNXNPSINX

FIRST THE NOISELESS CASE
X NPATLEAST2DNPRANDOMUNIFORM0 100 SIZE100T
X XASTYPENPFLOAT32
OBSERVATIONS
Y FXRAVEL
DY 15 10 NPRANDOMRANDOMYSHAPE
NOISE NPRANDOMNORMAL0 DY
Y NOISE
Y YASTYPENPFLOAT32
MESH THE INPUT SPACE FOR EVALUATIONS OF THE REAL FUNCTION THE PREDICTION AND
512 ENSEMBLE METHODS 1031

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 ITS MSE
XX NPATLEAST2DNPLINSPACE0 10 1000T
XX XXASTYPENPFLOAT32
ALPHA 095
CLF GRADIENTBOOSTINGREGRESSORLOSSQUANTILE ALPHAALPHA
NESTIMATORS250 MAXDEPTH3
LEARNINGRATE1 MINSAMPLESLEAF9
MINSAMPLESSPLIT9
CLFFITX Y
 MAKE THE PREDICTION ON THE MESHED XAXIS
YUPPER CLFPREDICTXX
CLFSETPARAMSALPHA10 ALPHA
CLFFITX Y
 MAKE THE PREDICTION ON THE MESHED XAXIS
YLOWER CLFPREDICTXX
CLFSETPARAMSLOSSLS
CLFFITX Y
 MAKE THE PREDICTION ON THE MESHED XAXIS
YPRED CLFPREDICTXX
 PLOT THE FUNCTION THE PREDICTION AND THE 90 CONFIDENCE INTERVAL BASED ON
 THE MSE
FIG PLTFIGURE
PLTPLOTXX FXX G LABELRFX XSINX
PLTPLOTX Y B MARKERSIZE10 LABELUOBSERVATIONS
PLTPLOTXX YPRED R LABELUPREDICTION
PLTPLOTXX YUPPER K
PLTPLOTXX YLOWER K
PLTFILLNPCONCATENATEXX XX1
NPCONCATENATEYUPPER YLOWER1
ALPHA5 FCB ECNONE LABEL90 PREDICTION INTERVAL
PLTXLABELX
PLTYLABELFX
PLTYLIM10 20
PLTLEGENDLOCUPPER LEFT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0275 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5129 GRADIENT BOOSTING REGULARIZATION
ILLUSTRATION OF THE EFFECT OF DIFFERENT REGULARIZATION STRATEGIES FOR GRADIENT BOOSTING THE EXAMPLE IS TAKEN FROM HASTIE ET AL 20091
1T HASTIE R TIBSHIRANI AND J FRIEDMAN “ELEMENTS OF STATISTICAL LEARNING ED 2” SPRINGER 2009
1032 CHAPTER 5 EXAMPLES

THE LOSS FUNCTION USED IS BINOMIAL DEVIANCE REGULARIZATION VIA SHRINKAGE LEARNINGRATE 10 IMPROVES PERFORMANCE CONSIDERABLY IN COMBINATION WITH SHRINKAGE STOCHASTIC GRADIENT BOOSTING SUBSAMPLE 10 CAN PRODUCE MORE ACCURATE MODELS BY REDUCING THE VARIANCE VIA BAGGING SUBSAMPLING WITHOUT SHRINKAGE USUALLY DOES POORLY ANOTHER STRATEGY TO REDUCE THE VARIANCE IS BY SUBSAMPLING THE FEATURES ANALOGOUS TO THE RANDOM SPLITS IN RANDOM FORESTS VIA THE MAXFEATURES PARAMETER

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PRINTDOC
 AUTHOR PETER PRETTENHOFER PETERPRETTENHOFERGMAILCOM

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IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT ENSEMBLE
FROM SKLEARN IMPORT DATASETS
X Y  DATASETSMAKEHASTIE102NSAMPLES12000 RANDOMSTATE1
X  XASTYPENPFLOAT32
 MAP LABELS FROM 1 1 TO 0 1
LABELS Y  NPUNIQUEY RETURNINVERSETRUE
XTRAIN XTEST  X2000 X2000
```

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YTRAIN YTEST Y2000 Y2000
ORIGINALPARAMS NESTIMATORS 1000 MAXLEAFNODES 4 MAXDEPTH NONE
‘→RANDOMSTATE 2
MINSAMPLESSPLIT 5
PLTFIGURE
FORLABEL COLOR SETTING INNO SHRINKAGE ORANGE
LEARNINGRATE 10 SUBSAMPLE 10
LEARNINGRATE01 TURQUOISE
LEARNINGRATE 01 SUBSAMPLE 10
SUBSAMPLE05 BLUE
LEARNINGRATE 10 SUBSAMPLE 05
LEARNINGRATE01 SUBSAMPLE05 GRAY
LEARNINGRATE 01 SUBSAMPLE 05
LEARNINGRATE01 MAXFEATURES2 MAGENTA
LEARNINGRATE 01 MAXFEATURES 2
PARAMS DICTORIGINALPARAMS
PARAMSUPDATESETTING
CLF ENSEMBLEGRADIENTBOOSTINGCLASSIFIER PARAMS
CLFFITXTRAIN YTRAIN
 COMPUTE TEST SET DEVIANCE
TESTDEVIANCE NPZEROSPARAMSNESTIMATORS DTYPENPFLOAT64
FORI YPRED INENUMERATECLFSTAGEDDECISIONFUNCTIONXTEST
 CLFLOSS ASSUMES THAT YTESTI IN 0 1
TESTDEVIANCEI CLFLOSSYTEST YPRED
PLTPLOTNPARANGETESTDEVIANCESHAPE0 15 TESTDEVIANCE5
 COLORCOLOR LABELLABEL
PLTLEGENDLOCUPPER LEFT
PLTXLABELBOOSTING ITERATIONS
PLTYLABELTEST SET DEVIANCE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 10180 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51210 PLOT CLASS PROBABILITIES CALCULATED BY THE VOTINGCLASSIFIER
PLOT THE CLASS PROBABILITIES OF THE FIRST SAMPLE IN A TOY DATASET PREDICTED BY THREE DIFFERENT CLASSIFIERS AND AVERAGED BY THEVOTINGCLASSIFIER
FIRST THREE EXAMPLARY CLASSIFIERS ARE INITIALIZED LOGISTICREGRESSION GAUSSIANNB AND RANDOMFORESTCLASSIFIER AND USED TO INITIALIZE A SOFTVOTING VOTINGCLASSIFIER WITH WEIGHTS 1 1 5 WHICH MEANS THAT THE PREDICTED PROBABILITIES OF THE RANDOMFORESTCLASSIFIER COUNT 5 TIMES AS MUCH AS THE WEIGHTS OF THE OTHER CLASSIFIERS WHEN THE AVERAGED PROBABILITY IS CALCULATED
TO VISUALIZE THE PROBABILITY WEIGHTING WE FIT EACH CLASSIFIER ON THE TRAINING SET AND PLOT THE PREDICTED CLASS PROBABILITIES

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FOR THE FIRST SAMPLE IN THIS EXAMPLE DATASET
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
FROM SKLEARNENSEMBLE IMPORT VOTINGCLASSIFIER
CLF1 LOGISTICREGRESSIONSOLVERLBFGS MAXITER1000 RANDOMSTATE123
CLF2 RANDOMFORESTCLASSIFIERNESTIMATORS100 RANDOMSTATE123
CLF3 GAUSSIANNB
X NPARRAY10 10 12 14 34 22 11 12
Y NPARRAY1 1 2 2
ECLF VOTINGCLASSIFIERESTIMATORSLR CLF1 RF CLF2 GNB CLF3
VOTINGSOFT
WEIGHTS1 1 5
 PREDICT CLASS PROBABILITIES FOR ALL CLASSIFIERS
PROBAS CFITX YPREDICTPROBAX FORCINCLF1 CLF2 CLF3 ECLF
 GET CLASS PROBABILITIES FOR THE FIRST SAMPLE IN THE DATASET

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CLASS11 PR0 0 FORPRINPROBAS
CLASS21 PR0 1 FORPRINPROBAS
 PLOTTING
N 4 NUMBER OF GROUPS
IND NPARANGEN GROUP POSITIONS
WIDTH 035 BAR WIDTH
FIG AX PLTSUBPLOTS
 BARS FOR CLASSIFIER 13
P1 AXBARIND NPHSTACKCLASS111 0 WIDTH
COLORGREEN EDGECOLORK
P2 AXBARIND WIDTH NPHSTACKCLASS211 0 WIDTH
COLORLIGHTGREEN EDGECOLORK
 BARS FOR VOTINGCLASSIFIER
P3 AXBARIND 0 0 0 CLASS111 WIDTH
COLORBLUE EDGECOLORK
P4 AXBARIND WIDTH 0 0 0 CLASS211 WIDTH
COLORSTEELBLUE EDGECOLORK
 PLOT ANNOTATIONS
PLTAXVLINE28 COLORK LINESTYLEDASHED
AXSETXTICKSIND WIDTH
AXSETXTICKLABELSLOGISTICREGRESSION NWEIGHT 1
GAUSSIANNB NWEIGHT 1
RANDOMFORESTCLASSIFIER NWEIGHT 5
VOTINGCLASSIFIER NAVERAGE PROBABILITIES
ROTATION40
HARIGHT
PLTYLIM0 1
PLTTITLECLASS PROBABILITIES FOR SAMPLE 1 BY DIFFERENT CLASSIFIERS
PLTLEGENDP10 P20 CLASS 1 CLASS 2 LOCUPPER LEFT
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0245 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51211 GRADIENT BOOSTING REGRESSION
DEMONSTRATE GRADIENT BOOSTING ON THE BOSTON HOUSING DATASET
THIS EXAMPLE FITS A GRADIENT BOOSTING MODEL WITH LEAST SQUARES LOSS AND 500 REGRESSION TREES OF DEPTH 4

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OUT
MSE 65493
PRINTDOC
 AUTHOR PETER PRETTENHOFER PETERPRETTENHOFERGMAILCOM

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IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT ENSEMBLE
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNUTILS IMPORT SHUFFLE
FROM SKLEARNMETRICS IMPORT MEANSQUAREDERROR

 LOAD DATA
BOSTON DATASETSLOADBOSTON
X Y SHUFFLEBOSTONDATA BOSTONTARGET RANDOMSTATE13
X XASTYPENPFLOAT32
OFFSET INTXSHAPE0 09
XTRAIN YTRAIN XOFFSET YOFFSET
XTEST YTEST XOFFSET YOFFSET

 FIT REGRESSION MODEL
PARAMS NESTIMATORS 500 MAXDEPTH 4 MINSAMPLESSPLIT 2
LEARNINGRATE 001 LOSS LS
512 ENSEMBLE METHODS 1037

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CLF ENSEMBLEGRADIENTBOOSTINGREGRESSOR PARAMS
CLFFITXTRAIN YTRAIN
MSE MEANSQUAREDERRORYTEST CLFPREDICTXTEST
PRINTMSE4F MSE

 PLOT TRAINING DEVIANCE
 COMPUTE TEST SET DEVIANCE
TESTSCORE NPZEROSPARAMSNESTIMATORS DTYPENPFLOAT64
FORI YPRED INENUMERATECLFSTAGEDPREDICTXTEST
TESTSCOREI CLFLOSSYTEST YPRED
PLTFIGUREFIGSIZE12 6
PLTSUBPLOT1 2 1
PLTTITLEDEVIANCE
PLTPLOTNPARANGEPARAMSNESTIMATORS 1 CLFTRAINSCORE B
LABELTRAINING SET DEVIANCE
PLTPLOTNPARANGEPARAMSNESTIMATORS 1 TESTSCORE R
LABELTEST SET DEVIANCE
PLTLEGENDLOCUPPER RIGHT
PLTXLABELBOOSTING ITERATIONS
PLTYLABELDEVIANCE

 PLOT FEATURE IMPORTANCE
FEATUREIMPORTANCE CLFFEATUREIMPORTANCES
 MAKE IMPORTANCES RELATIVE TO MAX IMPORTANCE
FEATUREIMPORTANCE 1000 FEATUREIMPORTANCE FEATUREIMPORTANCEMAX
SORTEDIDX NPARGSORTFEATUREIMPORTANCE
POS NPARANGESORTEDIDXSHAPE0 5
PLTSUBPLOT1 2 2
PLTBARHPOS FEATUREIMPORTANCESORTEDIDX ALIGNCENTER
PLTYTICKSPOS BOSTONFEATURENAMESSORTEDIDX
PLTXLABELRELATIVE IMPORTANCE
PLTTITLEVARIABLE IMPORTANCE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0416 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51212 TWOCLASS ADABOOST
THIS EXAMPLE FITS AN ADABOOSTED DECISION STUMP ON A NONLINEARLY SEPARABLE CLASSIFICATION DATASET COMPOSED OF TWO “GAUSSIAN QUANTILES” CLUSTERS SEE SKLEARNDATASETSMAKEGAUSSIANQUANTILES AND PLOTS THE DECISION BOUNDARY AND DECISION SCORES THE DISTRIBUTIONS OF DECISION SCORES ARE SHOWN SEPARATELY FOR SAMPLES OF CLASS A AND B THE PREDICTED CLASS LABEL FOR EACH SAMPLE IS DETERMINED BY THE SIGN OF THE DECISION SCORE SAMPLES WITH DECISION SCORES GREATER THAN ZERO ARE CLASSIFIED AS B AND ARE OTHERWISE CLASSIFIED AS A THE MAGNITUDE OF A DECISION SCORE DETERMINES THE DEGREE OF LIKENESS WITH THE PREDICTED CLASS LABEL ADDITIONALLY A NEW DATASET COULD BE CONSTRUCTED CONTAINING A DESIRED PURITY OF CLASS B FOR EXAMPLE BY ONLY SELECTING SAMPLES WITH A DECISION SCORE ABOVE SOME VALUE

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 AUTHOR NOEL DAWE NOELDAWEGMAILCOM

 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNENSEMBLE IMPORT ADABOOSTCLASSIFIER
FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
FROM SKLEARNDATASETS IMPORT MAKEGAUSSIANQUANTILES
 CONSTRUCT DATASET
X1 Y1 MAKEGAUSSIANQUANTILESCOV2
NSAMPLES200 NFEATURES2
NCLASSES2 RANDOMSTATE1
X2 Y2 MAKEGAUSSIANQUANTILESMEAN3 3 COV15
NSAMPLES300 NFEATURES2
NCLASSES2 RANDOMSTATE1
X NPCONCATENATEX1 X2
Y NPCONCATENATEY1 Y2 1
 CREATE AND FIT AN ADABOOSTED DECISION TREE
BDT ADABOOSTCLASSIFIERDECISIONTREECLASSIFIERMAXDEPTH1
ALGORITHMSAMME
NESTIMATORS200
BDTFITX Y
PLOTCOLORS BR
PLOTSTEP 002
CLASSNAMES AB
PLTFIGUREFIGSIZE10 5

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 PLOT THE DECISION BOUNDARIES
PLTSUBPLOT121
XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX PLOTSTEP
NPARANGEYMIN YMAX PLOTSTEP
Z BDTPREDICTNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
CS PLTCONTOURFXX YY Z CMAPPLTCMPAIRED
PLTAXISTIGHT
 PLOT THE TRAINING POINTS
FORI N C INZIPRANGE2 CLASSNAMES PLOTCOLORS
IDX NPWHEREY I
PLTSCATTERXIDX 0 XIDX 1
CC CMAPPLTCMPAIRED
S20 EDGECOLORK
LABELCLASS S N
PLTXLIMXMIN XMAX
PLTYLIMYMIN YMAX
PLTLEGENDLOCUPPER RIGHT
PLTXLABELX
PLTYLABELY
PLTTITLEDECISION BOUNDARY
 PLOT THE TWOCLASS DECISION SCORES
TWOCLASSOUTPUT BDTDECISIONFUNCTIONX
PLOTRANGE TWOCLASSOUTPUTMIN TWOCLASSOUTPUTMAX
PLTSUBPLOT122
FORI N C INZIPRANGE2 CLASSNAMES PLOTCOLORS
PLTHISTTWOCLASSOUTPUTY I
BINS10
RANGEPLOTRANGE
FACECOLORC
LABELCLASS S N
ALPHA5
EDGECOLORK
X1 X2 Y1 Y2 PLTAXIS
PLTAXISX1 X2 Y1 Y2 12
PLTLEGENDLOCUPPER RIGHT
PLTYLABELSAMPLES
PLTXLABELSCORE
PLTTITLEDECISION SCORES
PLTTIGHTLAYOUT
PLTSUBPLOTSADJUSTWSPACE035
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2255 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
1040 CHAPTER 5 EXAMPLES

51213 OOB ERRORS FOR RANDOM FORESTS
THERANDOMFORESTCLASSIFIER IS TRAINED USING BOOTSTRAP AGGREGATION WHERE EACH NEW TREE IS FIT FROM A BOOT
STRAP SAMPLE OF THE TRAINING OBSERVATIONS □□ □□ □□ THE OUTOFBAG OOB ERROR IS THE AVERAGE ERROR FOR EACH □□
CALCULATED USING PREDICTIONS FROM THE TREES THAT DO NOT CONTAIN □□IN THEIR RESPECTIVE BOOTSTRAP SAMPLE THIS ALLOWS THE
RANDOMFORESTCLASSIFIER TO BE FIT AND VALIDATED WHILST BEING TRAINED1
THE EXAMPLE BELOW DEMONSTRATES HOW THE OOB ERROR CAN BE MEASURED AT THE ADDITION OF EACH NEW TREE DURING TRAIN
ING THE RESULTING PLOT ALLOWS A PRACTITIONER TO APPROXIMATE A SUITABLE VALUE OF NESTIMATORS AT WHICH THE ERROR
STABILIZES
```
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM COLLECTIONS IMPORT ORDEREDDICT
FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
 AUTHOR KIAN HO HUIKIANHOGMAILCOM
 GILLES LOUPPE GLOUPPEGMAILCOM
 ANDREAS MUELLER AMUELLERAISUNIBONNDE

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1T HASTIE R TIBSHIRANI AND J FRIEDMAN “ELEMENTS OF STATISTICAL LEARNING ED 2” P592593 SPRINGER 2009
512 ENSEMBLE METHODS 1041
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RANDOMSTATE 123
 GENERATE A BINARY CLASSIFICATION DATASET
X Y MAKECLASSIFICATIONNSAMPLES500 NFEATURES25
NCLUSTERSPERCLASS1 NINFORMATIVE15
RANDOMSTATERANDOMSTATE
 NOTE SETTING THE WARMSTART CONSTRUCTION PARAMETER TO TRUE DISABLES
 SUPPORT FOR PARALLELIZED ENSEMBLES BUT IS NECESSARY FOR TRACKING THE OOB
 ERROR TRAJECTORY DURING TRAINING
ENSEMBLECLFS
RANDOMFORESTCLASSIFIER MAXFEATURESSQRT
RANDOMFORESTCLASSIFIERNESTIMATORS100
WARMSTARTTRUE OOBSCORETRUE
MAXFEATURESSQRT
RANDOMSTATERANDOMSTATE
RANDOMFORESTCLASSIFIER MAXFEATURESLOG2
RANDOMFORESTCLASSIFIERNESTIMATORS100
WARMSTARTTRUE MAXFEATURESLOG2
OOBSCORETRUE
RANDOMSTATERANDOMSTATE
RANDOMFORESTCLASSIFIER MAXFEATURESNONE
RANDOMFORESTCLASSIFIERNESTIMATORS100
WARMSTARTTRUE MAXFEATURESNONE
OOBSCORETRUE
RANDOMSTATERANDOMSTATE

 MAP A CLASSIFIER NAME TO A LIST OF NESTIMATORS ERROR RATE PAIRS
ERRORRATE ORDEREDDICTLABEL FORLABEL INENSEMBLECLFS
 RANGE OF NESTIMATORS VALUES TO EXPLORE
MINESTIMATORS 15
MAXESTIMATORS 175
FORLABEL CLF INENSEMBLECLFS
FORIINRANGEMINESTIMATORS MAXESTIMATORS 1
CLFSETPARAMSNESTIMATORSI
CLFFITX Y
 RECORD THE OOB ERROR FOR EACH NESTIMATORSI SETTING
OOBERROR 1 CLFOOBSCORE
ERRORRATELABELAPPENDI OOBERROR
 GENERATE THE OOB ERROR RATE VS NESTIMATORS PLOT
FORLABEL CLFERR INERRORRATEITEMS
XS YS ZIP CLFERR
PLTPLOTXS YS LABELLABEL
PLTXLIMMINESTIMATORS MAXESTIMATORS
PLTXLABELNESTIMATORS
PLTYLABELOOB ERROR RATE
PLTLEGENDLOCUPPER RIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 5517 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51214 HASHING FEATURE TRANSFORMATION USING TOTALLY RANDOM TREES
RANDOMTREESEMBEDDING PROVIDES A WAY TO MAP DATA TO A VERY HIGHDIMENSIONAL SPARSE REPRESENTATION WHICH MIGHT BE BENEFICIAL FOR CLASSIFICATION THE MAPPING IS COMPLETELY UNSUPERVISED AND VERY EFFICIENT
THIS EXAMPLE VISUALIZES THE PARTITIONS GIVEN BY SEVERAL TREES AND SHOWS HOW THE TRANSFORMATION CAN ALSO BE USED FOR NONLINEAR DIMENSIONALITY REDUCTION OR NONLINEAR CLASSIFICATION
POINTS THAT ARE NEIGHBORING OFTEN SHARE THE SAME LEAF OF A TREE AND THEREFORE SHARE LARGE PARTS OF THEIR HASHED REPRESENTATION THIS ALLOWS TO SEPARATE TWO CONCENTRIC CIRCLES SIMPLY BASED ON THE PRINCIPAL COMPONENTS OF THE TRANSFORMED DATA WITH TRUNCATED SVD
IN HIGHDIMENSIONAL SPACES LINEAR CLASSIFIERS OFTEN ACHIEVE EXCELLENT ACCURACY FOR SPARSE BINARY DATA BERNOULLINB IS PARTICULARLY WELLSUITED THE BOTTOM ROW COMPARES THE DECISION BOUNDARY OBTAINED BY BERNOULLINB IN THE TRANSFORMED SPACE WITH AN EXTRATREESCLASSIFIER FORESTS LEARNED ON THE ORIGINAL DATA

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IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKECIRCLES
FROM SKLEARNENSEMBLE IMPORT RANDOMTREESEMBEDDING EXTRATREESCLASSIFIER
FROM SKLEARNDECOMPOSITION IMPORT TRUNCATEDSVD
FROM SKLEARNNAIVEBAYES IMPORT BERNOULLINB
 MAKE A SYNTHETIC DATASET
X Y MAKECIRCLESFACTOR05 RANDOMSTATE0 NOISE005
 USE RANDOMTREESEMBEDDING TO TRANSFORM DATA
HASHER RANDOMTREESEMBEDDINGNESTIMATORS10 RANDOMSTATE0 MAXDEPTH3
XTRANSFORMED HASHERFITTRANSFORMX
 VISUALIZE RESULT AFTER DIMENSIONALITY REDUCTION USING TRUNCATED SVD
SVD TRUNCATEDSVDNCOMPONENTS2
XREDUCED SVDFITTRANSFORMXTRANSFORMED
 LEARN A NAIVE BAYES CLASSIFIER ON THE TRANSFORMED DATA
NB BERNOULLINB
NBFITXTRANSFORMED Y
 LEARN AN EXTRATREESCLASSIFIER FOR COMPARISON
TREES EXTRATREESCLASSIFIERMAXDEPTH3 NESTIMATORS10 RANDOMSTATE0
TREESFITX Y
 SCATTER PLOT OF ORIGINAL AND REDUCED DATA
FIG PLTFIGUREFIGSIZE9 8
AX PLTSUBPLOT221
AXSCATTERX 0 X 1 CY S50 EDGECOLORK
AXSETTITLEORIGINAL DATA 2D
AXSETXTICKS
AXSETYTICKS
AX PLTSUBPLOT222
AXSCATTERXREDUCED 0 XREDUCED 1 CY S50 EDGECOLORK
AXSETTITLETRUNCATED SVD REDUCTION 2D OF TRANSFORMED DATA DD
XTRANSFORMEDSHAPE1
AXSETXTICKS
AXSETYTICKS
 PLOT THE DECISION IN ORIGINAL SPACE FOR THAT WE WILL ASSIGN A COLOR
 TO EACH POINT IN THE MESH XMIN XMAXXYMIN YMAX
H 01
XMIN XMAX X 0MIN 5 X 0MAX 5
YMIN YMAX X 1MIN 5 X 1MAX 5
XX YY NPMESHGRIDNPARANGEXMIN XMAX H NPARANGEYMIN YMAX H
 TRANSFORM GRID USING RANDOMTREESEMBEDDING
TRANSFORMEDGRID HASHERTRANSFORMNPCXXRAVEL YYRAVEL
YGRIDPRED NBPREDICTPROBATRANSFORMEDGRID 1
AX PLTSUBPLOT223
AXSETTITLENAIVE BAYES ON TRANSFORMED DATA

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AXPCOLORMESHXX YY YGRIDPREDRESHAPEXXSHAPE
AXSCATTERX 0 X 1 CY S50 EDGECOLORK
AXSETYLIM14 14
AXSETXLIM14 14
AXSETXTICKS
AXSETYTICKS
 TRANSFORM GRID USING EXTRATREESCLASSIFIER
YGRIDPRED TREESPREDICTPROBANPCXXRAVEL YYRAVEL 1
AX PLTSUBPLOT224
AXSETTITLEEXTRATREES PREDICTIONS
AXPCOLORMESHXX YY YGRIDPREDRESHAPEXXSHAPE
AXSCATTERX 0 X 1 CY S50 EDGECOLORK
AXSETYLIM14 14
AXSETXLIM14 14
AXSETXTICKS
AXSETYTICKS
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0250 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51215 MULTICLASS ADABOOSTED DECISION TREES
THIS EXAMPLE REPRODUCES FIGURE 1 OF ZHU ET AL1AND SHOWS HOW BOOSTING CAN IMPROVE PREDICTION ACCURACY ON A MULTI CLASS PROBLEM THE CLASSIFICATION DATASET IS CONSTRUCTED BY TAKING A TENDIMENSIONAL STANDARD NORMAL DISTRIBUTION AND DEFINING THREE CLASSES SEPARATED BY NESTED CONCENTRIC TENDIMENSIONAL SPHERES SUCH THAT ROUGHLY EQUAL NUMBERS OF SAMPLES ARE IN EACH CLASS QUANTILES OF THE □2DISTRIBUTION
THE PERFORMANCE OF THE SAMME AND SAMMER1ALGORITHMS ARE COMPARED SAMMER USES THE PROBABILITY ESTIMATES TO UPDATE THE ADDITIVE MODEL WHILE SAMME USES THE CLASSIFICATIONS ONLY AS THE EXAMPLE ILLUSTRATES THE SAMMER ALGORITHM TYPICALLY CONVERGES FASTER THAN SAMME ACHIEVING A LOWER TEST ERROR WITH FEWER BOOSTING ITERATIONS THE ERROR OF EACH ALGORITHM ON THE TEST SET AFTER EACH BOOSTING ITERATION IS SHOWN ON THE LEFT THE CLASSIFICATION ERROR ON THE TEST SET OF EACH TREE IS SHOWN IN THE MIDDLE AND THE BOOST WEIGHT OF EACH TREE IS SHOWN ON THE RIGHT ALL TREES HAVE A WEIGHT OF ONE IN THE SAMMER ALGORITHM AND THEREFORE ARE NOT SHOWN
1
10 ZHU H ZOU S ROSSET T HASTIE “MULTICLASS ADABOOST” 2009
512 ENSEMBLE METHODS 1045

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IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKEGAUSSIANQUANTILES
FROM SKLEARNENSEMBLE IMPORT ADABOOSTCLASSIFIER
FROM SKLEARNMETRICS IMPORT ACCURACYSCORE
FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
X Y  MAKEGAUSSIANQUANTILESNSAMPLES13000 NFEATURES10
NCLASSES3 RANDOMSTATE1
NSPLIT  3000
XTRAIN XTEST  XNSPLIT XNSPLIT
YTRAIN YTEST  YNSPLIT YNSPLIT
BDTREAL  ADABOOSTCLASSIFIER
DECISIONTREECLASSIFIERMAXDEPTH2
NESTIMATORS600
LEARNINGRATE1
BDTDISCRETE  ADABOOSTCLASSIFIER
DECISIONTREECLASSIFIERMAXDEPTH2
NESTIMATORS600
LEARNINGRATE15
ALGORITHMSAMME
BDTREALFITXTRAIN YTRAIN
BDTDISCRETEFITXTRAIN YTRAIN
REALTESTERRORS
DISCRETETESTERRORS
FORREALTESTPREDICT DISCRETETRAINPREDICT INZIP
BDTREALSTAGEDPREDICTXTEST BDTDISCRETESTAGEDPREDICTXTEST
REALTESTERRORSAPPEND
1  ACCURACYSCOREREALTESTPREDICT YTEST
```

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DISCRETETESTERRORSAPPEND
1 ACCURACYSCOREDISCRETETRAINPREDICT YTEST
NTREESDISCRETE LENBDTDISCRETE
NTREESREAL LENBDTREAL
 BOOSTING MIGHT TERMINATE EARLY BUT THE FOLLOWING ARRAYS ARE ALWAYS
 NESTIMATORS LONG WE CROP THEM TO THE ACTUAL NUMBER OF TREES HERE
DISCRETEESTIMATORERRORS BDTDISCRETEESTIMATORERRORSNTREESDISCRETE
REALESTIMATORERRORS BDTREALESTIMATORERRORSNTREESREAL
DISCRETEESTIMATORWEIGHTS BDTDISCRETEESTIMATORWEIGHTSNTREESDISCRETE
PLTFIGUREFIGSIZE15 5
PLTSUBPLOT131
PLTPLOTRANGE1 NTREESDISCRETE 1
DISCRETETESTERRORS CBLACK LABELSAMME
PLTPLOTRANGE1 NTREESREAL 1
REALTESTERRORS CBLACK
LINESTYLEDASHED LABELSAMMER
PLTLEGEND
PLTYLIM018 062
PLTYLABELTEST ERROR
PLTXLABELNUMBER OF TREES
PLTSUBPLOT132
PLTPLOTRANGE1 NTREESDISCRETE 1 DISCRETEESTIMATORERRORS
B LABELSAMME ALPHA5
PLTPLOTRANGE1 NTREESREAL 1 REALESTIMATORERRORS
R LABELSAMMER ALPHA5
PLTLEGEND
PLTYLABELERROR
PLTXLABELNUMBER OF TREES
PLTYLIM2
MAXREALESTIMATORERRORSMAX
DISCRETEESTIMATORERRORSMAX 12
PLTXLIM20 LENBDTDISCRETE 20
PLTSUBPLOT133
PLTPLOTRANGE1 NTREESDISCRETE 1 DISCRETEESTIMATORWEIGHTS
B LABELSAMME
PLTLEGEND
PLTYLABELWEIGHT
PLTXLABELNUMBER OF TREES
PLTYLIM0 DISCRETEESTIMATORWEIGHTSMAX 12
PLTXLIM20 NTREESDISCRETE 20
 PREVENT OVERLAPPING YAXIS LABELS
PLTSUBPLOTSADJUSTWSPACE025
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 11401 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

51216 DISCRETE VERSUS REAL ADABOOST
THIS EXAMPLE IS BASED ON FIGURE 102 FROM HASTIE ET AL 20091AND ILLUSTRATES THE DIFFERENCE IN PERFORMANCE BETWEEN THE DISCRETE SAMME2BOOSTING ALGORITHM AND REAL SAMMER BOOSTING ALGORITHM BOTH ALGORITHMS ARE EVALUATED ON A BINARY CLASSIFICATION TASK WHERE THE TARGET Y IS A NONLINEAR FUNCTION OF 10 INPUT FEATURES
DISCRETE SAMME ADABOOST ADAPTS BASED ON ERRORS IN PREDICTED CLASS LABELS WHEREAS REAL SAMMER USES THE PRE DICTED CLASS PROBABILITIES
PRINTDOC
AUTHOR PETER PRETTENHOFER PETERPRETTENHOFERGMAILCOM
NOEL DAWE NOELDAWEGMAILCOM


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IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
FROM SKLEARNMETRICS IMPORT ZEROONELOSS
```
1T HASTIE R TIBSHIRANI AND J FRIEDMAN “ELEMENTS OF STATISTICAL LEARNING ED 2” SPRINGER 2009
2
10 ZHU H ZOU S ROSSET T HASTIE “MULTICLASS ADABOOST” 2009

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FROM SKLEARNENSEMBLE IMPORT ADABOOSTCLASSIFIER
NESTIMATORS 400
 A LEARNING RATE OF 1 MAY NOT BE OPTIMAL FOR BOTH SAMME AND SAMMER
LEARNINGRATE 1
X Y DATASETSMAKEHASTIE102NSAMPLES12000 RANDOMSTATE1
XTEST YTEST X2000 Y2000
XTRAIN YTRAIN X2000 Y2000
DTSTUMP DECISIONTREECLASSIFIERMAXDEPTH1 MINSAMPLESLEAF1
DTSTUMPFITXTRAIN YTRAIN
DTSTUMPERR 10 DTSTUMPSCOREXTEST YTEST
DT DECISIONTREECLASSIFIERMAXDEPTH9 MINSAMPLESLEAF1
DTFITXTRAIN YTRAIN
DTERR 10 DTSCOREXTEST YTEST
ADADISCRETE ADABOOSTCLASSIFIER
BASEESTIMATORDTSTUMP
LEARNINGRATELEARNINGRATE
NESTIMATORSNESTIMATORS
ALGORITHMSAMME
ADADISCRETEFITXTRAIN YTRAIN
ADAREAL ADABOOSTCLASSIFIER
BASEESTIMATORDTSTUMP
LEARNINGRATELEARNINGRATE
NESTIMATORSNESTIMATORS
ALGORITHMSAMMER
ADAREALFITXTRAIN YTRAIN
FIG PLTFIGURE
AX FIGADDSUBPLOT111
AXPLOT1 NESTIMATORS DTSTUMPERR 2 K
LABELDECISION STUMP ERROR
AXPLOT1 NESTIMATORS DTERR 2 K
LABELDECISION TREE ERROR
ADADISCRETEERR NPZEROSNESTIMATORS
FORI YPRED INENUMERATEADADISCRETESTAGEDPREDICTXTEST
ADADISCRETEERRI ZEROONELOSSYPRED YTEST
ADADISCRETEERRTRAIN NPZEROSNESTIMATORS
FORI YPRED INENUMERATEADADISCRETESTAGEDPREDICTXTRAIN
ADADISCRETEERRTRAINI ZEROONELOSSYPRED YTRAIN
ADAREALERR NPZEROSNESTIMATORS
FORI YPRED INENUMERATEADAREALSTAGEDPREDICTXTEST
ADAREALERRI ZEROONELOSSYPRED YTEST
ADAREALERRTRAIN NPZEROSNESTIMATORS
FORI YPRED INENUMERATEADAREALSTAGEDPREDICTXTRAIN
ADAREALERRTRAINI ZEROONELOSSYPRED YTRAIN

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AXPLOTNPARANGENESTIMATORS 1 ADADISCRETEERR
LABELDISCRETE ADABOOST TEST ERROR
COLORRED
AXPLOTNPARANGENESTIMATORS 1 ADADISCRETEERRTRAIN
LABELDISCRETE ADABOOST TRAIN ERROR
COLORBLUE
AXPLOTNPARANGENESTIMATORS 1 ADAREALERR
LABELREAL ADABOOST TEST ERROR
COLORORANGE
AXPLOTNPARANGENESTIMATORS 1 ADAREALERRTRAIN
LABELREAL ADABOOST TRAIN ERROR
COLORGREEN
AXSETYLIM00 05
AXSETXLABELNESTIMATORS
AXSETYLABELERROR RATE
LEG AXLEGENDLOCUPPER RIGHT FANCYBOXTRUE
LEGGETFRAMESETALPHA07
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 4579 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51217 EARLY STOPPING OF GRADIENT BOOSTING
GRADIENT BOOSTING IS AN ENSEMBLING TECHNIQUE WHERE SEVERAL WEAK LEARNERS REGRESSION TREES ARE COMBINED TO YIELD A POWERFUL SINGLE MODEL IN AN ITERATIVE FASHION
EARLY STOPPING SUPPORT IN GRADIENT BOOSTING ENABLES US TO FIND THE LEAST NUMBER OF ITERATIONS WHICH IS SUFFICIENT TO BUILD A MODEL THAT GENERALIZES WELL TO UNSEEN DATA
THE CONCEPT OF EARLY STOPPING IS SIMPLE WE SPECIFY A VALIDATIONFRACTION WHICH DENOTES THE FRACTION OF THE WHOLE DATASET THAT WILL BE KEPT ASIDE FROM TRAINING TO ASSESS THE VALIDATION LOSS OF THE MODEL THE GRADIENT BOOSTING MODEL IS TRAINED USING THE TRAINING SET AND EVALUATED USING THE VALIDATION SET WHEN EACH ADDITIONAL STAGE OF REGRESSION TREE IS ADDED THE VALIDATION SET IS USED TO SCORE THE MODEL THIS IS CONTINUED UNTIL THE SCORES OF THE MODEL IN THE LAST NITERNOCHANGE STAGES DO NOT IMPROVE BY ATLEAST TOL AFTER THAT THE MODEL IS CONSIDERED TO HAVE CONVERGED AND FURTHER ADDITION OF STAGES IS “STOPPED EARLY”
THE NUMBER OF STAGES OF THE FINAL MODEL IS AVAILABLE AT THE ATTRIBUTE NESTIMATORS
THIS EXAMPLE ILLUSTRATES HOW THE EARLY STOPPING CAN USED IN THE SKLEARNENSEMBLE GRADIENTBOOSTINGCLASSIFIER MODEL TO ACHIEVE ALMOST THE SAME ACCURACY AS COMPARED TO A MODEL BUILT WITHOUT EARLY STOPPING USING MANY FEWER ESTIMATORS THIS CAN SIGNIFICANTLY REDUCE TRAINING TIME MEMORY USAGE AND PREDICTION LATENCY
 AUTHORS VIGHNESH BIRODKAR VIGHNESHBIRODKARNYUEDU
 RAGHAV RV RVRAGHAV93GMAILCOM
 LICENSE BSD 3 CLAUSE
IMPORT TIME
IMPORT NUMPY AS NP

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IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT ENSEMBLE
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
PRINTDOC
DATALIST DATASETSLOADIRIS DATASETSLOADDIGITS
DATALIST DDATA DTARGET FORDINDATALIST
DATALIST DATASETSMAKEHASTIE102
NAMES IRIS DATA DIGITS DATA HASTIE DATA
NGB
SCOREGB
TIMEGB
NGBES
SCOREGBES
TIMEGBES
NESTIMATORS 500
FORX YINDATALIST
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y TESTSIZE02
RANDOMSTATE0
 WE SPECIFY THAT IF THE SCORES DONT IMPROVE BY ATLEAST 001 FOR THE LAST
 10 STAGES STOP FITTING ADDITIONAL STAGES
GBES ENSEMBLEGRADIENTBOOSTINGCLASSIFIERNESTIMATORSNESTIMATORS
VALIDATIONFRACTION02
NITERNOCHANGE5 TOL001
RANDOMSTATE0
GB ENSEMBLEGRADIENTBOOSTINGCLASSIFIERNESTIMATORSNESTIMATORS
RANDOMSTATE0
START TIMETIME
GBFITXTRAIN YTRAIN
TIMEGBAPPENDTIMETIME START
START TIMETIME
GBESFITXTRAIN YTRAIN
TIMEGBESAPPENDTIMETIME START
SCOREGBAPPENDGBSCOREXTEST YTEST
SCOREGBESAPPENDGBESSCOREXTEST YTEST
NGBAPPENDGBNESTIMATORS
NGBESAPPENDGBESNESTIMATORS
BARWIDTH 02
N LENDATALIST
INDEX NPARANGE0 N BARWIDTH BARWIDTH 25
INDEX INDEX0N

COMPARE SCORES WITH AND WITHOUT EARLY STOPPING
PLTFIGUREFIGSIZE9 5
BAR1 PLTBARINDEX SCOREGB BARWIDTH LABELWITHOUT EARLY STOPPING
COLORCRIMSON
BAR2 PLTBARINDEX BARWIDTH SCOREGBES BARWIDTH
LABELWITH EARLY STOPPING COLORCORAL
PLTXTICKSINDEX BARWIDTH NAMES
PLTYTICKSNPARANGE0 13 01
DEFAUTOLABELRECTS NESTIMATORS

ATTACH A TEXT LABEL ABOVE EACH BAR DISPLAYING NESTIMATORS OF EACH MODEL

FORI RECT INENUMERATERECTS
PLTTEXTRECTGETX RECTGETWIDTH 2
105RECTGETHEIGHT NEST D NESTIMATORSI
HACENTER VABOTTOM
AUTOLABELBAR1 NGB
AUTOLABELBAR2 NGBES
PLTYLIM0 13
PLTLEGENDLOCBEST
PLTGRIDTRUE
PLTXLABELDATASETS
PLTYLABELTEST SCORE
PLTSHOW

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COMPARE FIT TIMES WITH AND WITHOUT EARLY STOPPING
PLTFIGUREFIGSIZE9 5
BAR1 PLTBARINDEX TIMEGB BARWIDTH LABELWITHOUT EARLY STOPPING
COLORCRIMSON
BAR2 PLTBARINDEX BARWIDTH TIMEGBES BARWIDTH
LABELWITH EARLY STOPPING COLORCORAL
MAXY NPAMAXNPMAXIMUMTIMEGB TIMEGBES
PLTXTICKSINDEX BARWIDTH NAMES
PLTYTICKSNPLINSPACE0 13 MAXY 13
AUTOLABELBAR1 NGB
AUTOLABELBAR2 NGBES
PLTYLIM0 13 MAXY
PLTLEGENDLOCBEST
PLTGRIDTRUE
PLTXLABELDATASETS
PLTYLABELFIT TIME
PLTSHOW

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 15622 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51218 FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES
TRANSFORM YOUR FEATURES INTO A HIGHER DIMENSIONAL SPARSE SPACE THEN TRAIN A LINEAR MODEL ON THESE FEATURES
FIRST FIT AN ENSEMBLE OF TREES TOTALLY RANDOM TREES A RANDOM FOREST OR GRADIENT BOOSTED TREES ON THE TRAINING SET THEN EACH LEAF OF EACH TREE IN THE ENSEMBLE IS ASSIGNED A FIXED ARBITRARY FEATURE INDEX IN A NEW FEATURE SPACE THESE LEAF INDICES ARE THEN ENCODED IN A ONEHOT FASHION
EACH SAMPLE GOES THROUGH THE DECISIONS OF EACH TREE OF THE ENSEMBLE AND ENDS UP IN ONE LEAF PER TREE THE SAMPLE IS ENCODED BY SETTING FEATURE VALUES FOR THESE LEAVES TO 1 AND THE OTHER FEATURE VALUES TO 0
THE RESULTING TRANSFORMER HAS THEN LEARNED A SUPERVISED SPARSE HIGHDIMENSIONAL CATEGORICAL EMBEDDING OF THE DATA

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512 ENSEMBLE METHODS 1055

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AUTHOR TIM HEAD BETATIMGMAILCOM


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IMPORT NUMPY AS NP
NPRANDOMSEED10
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARNENSEMBLE IMPORT RANDOMTREESEMBEDDING RANDOMFORESTCLASSIFIER
GRADIENTBOOSTINGCLASSIFIER
FROM SKLEARNPREPROCESSING IMPORT ONEHOTENCODER
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNMETRICS IMPORT ROCCURVE
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
NESTIMATOR  10
X Y  MAKECLASSIFICATIONNSAMPLES80000
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLITX Y TESTSIZE05
 IT IS IMPORTANT TO TRAIN THE ENSEMBLE OF TREES ON A DIFFERENT SUBSET
 OF THE TRAINING DATA THAN THE LINEAR REGRESSION MODEL TO AVOID
 OVERFITTING IN PARTICULAR IF THE TOTAL NUMBER OF LEAVES IS
 SIMILAR TO THE NUMBER OF TRAINING SAMPLES
XTRAIN XTRAINLR YTRAIN YTRAINLR  TRAINTESTSPLIT
```

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XTRAIN YTRAIN TESTSIZE05
 UNSUPERVISED TRANSFORMATION BASED ON TOTALLY RANDOM TREES
RT RANDOMTREESEMBEDDINGMAXDEPTH3 NESTIMATORSNESTIMATOR
RANDOMSTATE0
RTLM LOGISTICREGRESSIONSOLVERLBFGS MAXITER1000
PIPELINE MAKEPIPELINERT RTLM
PIPELINEFITXTRAIN YTRAIN
YPREDRT PIPELINEPREDICTPROBAXTEST 1
FPRRTLM TPRRTLM   ROCCURVEYTEST YPREDRT
 SUPERVISED TRANSFORMATION BASED ON RANDOM FORESTS
RF RANDOMFORESTCLASSIFIERMAXDEPTH3 NESTIMATORSNESTIMATOR
RFENC ONEHOTENCODERCATEGORIESAUTO
RFLM LOGISTICREGRESSIONSOLVERLBFGS MAXITER1000
RFFITXTRAIN YTRAIN
RFENCFITRFAPPLYXTRAIN
RFLMFITRFENCTRANSFORMRFAPPLYXTRAINLR YTRAINLR
YPREDRFLM RFLMPREDICTPROBARFENCTRANSFORMRFAPPLYXTEST 1
FPRRFLM TPRRFLM   ROCCURVEYTEST YPREDRFLM
 SUPERVISED TRANSFORMATION BASED ON GRADIENT BOOSTED TREES
GRD GRADIENTBOOSTINGCLASSIFIERNESTIMATORSNESTIMATOR
GRDENC ONEHOTENCODERCATEGORIESAUTO
GRDLM LOGISTICREGRESSIONSOLVERLBFGS MAXITER1000
GRDFITXTRAIN YTRAIN
GRDENCFITGRDAPPLYXTRAIN 0
GRDLMFITGRDENCTRANSFORMGRDAPPLYXTRAINLR 0 YTRAINLR
YPREDGRDLM GRDLMPREDICTPROBA
GRDENCTRANSFORMGRDAPPLYXTEST 0 1
FPRGRDLM TPRGRDLM   ROCCURVEYTEST YPREDGRDLM
 THE GRADIENT BOOSTED MODEL BY ITSELF
YPREDGRD GRDPREDICTPROBAXTEST 1
FPRGRD TPRGRD   ROCCURVEYTEST YPREDGRD
 THE RANDOM FOREST MODEL BY ITSELF
YPREDRF RFPREDICTPROBAXTEST 1
FPRRF TPRRF   ROCCURVEYTEST YPREDRF
PLTFIGURE1
PLTPLOT0 1 0 1 K
PLTPLOTFPRRTLM TPRRTLM LABELRT LR
PLTPLOTFPRRF TPRRF LABELRF
PLTPLOTFPRRFLM TPRRFLM LABELRF LR
PLTPLOTFPRGRD TPRGRD LABELGBT
PLTPLOTFPRGRDLM TPRGRDLM LABELGBT LR
PLTXLABELFALSE POSITIVE RATE
PLTYLABELTRUE POSITIVE RATE
PLTTITLEROC CURVE
PLTLEGENDLOCBEST
PLTSHOW
PLTFIGURE2
PLTXLIM0 02

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PLTYLIM08 1
PLTPLOT0 1 0 1 K
PLTPLOTFPRRTLM TPRRTLM LABELRT LR
PLTPLOTFPRRF TPRRF LABELRF
PLTPLOTFPRRFLM TPRRFLM LABELRF LR
PLTPLOTFPRGRD TPRGRD LABELGBT
PLTPLOTFPRGRDLM TPRGRDLM LABELGBT LR
PLTXLABELFALSE POSITIVE RATE
PLTYLABELTRUE POSITIVE RATE
PLTTITLEROC CURVE ZOOMED IN AT TOP LEFT
PLTLEGENDLOCBEST
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2261 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51219 GRADIENT BOOSTING OUTOFBAG ESTIMATES
OUTOFBAG OOB ESTIMATES CAN BE A USEFUL HEURISTIC TO ESTIMATE THE “OPTIMAL” NUMBER OF BOOSTING ITERATIONS OOB ESTIMATES ARE ALMOST IDENTICAL TO CROSSVALIDATION ESTIMATES BUT THEY CAN BE COMPUTED ONTHEFLY WITHOUT THE NEED FOR REPEATED MODEL FITTING OOB ESTIMATES ARE ONLY AVAILABLE FOR STOCHASTIC GRADIENT BOOSTING IE SUBSAMPLE 1
0 THE ESTIMATES ARE DERIVED FROM THE IMPROVEMENT IN LOSS BASED ON THE EXAMPLES NOT INCLUDED IN THE BOOTSTRAP SAMPLE THE SOCALLED OUTOFBAG EXAMPLES THE OOB ESTIMATOR IS A PESSIMISTIC ESTIMATOR OF THE TRUE TEST LOSS BUT REMAINS A FAIRLY GOOD APPROXIMATION FOR A SMALL NUMBER OF TREES
THE FIGURE SHOWS THE CUMULATIVE SUM OF THE NEGATIVE OOB IMPROVEMENTS AS A FUNCTION OF THE BOOSTING ITERATION AS YOU CAN SEE IT TRACKS THE TEST LOSS FOR THE FIRST HUNDRED ITERATIONS BUT THEN DIVERGES IN A PESSIMISTIC WAY THE FIGURE ALSO SHOWS THE PERFORMANCE OF 3FOLD CROSS VALIDATION WHICH USUALLY GIVES A BETTER ESTIMATE OF THE TEST LOSS BUT IS COMPUTATIONALLY MORE DEMANDING
1058 CHAPTER 5 EXAMPLES

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OUT
ACCURACY 06840
PRINTDOC
 AUTHOR PETER PRETTENHOFER PETERPRETTENHOFERGMAILCOM

 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT ENSEMBLE
FROM SKLEARNMODELSELECTION IMPORT KFOLD
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SCIPYSPECIAL IMPORT EXPIT
 GENERATE DATA ADAPTED FROM G RIDGEWAYS GBM EXAMPLE
NSAMPLES 1000

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RANDOMSTATE NPRANDOMRANDOMSTATE13
X1 RANDOMSTATEUNIFORMSIZENSAMPLES
X2 RANDOMSTATEUNIFORMSIZENSAMPLES
X3 RANDOMSTATERANDINT0 4 SIZENSAMPLES
P EXPITNPSIN3 X1 4 X2 X3
Y RANDOMSTATEBINOMIAL1 P SIZENSAMPLES
X NPCX1 X2 X3
X XASTYPENPFLOAT32
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y TESTSIZE05
RANDOMSTATE9
 FIT CLASSIFIER WITH OUTOFBAG ESTIMATES
PARAMS NESTIMATORS 1200 MAXDEPTH 3 SUBSAMPLE 05
LEARNINGRATE 001 MINSAMPLESLEAF 1 RANDOMSTATE 3
CLF ENSEMBLEGRADIENTBOOSTINGCLASSIFIER PARAMS
CLFFITXTRAIN YTRAIN
ACC CLFSCOREXTEST YTEST
PRINTACCURACY 4FFORMATACC
NESTIMATORS PARAMSNESTIMATORS
X NPARANGENESTIMATORS 1
DEFHELDOUTSCORECLF XTEST YTEST
COMPUTE DEVIANCE SCORES ON XTEST AND YTEST
SCORE NPZEROSNESTIMATORS DTYPENPFLOAT64
FORI YPRED INENUMERATECLFSTAGEDDECISIONFUNCTIONXTEST
SCOREI CLFLOSSYTEST YPRED
RETURNSCORE
DEFCVESTIMATENSPLITSNONE
CV KFOLDNSPLITSNSPLITS
CVCLF ENSEMBLEGRADIENTBOOSTINGCLASSIFIER PARAMS
VALSCORES NPZEROSNESTIMATORS DTYPENPFLOAT64
FORTRAIN TEST INCVSPLITXTRAIN YTRAIN
CVCLFFITXTRAINTRAIN YTRAINTRAIN
VALSCORES HELDOUTSCORECVCLF XTRAINTEST YTRAINTEST
VALSCORES NSPLITS
RETURNVALSCORES
 ESTIMATE BEST NESTIMATOR USING CROSSVALIDATION
CVSCORE CVESTIMATE3
 COMPUTE BEST NESTIMATOR FOR TEST DATA
TESTSCORE HELDOUTSCORECLF XTEST YTEST
 NEGATIVE CUMULATIVE SUM OF OOB IMPROVEMENTS
CUMSUM NPCUMSUMCLFOOBIMPROVEMENT
 MIN LOSS ACCORDING TO OOB
OOBBESTITER XNPARGMINCUMSUM
1060 CHAPTER 5 EXAMPLES

```
 MIN LOSS ACCORDING TO TEST NORMALIZE SUCH THAT FIRST LOSS IS 0
TESTSCORE  TESTSCORE0
TESTBESTITER  XNPARGMINTESTSCORE
 MIN LOSS ACCORDING TO CV NORMALIZE SUCH THAT FIRST LOSS IS 0
CVSCORE  CVSCORE0
CVBESTITER  XNPARGMINCVSCORE
 COLOR BREW FOR THE THREE CURVES
OOBCOLOR  LISTMAP LAMBDAX X  2560 190 174 212
TESTCOLOR  LISTMAP LAMBDAX X  2560 127 201 127
CVCOLOR  LISTMAP LAMBDAX X  2560 253 192 134
 PLOT CURVES AND VERTICAL LINES FOR BEST ITERATIONS
PLTPLOTX CUMSUM LABELOOB LOSS COLOROOBCOLOR
PLTPLOTX TESTSCORE LABELTEST LOSS COLORTESTCOLOR
PLTPLOTX CVSCORE LABELCV LOSS COLORCVCOLOR
PLTAXVLINEXOOBBESTITER COLOROOBCOLOR
PLTAXVLINEXTESTBESTITER COLORTESTCOLOR
PLTAXVLINEXCVBESTITER COLORCVCOLOR
 ADD THREE VERTICAL LINES TO XTICKS
XTICKS  PLTXTICKS
XTICKSPOS  NPARRAYXTICKS0TOLIST
OOBBESTITER CVBESTITER TESTBESTITER
XTICKSLABEL  NPARRAYLISTMAP LAMBDAT INTT XTICKS0
OOB CV TEST
IND  NPARGSORTXTICKSPOS
XTICKSPOS  XTICKSPOSIND
XTICKSLABEL  XTICKSLABELIND
PLTXTICKSXTICKSPOS XTICKSLABEL
PLTLEGENDLOCUPPER RIGHT
PLTYLABELNORMALIZED LOSS
PLTXLABELNUMBER OF ITERATIONS
PLTSHOW
```
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2759 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51220 SINGLE ESTIMATOR VERSUS BAGGING BIASVARIANCE DECOMPOSITION
THIS EXAMPLE ILLUSTRATES AND COMPARES THE BIASVARIANCE DECOMPOSITION OF THE EXPECTED MEAN SQUARED ERROR OF A SINGLE ESTIMATOR AGAINST A BAGGING ENSEMBLE
IN REGRESSION THE EXPECTED MEAN SQUARED ERROR OF AN ESTIMATOR CAN BE DECOMPOSED IN TERMS OF BIAS VARIANCE AND NOISE ON AVERAGE OVER DATASETS OF THE REGRESSION PROBLEM THE BIAS TERM MEASURES THE AVERAGE AMOUNT BY WHICH THE PREDICTIONS OF THE ESTIMATOR DIFFER FROM THE PREDICTIONS OF THE BEST POSSIBLE ESTIMATOR FOR THE PROBLEM IE THE BAYES MODEL THE VARIANCE TERM MEASURES THE VARIABILITY OF THE PREDICTIONS OF THE ESTIMATOR WHEN FIT OVER DIFFERENT INSTANCES LS OF THE PROBLEM FINALLY THE NOISE MEASURES THE IRREDUCIBLE PART OF THE ERROR WHICH IS DUE THE VARIABILITY IN THE DATA
THE UPPER LEFT FIGURE ILLUSTRATES THE PREDICTIONS IN DARK RED OF A SINGLE DECISION TREE TRAINED OVER A RANDOM DATASET LS THE BLUE DOTS OF A TOY 1D REGRESSION PROBLEM IT ALSO ILLUSTRATES THE PREDICTIONS IN LIGHT RED OF OTHER SINGLE DECISION

TREES TRAINED OVER OTHER AND DIFFERENT RANDOMLY DRAWN INSTANCES LS OF THE PROBLEM INTUITIVELY THE VARIANCE TERM HERE CORRESPONDS TO THE WIDTH OF THE BEAM OF PREDICTIONS IN LIGHT RED OF THE INDIVIDUAL ESTIMATORS THE LARGER THE VARIANCE THE MORE SENSITIVE ARE THE PREDICTIONS FOR XTO SMALL CHANGES IN THE TRAINING SET THE BIAS TERM CORRESPONDS TO THE DIFFERENCE BETWEEN THE AVERAGE PREDICTION OF THE ESTIMATOR IN CYAN AND THE BEST POSSIBLE MODEL IN DARK BLUE ON THIS PROBLEM WE CAN THUS OBSERVE THAT THE BIAS IS QUITE LOW BOTH THE CYAN AND THE BLUE CURVES ARE CLOSE TO EACH OTHER WHILE THE VARIANCE IS LARGE THE RED BEAM IS RATHER WIDE

THE LOWER LEFT FIGURE PLOTS THE POINTWISE DECOMPOSITION OF THE EXPECTED MEAN SQUARED ERROR OF A SINGLE DECISION TREE IT CONFIRMS THAT THE BIAS TERM IN BLUE IS LOW WHILE THE VARIANCE IS LARGE IN GREEN IT ALSO ILLUSTRATES THE NOISE PART OF THE ERROR WHICH AS EXPECTED APPEARS TO BE CONSTANT AND AROUND 001

THE RIGHT FIGURES CORRESPOND TO THE SAME PLOTS BUT USING INSTEAD A BAGGING ENSEMBLE OF DECISION TREES IN BOTH FIGURES WE CAN OBSERVE THAT THE BIAS TERM IS LARGER THAN IN THE PREVIOUS CASE IN THE UPPER RIGHT FIGURE THE DIFFERENCE BETWEEN THE AVERAGE PREDICTION IN CYAN AND THE BEST POSSIBLE MODEL IS LARGER EG NOTICE THE OFFSET AROUND X2 IN THE LOWER RIGHT FIGURE THE BIAS CURVE IS ALSO SLIGHTLY HIGHER THAN IN THE LOWER LEFT FIGURE IN TERMS OF VARIANCE HOWEVER THE BEAM OF PREDICTIONS IS NARROWER WHICH SUGGESTS THAT THE VARIANCE IS LOWER INDEED AS THE LOWER RIGHT FIGURE CONFIRMS THE VARIANCE TERM IN GREEN IS LOWER THAN FOR SINGLE DECISION TREES OVERALL THE BIAS VARIANCE DECOMPOSITION IS THEREFORE NO LONGER THE SAME THE TRADEOFF IS BETTER FOR BAGGING AVERAGING SEVERAL DECISION TREES FIT ON BOOTSTRAP COPIES OF THE DATASET SLIGHTLY INCREASES THE BIAS TERM BUT ALLOWS FOR A LARGER REDUCTION OF THE VARIANCE WHICH RESULTS IN A LOWER OVERALL MEAN SQUARED ERROR COMPARE THE RED CURVES INT THE LOWER FIGURES THE SCRIPT OUTPUT ALSO CONFIRMS THIS INTUITION THE TOTAL ERROR OF THE BAGGING ENSEMBLE IS LOWER THAN THE TOTAL ERROR OF A SINGLE DECISION TREE AND THIS DIFFERENCE INDEED MAINLY STEMS FROM A REDUCED VARIANCE

FOR FURTHER DETAILS ON BIASVARIANCE DECOMPOSITION SEE SECTION 73 OF1

1T HASTIE R TIBSHIRANI AND J FRIEDMAN “ELEMENTS OF STATISTICAL LEARNING” SPRINGER 2009

REFERENCES
OUT
TREE 00255 ERROR 00003 BIAS2 00152 VAR 00098 NOISE
BAGGINGTREE 00196 ERROR 00004 BIAS2 00092 VAR 00098 NOISE
PRINTDOC
 AUTHOR GILLES LOUPPE GLOUPPEGMAILCOM
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNENSEMBLE IMPORT BAGGINGREGRESSOR
FROM SKLEARNTREE IMPORT DECISIONTREEREGRESSOR

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```
 SETTINGS
NREPEAT  50  NUMBER OF ITERATIONS FOR COMPUTING EXPECTATIONS
NTRAIN  50  SIZE OF THE TRAINING SET
NTEST  1000  SIZE OF THE TEST SET
NOISE  01  STANDARD DEVIATION OF THE NOISE
NPRANDOMSEED0
 CHANGE THIS FOR EXPLORING THE BIASVARIANCE DECOMPOSITION OF OTHER
 ESTIMATORS THIS SHOULD WORK WELL FOR ESTIMATORS WITH HIGH VARIANCE EG
 DECISION TREES OR KNN BUT POORLY FOR ESTIMATORS WITH LOW VARIANCE EG
 LINEAR MODELS
ESTIMATORS  TREE DECISIONTREEREGRESSOR
BAGGINGTREE BAGGINGREGRESSORDECISIONTREEREGRESSOR
NESTIMATORS  LENESTIMATORS
 GENERATE DATA
DEFFX
X  XRAVEL
RETURNNPEXPX 2  15 NPEXPX  2 2
DEFGENERATENSAMPLES NOISE NREPEAT1
X  NPRANDOMRANDNSAMPLES 10  5
X  NPSORTX
IFNREPEAT  1
Y  FX  NPRANDOMNORMAL00 NOISE NSAMPLES
ELSE
Y  NPZEROSNSAMPLES NREPEAT
FORIINRANGENREPEAT
Y I  FX  NPRANDOMNORMAL00 NOISE NSAMPLES
X  XRESHAPENSAMPLES 1
RETURNX Y
XTRAIN
YTRAIN
FORIINRANGENREPEAT
X Y  GENERATENSAMPLESNTRAIN NOISENOISE
XTRAINAPPENDX
YTRAINAPPENDY
XTEST YTEST  GENERATENSAMPLESNTEST NOISENOISE NREPEATNREPEAT
PLTFIGUREFIGSIZE10 8
 LOOP OVER ESTIMATORS TO COMPARE
FORN NAME ESTIMATOR INENUMERATEESTIMATORS
 COMPUTE PREDICTIONS
YPREDICT  NPZEROSNTEST NREPEAT
```

```
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FORIINRANGENREPEAT
ESTIMATORFITXTRAINI YTRAINI
YPREDICT I  ESTIMATORPREDICTXTEST
 BIAS2  VARIANCE  NOISE DECOMPOSITION OF THE MEAN SQUARED ERROR
YERROR  NPZEROSNTEST
FORIINRANGENREPEAT
FORJINRANGENREPEAT
YERROR  YTEST J  YPREDICT I 2
YERROR  NREPEAT NREPEAT
YNOISE  NPVARYTEST AXIS1
YBIAS  FXTEST  NPMEANYPREDICT AXIS1 2
YVAR  NPVARYPREDICT AXIS1
PRINT0 14F ERROR  24F BIAS2
  34F VAR  44F NOISEFORMATNAME
NPMEANYERROR
NPMEANYBIAS
NPMEANYVAR
NPMEANYNOISE
 PLOT FIGURES
PLTSUBPLOT2 NESTIMATORS N  1
PLTPLOTXTEST FXTEST B LABELFX
PLTPLOTXTRAIN0 YTRAIN0 B LABELLS  Y  FXNOISE
FORIINRANGENREPEAT
IFI  0
PLTPLOTXTEST YPREDICT I R LABELRYX
ELSE
PLTPLOTXTEST YPREDICT I R ALPHA005
PLTPLOTXTEST NPMEANYPREDICT AXIS1 C
LABELRMATHBBELS YX
PLTXLIM5 5
PLTTITLENAME
IFN  NESTIMATORS  1
PLTLEGENDLOC11 5
PLTSUBPLOT2 NESTIMATORS NESTIMATORS  N  1
PLTPLOTXTEST YERROR R LABELERRORX
PLTPLOTXTEST YBIAS B LABELBIAS2X
PLTPLOTXTEST YVAR G LABELVARIANCEX
PLTPLOTXTEST YNOISE C LABELNOISEX
PLTXLIM5 5
PLTYLIM0 01
IFN  NESTIMATORS  1
PLTLEGENDLOC11 5
PLTSUBPLOTSADJUSTRIGHT75
512 ENSEMBLE METHODS 1065
```

PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0515 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51221 PLOT THE DECISION SURFACES OF ENSEMBLES OF TREES ON THE IRIS DATASET
PLOT THE DECISION SURFACES OF FORESTS OF RANDOMIZED TREES TRAINED ON PAIRS OF FEATURES OF THE IRIS DATASET
THIS PLOT COMPARES THE DECISION SURFACES LEARNED BY A DECISION TREE CLASSIFIER FIRST COLUMN BY A RANDOM FOREST CLASSI FIER SECOND COLUMN BY AN EXTRA TREES CLASSIFIER THIRD COLUMN AND BY AN ADABOOST CLASSIFIER FOURTH COLUMN
IN THE FIRST ROW THE CLASSIFIERS ARE BUILT USING THE SEPAL WIDTH AND THE SEPAL LENGTH FEATURES ONLY ON THE SECOND ROW USING THE PETAL LENGTH AND SEPAL LENGTH ONLY AND ON THE THIRD ROW USING THE PETAL WIDTH AND THE PETAL LENGTH ONLY
IN DESCENDING ORDER OF QUALITY WHEN TRAINED OUTSIDE OF THIS EXAMPLE ON ALL 4 FEATURES USING 30 ESTIMATORS AND SCORED USING 10 FOLD CROSS VALIDATION WE SEE
EXTRATREESCLASSIFIER 095 SCORE
RANDOMFORESTCLASSIFIER 094 SCORE
ADABOOSTDECISIONTREEMAXDEPTH3 094 SCORE
DECISIONTREEMAXDEPTH NONE 094 SCORE
INCREASING MAXDEPTH FOR ADABOOST LOWERS THE STANDARD DEVIATION OF THE SCORES BUT THE AVERAGE SCORE DOES NOT IMPROVE
SEE THE CONSOLE’S OUTPUT FOR FURTHER DETAILS ABOUT EACH MODEL
IN THIS EXAMPLE YOU MIGHT TRY TO
1 VARY THE MAXDEPTH FOR THE DECISIONTREECLASSIFIER ANDADABOOSTCLASSIFIER
PERHAPS TRY MAXDEPTH3 FOR THEDECISIONTREECLASSIFIER ORMAXDEPTHNONE FOR ADABOOSTCLASSIFIER
2 VARYNESTIMATORS
IT IS WORTH NOTING THAT RANDOMFORESTS AND EXTRATREES CAN BE FITTED IN PARALLEL ON MANY CORES AS EACH TREE IS BUILT INDEPENDENTLY OF THE OTHERS ADABOOST’S SAMPLES ARE BUILT SEQUENTIALLY AND SO DO NOT USE MULTIPLE CORES

OUT
DECISIONTREE WITH FEATURES 0 1 HAS A SCORE OF 09266666666666666
RANDOMFOREST WITH 30 ESTIMATORS WITH FEATURES 0 1 HAS A SCORE OF 09266666666666666
EXTRATREES WITH 30 ESTIMATORS WITH FEATURES 0 1 HAS A SCORE OF 09266666666666666
ADABOOST WITH 30 ESTIMATORS WITH FEATURES 0 1 HAS A SCORE OF 084
DECISIONTREE WITH FEATURES 0 2 HAS A SCORE OF 09933333333333333
RANDOMFOREST WITH 30 ESTIMATORS WITH FEATURES 0 2 HAS A SCORE OF 09933333333333333
EXTRATREES WITH 30 ESTIMATORS WITH FEATURES 0 2 HAS A SCORE OF 09933333333333333
ADABOOST WITH 30 ESTIMATORS WITH FEATURES 0 2 HAS A SCORE OF 09933333333333333
DECISIONTREE WITH FEATURES 2 3 HAS A SCORE OF 09933333333333333
RANDOMFOREST WITH 30 ESTIMATORS WITH FEATURES 2 3 HAS A SCORE OF 09933333333333333
EXTRATREES WITH 30 ESTIMATORS WITH FEATURES 2 3 HAS A SCORE OF 09933333333333333
ADABOOST WITH 30 ESTIMATORS WITH FEATURES 2 3 HAS A SCORE OF 09933333333333333
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBCOLORS IMPORT LISTEDCOLORMAP

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FROM SKLEARNDATASETS IMPORT LOADIRIS
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER EXTRATREESCLASSIFIER
ADABOOSTCLASSIFIER
FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
 PARAMETERS
NCLASSES 3
NESTIMATORS 30
CMAP PLTCMRDYLBU
PLOTSTEP 002 FINE STEP WIDTH FOR DECISION SURFACE CONTOURS
PLOTSTEPCOARSER 05 STEP WIDTHS FOR COARSE CLASSIFIER GUESSES
RANDOMSEED 13 FIX THE SEED ON EACH ITERATION
 LOAD DATA
IRIS LOADIRIS
PLOTIDX 1
MODELS DECISIONTREECLASSIFIERMAXDEPTHNONE
RANDOMFORESTCLASSIFIERNESTIMATORSNESTIMATORS
EXTRATREESCLASSIFIERNESTIMATORSNESTIMATORS
ADABOOSTCLASSIFIERDECISIONTREECLASSIFIERMAXDEPTH3
NESTIMATORSNESTIMATORS
FORPAIRIN0 1 0 2 2 3
FORMODELINMODELS
 WE ONLY TAKE THE TWO CORRESPONDING FEATURES
X IRISDATA PAIR
Y IRISTARGET
 SHUFFLE
IDX NPARANGEXSHAPE0
NPRANDOMSEEDRANDOMSEED
NPRANDOMSHUFFLEIDX
X XIDX
Y YIDX
 STANDARDIZE
MEAN XMEANAXIS0
STD XSTDAXIS0
X X MEAN STD
 TRAIN
MODELFITX Y
SCORES MODELSCOREX Y
 CREATE A TITLE FOR EACH COLUMN AND THE CONSOLE BY USING STR AND
 SLICING AWAY USELESS PARTS OF THE STRING
MODELTITLE STRTYPEMODELSPLIT
12LENCLASSIFIER
MODELDETAILS MODELTITLE
IFHASATTRMODEL ESTIMATORS
MODELDETAILS   WITH ESTIMATORSFORMAT
LENMODELESTIMATORS
PRINTMODELDETAILS   WITH FEATURES PAIR
HAS A SCORE OF SCORES

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PLTSUBPLOT3 4 PLOTIDX
IFPLOTIDX LENMODELS
 ADD A TITLE AT THE TOP OF EACH COLUMN
PLTTITLEMODELTITLE FONTSIZE9
 NOW PLOT THE DECISION BOUNDARY USING A FINE MESH AS INPUT TO A
 FILLED CONTOUR PLOT
XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX PLOTSTEP
NPARANGEYMIN YMAX PLOTSTEP
 PLOT EITHER A SINGLE DECISIONTREECLASSIFIER OR ALPHA BLEND THE
 DECISION SURFACES OF THE ENSEMBLE OF CLASSIFIERS
IFISINSTANCEMODEL DECISIONTREECLASSIFIER
Z MODELPREDICTNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
CS PLTCONTOURFXX YY Z CMAPCMAP
ELSE
 CHOOSE ALPHA BLEND LEVEL WITH RESPECT TO THE NUMBER
 OF ESTIMATORS
 THAT ARE IN USE NOTING THAT ADABOOST CAN USE FEWER ESTIMATORS
 THAN ITS MAXIMUM IF IT ACHIEVES A GOOD ENOUGH FIT EARLY ON
ESTIMATORALPHA 10 LENMODELESTIMATORS
FORTREEINMODELESTIMATORS
Z TREEPREDICTNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
CS PLTCONTOURFXX YY Z ALPHAESTIMATORALPHA CMAPCMAP
 BUILD A COARSER GRID TO PLOT A SET OF ENSEMBLE CLASSIFICATIONS
 TO SHOW HOW THESE ARE DIFFERENT TO WHAT WE SEE IN THE DECISION
 SURFACES THESE POINTS ARE REGULARLY SPACE AND DO NOT HAVE A
 BLACK OUTLINE
XXCOARSER YYCOARSER NPMESHGRID
NPARANGEXMIN XMAX PLOTSTEPCOARSER
NPARANGEYMIN YMAX PLOTSTEPCOARSER
ZPOINTSCOARSER MODELPREDICTNPCXXCOARSERRAVEL
YYCOARSERRAVEL
RESHAPEXXCOARSERSHAPE
CSPOINTS PLTSCATTERXXCOARSER YYCOARSER S15
CZPOINTSCOARSER CMAPCMAP
EDGECOLORSNONE
 PLOT THE TRAINING POINTS THESE ARE CLUSTERED TOGETHER AND HAVE A
 BLACK OUTLINE
PLTSCATTERX 0 X 1 CY
CMAPLISTEDCOLORMAPR Y B
EDGECOLORK S20
PLOTIDX 1 MOVE ON TO THE NEXT PLOT IN SEQUENCE
PLTSUPTITLECLASSIFIERS ON FEATURE SUBSETS OF THE IRIS DATASET FONTSIZE12
PLTAXISTIGHT
PLTTIGHTLAYOUTHPAD02 WPAD02 PAD25
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 6177 SECONDS

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513 TUTORIAL EXERCISES
EXERCISES FOR THE TUTORIALS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5131 DIGITS CLASSIFICATION EXERCISE
A TUTORIAL EXERCISE REGARDING THE USE OF CLASSIFICATION TECHNIQUES ON THE DIGITS DATASET
THIS EXERCISE IS USED IN THE CLASSIFICATION PART OF THE SUPERVISED LEARNING PREDICTING AN OUTPUT VARIABLE FROM HIGH DIMENSIONAL OBSERVATIONS SECTION OF THE A TUTORIAL ON STATISTICALLEARNING FOR SCIENTIFIC DATA PROCESSING
OUT
KNN SCORE 0961111
LOGISTICREGRESSION SCORE 0933333
PRINTDOC
FROM SKLEARN IMPORT DATASETS NEIGHBORS LINEARMODEL
DIGITS DATASETSLOADDIGITS
XDIGITS DIGITSDATA DIGITSDATAMAX
YDIGITS DIGITSTARGET
NSAMPLES LENXDIGITS
XTRAIN XDIGITSINT9 NSAMPLES
YTRAIN YDIGITSINT9 NSAMPLES
XTEST XDIGITSINT9 NSAMPLES
YTEST YDIGITSINT9 NSAMPLES
KNN NEIGHBORSKNEIGHBORSCLASSIFIER
LOGISTIC LINEARMODELLOGISTICREGRESSIONSOLVERLBFGS MAXITER1000
MULTICLASSMULTINOMIAL
PRINTKNN SCORE F KNNFITXTRAIN YTRAINSCOREXTEST YTEST
PRINTLOGISTICREGRESSION SCORE F
 LOGISTICFITXTRAIN YTRAINSCOREXTEST YTEST
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0432 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
1070 CHAPTER 5 EXAMPLES

5132 CROSSVALIDATION ON DIGITS DATASET EXERCISE
A TUTORIAL EXERCISE USING CROSSVALIDATION WITH AN SVM ON THE DIGITS DATASET
THIS EXERCISE IS USED IN THE CROSSVALIDATION GENERATORS PART OF THE MODEL SELECTION CHOOSING ESTIMATORS AND THEIR PARAMETERS SECTION OF THE A TUTORIAL ON STATISTICALLEARNING FOR SCIENTIFIC DATA PROCESSING

```
PRINTDOC
IMPORT NUMPY AS NP
FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
FROM SKLEARN IMPORT DATASETS SVM
DIGITS  DATASETSLOADDIGITS
X  DIGITSDATA
Y  DIGITSTARGET
SVC  SVMSVCKERNELLINEAR
CS  NPLOGSPACE10 0 10
SCORES  LIST
SCORESSTD  LIST
FORCINCS
SVCC  C
THISSCORES  CROSSVALSCORESVC X Y CV5 NJOBS1
```

SCIKITLEARN USER GUIDE RELEASE 0213
SCORESAPPENDNPMEANTHISSCORES
SCORESSTDAPPENDNPSTDTHISSCORES
 DO THE PLOTTING
IMPORT MATPLOTLIBPYPLOT AS PLT
PLTFIGURE
PLTSEMILOGXCS SCORES
PLTSEMILOGXCS NPARRAYSCORES NPARRAYSCORESSTD B
PLTSEMILOGXCS NPARRAYSCORES NPARRAYSCORESSTD B
LOCS LABELS PLTYTICKS
PLTYTICKSLOCS LISTMAP LAMBDAX G X LOCS
PLTYLABELCV SCORE
PLTXLABELPARAMETER C
PLTYLIM0 11
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 8826 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5133 SVM EXERCISE
A TUTORIAL EXERCISE FOR USING DIFFERENT SVM KERNELS
THIS EXERCISE IS USED IN THE USING KERNELS PART OF THE SUPERVISED LEARNING PREDICTING AN OUTPUT VARIABLE FROM HIGH DIMENSIONAL OBSERVATIONS SECTION OF THE A TUTORIAL ON STATISTICALLEARNING FOR SCIENTIFIC DATA PROCESSING

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•

```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS SVM
IRIS  DATASETSLOADIRIS
X  IRISDATA
Y  IRISTARGET
X  XY  0 2
Y  YY  0
NSAMPLE  LENX
NPRANDOMSEED0
ORDER  NPRANDOMPERMUTATIONNSAMPLE
X  XORDER
Y  YORDERASTYPENPFLOAT
XTRAIN  XINT9 NSAMPLE
YTRAIN  YINT9 NSAMPLE
XTEST  XINT9 NSAMPLE
YTEST  YINT9 NSAMPLE
 FIT THE MODEL
```

513 TUTORIAL EXERCISES 1075

SCIKITLEARN USER GUIDE RELEASE 0213
FORKERNELINLINEAR RBF POLY
CLF SVMSVCKERNELKERNEL GAMMA10
CLFFITXTRAIN YTRAIN
PLTFIGURE
PLTCLF
PLTSCATTERX 0 X 1 CY ZORDER10 CMAPPLTCMPAIRED
EDGECOLORK S20
 CIRCLE OUT THE TEST DATA
PLTSCATTERXTEST 0 XTEST 1 S80 FACECOLORSNONE
ZORDER10 EDGECOLORK
PLTAXISTIGHT
XMIN X 0MIN
XMAX X 0MAX
YMIN X 1MIN
YMAX X 1MAX
XX YY NPMGRIDXMINXMAX200J YMINYMAX200J
Z CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
PLTPCOLORMESHXX YY Z 0 CMAPPLTCMPAIRED
PLTCONTOURXX YY Z COLORSK K K
LINESTYLES   LEVELS5 0 5
PLTTITLEKERNEL
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 5320 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5134 CROSSVALIDATION ON DIABETES DATASET EXERCISE
A TUTORIAL EXERCISE WHICH USES CROSSVALIDATION WITH LINEAR MODELS
THIS EXERCISE IS USED IN THE CROSSVALIDATED ESTIMATORS PART OF THE MODEL SELECTION CHOOSING ESTIMATORS AND THEIR PARAMETERS SECTION OF THE A TUTORIAL ON STATISTICALLEARNING FOR SCIENTIFIC DATA PROCESSING

SCIKITLEARN USER GUIDE RELEASE 0213
OUT
ANSWER TO THE BONUS QUESTION HOW MUCH CAN YOU TRUST THE SELECTION OF ALPHA
ALPHA PARAMETERS MAXIMISING THE GENERALIZATION SCORE ON DIFFERENT
SUBSETS OF THE DATA
FOLD 0 ALPHA 005968 SCORE 054209
FOLD 1 ALPHA 004520 SCORE 015523
FOLD 2 ALPHA 007880 SCORE 045193
ANSWER NOT VERY MUCH SINCE WE OBTAINED DIFFERENT ALPHAS FOR DIFFERENT
SUBSETS OF THE DATA AND MOREOVER THE SCORES FOR THESE ALPHAS DIFFER
QUITE SUBSTANTIALLY
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNLINEARMODEL IMPORT LASSOCV
513 TUTORIAL EXERCISES 1077

```
SCIKITLEARN USER GUIDE RELEASE 0213
FROM SKLEARNLINEARMODEL IMPORT LASSO
FROM SKLEARNMODELSELECTION IMPORT KFOLD
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
DIABETES  DATASETSLOADDIABETES
X  DIABETESDATA150
Y  DIABETESTARGET150
LASSO  LASSORANDOMSTATE0 MAXITER10000
ALPHAS  NPLOGSPACE4 05 30
TUNEDPARAMETERS  ALPHA ALPHAS
NFOLDS  5
CLF  GRIDSEARCHCVLASSO TUNEDPARAMETERS CVNFOLDS REFITFALSE
CLFFITX Y
SCORES  CLFCVRESULTSMEANTESTSCORE
SCORESSTD  CLFCVRESULTSSTDTESTSCORE
PLTFIGURESETSIZEINCHES8 6
PLTSEMILOGXALPHAS SCORES
 PLOT ERROR LINES SHOWING  STD ERRORS OF THE SCORES
STDERROR  SCORESSTD  NPSQRTNFOLDS
PLTSEMILOGXALPHAS SCORES  STDERROR B
PLTSEMILOGXALPHAS SCORES  STDERROR B
 ALPHA02 CONTROLS THE TRANSLUCENCY OF THE FILL COLOR
PLTFILLBETWEENALPHAS SCORES  STDERROR SCORES  STDERROR ALPHA02
PLTYLABELCV SCORE  STD ERROR
PLTXLABELALPHA
PLTAXHLINENPMAXSCORES LINESTYLE COLOR5
PLTXLIMALPHAS0 ALPHAS1

 BONUS HOW MUCH CAN YOU TRUST THE SELECTION OF ALPHA
 TO ANSWER THIS QUESTION WE USE THE LASSOCV OBJECT THAT SETS ITS ALPHA
 PARAMETER AUTOMATICALLY FROM THE DATA BY INTERNAL CROSSVALIDATION IE IT
 PERFORMS CROSSVALIDATION ON THE TRAINING DATA IT RECEIVES
 WE USE EXTERNAL CROSSVALIDATION TO SEE HOW MUCH THE AUTOMATICALLY OBTAINED
 ALPHAS DIFFER ACROSS DIFFERENT CROSSVALIDATION FOLDS
LASSOCV  LASSOCVALPHASALPHAS CV5 RANDOMSTATE0 MAXITER10000
KFOLD  KFOLD3
PRINTANSWER TO THE BONUS QUESTION
HOW MUCH CAN YOU TRUST THE SELECTION OF ALPHA
PRINT
PRINTALPHA PARAMETERS MAXIMISING THE GENERALIZATION SCORE ON DIFFERENT
PRINTSUBSETS OF THE DATA
FORK TRAIN TEST INENUMERATEKFOLDSPLITX Y
LASSOCVFITXTRAIN YTRAIN
PRINTFOLD 0 ALPHA 15F SCORE 25F
FORMATK LASSOCVALPHA LASSOCVSCOREXTEST YTEST
PRINT
PRINTANSWER NOT VERY MUCH SINCE WE OBTAINED DIFFERENT ALPHAS FOR DIFFERENT
PRINTSUBSETS OF THE DATA AND MOREOVER THE SCORES FOR THESE ALPHAS DIFFER
1078 CHAPTER 5 EXAMPLES
```

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTQUITE SUBSTANTIALLY
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0294 SECONDS
514 FEATURE SELECTION
EXAMPLES CONCERNING THE SKLEARNFEATURESELECTION MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5141 RECURSIVE FEATURE ELIMINATION
A RECURSIVE FEATURE ELIMINATION EXAMPLE SHOWING THE RELEVANCE OF PIXELS IN A DIGIT CLASSIFICATION TASK
NOTE SEE ALSO RECURSIVE FEATURE ELIMINATION WITH CROSSVALIDATION

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNDATASETS IMPORT LOADDIGITS
FROM SKLEARNFEATURESELECTION IMPORT RFE
IMPORT MATPLOTLIBPYPLOT AS PLT
 LOAD THE DIGITS DATASET
DIGITS LOADDIGITS
X DIGITSIMAGESRESHAPELENDIGITSIMAGES 1
Y DIGITSTARGET
 CREATE THE RFE OBJECT AND RANK EACH PIXEL
SVC SVCKERNELLINEAR C1
RFE RFEESTIMATORSVC NFEATURESTOSELECT1 STEP1
RFEFITX Y
RANKING RFERANKINGRESHAPEDIGITSIMAGES0SHAPE
 PLOT PIXEL RANKING
PLTMATSHOWRANKING CMAPPLTCMBLUES
PLTCOLORBAR
PLTTITLERANKING OF PIXELS WITH RFE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3436 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5142 COMPARISON OF FTEST AND MUTUAL INFORMATION
THIS EXAMPLE ILLUSTRATES THE DIFFERENCES BETWEEN UNIVARIATE FTEST STATISTICS AND MUTUAL INFORMATION
WE CONSIDER 3 FEATURES X1 X2 X3 DISTRIBUTED UNIFORMLY OVER 0 1 THE TARGET DEPENDS ON THEM AS FOLLOWS
Y X1 SIN6 PI X2 01 N0 1 THAT IS THE THIRD FEATURES IS COMPLETELY IRRELEVANT
THE CODE BELOW PLOTS THE DEPENDENCY OF Y AGAINST INDIVIDUAL XI AND NORMALIZED VALUES OF UNIVARIATE FTESTS STATISTICS AND MUTUAL INFORMATION
AS FTEST CAPTURES ONLY LINEAR DEPENDENCY IT RATES X1 AS THE MOST DISCRIMINATIVE FEATURE ON THE OTHER HAND MUTUAL INFORMATION CAN CAPTURE ANY KIND OF DEPENDENCY BETWEEN VARIABLES AND IT RATES X2 AS THE MOST DISCRIMINATIVE FEATURE WHICH PROBABLY AGREES BETTER WITH OUR INTUITIVE PERCEPTION FOR THIS EXAMPLE BOTH METHODS CORRECTLY MARKS X3 AS IRRELEVANT

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNFEATURESELECTION IMPORT FREGRESSION MUTUALINFOREGRESSION
NPRANDOMSEED0
X NPRANDOMRAND1000 3
Y X 0 NPSIN6 NPPIX 1 01 NPRANDOMRANDN1000
FTEST   FREGRESSIONX Y
FTEST NPMAXFTEST
MI MUTUALINFOREGRESSIONX Y
MI NPMAXMI
PLTFIGUREFIGSIZE15 5
FORIINRANGE3
PLTSUBPLOT1 3 I 1
PLTSCATTERX I Y EDGECOLORBLACK S20
PLTXLABELXFORMATI 1 FONTSIZE14
IFI 0
PLTYLABELY FONTSIZE14
PLTTITLEFTEST2F MI2FFORMATFTESTI MII
FONTSIZE16
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0062 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5143 PIPELINE ANOVA SVM
SIMPLE USAGE OF PIPELINE THAT RUNS SUCCESSIVELY A UNIVARIATE FEATURE SELECTION WITH ANOVA AND THEN A SVM OF THE SELECTED FEATURES
USING A SUBPIPELINE THE FITTED COEFFICIENTS CAN BE MAPPED BACK INTO THE ORIGINAL FEATURE SPACE
OUT
514 FEATURE SELECTION 1081

PRECISION RECALL F1SCORE SUPPORT
0 075 050 060 6
1 067 100 080 6
2 067 080 073 5
3 100 075 086 8
ACCURACY 076 25
MACRO AVG 077 076 075 25
WEIGHTED AVG 079 076 076 25
023912131 0 0 0 03236911 0
0 0 0 0 0 0
010836648 0 0 0 0 0
0 0
043878747 0 0 0 051415652 0
0 0 0 0 0 0
004845652 0 0 0 0 0
0 0
065382998 0 0 0 057962856 0
0 0 0 0 0 0
004736524 0 0 0 0 0
0 0
054403412 0 0 0 058478491 0
0 0 0 0 0 0
011344659 0 0 0 0 0
0 0

```
FROM SKLEARN IMPORT SVM
FROM SKLEARNDATASETS IMPORT SAMPLESGENERATOR
FROM SKLEARNFEATURESELECTION IMPORT SELECTKBEST FREGRESSION
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNMETRICS IMPORT CLASSIFICATIONREPORT
PRINTDOC
 IMPORT SOME DATA TO PLAY WITH
X Y  SAMPLESGENERATORMAKECLASSIFICATION
NFEATURES20 NINFORMATIVE3 NREDUNDANT0 NCLASSES4
NCLUSTERSPERCLASS2
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLITX Y RANDOMSTATE42
 ANOVA SVMC
 1 ANOVA FILTER TAKE 3 BEST RANKED FEATURES
ANOVAFILTER  SELECTKBESTFREGRESSION K3
 2 SVM
CLF  SVMLINEARSVC
ANOVASVM  MAKEPIPELINEANOVAFILTER CLF
ANOVASVMFITXTRAIN YTRAIN
YPRED  ANOVASVMPREDICTXTEST
```

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTCLASSIFICATIONREPORTYTEST YPRED
COEF ANOVASVM1INVERSETRANSFORMANOVASVMLINEARSVCCOEF
PRINTCOEF
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0008 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5144 RECURSIVE FEATURE ELIMINATION WITH CROSSVALIDATION
A RECURSIVE FEATURE ELIMINATION EXAMPLE WITH AUTOMATIC TUNING OF THE NUMBER OF FEATURES SELECTED WITH CROSSVALIDATION
OUT
OPTIMAL NUMBER OF FEATURES 3
514 FEATURE SELECTION 1083

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNMODELSELECTION IMPORT STRATIFIEDKFOLD
FROM SKLEARNFEATURESELECTION IMPORT RFECV
FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
 BUILD A CLASSIFICATION TASK USING 3 INFORMATIVE FEATURES
X Y MAKECLASSIFICATIONNSAMPLES1000 NFEATURES25 NINFORMATIVE3
NREDUNDANT2 NREPEATED0 NCLASSES8
NCLUSTERSPERCLASS1 RANDOMSTATE0
 CREATE THE RFE OBJECT AND COMPUTE A CROSSVALIDATED SCORE
SVC SVCKERNELLINEAR
 THE ACCURACY SCORING IS PROPORTIONAL TO THE NUMBER OF CORRECT
 CLASSIFICATIONS
RFECV RFECVESTIMATORSVC STEP1 CVSTRATIFIEDKFOLD2
SCORINGACCURACY
RFECVFITX Y
PRINTOPTIMAL NUMBER OF FEATURES D RFECVNFEATURES
 PLOT NUMBER OF FEATURES VS CROSSVALIDATION SCORES
PLTFIGURE
PLTXLABELNUMBER OF FEATURES SELECTED
PLTYLABELCROSS VALIDATION SCORE NB OF CORRECT CLASSIFICATIONS
PLTPLOTRANGE1 LENRFECVGRIDSCORES 1 RFECVGRIDSCORES
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1806 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5145 FEATURE SELECTION USING SELECTFROMMODEL AND LASSOCV
USE SELECTFROMMODEL METATRANSFORMER ALONG WITH LASSO TO SELECT THE BEST COUPLE OF FEATURES FROM THE BOSTON DATASET

SCIKITLEARN USER GUIDE RELEASE 0213
 AUTHOR MANOJ KUMAR MKS542NYUEDU
 LICENSE BSD 3 CLAUSE
PRINTDOC
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNDATASETS IMPORT LOADBOSTON
FROM SKLEARNFEATURESELECTION IMPORT SELECTFROMMODEL
FROM SKLEARNLINEARMODEL IMPORT LASSOCV
 LOAD THE BOSTON DATASET
BOSTON LOADBOSTON
X Y BOSTONDATA BOSTONTARGET
 WE USE THE BASE ESTIMATOR LASSOCV SINCE THE L1 NORM PROMOTES SPARSITY OF FEATURES
CLF LASSOCVCV5
 SET A MINIMUM THRESHOLD OF 025
SFM SELECTFROMMODELCLF THRESHOLD025
SFMFITX Y
NFEATURES SFMTRANSFORMXSHAPE1
 RESET THE THRESHOLD TILL THE NUMBER OF FEATURES EQUALS TWO
 NOTE THAT THE ATTRIBUTE CAN BE SET DIRECTLY INSTEAD OF REPEATEDLY
514 FEATURE SELECTION 1085

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FITTING THE METATRANSFORMER
WHILENFEATURES 2
SFMTHRESHOLD 01
XTRANSFORM SFMTRANSFORMX
NFEATURES XTRANSFORMSHAPE1
PLOT THE SELECTED TWO FEATURES FROM X
PLTTITLE
FEATURES SELECTED FROM BOSTON USING SELECTFROMMODEL WITH
THRESHOLD 03F SFMTHRESHOLD
FEATURE1 XTRANSFORM 0
FEATURE2 XTRANSFORM 1
PLTPLOTFEATURE1 FEATURE2 R
PLTXLABELFEATURE NUMBER 1
PLTYLABELFEATURE NUMBER 2
PLTYLIMNPMINFEATURE2 NPMAXFEATURE2
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0056 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5146 TEST WITH PERMUTATIONS THE SIGNIFICANCE OF A CLASSIFICATION SCORE
IN ORDER TO TEST IF A CLASSIFICATION SCORE IS SIGNIFICATIVE A TECHNIQUE IN REPEATING THE CLASSIFICATION PROCEDURE AFTER RAN
DOMIZING PERMUTING THE LABELS THE PVALUE IS THEN GIVEN BY THE PERCENTAGE OF RUNS FOR WHICH THE SCORE OBTAINED IS
GREATER THAN THE CLASSIFICATION SCORE OBTAINED IN THE FIRST PLACE

SCIKITLEARN USER GUIDE RELEASE 0213
OUT
CLASSIFICATION SCORE 05133333333333333 PVALUE 0009900990099009901
 AUTHOR ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
 LICENSE BSD 3 CLAUSE
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNMODELSELECTION IMPORT STRATIFIEDKFOLD
FROM SKLEARNMODELSELECTION IMPORT PERMUTATIONTESTSCORE
FROM SKLEARN IMPORT DATASETS

 LOADING A DATASET
IRIS DATASETSLOADIRIS
514 FEATURE SELECTION 1087

SCIKITLEARN USER GUIDE RELEASE 0213
X IRISDATA
Y IRISTARGET
NCLASSES NPUNIQUEYSIZE
 SOME NOISY DATA NOT CORRELATED
RANDOM NPRANDOMRANDOMSTATESEED0
E RANDOMNORMALSIZELENX 2200
 ADD NOISY DATA TO THE INFORMATIVE FEATURES FOR MAKE THE TASK HARDER
X NPCX E
SVM SVCKERNELLINEAR
CV STRATIFIEDKFOLD2
SCORE PERMUTATIONSCORES PVALUE PERMUTATIONTESTSCORE
SVM X Y SCORINGACCURACY CVCV NPERMUTATIONS100 NJOBS1
PRINTCLASSIFICATION SCORE SPVALUE S SCORE PVALUE

 VIEW HISTOGRAM OF PERMUTATION SCORES
PLTHISTPERMUTATIONSCORES 20 LABELPERMUTATION SCORES
EDGECOLORBLACK
YLIM PLTYLIM
 BUG VLINES LINESTYLE FAILS ON OLDER VERSIONS OF MATPLOTLIB
 PLTVLINESSCORE YLIM0 YLIM1 LINESTYLE
 COLORG LINEWIDTH3 LABELCLASSIFICATION SCORE
  PVALUE S PVALUE
 PLTVLINES10 NCLASSES YLIM0 YLIM1 LINESTYLE
 COLORK LINEWIDTH3 LABELLUCK
PLTPLOT2 SCORE YLIM G LINEWIDTH3
LABELCLASSIFICATION SCORE
 PVALUE S PVALUE
PLTPLOT2 1 NCLASSES YLIM K LINEWIDTH3 LABELLUCK
PLTYLIMYLIM
PLTLEGEND
PLTXLABELSCORE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 7883 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5147 UNIVARIATE FEATURE SELECTION
AN EXAMPLE SHOWING UNIVARIATE FEATURE SELECTION
NOISY NON INFORMATIVE FEATURES ARE ADDED TO THE IRIS DATA AND UNIVARIATE FEATURE SELECTION IS APPLIED FOR EACH FEATURE
WE PLOT THE PVALUES FOR THE UNIVARIATE FEATURE SELECTION AND THE CORRESPONDING WEIGHTS OF AN SVM WE CAN SEE THAT
UNIVARIATE FEATURE SELECTION SELECTS THE INFORMATIVE FEATURES AND THAT THESE HAVE LARGER SVM WEIGHTS
IN THE TOTAL SET OF FEATURES ONLY THE 4 FIRST ONES ARE SIGNIFICANT WE CAN SEE THAT THEY HAVE THE HIGHEST SCORE WITH
UNIVARIATE FEATURE SELECTION THE SVM ASSIGNS A LARGE WEIGHT TO ONE OF THESE FEATURES BUT ALSO SELECTS MANY OF THE
NONINFORMATIVE FEATURES APPLYING UNIVARIATE FEATURE SELECTION BEFORE THE SVM INCREASES THE SVM WEIGHT ATTRIBUTED

TO THE SIGNIFICANT FEATURES AND WILL THUS IMPROVE CLASSIFICATION
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS SVM
FROM SKLEARNFEATURESELECTION IMPORT SELECTPERCENTILE FCLASSIF

IMPORT SOME DATA TO PLAY WITH
THE IRIS DATASET
IRIS DATASETSLOADIRIS
SOME NOISY DATA NOT CORRELATED
E NPRANDOMUNIFORM0 01 SIZELENIRISDATA 20
ADD THE NOISY DATA TO THE INFORMATIVE FEATURES
X NPHSTACKIRISDATA E
Y IRISTARGET
PLTFIGURE1
PLTCLF

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XINDICES NPARANGEXSHAPE1

 UNIVARIATE FEATURE SELECTION WITH FTEST FOR FEATURE SCORING
 WE USE THE DEFAULT SELECTION FUNCTION THE 10 MOST SIGNIFICANT FEATURES
SELECTOR SELECTPERCENTILEFCLASSIF PERCENTILE10
SELECTORFITX Y
SCORES NPLOG10SELECTORPVALUES
SCORES SCORESMAX
PLTBARXINDICES 45 SCORES WIDTH2
LABELRUNIVARIATE SCORE LOGPVALUE COLORDARKORANGE
EDGECOLORBLACK

 COMPARE TO THE WEIGHTS OF AN SVM
CLF SVMSVCKERNELLINEAR
CLFFITX Y
SVMWEIGHTS CLFCOEF 2SUMAXIS0
SVMWEIGHTS SVMWEIGHTSMAX
PLTBARXINDICES 25 SVMWEIGHTS WIDTH2 LABELSVM WEIGHT
COLORNAVY EDGECOLORBLACK
CLFSELECTED SVMSVCKERNELLINEAR
CLFSELECTEDFITSELECTORTRANSFORMX Y
SVMWEIGHTSSELECTED CLFSELECTEDCOEF 2SUMAXIS0
SVMWEIGHTSSELECTED SVMWEIGHTSSELECTEDMAX
PLTBARXINDICESSELECTORGETSUPPORT 05 SVMWEIGHTSSELECTED
WIDTH2 LABELSVM WEIGHTS AFTER SELECTION COLORC
EDGECOLORBLACK
PLTTITLECOMPARING FEATURE SELECTION
PLTXLABELFEATURE NUMBER
PLTYTICKS
PLTAXISTIGHT
PLTLEGENDLOCUPPER RIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0045 SECONDS
515 GAUSSIAN PROCESS FOR MACHINE LEARNING
EXAMPLES CONCERNING THE SKLEARNGAUSSIANPROCESS MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
1090 CHAPTER 5 EXAMPLES

5151 ILLUSTRATION OF GAUSSIAN PROCESS CLASSIFICATION GPC ON THE XOR DATASET
THIS EXAMPLE ILLUSTRATES GPC ON XOR DATA COMPARED ARE A STATIONARY ISOTROPIC KERNEL RBF AND A NONSTATIONARY KERNEL DOTPRODUCT ON THIS PARTICULAR DATASET THE DOTPRODUCT KERNEL OBTAINS CONSIDERABLY BETTER RESULTS BECAUSE THE CLASSBOUNDARIES ARE LINEAR AND COINCIDE WITH THE COORDINATE AXES IN GENERAL STATIONARY KERNELS OFTEN OBTAIN BETTER RESULTS

```
PRINTDOC
 AUTHORS JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDE

 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSCLASSIFIER
FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT RBF DOTPRODUCT
XX YY  NPMESHGRIDNPLINSPACE3 3 50
NPLINSPACE3 3 50
RNG  NPRANDOMRANDOMSTATE0
X  RNGRANDN200 2
Y  NPLOGICALXORX 0  0 X 1  0
 FIT THE MODEL
PLTFIGUREFIGSIZE10 5
KERNELS  10 RBFLENGTHSCALE10 10 DOTPRODUCTSIGMA010 2
FORI KERNEL INENUMERATEKERNELS
CLF  GAUSSIANPROCESSCLASSIFIERKERNELKERNEL WARMSTARTTRUEFITX Y
 PLOT THE DECISION FUNCTION FOR EACH DATAPOINT ON THE GRID
Z  CLFPREDICTPROBANPVSTACKXXRAVEL YYRAVELT 1
Z  ZRESHAPEXXSHAPE
```

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PLTSUBPLOT1 2 I 1
IMAGE PLTIMSHOWZ INTERPOLATIONNEAREST
EXTENTXXMIN XXMAX YYMIN YYMAX
ASPECTAUTO ORIGINLOWER CMAPPLTCMPUORR
CONTOURS PLTCONTOURXX YY Z LEVELS05 LINEWIDTHS2
COLORSK
PLTSCATTERX 0 X 1 S30 CY CMAPPLTCMPAIRED
EDGECOLORS0 0 0
PLTXTICKS
PLTYTICKS
PLTAXIS3 3 3 3
PLTCOLORBARIMAGE
PLTTITLE SNLOGMARGINALLIKELIHOOD 3F
 CLFKERNEL CLFLOGMARGINALLIKELIHOODCLFKERNELTHETA
FONTSIZE12
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0686 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5152 GAUSSIAN PROCESS CLASSIFICATION GPC ON IRIS DATASET
THIS EXAMPLE ILLUSTRATES THE PREDICTED PROBABILITY OF GPC FOR AN ISOTROPIC AND ANISOTROPIC RBF KERNEL ON A TWO DIMENSIONAL VERSION FOR THE IRISDATASET THE ANISOTROPIC RBF KERNEL OBTAINS SLIGHTLY HIGHER LOGMARGINALLIKELIHOOD BY ASSIGNING DIFFERENT LENGTHSCALES TO THE TWO FEATURE DIMENSIONS
PRINTDOC
IMPORT NUMPY AS NP

SCIKITLEARN USER GUIDE RELEASE 0213
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSCLASSIFIER
FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT RBF
 IMPORT SOME DATA TO PLAY WITH
IRIS DATASETSLOADIRIS
X IRISDATA 2 WE ONLY TAKE THE FIRST TWO FEATURES
Y NPARRAYIRISTARGET DTYPEINT
H 02 STEP SIZE IN THE MESH
KERNEL 10 RBF10
GPCRBFISOTROPIC GAUSSIANPROCESSCLASSIFIERKERNELKERNELFITX Y
KERNEL 10 RBF10 10
GPCRBFANISOTROPIC GAUSSIANPROCESSCLASSIFIERKERNELKERNELFITX Y
 CREATE A MESH TO PLOT IN
XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX H
NPARANGEYMIN YMAX H
TITLES ISOTROPIC RBF ANISOTROPIC RBF
PLTFIGUREFIGSIZE10 5
FORI CLFINENUMERATEGPCRBFISOTROPIC GPCRBFANISOTROPIC
 PLOT THE PREDICTED PROBABILITIES FOR THAT WE WILL ASSIGN A COLOR TO
 EACH POINT IN THE MESH XMIN MMAXXYMIN YMAX
PLTSUBPLOT1 2 I 1
Z CLFPREDICTPROBANPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE0 XXSHAPE1 3
PLTIMSHOWZ EXTENTXMIN XMAX YMIN YMAX ORIGINLOWER
 PLOT ALSO THE TRAINING POINTS
PLTSCATTERX 0 X 1 CNPARRAYR G BY
EDGECOLORS0 0 0
PLTXLABELSEPAL LENGTH
PLTYLABELSEPAL WIDTH
PLTXLIMXXMIN XXMAX
PLTYLIMYYMIN YYMAX
PLTXTICKS
PLTYTICKS
PLTTITLE S LML3F
TITLESI CLFLOGMARGINALLIKELIHOODCLFKERNELTHETA
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 4265 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5153 COMPARISON OF KERNEL RIDGE AND GAUSSIAN PROCESS REGRESSION
BOTH KERNEL RIDGE REGRESSION KRR AND GAUSSIAN PROCESS REGRESSION GPR LEARN A TARGET FUNCTION BY EMPLOYING INTERNALLY THE “KERNEL TRICK” KRR LEARNS A LINEAR FUNCTION IN THE SPACE INDUCED BY THE RESPECTIVE KERNEL WHICH CORRESPONDS TO A NONLINEAR FUNCTION IN THE ORIGINAL SPACE THE LINEAR FUNCTION IN THE KERNEL SPACE IS CHOSEN BASED ON THE MEANSQUARED ERROR LOSS WITH RIDGE REGULARIZATION GPR USES THE KERNEL TO DEFINE THE COVARIANCE OF A PRIOR DISTRIBUTION OVER THE TARGET FUNCTIONS AND USES THE OBSERVED TRAINING DATA TO DEFINE A LIKELIHOOD FUNCTION BASED ON BAYES THEOREM A GAUSSIAN POSTERIOR DISTRIBUTION OVER TARGET FUNCTIONS IS DEFINED WHOSE MEAN IS USED FOR PREDICTION
A MAJOR DIFFERENCE IS THAT GPR CAN CHOOSE THE KERNEL’S HYPERPARAMETERS BASED ON GRADIENTASCENT ON THE MARGINAL LIKELIHOOD FUNCTION WHILE KRR NEEDS TO PERFORM A GRID SEARCH ON A CROSSVALIDATED LOSS FUNCTION MEANSQUARED ERROR LOSS A FURTHER DIFFERENCE IS THAT GPR LEARNS A GENERATIVE PROBABILISTIC MODEL OF THE TARGET FUNCTION AND CAN THUS PROVIDE MEANINGFUL CONFIDENCE INTERVALS AND POSTERIOR SAMPLES ALONG WITH THE PREDICTIONS WHILE KRR ONLY PROVIDES PREDICTIONS
THIS EXAMPLE ILLUSTRATES BOTH METHODS ON AN ARTIFICIAL DATASET WHICH CONSISTS OF A SINUSOIDAL TARGET FUNCTION AND STRONG NOISE THE FIGURE COMPARES THE LEARNED MODEL OF KRR AND GPR BASED ON A EXPSINESQUARED KERNEL WHICH IS SUITED FOR LEARNING PERIODIC FUNCTIONS THE KERNEL’S HYPERPARAMETERS CONTROL THE SMOOTHNESS L AND PERIODICITY OF THE KERNEL P MOREOVER THE NOISE LEVEL OF THE DATA IS LEARNED EXPLICITLY BY GPR BY AN ADDITIONAL WHITEKERNEL COMPONENT IN THE KERNEL AND BY THE REGULARIZATION PARAMETER ALPHA OF KRR
THE FIGURE SHOWS THAT BOTH METHODS LEARN REASONABLE MODELS OF THE TARGET FUNCTION GPR CORRECTLY IDENTIFIES THE PERIODICITY OF THE FUNCTION TO BE ROUGHLY 2PI 628 WHILE KRR CHOOSES THE DOUBLED PERIODICITY 4PI BESIDES THAT GPR PROVIDES REASONABLE CONFIDENCE BOUNDS ON THE PREDICTION WHICH ARE NOT AVAILABLE FOR KRR A MAJOR DIFFERENCE BETWEEN THE TWO METHODS IS THE TIME REQUIRED FOR FITTING AND PREDICTING WHILE FITTING KRR IS FAST IN PRINCIPLE THE GRIDSEARCH FOR HYPERPARAMETER OPTIMIZATION SCALES EXPONENTIALLY WITH THE NUMBER OF HYPERPARAMETERS “CURSE OF DIMENSIONALITY” THE GRADIENTBASED OPTIMIZATION OF THE PARAMETERS IN GPR DOES NOT SUFFER FROM THIS EXPONENTIAL SCALING AND IS THUS CONSIDERABLE FASTER ON THIS EXAMPLE WITH 3DIMENSIONAL HYPERPARAMETER SPACE THE TIME FOR PREDICTING IS SIMILAR HOWEVER GENERATING THE VARIANCE OF THE PREDICTIVE DISTRIBUTION OF GPR TAKES CONSIDERABLE LONGER THAN JUST PREDICTING THE MEAN
OUT
TIME FOR KRR FITTING 3180
TIME FOR GPR FITTING 0096
TIME FOR KRR PREDICTION 0009

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TIME FOR GPR PREDICTION 0010
TIME FOR GPR PREDICTION WITH STANDARDDEVIATION 0014
PRINTDOC
 AUTHORS JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDE
 LICENSE BSD 3 CLAUSE
IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNKERNELRIDGE IMPORT KERNELRIDGE
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSREGRESSOR
FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT WHITEKERNEL EXPSINESQUARED
RNG NPRANDOMRANDOMSTATE0
 GENERATE SAMPLE DATA
X 15RNGRAND100 1
Y NPSINXRAVEL
Y 305 RNGRANDXSHAPE0 ADD NOISE
 FIT KERNELRIDGE WITH PARAMETER SELECTION BASED ON 5FOLD CROSS VALIDATION
PARAMGRID ALPHA 1E0 1E1 1E2 1E3
KERNEL EXPSINESQUAREDL P
FORLINNPLOGSPACE2 2 10
FORPINNPLOGSPACE0 2 10
KR GRIDSEARCHCVKERNELRIDGE CV5 PARAMGRIDPARAMGRID
STIME TIMETIME
KRFITX Y
PRINTTIME FOR KRR FITTING 3F TIMETIME STIME
GPKERNEL EXPSINESQUARED10 50 PERIODICITYBOUNDS1E2 1E1
 WHITEKERNEL1E1
GPR GAUSSIANPROCESSREGRESSORKERNELGPKERNEL
STIME TIMETIME
GPRFITX Y
PRINTTIME FOR GPR FITTING 3F TIMETIME STIME
 PREDICT USING KERNEL RIDGE
XPLOT NPLINSPACE0 20 10000 NONE
STIME TIMETIME
YKR KRPREDICTXPLOT
PRINTTIME FOR KRR PREDICTION 3F TIMETIME STIME
 PREDICT USING GAUSSIAN PROCESS REGRESSOR
STIME TIMETIME
YGPR GPRPREDICTXPLOT RETURNSTDFALSE
515 GAUSSIAN PROCESS FOR MACHINE LEARNING 1095

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PRINTTIME FOR GPR PREDICTION 3F TIMETIME STIME
STIME TIMETIME
YGPR YSTD GPRPREDICTXPLOT RETURNSTDTRUE
PRINTTIME FOR GPR PREDICTION WITH STANDARDDEVIATION 3F
 TIMETIME STIME
 PLOT RESULTS
PLTFIGUREFIGSIZE10 5
LW 2
PLTSCATTERX Y CK LABELDATA
PLTPLOTXPLOT NPSINXPLOT COLORNAVY LWLW LABELTRUE
PLTPLOTXPLOT YKR COLORTURQUOISE LWLW
LABELKRR S KRBESTPARAMS
PLTPLOTXPLOT YGPR COLORDARKORANGE LWLW
LABELGPR S GPRKERNEL
PLTFILLBETWEENXPLOT 0 YGPR YSTD YGPR YSTD COLORDARKORANGE
ALPHA02
PLTXLABELDATA
PLTYLABELTARGET
PLTXLIM0 20
PLTYLIM4 4
PLTTITLEGPR VERSUS KERNEL RIDGE
PLTLEGENDLOCBEST SCATTERPOINTS1 PROPSIZE 8
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3377 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5154 ILLUSTRATION OF PRIOR AND POSTERIOR GAUSSIAN PROCESS FOR DIFFERENT KERNELS
THIS EXAMPLE ILLUSTRATES THE PRIOR AND POSTERIOR OF A GPR WITH DIFFERENT KERNELS MEAN STANDARD DEVIATION AND 10
SAMPLES ARE SHOWN FOR BOTH PRIOR AND POSTERIOR
1096 CHAPTER 5 EXAMPLES

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PRINTDOC

AUTHORS JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDE


```
IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSREGRESSOR
FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT RBF MATERN RATIONALQUADRATIC
EXPSINESQUARED DOTPRODUCT
CONSTANTKERNEL
KERNELS  10 RBFLENGTHSCALE10 LENGTHSCALEBOUNDS1E1 100
```

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10RATIONALQUADRATICLENGTHSCALE10 ALPHA01
10EXPSINESQUAREDLENGTHSCALE10 PERIODICITY30
LENGTHSCALEBOUNDS01 100
PERIODICITYBOUNDS10 100
CONSTANTKERNEL01 001 100
DOTPRODUCTSIGMA010 SIGMA0BOUNDS01 100 2
10MATERNLENGTHSCALE10 LENGTHSCALEBOUNDS1E1 100
NU15
FORKERNELINKERNELS
SPECIFY GAUSSIAN PROCESS
GP GAUSSIANPROCESSREGRESSORKERNELKERNEL
PLOT PRIOR
PLTFIGUREFIGSIZE8 8
PLTSUBPLOT2 1 1
X NPLINSPACE0 5 100
YMEAN YSTD GPPREDICTX NPNEWAXIS RETURNSTDTRUE
PLTPLOTX YMEAN K LW3 ZORDER9
PLTFILLBETWEENX YMEAN YSTD YMEAN YSTD
ALPHA02 COLORK
YSAMPLES GPSAMPLEYX NPNEWAXIS 10
PLTPLOTX YSAMPLES LW1
PLTXLIM0 5
PLTYLIM3 3
PLTTITLEPRIOR KERNEL S KERNEL FONTSIZE12
GENERATE DATA AND FIT GP
RNG NPRANDOMRANDOMSTATE4
X RNGUNIFORM0 5 10 NPNEWAXIS
Y NPSINX 0 25 2
GPFITX Y
PLOT POSTERIOR
PLTSUBPLOT2 1 2
X NPLINSPACE0 5 100
YMEAN YSTD GPPREDICTX NPNEWAXIS RETURNSTDTRUE
PLTPLOTX YMEAN K LW3 ZORDER9
PLTFILLBETWEENX YMEAN YSTD YMEAN YSTD
ALPHA02 COLORK
YSAMPLES GPSAMPLEYX NPNEWAXIS 10
PLTPLOTX YSAMPLES LW1
PLTSCATTERX 0 Y CR S50 ZORDER10 EDGECOLORS0 0 0
PLTXLIM0 5
PLTYLIM3 3
PLTTITLEPOSTERIOR KERNEL SNLOGLIKELIHOOD 3F
GPKERNEL GPLOGMARGINALLIKELIHOODGPKERNELTHETA
FONTSIZE12
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1458 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
1102 CHAPTER 5 EXAMPLES

5155 ISOPROBABILITY LINES FOR GAUSSIAN PROCESSES CLASSIFICATION GPC
A TWODIMENSIONAL CLASSIFICATION EXAMPLE SHOWING ISOPROBABILITY LINES FOR THE PREDICTED PROBABILITIES
OUT
LEARNED KERNEL 00256 2DOTPRODUCTSIGMA0572 2
PRINTDOC
 AUTHOR VINCENT DUBOURG VINCENTDUBOURGGMAILCOM
 ADAPTED TO GAUSSIANPROCESSCLASSIFIER
 JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDE
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM MATPLOTLIB IMPORT CM
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSCLASSIFIER

FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT DOTPRODUCT CONSTANTKERNEL ASC
 A FEW CONSTANTS
LIM 8
DEFGX
THE FUNCTION TO PREDICT CLASSIFICATION WILL THEN CONSIST IN PREDICTING
WHETHER GX 0 OR NOT
RETURN5 X 1 5 X 0 2
 DESIGN OF EXPERIMENTS
X NPARRAY461611719 600099547
410469096 532782448
000000000 050000000
617289014 46984743
13109306 693271427
503823144 310584743
287600388 674310541
521301203 426386883
 OBSERVATIONS
Y NPARRAYGX 0 DTYPEINT
 INSTANTIATE AND FIT GAUSSIAN PROCESS MODEL
KERNEL C01 1E5 NPINF DOTPRODUCTSIGMA001 2
GP GAUSSIANPROCESSCLASSIFIERKERNELKERNEL
GPFITX Y
PRINTLEARNED KERNEL S GPKERNEL
 EVALUATE REAL FUNCTION AND THE PREDICTED PROBABILITY
RES 50
X1 X2 NPMESHGRIDNPLINSPACE LIM LIM RES
NPLINSPACE LIM LIM RES
XX NPVSTACKX1RESHAPEX1SIZE X2RESHAPEX2SIZET
YTRUE GXX
YPROB GPPREDICTPROBAXX 1
YTRUE YTRUERESHAPERES RES
YPROB YPROBRESHAPERES RES
 PLOT THE PROBABILISTIC CLASSIFICATION ISOVALUES
FIG PLTFIGURE1
AX FIGGCA
AXAXESSETASPECTEQUAL
PLTXTICKS
PLTYTICKS
AXSETXTICKLABELS
AXSETYTICKLABELS
PLTXLABELX1
PLTYLABELX2
CAX PLTIMSHOWYPROB CMAPCMGRAYR ALPHA08
EXTENTLIM LIM LIM LIM
NORM PLTMATPLOTLIBCOLORSNORMALIZEVMIN0 VMAX09
CB PLTCOLORBARCAX TICKS0 02 04 06 08 1 NORMNORM
CBSETLABELRRM MATHBBPLEFTWIDEHATGMATHBFX LEQ 0RIGHT
PLTCLIM0 1

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PLTPLOTXY 0 0 XY 0 1 R MARKERSIZE12
PLTPLOTXY 0 0 XY 0 1 B MARKERSIZE12
PLTCONTOURX1 X2 YTRUE 0 COLORSK LINESTYLESDASHDOT
CS PLTCONTOURX1 X2 YPROB 0666 COLORSB
LINESTYLESSOLID
PLTCLABELCS FONTSIZE11
CS PLTCONTOURX1 X2 YPROB 05 COLORSK
LINESTYLESDASHED
PLTCLABELCS FONTSIZE11
CS PLTCONTOURX1 X2 YPROB 0334 COLORSR
LINESTYLESSOLID
PLTCLABELCS FONTSIZE11
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0098 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5156 PROBABILISTIC PREDICTIONS WITH GAUSSIAN PROCESS CLASSIFICATION GPC
THIS EXAMPLE ILLUSTRATES THE PREDICTED PROBABILITY OF GPC FOR AN RBF KERNEL WITH DIFFERENT CHOICES OF THE HYPERPARAM
ETERS THE FIRST FIGURE SHOWS THE PREDICTED PROBABILITY OF GPC WITH ARBITRARILY CHOSEN HYPERPARAMETERS AND WITH THE
HYPERPARAMETERS CORRESPONDING TO THE MAXIMUM LOGMARGINALLIKELIHOOD LML
WHILE THE HYPERPARAMETERS CHOSEN BY OPTIMIZING LML HAVE A CONSIDERABLE LARGER LML THEY PERFORM SLIGHTLY WORSE
ACCORDING TO THE LOGLOSS ON TEST DATA THE FIGURE SHOWS THAT THIS IS BECAUSE THEY EXHIBIT A STEEP CHANGE OF THE CLASS
PROBABILITIES AT THE CLASS BOUNDARIES WHICH IS GOOD BUT HAVE PREDICTED PROBABILITIES CLOSE TO 05 FAR AWAY FROM THE
CLASS BOUNDARIES WHICH IS BAD THIS UNDESIRABLE EFFECT IS CAUSED BY THE LAPLACE APPROXIMATION USED INTERNALLY BY
GPC
THE SECOND FIGURE SHOWS THE LOGMARGINALLIKELIHOOD FOR DIFFERENT CHOICES OF THE KERNEL’S HYPERPARAMETERS HIGHLIGHTING
THE TWO CHOICES OF THE HYPERPARAMETERS USED IN THE FIRST FIGURE BY BLACK DOTS
515 GAUSSIAN PROCESS FOR MACHINE LEARNING 1105

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OUT

LOG MARGINAL LIKELIHOOD INITIAL 17598
LOG MARGINAL LIKELIHOOD OPTIMIZED 3875
ACCURACY 1000 INITIAL 1000 OPTIMIZED
LOGLOSS 0214 INITIAL 0319 OPTIMIZED

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IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM SKLEARNMETRICSCLASSIFICATION IMPORT ACCURACYSCORE LOGLOSS
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSCLASSIFIER
FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT RBF

```
 GENERATE DATA
TRAINSIZE  50
RNG  NPRANDOMRANDOMSTATE0
X  RNGUNIFORM0 5 100 NPNEWAXIS
Y  NPARRAYX 0  25 DTYPEINT
 SPECIFY GAUSSIAN PROCESSES WITH FIXED AND OPTIMIZED HYPERPARAMETERS
GPFIX  GAUSSIANPROCESSCLASSIFIERKERNEL10 RBFLENGTHSCALE10
OPTIMIZERNONE
GPFIXFITXTRAINSIZE YTRAINSIZE
GPOPT  GAUSSIANPROCESSCLASSIFIERKERNEL10 RBFLENGTHSCALE10
GPOPTFITXTRAINSIZE YTRAINSIZE
PRINTLOG MARGINAL LIKELIHOOD INITIAL 3F
 GPFIXLOGMARGINALLIKELIHOODGPFIXKERNELTHETA
PRINTLOG MARGINAL LIKELIHOOD OPTIMIZED 3F
 GPOPTLOGMARGINALLIKELIHOODGPOPTKERNELTHETA
PRINTACCURACY 3FINITIAL 3FOPTIMIZED
 ACCURACYSCOREYTRAINSIZE GPFIXPREDICTXTRAINSIZE
ACCURACYSCOREYTRAINSIZE GPOPTPREDICTXTRAINSIZE
PRINTLOGLOSS 3FINITIAL 3FOPTIMIZED
 LOGLOSSYTRAINSIZE GPFIXPREDICTPROBAXTRAINSIZE 1
LOGLOSSYTRAINSIZE GPOPTPREDICTPROBAXTRAINSIZE 1
 PLOT POSTERIORS
PLTFIGURE
PLTSCATTERXTRAINSIZE 0 YTRAINSIZE CK LABELTRAIN DATA
EDGECOLORS0 0 0
PLTSCATTERXTRAINSIZE 0 YTRAINSIZE CG LABELTEST DATA
EDGECOLORS0 0 0
X  NPLINSPACE0 5 100
PLTPLOTX GPFIXPREDICTPROBAX NPNEWAXIS 1 R
LABELINITIAL KERNEL S  GPFIXKERNEL
PLTPLOTX GPOPTPREDICTPROBAX NPNEWAXIS 1 B
LABELOPTIMIZED KERNEL S  GPOPTKERNEL
PLTXLABELFEATURE
PLTYLABELCLASS 1 PROBABILITY
PLTXLIM0 5
PLTYLIM025 15
PLTLEGENDLOCBEST
 PLOT LML LANDSCAPE
PLTFIGURE
THETA0  NPLOGSPACE0 8 30
THETA1  NPLOGSPACE1 1 29
THETA0 THETA1  NPMESHGRIDTHETA0 THETA1
LML  GPOPTLOGMARGINALLIKELIHOODNPLOGTHETA0I J THETA1I J
FORIINRANGETHETA0SHAPE0 FORJINRANGETHETA0SHAPE1
LML  NPARRAYLMLT
PLTPLOTNPEXPGPFIXKERNELTHETA0 NPEXPGPFIXKERNELTHETA1
KO ZORDER10
PLTPLOTNPEXPGPOPTKERNELTHETA0 NPEXPGPOPTKERNELTHETA1
KO ZORDER10
PLTPCOLORTHETA0 THETA1 LML
PLTXSCALELOG
```

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PLTYSCALELOG
PLTCOLORBAR
PLTXLABELMAGNITUDE
PLTYLABELLENGTHSCALE
PLTTITLELOGMARGINALLIKELIHOOD
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2514 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5157 GAUSSIAN PROCESS REGRESSION GPR WITH NOISELEVEL ESTIMATION
THIS EXAMPLE ILLUSTRATES THAT GPR WITH A SUMKERNEL INCLUDING A WHITEKERNEL CAN ESTIMATE THE NOISE LEVEL OF DATA
AN ILLUSTRATION OF THE LOGMARGINALLIKELIHOOD LML LANDSCAPE SHOWS THAT THERE EXIST TWO LOCAL MAXIMA OF LML THE
FIRST CORRESPONDS TO A MODEL WITH A HIGH NOISE LEVEL AND A LARGE LENGTH SCALE WHICH EXPLAINS ALL VARIATIONS IN THE DATA
BY NOISE THE SECOND ONE HAS A SMALLER NOISE LEVEL AND SHORTER LENGTH SCALE WHICH EXPLAINS MOST OF THE VARIATION BY
THE NOISEFREE FUNCTIONAL RELATIONSHIP THE SECOND MODEL HAS A HIGHER LIKELIHOOD HOWEVER DEPENDING ON THE INITIAL
VALUE FOR THE HYPERPARAMETERS THE GRADIENTBASED OPTIMIZATION MIGHT ALSO CONVERGE TO THE HIGHNOISE SOLUTION IT IS
THUS IMPORTANT TO REPEAT THE OPTIMIZATION SEVERAL TIMES FOR DIFFERENT INITIALIZATIONS
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```
IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM MATPLOTLIBCOLORS IMPORT LOGNORM
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSREGRESSOR
FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT RBF WHITEKERNEL
RNG  NPRANDOMRANDOMSTATE0
X  RNGUNIFORM0 5 20 NPNEWAXIS
Y  05 NPSIN3 X 0  RNGNORMAL0 05 XSHAPE0
 FIRST RUN
PLTFIGURE
KERNEL  10 RBFLENGTHSCALE1000 LENGTHSCALEBOUNDS1E2 1E3
 WHITEKERNELNOISELEVEL1 NOISELEVELBOUNDS1E10 1E1
GP  GAUSSIANPROCESSREGRESSORKERNELKERNEL
ALPHA00FITX Y
X  NPLINSPACE0 5 100
YMEAN YCOV  GPPREDICTX NPNEWAXIS RETURNCOVTRUE
```

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PLTPLOTX YMEAN K LW3 ZORDER9
PLTFILLBETWEENX YMEAN NPSQRTNPDIAGYCOV
YMEAN NPSQRTNPDIAGYCOV
ALPHA05 COLORK
PLTPLOTX 05 NPSIN3 X R LW3 ZORDER9
PLTSCATTERX 0 Y CR S50 ZORDER10 EDGECOLORS0 0 0
PLTTITLEINITIAL SNOPTIMUM SNLOGMARGINALLIKELIHOOD S
 KERNEL GPKERNEL
GPLOGMARGINALLIKELIHOODGPKERNELTHETA
PLTTIGHTLAYOUT
 SECOND RUN
PLTFIGURE
KERNEL 10 RBFLENGTHSCALE10 LENGTHSCALEBOUNDS1E2 1E3
 WHITEKERNELNOISELEVEL1E5 NOISELEVELBOUNDS1E10 1E1
GP GAUSSIANPROCESSREGRESSORKERNELKERNEL
ALPHA00FITX Y
X NPLINSPACE0 5 100
YMEAN YCOV GPPREDICTX NPNEWAXIS RETURNCOVTRUE
PLTPLOTX YMEAN K LW3 ZORDER9
PLTFILLBETWEENX YMEAN NPSQRTNPDIAGYCOV
YMEAN NPSQRTNPDIAGYCOV
ALPHA05 COLORK
PLTPLOTX 05 NPSIN3 X R LW3 ZORDER9
PLTSCATTERX 0 Y CR S50 ZORDER10 EDGECOLORS0 0 0
PLTTITLEINITIAL SNOPTIMUM SNLOGMARGINALLIKELIHOOD S
 KERNEL GPKERNEL
GPLOGMARGINALLIKELIHOODGPKERNELTHETA
PLTTIGHTLAYOUT
 PLOT LML LANDSCAPE
PLTFIGURE
THETA0 NPLOGSPACE2 3 49
THETA1 NPLOGSPACE2 0 50
THETA0 THETA1 NPMESHGRIDTHETA0 THETA1
LML GPLOGMARGINALLIKELIHOODNPLOG036 THETA0I J THETA1I J
FORIINRANGETHETA0SHAPE0 FORJINRANGETHETA0SHAPE1
LML NPARRAYLMLT
VMIN VMAX LMLMIN LMLMAX
VMAX 50
LEVEL NPAROUNDNPLOGSPACENPLOG10VMIN NPLOG10VMAX 50 DECIMALS1
PLTCONTOURTHETA0 THETA1 LML
LEVELSLEVEL NORMLOGNORMVMINVMIN VMAXVMAX
PLTCOLORBAR
PLTXSCALELOG
PLTYSCALELOG
PLTXLABELLENGTHSCALE
PLTYLABELNOISELEVEL
PLTTITLELOGMARGINALLIKELIHOOD
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2874 SECONDS
1112 CHAPTER 5 EXAMPLES

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5158 GAUSSIAN PROCESSES REGRESSION BASIC INTRODUCTORY EXAMPLE
A SIMPLE ONEDIMENSIONAL REGRESSION EXAMPLE COMPUTED IN TWO DIFFERENT WAYS
1 A NOISEFREE CASE
2 A NOISY CASE WITH KNOWN NOISELEVEL PER DATAPOINT
IN BOTH CASES THE KERNEL'S PARAMETERS ARE ESTIMATED USING THE MAXIMUM LIKELIHOOD PRINCIPLE
THE FIGURES ILLUSTRATE THE INTERPOLATING PROPERTY OF THE GAUSSIAN PROCESS MODEL AS WELL AS ITS PROBABILISTIC NATURE IN THE FORM OF A POINTWISE 95 CONFIDENCE INTERVAL
NOTE THAT THE PARAMETER ALPHA IS APPLIED AS A TIKHONOV REGULARIZATION OF THE ASSUMED COVARIANCE BETWEEN THE TRAINING POINTS
•
515 GAUSSIAN PROCESS FOR MACHINE LEARNING 1113

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 AUTHOR VINCENT DUBOURG VINCENTDUBOURGGMAILCOM
 JAKE VANDERPLAS VANDERPLASASTROWASHINGTONEDU
 JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDES
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSREGRESSOR
FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT RBF CONSTANTKERNEL ASC
NPRANDOMSEED1
DEFFX
THE FUNCTION TO PREDICT
RETURNXNPSINX

 FIRST THE NOISELESS CASE
X NPATLEAST2D1 3 5 6 7 8T
 OBSERVATIONS
Y FXRAVEL
1114 CHAPTER 5 EXAMPLES

```
 MESH THE INPUT SPACE FOR EVALUATIONS OF THE REAL FUNCTION THE PREDICTION AND
 ITS MSE
X  NPATLEAST2DNPLINSPACE0 10 1000T
 INSTANTIATE A GAUSSIAN PROCESS MODEL
KERNEL  C10 1E3 1E3 RBF10 1E2 1E2
GP  GAUSSIANPROCESSREGRESSORKERNELKERNEL NRESTARTSOPTIMIZER9
 FIT TO DATA USING MAXIMUM LIKELIHOOD ESTIMATION OF THE PARAMETERS
GPFITX Y
 MAKE THE PREDICTION ON THE MESHED XAXIS ASK FOR MSE AS WELL
YPRED SIGMA  GPPREDICTX RETURNSTDTRUE
 PLOT THE FUNCTION THE PREDICTION AND THE 95 CONFIDENCE INTERVAL BASED ON
 THE MSE
PLTFIGURE
PLTPLOTX FX R LABELRFX  XSINX
PLTPLOTX Y R MARKERSIZE10 LABELOBSERVATIONS
PLTPLOTX YPRED B LABELPREDICTION
PLTFILLNPCONCATENATEX X1
NPCONCATENATEYPRED  19600 SIGMA
YPRED  19600 SIGMA1
ALPHA5 FCB ECNONE LABEL95  CONFIDENCE INTERVAL
PLTXLABELX
PLTYLABELFX
PLTYLIM10 20
PLTLEGENDLOCUPPER LEFT

 NOW THE NOISY CASE
X  NPLINSPACE01 99 20
X  NPATLEAST2DXT
 OBSERVATIONS AND NOISE
Y  FXRAVEL
DY  05  10 NPRANDOMRANDOMYSHAPE
NOISE  NPRANDOMNORMAL0 DY
Y  NOISE
 INSTANTIATE A GAUSSIAN PROCESS MODEL
GP  GAUSSIANPROCESSREGRESSORKERNELKERNEL ALPHADY 2
NRESTARTSOPTIMIZER10
 FIT TO DATA USING MAXIMUM LIKELIHOOD ESTIMATION OF THE PARAMETERS
GPFITX Y
 MAKE THE PREDICTION ON THE MESHED XAXIS ASK FOR MSE AS WELL
YPRED SIGMA  GPPREDICTX RETURNSTDTRUE
 PLOT THE FUNCTION THE PREDICTION AND THE 95 CONFIDENCE INTERVAL BASED ON
 THE MSE
PLTFIGURE
PLTPLOTX FX R LABELRFX  XSINX
PLTERRORBARXRAVEL Y DY FMTR MARKERSIZE10 LABELOBSERVATIONS
PLTPLOTX YPRED B LABELPREDICTION
PLTFILLNPCONCATENATEX X1
NPCONCATENATEYPRED  19600 SIGMA
```

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YPRED 19600 SIGMA1
ALPHA5 FCB ECNONE LABEL95 CONFIDENCE INTERVAL
PLTXLABELX
PLTYLABELFX
PLTYLIM10 20
PLTLEGENDLOCUPPER LEFT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0284 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5159 GAUSSIAN PROCESS REGRESSION GPR ON MAUNA LOA CO2 DATA
THIS EXAMPLE IS BASED ON SECTION 543 OF “GAUSSIAN PROCESSES FOR MACHINE LEARNING” RW2006 IT ILLUSTRATES AN EXAMPLE OF COMPLEX KERNEL ENGINEERING AND HYPERPARAMETER OPTIMIZATION USING GRADIENT ASCENT ON THE LOGMARGINAL LIKELIHOOD THE DATA CONSISTS OF THE MONTHLY AVERAGE ATMOSPHERIC CO2 CONCENTRATIONS IN PARTS PER MILLION BY VOLUME PPMV COLLECTED AT THE MAUNA LOA OBSERVATORY IN HAWAII BETWEEN 1958 AND 2001 THE OBJECTIVE IS TO MODEL THE CO2 CONCENTRATION AS A FUNCTION OF THE TIME T
THE KERNEL IS COMPOSED OF SEVERAL TERMS THAT ARE RESPONSIBLE FOR EXPLAINING DIFFERENT PROPERTIES OF THE SIGNAL
• A LONG TERM SMOOTH RISING TREND IS TO BE EXPLAINED BY AN RBF KERNEL THE RBF KERNEL WITH A LARGE LENGTHSCALE ENFORCES THIS COMPONENT TO BE SMOOTH IT IS NOT ENFORCED THAT THE TREND IS RISING WHICH LEAVES THIS CHOICE TO THE GP THE SPECIFIC LENGTHSCALE AND THE AMPLITUDE ARE FREE HYPERPARAMETERS
• A SEASONAL COMPONENT WHICH IS TO BE EXPLAINED BY THE PERIODIC EXPSINESQUARED KERNEL WITH A FIXED PERIODICITY OF 1 YEAR THE LENGTHSCALE OF THIS PERIODIC COMPONENT CONTROLLING ITS SMOOTHNESS IS A FREE PARAMETER IN ORDER TO ALLOW DECAYING AWAY FROM EXACT PERIODICITY THE PRODUCT WITH AN RBF KERNEL IS TAKEN THE LENGTHSCALE OF THIS RBF COMPONENT CONTROLS THE DECAY TIME AND IS A FURTHER FREE PARAMETER
• SMALLER MEDIUM TERM IRREGULARITIES ARE TO BE EXPLAINED BY A RATIONALQUADRATIC KERNEL COMPONENT WHOSE LENGTH SCALE AND ALPHA PARAMETER WHICH DETERMINES THE DIFFUSENESS OF THE LENGTHSCALES ARE TO BE DETERMINED AC CORDING TO RW2006 THESE IRREGULARITIES CAN BETTER BE EXPLAINED BY A RATIONALQUADRATIC THAN AN RBF KERNEL COMPONENT PROBABLY BECAUSE IT CAN ACCOMMODATE SEVERAL LENGTHSCALES
• A “NOISE” TERM CONSISTING OF AN RBF KERNEL CONTRIBUTION WHICH SHALL EXPLAIN THE CORRELATED NOISE COMPONENTS SUCH AS LOCAL WEATHER PHENOMENA AND A WHITEKERNEL CONTRIBUTION FOR THE WHITE NOISE THE RELATIVE AMPLITUDES AND THE RBF’S LENGTH SCALE ARE FURTHER FREE PARAMETERS
MAXIMIZING THE LOGMARGINALLIKELIHOOD AFTER SUBTRACTING THE TARGET’S MEAN YIELDS THE FOLLOWING KERNEL WITH AN LML OF 83214
3442RBFLENGTHSCALE418
 3272RBFLENGTHSCALE180 EXPSINESQUAREDLENGTHSCALE144
PERIODICITY1
 04462RATIONALQUADRATICALPHA177 LENGTHSCALE0957
 01972RBFLENGTHSCALE0138 WHITEKERNELNOISELEVEL00336
THUS MOST OF THE TARGET SIGNAL 344PPM IS EXPLAINED BY A LONGTERM RISING TREND LENGTHSCALE 418 YEARS THE PERIODIC COMPONENT HAS AN AMPLITUDE OF 327PPM A DECAY TIME OF 180 YEARS AND A LENGTHSCALE OF 144 THE LONG DECAY TIME INDICATES THAT WE HAVE A LOCALLY VERY CLOSE TO PERIODIC SEASONAL COMPONENT THE CORRELATED NOISE HAS AN AMPLITUDE OF 0197PPM WITH A LENGTH SCALE OF 0138 YEARS AND A WHITENOISE CONTRIBUTION OF 0197PPM THUS THE

OVERALL NOISE LEVEL IS VERY SMALL INDICATING THAT THE DATA CAN BE VERY WELL EXPLAINED BY THE MODEL THE FIGURE SHOWS
ALSO THAT THE MODEL MAKES VERY CONFIDENT PREDICTIONS UNTIL AROUND 2015
OUT
GPML KERNEL 66 2RBFLENGTHSCALE67 24 2RBFLENGTHSCALE90
‹→EXPSINESQUAREDLENGTHSCALE13 PERIODICITY1 066 2
‹→RATIONALQUADRATICALPHA078 LENGTHSCALE12 018 2RBFLENGTHSCALE0134
‹→ WHITEKERNELNOISELEVEL00361
LOGMARGINALLIKELIHOOD 117023
LEARNED KERNEL 448 2RBFLENGTHSCALE516 264 2RBFLENGTHSCALE915
‹→EXPSINESQUAREDLENGTHSCALE148 PERIODICITY1 0536 2
‹→RATIONALQUADRATICALPHA289 LENGTHSCALE0968 0188 2RBFLENGTHSCALE0
‹→122 WHITEKERNELNOISELEVEL00367
LOGMARGINALLIKELIHOOD 115050
 AUTHORS JAN HENDRIK METZEN JHMINFORMATIKUNIBREMENDE

 LICENSE BSD 3 CLAUSE

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IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM SKLEARNDATASETS IMPORT FETCHOPENML
FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSREGRESSOR
FROM SKLEARNGAUSSIANPROCESSKERNELS
IMPORTRBF WHITEKERNEL RATIONALQUADRATIC EXPSINESQUARED
PRINTDOC
DEFLOADMAUNALOAATMOSPHERICCO2
MLDATA FETCHOPENMLDATAID41187
MONTHS
PPMVSUMS
COUNTS
Y MLDATADATA 0
M MLDATADATA 1
MONTHFLOAT Y M 1 12
PPMVS MLDATATARGET
FORMONTH PPMV INZIPMONTHFLOAT PPMVS
IF NOTMONTHSORMONTH MONTHS1
MONTHSAPPENDMONTH
PPMVSUMSAPPENDPPMV
COUNTSAPPEND1
ELSE
 AGGREGATE MONTHLY SUM TO PRODUCE AVERAGE
PPMVSUMS1 PPMV
COUNTS1 1
MONTHS NPASARRAYMONTHSRESHAPE1 1
AVGPPMVS NPASARRAYPPMVSUMS COUNTS
RETURNMONTHS AVGPPMVS
X Y LOADMAUNALOAATMOSPHERICCO2
 KERNEL WITH PARAMETERS GIVEN IN GPML BOOK
K1 660 2RBFLENGTHSCALE670 LONG TERM SMOOTH RISING TREND
K2 24 2RBFLENGTHSCALE900
EXPSINESQUAREDLENGTHSCALE13 PERIODICITY10 SEASONAL COMPONENT
 MEDIUM TERM IRREGULARITY
K3 066 2
RATIONALQUADRATICLENGTHSCALE12 ALPHA078
K4 018 2RBFLENGTHSCALE0134
 WHITEKERNELNOISELEVEL019 2 NOISE TERMS
KERNELGPML K1 K2 K3 K4
GP GAUSSIANPROCESSREGRESSORKERNELKERNELGPML ALPHA0
OPTIMIZERNONE NORMALIZEYTRUE
GPFITX Y
PRINTGPML KERNEL S GPKERNEL
PRINTLOGMARGINALLIKELIHOOD 3F
 GPLOGMARGINALLIKELIHOODGPKERNELTHETA

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KERNEL WITH OPTIMIZED PARAMETERS
K1 500 2RBFLENGTHSCALE500 LONG TERM SMOOTH RISING TREND
K2 20 2RBFLENGTHSCALE1000
EXPSINESQUAREDLENGTHSCALE10 PERIODICITY10
PERIODICITYBOUNDSFIXED SEASONAL COMPONENT
MEDIUM TERM IRREGULARITIES
K3 05 2RATIONALQUADRATICLENGTHSCALE10 ALPHA10
K4 01 2RBFLENGTHSCALE01
WHITEKERNELNOISELEVEL01 2
NOISELEVELBOUNDS1E3 NPINF NOISE TERMS
KERNEL K1 K2 K3 K4
GP GAUSSIANPROCESSREGRESSORKERNELKERNEL ALPHA0
NORMALIZEYTRUE
GPFITX Y
PRINTNLEARNED KERNEL S GPKERNEL
PRINTLOGMARGINALLIKELIHOOD 3F
GPLOGMARGINALLIKELIHOODGPKERNELTHETA
X NPLINSPACEXMIN XMAX 30 1000 NPNEWAXIS
YPRED YSTD GPPREDICTX RETURNSTDTRUE
ILLUSTRATION
PLTSCATTERX Y CK
PLTPLOTX YPRED
PLTFILLBETWEENX 0 YPRED YSTD YPRED YSTD
ALPHA05 COLORK
PLTXLIMXMIN XMAX
PLTXLABELYEAR
PLTYLABELRCO2 IN PPM
PLTTITLERATMOSPHERIC CO2 CONCENTRATION AT MAUNA LOA
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 11550 SECONDS
516 MISSING VALUE IMPUTATION
EXAMPLES CONCERNING THE SKLEARNIMPUTE MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5161 IMPUTING MISSING VALUES WITH VARIANTS OF ITERATIVEIMPUTER
THESKLEARNIMPUTEITERATIVEIMPUTER CLASS IS VERY FLEXIBLE IT CAN BE USED WITH A VARIETY OF ESTIMATORS
TO DO ROUNDROBIN REGRESSION TREATING EVERY VARIABLE AS AN OUTPUT IN TURN
IN THIS EXAMPLE WE COMPARE SOME ESTIMATORS FOR THE PURPOSE OF MISSING FEATURE IMPUTATION WITH SKLEARNIMPUTE
ITERATIVEIMPUTER
•BAYESIANRIDGE REGULARIZED LINEAR REGRESSION

•DECISIONTREEREGRESSOR NONLINEAR REGRESSION
•EXTRATREESREGRESSOR SIMILAR TO MISSFOREST IN R
•KNEIGHBORSREGRESSOR COMPARABLE TO OTHER KNN IMPUTATION APPROACHES
OF PARTICULAR INTEREST IS THE ABILITY OF SKLEARNIMPUTEITERATIVEIMPUTER TO MIMIC THE BEHAVIOR OF MISS
FOREST A POPULAR IMPUTATION PACKAGE FOR R IN THIS EXAMPLE WE HAVE CHOSEN TO USE SKLEARNENSEMBLE
EXTRATREESREGRESSOR INSTEAD OFSKLEARNENSEMBLERANDOMFORESTREGRESSOR AS IN MISSFOREST
DUE TO ITS INCREASED SPEED
NOTE THATSKLEARNNEIGHBORSKNEIGHBORSREGRESSOR IS DIFFERENT FROM KNN IMPUTATION WHICH LEARNS
FROM SAMPLES WITH MISSING VALUES BY USING A DISTANCE METRIC THAT ACCOUNTS FOR MISSING VALUES RATHER THAN IMPUT
ING THEM
THE GOAL IS TO COMPARE DIFFERENT ESTIMATORS TO SEE WHICH ONE IS BEST FOR THE SKLEARNIMPUTE
ITERATIVEIMPUTER WHEN USING A SKLEARNLINEARMODELBAYESIANRIDGE ESTIMATOR ON THE CALIFORNIA
HOUSING DATASET WITH A SINGLE VALUE RANDOMLY REMOVED FROM EACH ROW
FOR THIS PARTICULAR PATTERN OF MISSING VALUES WE SEE THAT SKLEARNENSEMBLEEXTRATREESREGRESSOR AND
SKLEARNLINEARMODELBAYESIANRIDGE GIVE THE BEST RESULTS
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT PANDAS AS PD
 TO USE THIS EXPERIMENTAL FEATURE WE NEED TO EXPLICITLY ASK FOR IT
FROM SKLEARNEXPERIMENTAL IMPORT ENABLEITERATIVEIMPUTER NOQA
FROM SKLEARNDATASETS IMPORT FETCHCALIFORNIAHOUSING
FROM SKLEARNIMPUTE IMPORT SIMPLEIMPUTER
FROM SKLEARNIMPUTE IMPORT ITERATIVEIMPUTER
FROM SKLEARNLINEARMODEL IMPORT BAYESIANRIDGE
FROM SKLEARNTREE IMPORT DECISIONTREEREGRESSOR
FROM SKLEARNENSEMBLE IMPORT EXTRATREESREGRESSOR
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSREGRESSOR
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE

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NSPLITS 5
RNG NPRANDOMRANDOMSTATE0
XFULL YFULL FETCHCALIFORNIAHOUSINGRETURNXYTRUE
 2K SAMPLES IS ENOUGH FOR THE PURPOSE OF THE EXAMPLE
 REMOVE THE FOLLOWING TWO LINES FOR A SLOWER RUN WITH DIFFERENT ERROR BARS
XFULL XFULL10
YFULL YFULL10
NSAMPLES NFEATURES XFULLSHAPE
 ESTIMATE THE SCORE ON THE ENTIRE DATASET WITH NO MISSING VALUES
BRESTIMATOR BAYESIANRIDGE
SCOREFULLDATA PDDATAFRAME
CROSSVALSCORE
BRESTIMATOR XFULL YFULL SCORINGNEGMEANSQUAREDERROR
CVNSPLITS

COLUMNSFULL DATA

 ADD A SINGLE MISSING VALUE TO EACH ROW
XMISSING XFULLCOPY
YMISSING YFULL
MISSINGSAMPLES NPARANGENSAMPLES
MISSINGFEATURES RNGCHOICENFEATURES NSAMPLES REPLACETRUE
XMISSINGMISSINGSAMPLES MISSINGFEATURES NPNAN
 ESTIMATE THE SCORE AFTER IMPUTATION MEAN AND MEDIAN STRATEGIES
SCORESIMPLEIMPUTER PDDATAFRAME
FORSTRATEGY INMEAN MEDIAN
ESTIMATOR MAKEPIPELINE
SIMPLEIMPUTERMISSINGVALUESNPNAN STRATEGYSTRATEGY
BRESTIMATOR

SCORESIMPLEIMPUTERSTRATEGY CROSSVALSCORE
ESTIMATOR XMISSING YMISSING SCORINGNEGMEANSQUAREDERROR
CVNSPLITS

 ESTIMATE THE SCORE AFTER ITERATIVE IMPUTATION OF THE MISSING VALUES
 WITH DIFFERENT ESTIMATORS
ESTIMATORS
BAYESIANRIDGE
DECISIONTREEREGRESSORMAXFEATURESSQRT RANDOMSTATE0
EXTRATREESREGRESSORNESTIMATORS10 RANDOMSTATE0
KNEIGHBORSREGRESSORNNEIGHBORS15

SCOREITERATIVEIMPUTER PDDATAFRAME
FORIMPUTEESTIMATOR INESTIMATORS
ESTIMATOR MAKEPIPELINE
ITERATIVEIMPUTERRANDOMSTATE0 ESTIMATORIMPUTEESTIMATOR
BRESTIMATOR

SCOREITERATIVEIMPUTERIMPUTEESTIMATORCLASSNAME
CROSSVALSCORE
ESTIMATOR XMISSING YMISSING SCORINGNEGMEANSQUAREDERROR
CVNSPLITS

```
SCORES  PDCONCAT
SCOREFULLDATA SCORESIMPLEIMPUTER SCOREITERATIVEIMPUTER
KEYSORIGINAL SIMPLEIMPUTER ITERATIVEIMPUTER AXIS1

 PLOT BOSTON RESULTS
FIG AX  PLTSUBPLOTSFIGSIZE13 6
MEANS  SCORESMEAN
ERRORS  SCORESSTD
MEANSPLOTBARHXERRERRORS AXAX
AXSETTITLECALIFORNIA HOUSING REGRESSION WITH DIFFERENT IMPUTATION METHODS
AXSETXLABELMSE SMALLER IS BETTER
AXSETYTICKSNPARANGEMEANSSHAPE0
AXSETYTICKLABELS W JOINLABEL FORLABELINMEANSINDEXGETVALUES
PLTTIGHTLAYOUTPAD1
PLTSHOW
```

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 19017 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5162 IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR

MISSING VALUES CAN BE REPLACED BY THE MEAN THE MEDIAN OR THE MOST FREQUENT VALUE USING THE BASIC SKLEARN IMPUTESIMPLEIMPUTER THE MEDIAN IS A MORE ROBUST ESTIMATOR FOR DATA WITH HIGH MAGNITUDE VARIABLES WHICH COULD DOMINATE RESULTS OTHERWISE KNOWN AS A ‘LONG TAIL’

ANOTHER OPTION IS THE SKLEARNIMPUTEITERATIVEIMPUTER THIS USES ROUNDROBIN LINEAR REGRESSION TREATING EVERY VARIABLE AS AN OUTPUT IN TURN THE VERSION IMPLEMENTED ASSUMES GAUSSIAN OUTPUT VARIABLES IF YOUR FEATURES ARE OBVIOUSLY NONNORMAL CONSIDER TRANSFORMING THEM TO LOOK MORE NORMAL SO AS TO POTENTIALLY IMPROVE PERFORMANCE

IN ADDITION OF USING AN IMPUTING METHOD WE CAN ALSO KEEP AN INDICATION OF THE MISSING INFORMATION USING SKLEARN IMPUTEMISSINGINDICATOR WHICH MIGHT CARRY SOME INFORMATION

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
 TO USE THE EXPERIMENTAL ITERATIVEIMPUTER WE NEED TO EXPLICITLY ASK FOR IT
FROM SKLEARNEXPERIMENTAL IMPORT ENABLEITERATIVEIMPUTER NOQA
FROM SKLEARNDATASETS IMPORT LOADDIABETES
FROM SKLEARNDATASETS IMPORT LOADBOSTON
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTREGRESSOR
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE MAKEUNION
FROM SKLEARNIMPUTE IMPORT SIMPLEIMPUTER ITERATIVEIMPUTER MISSINGINDICATOR
FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
RNG NPRANDOMRANDOMSTATE0
NSPLITS 5
REGRESSOR RANDOMFORESTREGRESSORRANDOMSTATE0 NESTIMATORS100
DEFGETSCORESFORIMPUTERIMPUTER XMISSING YMISSING
ESTIMATOR MAKEPIPELINE
MAKEUNIONIMPUTER MISSINGINDICATORMISSINGVALUES0
REGRESSOR
IMPUTESCORES CROSSVALSCOREESTIMATOR XMISSING YMISSING
SCORINGNEGMEANSQUAREDERROR
CVNSPLITS
RETURNIMPUTESCORES
DEFGETRESULTSDATASET
XFULL YFULL DATASETDATA DATASETTARGET
NSAMPLES XFULLSHAPE0
NFEATURES XFULLSHAPE1
 ESTIMATE THE SCORE ON THE ENTIRE DATASET WITH NO MISSING VALUES
516 MISSING VALUE IMPUTATION 1123

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FULLSCORES CROSSVALSCOREREGRESSOR XFULL YFULL
SCORINGNEGMEANSQUAREDERROR
CVNSPLITS
 ADD MISSING VALUES IN 75 OF THE LINES
MISSINGRATE 075
NMISSINGSAMPLES INTNPFLOORNSAMPLES MISSINGRATE
MISSINGSAMPLES NPHSTACKNPZEROSNSAMPLES NMISSINGSAMPLES
DTYPENPBOOL
NPONESNMISSINGSAMPLES
DTYPENPBOOL
RNGSHUFFLEMISSINGSAMPLES
MISSINGFEATURES RNGRANDINT0 NFEATURES NMISSINGSAMPLES
XMISSING XFULLCOPY
XMISSINGNPWHEREMISSINGSAMPLES0 MISSINGFEATURES 0
YMISSING YFULLCOPY
 ESTIMATE THE SCORE AFTER REPLACING MISSING VALUES BY 0
IMPUTER SIMPLEIMPUTERMISSINGVALUES0
STRATEGYCONSTANT
FILLVALUE0
ZEROIMPUTESCORES GETSCORESFORIMPUTERIMPUTER XMISSING YMISSING
 ESTIMATE THE SCORE AFTER IMPUTATION MEAN STRATEGY OF THE MISSING VALUES
IMPUTER SIMPLEIMPUTERMISSINGVALUES0 STRATEGYMEAN
MEANIMPUTESCORES GETSCORESFORIMPUTERIMPUTER XMISSING YMISSING
 ESTIMATE THE SCORE AFTER ITERATIVE IMPUTATION OF THE MISSING VALUES
IMPUTER ITERATIVEIMPUTERMISSINGVALUES0
RANDOMSTATE0
NNEARESTFEATURES5
ITERATIVEIMPUTESCORES GETSCORESFORIMPUTERIMPUTER
XMISSING
YMISSING
RETURNFULLSCORESMEAN FULLSCORESSTD
ZEROIMPUTESCORESMEAN ZEROIMPUTESCORESSTD
MEANIMPUTESCORESMEAN MEANIMPUTESCORESSTD
ITERATIVEIMPUTESCORESMEAN ITERATIVEIMPUTESCORESSTD
RESULTSDIABETES NPARRAYGETRESULTSLOADDIABETES
MSESDIABETES RESULTSDIABETES 0 1
STDSDIABETES RESULTSDIABETES 1
RESULTSBOSTON NPARRAYGETRESULTSLOADBOSTON
MSESBOSTON RESULTSBOSTON 0 1
STDSBOSTON RESULTSBOSTON 1
NBARS LENMSESDIABETES
XVAL NPARANGENBARS
XLABELS FULL DATA
ZERO IMPUTATION
MEAN IMPUTATION
MULTIVARIATE IMPUTATION
COLORS R G B ORANGE
1124 CHAPTER 5 EXAMPLES

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PLOT DIABETES RESULTS
PLTFIGUREFIGSIZE12 6
AX1 PLTSUBPLOT121
FORJINXVAL
AX1BARHJ MSESDIABETESJ XERRSTDSDIABETESJ
COLORCOLORSJ ALPHA06 ALIGNCENTER
AX1SETTITLEIMPUTATION TECHNIQUES WITH DIABETES DATA
AX1SETXLIMLEFTNPMINMSESDIABETES 09
RIGHTNPMAXMSESDIABETES 11
AX1SETYTICKSXVAL
AX1SETXLABELMSE
AX1INVERTYAXIS
AX1SETYTICKLABELSXLABELS
PLOT BOSTON RESULTS
AX2 PLTSUBPLOT122
FORJINXVAL
AX2BARHJ MSESBOSTONJ XERRSTDSBOSTONJ
COLORCOLORSJ ALPHA06 ALIGNCENTER
AX2SETTITLEIMPUTATION TECHNIQUES WITH BOSTON DATA
AX2SETYTICKSXVAL
AX2SETXLABELMSE
AX2INVERTYAXIS
AX2SETYTICKLABELS NBARS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 11569 SECONDS
517 INSPECTION
EXAMPLES RELATED TO THE SKLEARNINSPECTION MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5171 PARTIAL DEPENDENCE PLOTS
PARTIAL DEPENDENCE PLOTS SHOW THE DEPENDENCE BETWEEN THE TARGET FUNCTION2AND A SET OF ‘TARGET’ FEATURES MARGINALIZING OVER THE VALUES OF ALL OTHER FEATURES THE COMPLEMENT FEATURES DUE TO THE LIMITS OF HUMAN PERCEPTION THE SIZE OF THE TARGET FEATURE SET MUST BE SMALL USUALLY ONE OR TWO THUS THE TARGET FEATURES ARE USUALLY CHOSEN AMONG THE MOST IMPORTANT FEATURES
THIS EXAMPLE SHOWS HOW TO OBTAIN PARTIAL DEPENDENCE PLOTS FROM A MLPREGRESSOR AND A GRADIENTBOOSTINGREGRESSOR TRAINED ON THE CALIFORNIA HOUSING DATASET THE EXAMPLE IS TAKEN FROM1
THE PLOTS SHOW FOUR 1WAY AND TWO 1WAY PARTIAL DEPENDENCE PLOTS OMMITTED FOR MLPREGRESSOR DUE TO COMPUTA TION TIME THE TARGET VARIABLES FOR THE ONEWAY PDP ARE MEDIAN INCOME MEDINC AVERAGE OCCUPANTS PER HOUSEHOLD AVGOCCUP MEDIAN HOUSE AGE HOUSEAGE AND AVERAGE ROOMS PER HOUSEHOLD AVEROOMS
2FOR CLASSIFICATION YOU CAN THINK OF IT AS THE REGRESSION SCORE BEFORE THE LINK FUNCTION
1T HASTIE R TIBSHIRANI AND J FRIEDMAN “ELEMENTS OF STATISTICAL LEARNING ED 2” SPRINGER 2009

WE CAN CLEARLY SEE THAT THE MEDIAN HOUSE PRICE SHOWS A LINEAR RELATIONSHIP WITH THE MEDIAN INCOME TOP LEFT AND THAT THE HOUSE PRICE DROPS WHEN THE AVERAGE OCCUPANTS PER HOUSEHOLD INCREASES TOP MIDDLE THE TOP RIGHT PLOT SHOWS THAT THE HOUSE AGE IN A DISTRICT DOES NOT HAVE A STRONG INFLUENCE ON THE MEDIAN HOUSE PRICE SO DOES THE AVERAGE ROOMS PER HOUSEHOLD THE TICK MARKS ON THE XAXIS REPRESENT THE DECILES OF THE FEATURE VALUES IN THE TRAINING DATA
WE ALSO OBSERVE THAT MLPREGRESSOR HAS MUCH SMOOTHER PREDICTIONS THAN GRADIENTBOOSTINGREGRESSOR
FOR THE PLOTS TO BE COMPARABLE IT IS NECESSARY TO SUBTRACT THE AVERAGE VALUE OF THE TARGET Y THE ‘RECURSION’ METHOD USED BY DEFAULT FOR GRADIENTBOOSTINGREGRESSOR DOES NOT ACCOUNT FOR THE INITIAL PREDICTOR IN OUR CASE THE AVERAGE TARGET SETTING THE TARGET AVERAGE TO 0 AVOIDS THIS BIAS
PARTIAL DEPENDENCE PLOTS WITH TWO TARGET FEATURES ENABLE US TO VISUALIZE INTERACTIONS AMONG THEM THE TWOWAY PARTIAL DEPENDENCE PLOT SHOWS THE DEPENDENCE OF MEDIAN HOUSE PRICE ON JOINT VALUES OF HOUSE AGE AND AVERAGE OCCUPANTS PER HOUSEHOLD WE CAN CLEARLY SEE AN INTERACTION BETWEEN THE TWO FEATURES FOR AN AVERAGE OCCUPANCY GREATER THAN TWO THE HOUSE PRICE IS NEARLY INDEPENDENT OF THE HOUSE AGE WHEREAS FOR VALUES LESS THAN TWO THERE IS A STRONG DEPENDENCE ON AGE
ON A THIRD FIGURE WE HAVE PLOTTED THE SAME PARTIAL DEPENDENCE PLOT THIS TIME IN 3 DIMENSIONS
•

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•

517 INSPECTION 1127

•
OUT
TRAINING MLPREGRESSOR
COMPUTING PARTIAL DEPENDENCE PLOTS
TRAINING GRADIENTBOOSTINGREGRESSOR
COMPUTING PARTIAL DEPENDENCE PLOTS
CUSTOM 3D PLOT VIA PARTIALDEPENDENCE
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MPLTOOLKITSMPLOT3D IMPORT AXES3D
FROM SKLEARNINSPECTION IMPORT PARTIALDEPENDENCE
FROM SKLEARNINSPECTION IMPORT PLOTPARTIALDEPENDENCE
FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGREGRESSOR
FROM SKLEARNNEURALNETWORK IMPORT MLPREGRESSOR
FROM SKLEARNDATASETSCALIFORNIAHOUSING IMPORT FETCHCALIFORNIAHOUSING
DEFMAIN

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CALHOUSING FETCHCALIFORNIAHOUSING
X Y CALHOUSINGDATA CALHOUSINGTARGET
NAMES CALHOUSINGFEATURENAMES
 CENTER TARGET TO AVOID GRADIENT BOOSTING INIT BIAS GRADIENT BOOSTING
 WITH THE RECURSION METHOD DOES NOT ACCOUNT FOR THE INITIAL ESTIMATOR
 HERE THE AVERAGE TARGET BY DEFAULT
Y YMEAN
PRINTTRAINING MLPREGRESSOR
EST MLPREGRESSORACTIVATIONLOGISTIC
ESTFITX Y
PRINTCOMPUTING PARTIAL DEPENDENCE PLOTS
 WE DONT COMPUTE THE 2WAY PDP 5 1 HERE BECAUSE IT IS A LOT SLOWER
 WITH THE BRUTE METHOD
FEATURES 0 5 1 2
PLOTPARTIALDEPENDENCEEST X FEATURES FEATURENAMESNAMES
NJOBS3 GRIDRESOLUTION50
FIG PLTGCF
FIGSUPTITLEPARTIAL DEPENDENCE OF HOUSE VALUE ON NONLOCATION FEATURES N
FOR THE CALIFORNIA HOUSING DATASET WITH MLPREGRESSOR
PLTSUBPLOTSADJUSTTOP09 TIGHTLAYOUT CAUSES OVERLAP WITH SUPTITLE
PRINTTRAINING GRADIENTBOOSTINGREGRESSOR
EST GRADIENTBOOSTINGREGRESSORNESTIMATORS100 MAXDEPTH4
LEARNINGRATE01 LOSSHUBER
RANDOMSTATE1
ESTFITX Y
PRINTCOMPUTING PARTIAL DEPENDENCE PLOTS
FEATURES 0 5 1 2 5 1
PLOTPARTIALDEPENDENCEEST X FEATURES FEATURENAMESNAMES
NJOBS3 GRIDRESOLUTION50
FIG PLTGCF
FIGSUPTITLEPARTIAL DEPENDENCE OF HOUSE VALUE ON NONLOCATION FEATURES N
FOR THE CALIFORNIA HOUSING DATASET WITH GRADIENT BOOSTING
PLTSUBPLOTSADJUSTTOP09
PRINTCUSTOM 3D PLOT VIA PARTIALDEPENDENCE
FIG PLTFIGURE
TARGETFEATURE 1 5
PDP AXES PARTIALDEPENDENCEEST X TARGETFEATURE
GRIDRESOLUTION50
XX YY NPMESHGRIDAXES0 AXES1
Z PDP0T
AX AXES3DFIG
SURF AXPLOTSURFACEXX YY Z RSTRIDE1 CSTRIDE1
CMAPPLTCMBUPU EDGECOLORK
AXSETXLABELNAMESTARGETFEATURE0
AXSETYLABELNAMESTARGETFEATURE1
AXSETZLABELPARTIAL DEPENDENCE
 PRETTY INIT VIEW
AXVIEWINITELEV22 AZIM122
PLTCOLORBARSURF
PLTSUPTITLEPARTIAL DEPENDENCE OF HOUSE VALUE ON MEDIAN N
AGE AND AVERAGE OCCUPANCY WITH GRADIENT BOOSTING
PLTSUBPLOTSADJUSTTOP09

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PLTSHOW
 NEEDED ON WINDOWS BECAUSE PLOTPARTIALDEPENDENCE USES MULTIPROCESSING
IFNAME MAIN
MAIN
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 24838 SECONDS
518 GENERALIZED LINEAR MODELS
EXAMPLES CONCERNING THE SKLEARNLINEARMODEL MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5181 LASSO PATH USING LARS
COMPUTES LASSO PATH ALONG THE REGULARIZATION PARAMETER USING THE LARS ALGORITHM ON THE DIABETES DATASET EACH COLOR REPRESENTS A DIFFERENT FEATURE OF THE COEFFICIENT VECTOR AND THIS IS DISPLAYED AS A FUNCTION OF THE REGULARIZATION PARAMETER
1130 CHAPTER 5 EXAMPLES

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OUT
COMPUTING REGULARIZATION PATH USING THE LARS

PRINTDOC
 AUTHOR FABIAN PEDREGOSA FABIANPEDREGOSAINRIAFR
 ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT LINEARMODEL
FROM SKLEARN IMPORT DATASETS
DIABETES DATASETSLOADDIABETES
X DIABETESDATA
Y DIABETESTARGET

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PRINTCOMPUTING REGULARIZATION PATH USING THE LARS
  COEFS LINEARMODELLARSPATHX Y METHODLASSO VERBOSETRUE
XX NPSUMNPABSCOEFST AXIS1
XX XX1
PLTPLOTXX COEFST
YMIN YMAX PLTYLIM
PLTVLINESXX YMIN YMAX LINESTYLEDASHED
PLTXLABELCOEF MAXCOEF
PLTYLABELCOEFFICIENTS
PLTTITLELASSO PATH
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0025 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5182 PLOT RIDGE COEFFICIENTS AS A FUNCTION OF THE REGULARIZATION
SHOWS THE EFFECT OF COLLINEARITY IN THE COEFFICIENTS OF AN ESTIMATOR
RIDGE REGRESSION IS THE ESTIMATOR USED IN THIS EXAMPLE EACH COLOR REPRESENTS A DIFFERENT FEATURE OF THE COEFFICIENT VECTOR AND THIS IS DISPLAYED AS A FUNCTION OF THE REGULARIZATION PARAMETER
THIS EXAMPLE ALSO SHOWS THE USEFULNESS OF APPLYING RIDGE REGRESSION TO HIGHLY ILLCONDITIONED MATRICES FOR SUCH MATRICES A SLIGHT CHANGE IN THE TARGET VARIABLE CAN CAUSE HUGE VARIANCES IN THE CALCULATED WEIGHTS IN SUCH CASES IT IS USEFUL TO SET A CERTAIN REGULARIZATION ALPHA TO REDUCE THIS VARIATION NOISE
WHEN ALPHA IS VERY LARGE THE REGULARIZATION EFFECT DOMINATES THE SQUARED LOSS FUNCTION AND THE COEFFICIENTS TEND TO ZERO AT THE END OF THE PATH AS ALPHA TENDS TOWARD ZERO AND THE SOLUTION TENDS TOWARDS THE ORDINARY LEAST SQUARES COEFFICIENTS EXHIBIT BIG OSCILLATIONS IN PRACTISE IT IS NECESSARY TO TUNE ALPHA IN SUCH A WAY THAT A BALANCE IS MAINTAINED BETWEEN BOTH
1132 CHAPTER 5 EXAMPLES

```
SCIKITLEARN USER GUIDE RELEASE 0213
 AUTHOR FABIAN PEDREGOSA  FABIANPEDREGOSAINRIAFR
 LICENSE BSD 3 CLAUSE
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT LINEARMODEL
 X IS THE 10X10 HILBERT MATRIX
X  1  NPARANGE1 11  NPARANGE0 10 NPNEWAXIS
Y  NPONES10

 COMPUTE PATHS
NALPHAS  200
ALPHAS  NPLOGSPACE10 2 NALPHAS
COEFS
FORAINALPHAS
RIDGE  LINEARMODELRIDGEALPHAA FITINTERCEPTFALSE
RIDGEFITX Y
COEFSAPPENDRIDGECOEF
```

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DISPLAY RESULTS
AX PLTGCA
AXPLOTALPHAS COEFS
AXSETXSCALELOG
AXSETXLIMAXGETXLIM1 REVERSE AXIS
PLTXLABELALPHA
PLTYLABELWEIGHTS
PLTTITLERIDGE COEFFICIENTS AS A FUNCTION OF THE REGULARIZATION
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0161 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5183 SGD MAXIMUM MARGIN SEPARATING HYPERPLANE
PLOT THE MAXIMUM MARGIN SEPARATING HYPERPLANE WITHIN A TWOCLASS SEPARABLE DATASET USING A LINEAR SUPPORT VECTOR MACHINES CLASSIFIER TRAINED USING SGD
1134 CHAPTER 5 EXAMPLES

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
FROM SKLEARNDATASETSSAMPLESGENERATOR IMPORT MAKEBLOBS
WE CREATE 50 SEPARABLE POINTS
X Y MAKEBLOBSNSAMPLES50 CENTERS2 RANDOMSTATE0 CLUSTERSTD060
FIT THE MODEL
CLF SGDCLASSIFIERLOSSHINGE ALPHA001 MAXITER200
FITINTERCEPTTRUE TOL1E3
CLFFITX Y
PLOT THE LINE THE POINTS AND THE NEAREST VECTORS TO THE PLANE
XX NPLINSPACE1 5 10
YY NPLINSPACE1 5 10
X1 X2 NPMESHGRIDXX YY
Z NPEMPTYX1SHAPE
FORI J VAL INNPNDENUMERATEX1
X1 VAL
X2 X2I J
P CLFDECISIONFUNCTIONX1 X2
ZI J P0
LEVELS 10 00 10
LINESTYLES DASHED SOLID DASHED
COLORS K
PLTCONTOURX1 X2 Z LEVELS COLORSCOLORS LINESTYLESLINESTYLES
PLTSCATTERX 0 X 1 CY CMAPPLTCMPAIRED
EDGECOLORBLACK S20
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0020 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5184 SGD CONVEX LOSS FUNCTIONS
A PLOT THAT COMPARES THE VARIOUS CONVEX LOSS FUNCTIONS SUPPORTED BY SKLEARNLINEARMODEL
SGDCLASSIFIER
518 GENERALIZED LINEAR MODELS 1135

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
DEFMODIFIEDHUBERLOSSYTRUE YPRED
Z YPRED YTRUE
LOSS 4 Z
LOSSZ 1 1 ZZ 1 2
LOSSZ 1 0
RETURNLOSS
XMIN XMAX 4 4
XX NPLINSPACEXMIN XMAX 100
LW 2
PLTPLOTXMIN 0 0 XMAX 1 1 0 0 COLORGOLD LWLW
LABELZEROONE LOSS
PLTPLOTXX NPWHEREXX 1 1 XX 0 COLORTEAL LWLW
LABELHINGE LOSS
PLTPLOTXX NPMINIMUMXX 0 COLORYELLOWGREEN LWLW
LABELPERCEPTRON LOSS
PLTPLOTXX NPLOG21 NPEXPXX COLORCORNFLOWERBLUE LWLW
LABELLOG LOSS
PLTPLOTXX NPWHEREXX 1 1 XX 0 2 COLORORANGE LWLW

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LABELSQUARED HINGE LOSS
PLTPLOTXX MODIFIEDHUBERLOSSXX 1 COLORDARKORCHID LWLW
LINESTYLE LABELMODIFIED HUBER LOSS
PLTYLIM0 8
PLTLEGENDLOCUPPER RIGHT
PLTXLABELRDECISION FUNCTION FX
PLTYLABELLY1 FX
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0019 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5185 ORDINARY LEAST SQUARES AND RIDGE REGRESSION VARIANCE
DUE TO THE FEW POINTS IN EACH DIMENSION AND THE STRAIGHT LINE THAT LINEAR REGRESSION USES TO FOLLOW THESE POINTS AS WELL AS IT CAN NOISE ON THE OBSERVATIONS WILL CAUSE GREAT VARIANCE AS SHOWN IN THE FIRST PLOT EVERY LINE'S SLOPE CAN VARY QUITE A BIT FOR EACH PREDICTION DUE TO THE NOISE INDUCED IN THE OBSERVATIONS
RIDGE REGRESSION IS BASICALLY MINIMIZING A PENALISED VERSION OF THE LEASTSQUARED FUNCTION THE PENALISING SHRINKS THE VALUE OF THE REGRESSION COEFFICIENTS DESPITE THE FEW DATA POINTS IN EACH DIMENSION THE SLOPE OF THE PREDICTION IS MUCH MORE STABLE AND THE VARIANCE IN THE LINE ITSELF IS GREATLY REDUCED IN COMPARISON TO THAT OF THE STANDARD LINEAR REGRESSION
•

•

```
PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT LINEARMODEL
XTRAIN  NPC5 1T
YTRAIN  5 1
XTEST  NPC0 2T
NPRANDOMSEED0
CLASSIFIERS  DICTOLSLINEARMODELLINEARREGRESSION
RIDGELINEARMODELRIDGEALPHA1
FORNAME CLF INCLASSIFIERSITEMS
FIG AX  PLTSUBPLOTSFIGSIZE4 3
FORINRANGE6
THISX  1 NPRANDOMNORMALSIZE2 1  XTRAIN
CLFFITTHISX YTRAIN
AXPLOTXTEST CLFPREDICTXTEST COLORGRAY
AXSCATTERTHISX YTRAIN S3 CGRAY MARKERO ZORDER10
CLFFITXTRAIN YTRAIN
AXPLOTXTEST CLFPREDICTXTEST LINEWIDTH2 COLORBLUE
AXSCATTERXTRAIN YTRAIN S30 CRED MARKER ZORDER10
AXSETTITLENAME
AXSETXLIM0 2
```

SCIKITLEARN USER GUIDE RELEASE 0213
AXSETYLIM0 16
AXSETXLABELX
AXSETYLABELY
FIGTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0130 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5186 PLOT RIDGE COEFFICIENTS AS A FUNCTION OF THE L2 REGULARIZATION
RIDGE REGRESSION IS THE ESTIMATOR USED IN THIS EXAMPLE EACH COLOR IN THE LEFT PLOT REPRESENTS ONE DIFFERENT DIMENSION OF THE COEFFICIENT VECTOR AND THIS IS DISPLAYED AS A FUNCTION OF THE REGULARIZATION PARAMETER THE RIGHT PLOT SHOWS HOW EXACT THE SOLUTION IS THIS EXAMPLE ILLUSTRATES HOW A WELL DEFINED SOLUTION IS FOUND BY RIDGE REGRESSION AND HOW REGULARIZATION AFFECTS THE COEFFICIENTS AND THEIR VALUES THE PLOT ON THE RIGHT SHOWS HOW THE DIFFERENCE OF THE COEFFICIENTS FROM THE ESTIMATOR CHANGES AS A FUNCTION OF REGULARIZATION
IN THIS EXAMPLE THE DEPENDENT VARIABLE Y IS SET AS A FUNCTION OF THE INPUT FEATURES Y XW C THE COEFFICIENT VECTOR W IS RANDOMLY SAMPLED FROM A NORMAL DISTRIBUTION WHEREAS THE BIAS TERM C IS SET TO A CONSTANT
AS ALPHA TENDS TOWARD ZERO THE COEFFICIENTS FOUND BY RIDGE REGRESSION STABILIZE TOWARDS THE RANDOMLY SAMPLED VECTOR W FOR BIG ALPHA STRONG REGULARISATION THE COEFFICIENTS ARE SMALLER EVENTUALLY CONVERGING AT 0 LEADING TO A SIMPLER AND BIASED SOLUTION THESE DEPENDENCIES CAN BE OBSERVED ON THE LEFT PLOT
THE RIGHT PLOT SHOWS THE MEAN SQUARED ERROR BETWEEN THE COEFFICIENTS FOUND BY THE MODEL AND THE CHOSEN VECTOR W LESS REGULARISED MODELS RETRIEVE THE EXACT COEFFICIENTS ERROR IS EQUAL TO 0 STRONGER REGULARISED MODELS INCREASE THE ERROR
PLEASE NOTE THAT IN THIS EXAMPLE THE DATA IS NONNOISY HENCE IT IS POSSIBLE TO EXTRACT THE EXACT COEFFICIENTS
 AUTHOR KORNEL KIELCZEWSKI KORNELKPLUSNETPL
PRINTDOC
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
FROM SKLEARNLINEARMODEL IMPORT RIDGE

SCIKITLEARN USER GUIDE RELEASE 0213
FROM SKLEARNMETRICS IMPORT MEANSQUAREDERROR
CLF RIDGE
X Y W MAKEREGRESSIONNSAMPLES10 NFEATURES10 COEFTRUE
RANDOMSTATE1 BIAS35
COEFS
ERRORS
ALPHAS NPLOGSPACE6 6 200
 TRAIN THE MODEL WITH DIFFERENT REGULARISATION STRENGTHS
FORAINALPHAS
CLFSETPARAMSALPHAA
CLFFITX Y
COEFSAPPENDCLFCOEF
ERRORSAPPENDMEANSQUAREDERRORCLFCOEF W
 DISPLAY RESULTS
PLTFIGUREFIGSIZE20 6
PLTSUBPLOT121
AX PLTGCA
AXPLOTALPHAS COEFS
AXSETXSCALELOG
PLTXLABELALPHA
PLTYLABELWEIGHTS
PLTTITLERIDGE COEFFICIENTS AS A FUNCTION OF THE REGULARIZATION
PLTAXISTIGHT
PLTSUBPLOT122
AX PLTGCA
AXPLOTALPHAS ERRORS
AXSETXSCALELOG
PLTXLABELALPHA
PLTYLABELERROR
PLTTITLECOEFFICIENT ERROR AS A FUNCTION OF THE REGULARIZATION
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0126 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5187 SGD PENALTIES
CONTOURS OF WHERE THE PENALTY IS EQUAL TO 1 FOR THE THREE PENALTIES L1 L2 AND ELASTICNET
ALL OF THE ABOVE ARE SUPPORTED BY SKLEARNLINEARMODELSTOCHASTICGRADIENT
1140 CHAPTER 5 EXAMPLES

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
L1COLOR NAVY
L2COLOR C
ELASTICNETCOLOR DARKORANGE
LINE NPLINSPACE15 15 1001
XX YY NPMESHGRIDLINE LINE
L2 XX 2 YY2
L1 NPABSXX NPABSYY
RHO 05
518 GENERALIZED LINEAR MODELS 1141

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ELASTICNET RHO L1 1 RHO L2
PLTFIGUREFIGSIZE10 10 DPI100
AX PLTGCA
ELASTICNETCONTOUR PLTCONTOURXX YY ELASTICNET LEVELS1
COLORSELASTICNETCOLOR
L2CONTOUR PLTCONTOURXX YY L2 LEVELS1 COLORSL2COLOR
L1CONTOUR PLTCONTOURXX YY L1 LEVELS1 COLORSL1COLOR
AXSETASPECTEQUAL
AXSPINESLEFTSETPOSITIONCENTER
AXSPINESRIGHTSETCOLORNONE
AXSPINESBOTTOMSETPOSITIONCENTER
AXSPINESTOPSETCOLORNONE
PLTCLABELELASTICNETCONTOUR INLINE1 FONTSIZE18
FMT10 ELASTICNET MANUAL1 1
PLTCLABELL2CONTOUR INLINE1 FONTSIZE18
FMT10 L2 MANUAL1 1
PLTCLABELL1CONTOUR INLINE1 FONTSIZE18
FMT10 L1 MANUAL1 1
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0247 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5188 REGULARIZATION PATH OF L1 LOGISTIC REGRESSION
TRAIN L1PENALIZED LOGISTIC REGRESSION MODELS ON A BINARY CLASSIFICATION PROBLEM DERIVED FROM THE IRIS DATASET
THE MODELS ARE ORDERED FROM STRONGEST REGULARIZED TO LEAST REGULARIZED THE 4 COEFFICIENTS OF THE MODELS ARE COLLECTED AND PLOTTED AS A “REGULARIZATION PATH” ON THE LEFTHAND SIDE OF THE FIGURE STRONG REGULARIZERS ALL THE COEFFICIENTS ARE EXACTLY 0 WHEN REGULARIZATION GETS PROGRESSIVELY LOOSER COEFFICIENTS CAN GET NONZERO VALUES ONE AFTER THE OTHER
HERE WE CHOOSE THE SAGA SOLVER BECAUSE IT CAN EFFICIENTLY OPTIMIZE FOR THE LOGISTIC REGRESSION LOSS WITH A NON SMOOTH SPARSITY INDUCING L1 PENALTY
ALSO NOTE THAT WE SET A LOW VALUE FOR THE TOLERANCE TO MAKE SURE THAT THE MODEL HAS CONVERGED BEFORE COLLECTING THE COEFFICIENTS
WE ALSO USE WARMSTARTTRUE WHICH MEANS THAT THE COEFFICIENTS OF THE MODELS ARE REUSED TO INITIALIZE THE NEXT MODEL FIT TO SPEEDUP THE COMPUTATION OF THE FULLPATH

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OUT
COMPUTING REGULARIZATION PATH
THIS TOOK 2008S
PRINTDOC
 AUTHOR ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
 LICENSE BSD 3 CLAUSE
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT LINEARMODEL
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNSVM IMPORT L1MINC
IRIS DATASETSLOADIRIS
X IRISDATA
Y IRISTARGET

SCIKITLEARN USER GUIDE RELEASE 0213
X XY 2
Y YY 2
X XMAX NORMALIZE X TO SPEEDUP CONVERGENCE

 DEMO PATH FUNCTIONS
CS L1MINCX Y LOSSLOG NPLOGSPACE0 7 16
PRINTCOMPUTING REGULARIZATION PATH
START TIME
CLF LINEARMODELLOGISTICREGRESSIONPENALTYL1 SOLVERSAGA
TOL1E6 MAXITERINT1E6
WARMSTARTTRUE
COEFS
FORCINCS
CLFSETPARAMSCC
CLFFITX Y
COEFSAPPENDCLFCOEFRAVELCOPY
PRINTTHIS TOOK 03FS TIME START
COEFS NPARRAYCOEFS
PLTPLOTNPLOG10CS COEFS MARKERO
YMIN YMAX PLTYLIM
PLTXLABELLOGC
PLTYLABELCOEFFICIENTS
PLTTITLELOGISTIC REGRESSION PATH
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2022 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5189 POLYNOMIAL INTERPOLATION
THIS EXAMPLE DEMONSTRATES HOW TO APPROXIMATE A FUNCTION WITH A POLYNOMIAL OF DEGREE NDEGREE BY USING RIDGE REGRESSION CONCRETELY FROM NSAMPLES 1D POINTS IT SUFFICES TO BUILD THE VANDERMONDE MATRIX WHICH IS NSAMPLES X NDEGREE1 AND HAS THE FOLLOWING FORM
1 X1 X1 2 X1 3   1 X2 X2 2 X2 3
INTUITIVELY THIS MATRIX CAN BE INTERPRETED AS A MATRIX OF PSEUDO FEATURES THE POINTS RAISED TO SOME POWER THE MATRIX IS AKIN TO BUT DIFFERENT FROM THE MATRIX INDUCED BY A POLYNOMIAL KERNEL
THIS EXAMPLE SHOWS THAT YOU CAN DO NONLINEAR REGRESSION WITH A LINEAR MODEL USING A PIPELINE TO ADD NONLINEAR FEATURES KERNEL METHODS EXTEND THIS IDEA AND CAN INDUCE VERY HIGH EVEN INFINITE DIMENSIONAL FEATURE SPACES

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
 AUTHOR MATHIEU BLONDEL
 JAKE VANDERPLAS
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNLINEARMODEL IMPORT RIDGE
FROM SKLEARNPREPROCESSING IMPORT POLYNOMIALFEATURES
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
DEFFX
 FUNCTION TO APPROXIMATE BY POLYNOMIAL INTERPOLATION
RETURNXNPSINX
 GENERATE POINTS USED TO PLOT
XPLOT NPLINSPACE0 10 100
 GENERATE POINTS AND KEEP A SUBSET OF THEM
X NPLINSPACE0 10 100
RNG NPRANDOMRANDOMSTATE0
RNGSHUFFLEX
518 GENERALIZED LINEAR MODELS 1145

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X NPSORTX20
Y FX
 CREATE MATRIX VERSIONS OF THESE ARRAYS
X X NPNEWAXIS
XPLOT XPLOT NPNEWAXIS
COLORS TEAL YELLOWGREEN GOLD
LW 2
PLTPLOTXPLOT FXPLOT COLORCORNFLOWERBLUE LINEWIDTHLW
LABELGROUND TRUTH
PLTSCATTERX Y COLORNAVY S30 MARKERO LABELTRAINING POINTS
FORCOUNT DEGREE INENUMERATE3 4 5
MODEL MAKEPIPELINEPOLYNOMIALFEATURESDEGREE RIDGE
MODELFITX Y
YPLOT MODELPREDICTXPLOT
PLTPLOTXPLOT YPLOT COLORCOLORSCOUNT LINEWIDTHLW
LABELDEGREE D DEGREE
PLTLEGENDLOCLOWER LEFT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0020 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51810 LOGISTIC FUNCTION
SHOWN IN THE PLOT IS HOW THE LOGISTIC REGRESSION WOULD IN THIS SYNTHETIC DATASET CLASSIFY VALUES AS EITHER 0 OR 1 IE
CLASS ONE OR TWO USING THE LOGISTIC CURVE
1146 CHAPTER 5 EXAMPLES

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PRINTDOC
 CODE SOURCE GAEL VAROQUAUX
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT LINEARMODEL
FROM SCIPYSPECIAL IMPORT EXPIT
 GENERAL A TOY DATASETS ITS JUST A STRAIGHT LINE WITH SOME GAUSSIAN NOISE
XMIN XMAX 5 5
NSAMPLES 100
NPRANDOMSEED0
X NPRANDOMNORMALSIZENSAMPLES
Y X 0ASTYPENPFLOAT
XX 0 4
X 3 NPRANDOMNORMALSIZENSAMPLES
X X NPNEWAXIS
 FIT THE CLASSIFIER
CLF LINEARMODELLOGISTICREGRESSIONC1E5 SOLVERLBFGS
CLFFITX Y
 AND PLOT THE RESULT
PLTFIGURE1 FIGSIZE4 3
PLTCLF
PLTSCATTERXRAVEL Y COLORBLACK ZORDER20
XTEST NPLINSPACE5 10 300
LOSS EXPITXTEST CLFCOEF CLFINTERCEPTRAVEL
PLTPLOTXTEST LOSS COLORRED LINEWIDTH3
OLS LINEARMODELLINEARREGRESSION
OLSFITX Y
PLTPLOTXTEST OLSCOEF XTEST OLSINTERCEPT LINEWIDTH1
PLTAXHLINE5 COLOR5
PLTYLABELY
PLTXLABELX
PLTXTICKSRANGE5 10
PLTYTICKS0 05 1
PLTYLIM25 125
PLTXLIM4 10
PLTLEGENDLOGISTIC REGRESSION MODEL LINEAR REGRESSION MODEL
LOCLOWER RIGHT FONTSIZESMALL
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0046 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

51811 SGD WEIGHTED SAMPLES

PLOT DECISION FUNCTION OF A WEIGHTED DATASET WHERE THE SIZE OF POINTS IS PROPORTIONAL TO ITS WEIGHT

```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT LINEARMODEL
 WE CREATE 20 POINTS
NPRANDOMSEED0
X  NPRNPRANDOMRANDN10 2  1 1 NPRANDOMRANDN10 2
Y  1 10  1 10
SAMPLEWEIGHT  100 NPABSNPRANDOMRANDN20
 AND ASSIGN A BIGGER WEIGHT TO THE LAST 10 SAMPLES
SAMPLEWEIGHT10  10
 PLOT THE WEIGHTED DATA POINTS
XX YY  NPMESHGRIDNPLINSPACE4 5 500 NPLINSPACE4 5 500
PLTFIGURE
PLTSCATTERX 0 X 1 CY SSAMPLEWEIGHT ALPHA09
CMAPPLTCMBONE EDGECOLORBLACK
 FIT THE UNWEIGHTED MODEL
CLF  LINEARMODELSGDCLASSIFIERALPHA001 MAXITER100 TOL1E3
```

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CLFFITX Y
Z CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
NOWEIGHTS PLTCONTOURXX YY Z LEVELS0 LINESTYLESSOLID
 FIT THE WEIGHTED MODEL
CLF LINEARMODELSGDCLASSIFIERALPHA001 MAXITER100 TOL1E3
CLFFITX Y SAMPLEWEIGHTSAMPLEWEIGHT
Z CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
SAMPLESWEIGHTS PLTCONTOURXX YY Z LEVELS0 LINESTYLESDASHED
PLTLEGENDNOWEIGHTSCOLLECTIONS0 SAMPLESWEIGHTSCOLLECTIONS0
NO WEIGHTS WITH WEIGHTS LOCLOWER LEFT
PLTXTICKS
PLTYTICKS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0086 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51812 LOGISTIC REGRESSION 3CLASS CLASSIFIER
SHOW BELOW IS A LOGISTICREGRESSION CLASSIFIERS DECISION BOUNDARIES ON THE FIRST TWO DIMENSIONS SEPAL LENGTH AND WIDTH OF THE IRIS DATASET THE DATAPOINTS ARE COLORED ACCORDING TO THEIR LABELS
PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE

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IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARN IMPORT DATASETS
 IMPORT SOME DATA TO PLAY WITH
IRIS DATASETSLOADIRIS
X IRISDATA 2 WE ONLY TAKE THE FIRST TWO FEATURES
Y IRISTARGET
LOGREG LOGISTICREGRESSIONC1E5 SOLVERLBFGS MULTICLASSMULTINOMIAL
 CREATE AN INSTANCE OF LOGISTIC REGRESSION CLASSIFIER AND FIT THE DATA
LOGREGFITX Y
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
XMIN XMAX X 0MIN 5 X 0MAX 5
YMIN YMAX X 1MIN 5 X 1MAX 5
H 02 STEP SIZE IN THE MESH
XX YY NPMESHGRIDNPARANGEXMIN XMAX H NPARANGEYMIN YMAX H
Z LOGREGPREDICTNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
PLTFIGURE1 FIGSIZE4 3
PLTPCOLORMESHXX YY Z CMAPPLTCMPAIRED
 PLOT ALSO THE TRAINING POINTS
PLTSCATTERX 0 X 1 CY EDGECOLORSK CMAPPLTCMPAIRED
PLTXLABELSEPAL LENGTH
PLTYLABELSEPAL WIDTH
PLTXLIMXXMIN XXMAX
PLTYLIMYYMIN YYMAX
PLTXTICKS
PLTYTICKS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0083 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51813 LINEAR REGRESSION EXAMPLE
THIS EXAMPLE USES THE ONLY THE FIRST FEATURE OF THE DIABETES DATASET IN ORDER TO ILLUSTRATE A TWODIMENSIONAL PLOT OF
THIS REGRESSION TECHNIQUE THE STRAIGHT LINE CAN BE SEEN IN THE PLOT SHOWING HOW LINEAR REGRESSION ATTEMPTS TO DRAW A
STRAIGHT LINE THAT WILL BEST MINIMIZE THE RESIDUAL SUM OF SQUARES BETWEEN THE OBSERVED RESPONSES IN THE DATASET AND THE
RESPONSES PREDICTED BY THE LINEAR APPROXIMATION
THE COEFFICIENTS THE RESIDUAL SUM OF SQUARES AND THE VARIANCE SCORE ARE ALSO CALCULATED

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OUT
COEFFICIENTS
93823786125
MEAN SQUARED ERROR 254807
VARIANCE SCORE 047
PRINTDOC
 CODE SOURCE JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARN IMPORT DATASETS LINEARMODEL
FROM SKLEARNMETRICS IMPORT MEANSQUAREDERROR R2SCORE
 LOAD THE DIABETES DATASET
DIABETES DATASETSLOADDIABETES

SCIKITLEARN USER GUIDE RELEASE 0213
 USE ONLY ONE FEATURE
DIABETESX DIABETESDATA NPNEWAXIS 2
 SPLIT THE DATA INTO TRAININGTESTING SETS
DIABETESXTRAIN DIABETESX20
DIABETESXTEST DIABETESX20
 SPLIT THE TARGETS INTO TRAININGTESTING SETS
DIABETESYTRAIN DIABETESTARGET20
DIABETESYTEST DIABETESTARGET20
 CREATE LINEAR REGRESSION OBJECT
REGR LINEARMODELLINEARREGRESSION
 TRAIN THE MODEL USING THE TRAINING SETS
REGRFITDIABETESXTRAIN DIABETESYTRAIN
 MAKE PREDICTIONS USING THE TESTING SET
DIABETESYPRED REGRPREDICTDIABETESXTEST
 THE COEFFICIENTS
PRINTCOEFFICIENTS N REGRCOEF
 THE MEAN SQUARED ERROR
PRINTMEAN SQUARED ERROR 2F
 MEANSQUAREDERRORDIABETESYTEST DIABETESYPRED
 EXPLAINED VARIANCE SCORE 1 IS PERFECT PREDICTION
PRINTVARIANCE SCORE 2F R2SCOREDIABETESYTEST DIABETESYPRED
 PLOT OUTPUTS
PLTSCATTERDIABETESXTEST DIABETESYTEST COLORBLACK
PLTPLOTDIABETESXTEST DIABETESYPRED COLORBLUE LINEWIDTH3
PLTXTICKS
PLTYTICKS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0175 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51814 ROBUST LINEAR MODEL ESTIMATION USING RANSAC
IN THIS EXAMPLE WE SEE HOW TO ROBUSTLY FIT A LINEAR MODEL TO FAULTY DATA USING THE RANSAC ALGORITHM

SCIKITLEARN USER GUIDE RELEASE 0213
OUT
ESTIMATED COEFFICIENTS TRUE LINEAR REGRESSION RANSAC
821903908407869 5417236387 8208533159
IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM SKLEARN IMPORT LINEARMODEL DATASETS
NSAMPLES 1000
NOUTLIERS 50
X Y COEF DATASETSMAKEREGRESSIONNSAMPLESNSAMPLES NFEATURES1
NINFORMATIVE1 NOISE10
COEFTRUE RANDOMSTATE0
 ADD OUTLIER DATA
NPRANDOMSEED0
518 GENERALIZED LINEAR MODELS 1153

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XNOUTLIERS 3 05 NPRANDOMNORMALSIZENOUTLIERS 1
YNOUTLIERS 3 10 NPRANDOMNORMALSIZENOUTLIERS
 FIT LINE USING ALL DATA
LR LINEARMODELLINEARREGRESSION
LRFITX Y
 ROBUSTLY FIT LINEAR MODEL WITH RANSAC ALGORITHM
RANSAC LINEARMODELRANSACREGRESSOR
RANSACFITX Y
INLIERMASK RANSACINLIERMASK
OUTLIERMASK NPLOGICALNOTINLIERMASK
 PREDICT DATA OF ESTIMATED MODELS
LINEX NPARANGEXMIN XMAX NPNEWAXIS
LINEY LRPREDICTLINEX
LINEYRANSAC RANSACPREDICTLINEX
 COMPARE ESTIMATED COEFFICIENTS
PRINTESTIMATED COEFFICIENTS TRUE LINEAR REGRESSION RANSAC
PRINTCOEF LRCOEF RANSACESTIMATORCOEF
LW 2
PLTSCATTERXINLIERMASK YINLIERMASK COLORYELLOWGREEN MARKER
LABELINLIERS
PLTSCATTERXOUTLIERMASK YOUTLIERMASK COLORGOLD MARKER
LABELOUTLIERS
PLTPLOTLINEX LINEY COLORNAVY LINEWIDTHLW LABELLINEAR REGRESSOR
PLTPLOTLINEX LINEYRANSAC COLORCORNFLOWERBLUE LINEWIDTHLW
LABELRANSAC REGRESSOR
PLTLEGENDLOCLOWER RIGHT
PLTXLABELINPUT
PLTYLABELRESPONSE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0028 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51815 SPARSITY EXAMPLE FITTING ONLY FEATURES 1 AND 2
FEATURES 1 AND 2 OF THE DIABETESDATASET ARE FITTED AND PLOTTED BELOW IT ILLUSTRATES THAT ALTHOUGH FEATURE 2 HAS A STRONG COEFFICIENT ON THE FULL MODEL IT DOES NOT GIVE US MUCH REGARDING YWHEN COMPARED TO JUST FEATURE 1

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518 GENERALIZED LINEAR MODELS 1155

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PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM MPLTOOLKITSMPLOT3D IMPORT AXES3D
FROM SKLEARN IMPORT DATASETS LINEARMODEL
DIABETES  DATASETSLOADDIABETES
INDICES  0 1
XTRAIN  DIABETESDATA20 INDICES
XTEST  DIABETESDATA20 INDICES
YTRAIN  DIABETESTARGET20
YTEST  DIABETESTARGET20
OLS  LINEARMODELLINEARREGRESSION
OLSFITXTRAIN YTRAIN

 PLOT THE FIGURE
DEFPLOTFIGSFIGNUM ELEV AZIM XTRAIN CLF
FIG  PLTFIGUREFIGNUM FIGSIZE4 3
PLTCLF
AX  AXES3DFIG ELEVELEV AZIMAZIM
AXSCATTERXTRAIN 0 XTRAIN 1 YTRAIN CK MARKER
AXPLOTSURFACENPARRAY1 1 15 15
NPARRAY1 15 1 15
CLFPREDICTNPARRAY1 1 15 15
1 15 1 15T
RESHAPE2 2
```

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ALPHA5
AXSETXLABELX1
AXSETYLABELX2
AXSETZLABELY
AXWXAXISSETTICKLABELS
AXWYAXISSETTICKLABELS
AXWZAXISSETTICKLABELS
GENERATE THE THREE DIFFERENT FIGURES FROM DIFFERENT VIEWS
ELEV 435
AZIM 110
PLOTFIGS1 ELEV AZIM XTRAIN OLS
ELEV 5
AZIM 0
PLOTFIGS2 ELEV AZIM XTRAIN OLS
ELEV 5
AZIM 90
PLOTFIGS3 ELEV AZIM XTRAIN OLS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0197 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51816 LASSO ON DENSE AND SPARSE DATA
WE SHOW THAT LINEARMODELLASSO PROVIDES THE SAME RESULTS FOR DENSE AND SPARSE DATA AND THAT IN THE CASE OF SPARSE DATA THE SPEED IS IMPROVED
OUT
 DENSE MATRICES
SPARSE LASSO DONE IN 0186067S
DENSE LASSO DONE IN 0034536S
DISTANCE BETWEEN COEFFICIENTS 9043732562018544E14
 SPARSE MATRICES
MATRIX DENSITY 06263000000000001
SPARSE LASSO DONE IN 0284597S
DENSE LASSO DONE IN 0955330S
DISTANCE BETWEEN COEFFICIENTS 7344760355532163E12
PRINTDOC
FROM TIME IMPORT TIME
FROM SCIPY IMPORT SPARSE
FROM SCIPY IMPORT LINALG

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FROM SKLEARNDATASETSSAMPLESGENERATOR IMPORT MAKEREGRESSION
FROM SKLEARNLINEARMODEL IMPORT LASSO

 THE TWO LASSO IMPLEMENTATIONS ON DENSE DATA
PRINT DENSE MATRICES
X Y MAKEREGRESSIONNSAMPLES200 NFEATURES5000 RANDOMSTATE0
XSP SPARSECOOMATRIXX
ALPHA 1
SPARSELASSO LASSOALPHAALPHA FITINTERCEPTFALSE MAXITER1000
DENSELASSO LASSOALPHAALPHA FITINTERCEPTFALSE MAXITER1000
T0 TIME
SPARSELASSOFITXSP Y
PRINTSPARSE LASSO DONE IN FS TIME T0
T0 TIME
DENSELASSOFITX Y
PRINTDENSE LASSO DONE IN FS TIME T0
PRINTDISTANCE BETWEEN COEFFICIENTS S
 LINALGNORMSPARSELASSOCOEF DENSELASSOCOEF

 THE TWO LASSO IMPLEMENTATIONS ON SPARSE DATA
PRINT SPARSE MATRICES
XS XCOPY
XSXS 25 00
XS SPARSECOOMATRIXXS
XS XSTOCSC
PRINTMATRIX DENSITY S   XSNNZ FLOATXSIZE 100
ALPHA 01
SPARSELASSO LASSOALPHAALPHA FITINTERCEPTFALSE MAXITER10000
DENSELASSO LASSOALPHAALPHA FITINTERCEPTFALSE MAXITER10000
T0 TIME
SPARSELASSOFITXS Y
PRINTSPARSE LASSO DONE IN FS TIME T0
T0 TIME
DENSELASSOFITXSTOARRAY Y
PRINTDENSE LASSO DONE IN FS TIME T0
PRINTDISTANCE BETWEEN COEFFICIENTS S
 LINALGNORMSPARSELASSOCOEF DENSELASSOCOEF
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1565 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
1158 CHAPTER 5 EXAMPLES

51817 HUBERREGRESSOR VS RIDGE ON DATASET WITH STRONG OUTLIERS
FIT RIDGE AND HUBERREGRESSOR ON A DATASET WITH OUTLIERS
THE EXAMPLE SHOWS THAT THE PREDICTIONS IN RIDGE ARE STRONGLY INFLUENCED BY THE OUTLIERS PRESENT IN THE DATASET THE HUBER REGRESSOR IS LESS INFLUENCED BY THE OUTLIERS SINCE THE MODEL USES THE LINEAR LOSS FOR THESE AS THE PARAMETER EPSILON IS INCREASED FOR THE HUBER REGRESSOR THE DECISION FUNCTION APPROACHES THAT OF THE RIDGE
AUTHORS MANOJ KUMAR MKS542NYUEDU
LICENSE BSD 3 CLAUSE

```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
FROM SKLEARNLINEARMODEL IMPORT HUBERREGRESSOR RIDGE
 GENERATE TOY DATA
RNG  NPRANDOMRANDOMSTATE0
X Y  MAKEREGRESSIONNSAMPLES20 NFEATURES1 RANDOMSTATE0 NOISE40
BIAS1000
 ADD FOUR STRONG OUTLIERS TO THE DATASET
XOUTLIERS  RNGNORMAL0 05 SIZE4 1
```

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YOUTLIERS RNGNORMAL0 20 SIZE4
XOUTLIERS2   XMAX XMEAN 4
XOUTLIERS2   XMIN XMEAN 4
YOUTLIERS2 YMIN YMEAN 4
YOUTLIERS2 YMAX YMEAN 4
X NPVSTACKX XOUTLIERS
Y NPCONCATENATEY YOUTLIERS
PLTPLOTX Y B
 FIT THE HUBER REGRESSOR OVER A SERIES OF EPSILON VALUES
COLORS R B Y M
X NPLINSPACEXMIN XMAX 7
EPSILONVALUES 135 15 175 19
FORK EPSILON INENUMERATEEPSILONVALUES
HUBER HUBERREGRESSORFITINTERCEPTTRUE ALPHA00 MAXITER100
EPSILONEPSILON
HUBERFITX Y
COEF HUBERCOEF X HUBERINTERCEPT
PLTPLOTX COEF COLORSK LABELHUBER LOSS S EPSILON
 FIT A RIDGE REGRESSOR TO COMPARE IT TO HUBER REGRESSOR
RIDGE RIDGEFITINTERCEPTTRUE ALPHA00 RANDOMSTATE0 NORMALIZETRUE
RIDGEFITX Y
COEFRIDGE RIDGECOEF
COEF RIDGECOEF X RIDGEINTERCEPT
PLTPLOTX COEF G LABELRIDGE REGRESSION
PLTTITLECOMPARISON OF HUBERREGRESSOR VS RIDGE
PLTXLABELX
PLTYLABELY
PLTLEGENDLOC0
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0032 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51818 JOINT FEATURE SELECTION WITH MULTITASK LASSO
THE MULTITASK LASSO ALLOWS TO FIT MULTIPLE REGRESSION PROBLEMS JOINTLY ENFORCING THE SELECTED FEATURES TO BE THE SAME ACROSS TASKS THIS EXAMPLE SIMULATES SEQUENTIAL MEASUREMENTS EACH TASK IS A TIME INSTANT AND THE RELEVANT FEATURES VARY IN AMPLITUDE OVER TIME WHILE BEING THE SAME THE MULTITASK LASSO IMPOSES THAT FEATURES THAT ARE SELECTED AT ONE TIME POINT ARE SELECT FOR ALL TIME POINT THIS MAKES FEATURE SELECTION BY THE LASSO MORE STABLE

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518 GENERALIZED LINEAR MODELS 1161

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PRINTDOC
 AUTHOR ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
 LICENSE BSD 3 CLAUSE
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNLINEARMODEL IMPORT MULTITASKLASSO LASSO
RNG  NPRANDOMRANDOMSTATE42
 GENERATE SOME 2D COEFFICIENTS WITH SINE WAVES WITH RANDOM FREQUENCY AND PHASE
NSAMPLES NFEATURES NTASKS  100 30 40
NRELEVANTFEATURES  5
COEF  NPZEROSNTASKS NFEATURES
TIMES  NPLINSPACE0 2 NPPI NTASKS
FORKINRANGENRELEVANTFEATURES
COEF K  NPSIN1  RNGRANDN1 TIMES  3 RNGRANDN1
X  RNGRANDNNSAMPLES NFEATURES
Y  NPDOTX COEFT  RNGRANDNNSAMPLES NTASKS
COEFLASSO  NPARRAYLASSOALPHA05FITX YCOEF FORYINYT
COEFMULTITASKLASSO  MULTITASKLASSOALPHA1FITX YCOEF

 PLOT SUPPORT AND TIME SERIES
FIG  PLTFIGUREFIGSIZE8 5
PLTSUBPLOT1 2 1
PLTSPYCOEFLASSO
PLTXLABELFEATURE
PLTYLABELTIME OR TASK
PLTTEXT10 5 LASSO
PLTSUBPLOT1 2 2
PLTSPYCOEFMULTITASKLASSO
PLTXLABELFEATURE
PLTYLABELTIME OR TASK
PLTTEXT10 5 MULTITASKLASSO
FIGSUPTITLECOEFFICIENT NONZERO LOCATION
FEATURETOPLOT  0
PLTFIGURE
LW  2
PLTPLOTCOEF FEATURETOPLOT COLORSEAGREEN LINEWIDTHLW
LABELGROUND TRUTH
PLTPLOTCOEFLASSO FEATURETOPLOT COLORCORNFLOWERBLUE LINEWIDTHLW
LABELLASSO
PLTPLOTCOEFMULTITASKLASSO FEATURETOPLOT COLORGOLD LINEWIDTHLW
LABELMULTITASKLASSO
PLTLEGENDLOCUPPER CENTER
PLTAXISTIGHT
PLTYLIM11 11
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT  0 MINUTES 0061 SECONDS
```

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51819 COMPARING VARIOUS ONLINE SOLVERS
AN EXAMPLE SHOWING HOW DIFFERENT ONLINE SOLVERS PERFORM ON THE HANDWRITTEN DIGITS DATASET
OUT
TRAINING SGD
TRAINING ASGD
TRAINING PERCEPTRON
TRAINING PASSIVEAGGRESSIVE I
TRAINING PASSIVEAGGRESSIVE II
TRAINING SAG
AUTHOR ROB ZINKOV ROB AT ZINKOV DOT COM
LICENSE BSD 3 CLAUSE

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IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER PERCEPTRON
FROM SKLEARNLINEARMODEL IMPORT PASSIVEAGGRESSIVECLASSIFIER
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
HELDOUT 095 090 075 050 001
ROUNDS 20
DIGITS DATASETSLOADDIGITS
X Y DIGITSDATA DIGITSTARGET
CLASSIFIERS
SGD SGDCLASSIFIERMAXITER100 TOL1E3
ASGD SGDCLASSIFIERAVERAGETRUE MAXITER1000 TOL1E3
PERCEPTRON PERCEPTRONTOL1E3
PASSIVEAGGRESSIVE I PASSIVEAGGRESSIVECLASSIFIERLOSSHINGE
C10 TOL1E4
PASSIVEAGGRESSIVE II PASSIVEAGGRESSIVECLASSIFIERLOSSSQUAREDHINGE
C10 TOL1E4
SAG LOGISTICREGRESSIONSOLVERSAG TOL1E1 C1E4 XSHAPE0
MULTICLASSAUTO

XX 1 NPARRAYHELDOUT
FORNAME CLF INCLASSIFIERS
PRINTTRAINING S NAME
RNG NPRANDOMRANDOMSTATE42
YY
FORIINHELDOUT
YY
FORRINRANGEROUNDS
XTRAIN XTEST YTRAIN YTEST
TRAINTESTSPLITX Y TESTSIZEI RANDOMSTATERNG
CLFFITXTRAIN YTRAIN
YPRED CLFPREDICTXTEST
YYAPPEND1 NPMEANYPRED YTEST
YYAPPENDNPMEANYY
PLTPLOTXX YY LABELNAME
PLTLEGENDLOCUPPER RIGHT
PLTXLABELPROPORTION TRAIN
PLTYLABELTEST ERROR RATE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 24266 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51820 ORTHOGONAL MATCHING PURSUIT
USING ORTHOGONAL MATCHING PURSUIT FOR RECOVERING A SPARSE SIGNAL FROM A NOISY MEASUREMENT ENCODED WITH A DICTIONARY
1164 CHAPTER 5 EXAMPLES

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PRINTDOC
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNLINEARMODEL IMPORT ORTHOGONALMATCHINGPURSUIT
FROM SKLEARNLINEARMODEL IMPORT ORTHOGONALMATCHINGPURSUITCV
FROM SKLEARNDATASETS IMPORT MAKESPARSECODEDSIGNAL
NCOMPONENTS NFEATURES 512 100
NNONZEROCOEFS 17
 GENERATE THE DATA
 Y XW
 X0 NNONZEROCOEFS

SCIKITLEARN USER GUIDE RELEASE 0213
Y X W MAKESPARSECODEDSIGNALNSAMPLES1
NCOMPONENTSNCOMPONENTS
NFEATURESNFEATURES
NNONZEROCOEFSNNONZEROCOEFS
RANDOMSTATE0
IDX WNONZERO
 DISTORT THE CLEAN SIGNAL
YNOISY Y 005 NPRANDOMRANDNLENY
 PLOT THE SPARSE SIGNAL
PLTFIGUREFIGSIZE7 7
PLTSUBPLOT4 1 1
PLTXLIM0 512
PLTTITLESPARSE SIGNAL
PLTSTEMIDX WIDX
 PLOT THE NOISEFREE RECONSTRUCTION
OMP ORTHOGONALMATCHINGPURSUITNNONZEROCOEFSNNONZEROCOEFS
OMPFITX Y
COEF OMPCOEF
IDXR COEFNONZERO
PLTSUBPLOT4 1 2
PLTXLIM0 512
PLTTITLERECOVERED SIGNAL FROM NOISEFREE MEASUREMENTS
PLTSTEMIDXR COEFIDXR
 PLOT THE NOISY RECONSTRUCTION
OMPFITX YNOISY
COEF OMPCOEF
IDXR COEFNONZERO
PLTSUBPLOT4 1 3
PLTXLIM0 512
PLTTITLERECOVERED SIGNAL FROM NOISY MEASUREMENTS
PLTSTEMIDXR COEFIDXR
 PLOT THE NOISY RECONSTRUCTION WITH NUMBER OF NONZEROS SET BY CV
OMPCV ORTHOGONALMATCHINGPURSUITCVCV5
OMPCVFITX YNOISY
COEF OMPCVCOEF
IDXR COEFNONZERO
PLTSUBPLOT4 1 4
PLTXLIM0 512
PLTTITLERECOVERED SIGNAL FROM NOISY MEASUREMENTS WITH CV
PLTSTEMIDXR COEFIDXR
PLTSUBPLOTSADJUST006 004 094 090 020 038
PLTSUPTITLESPARSE SIGNAL RECOVERY WITH ORTHOGONAL MATCHING PURSUIT
FONTSIZE16
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0499 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
1166 CHAPTER 5 EXAMPLES

51821 MNIST CLASSFIFICATION USING MULTINOMIAL LOGISTIC L1
HERE WE FIT A MULTINOMIAL LOGISTIC REGRESSION WITH L1 PENALTY ON A SUBSET OF THE MNIST DIGITS CLASSIFICATION TASK WE USE THE SAGA ALGORITHM FOR THIS PURPOSE THIS A SOLVER THAT IS FAST WHEN THE NUMBER OF SAMPLES IS SIGNIFICANTLY LARGER THAN THE NUMBER OF FEATURES AND IS ABLE TO FINELY OPTIMIZE NONSMOOTH OBJECTIVE FUNCTIONS WHICH IS THE CASE WITH THE L1PENALTY TEST ACCURACY REACHES 08 WHILE WEIGHT VECTORS REMAINS SPARSE AND THEREFORE MORE EASILY INTERPRETABLE NOTE THAT THIS ACCURACY OF THIS L1PENALIZED LINEAR MODEL IS SIGNIFICANTLY BELOW WHAT CAN BE REACHED BY AN L2PENALIZED LINEAR MODEL OR A NONLINEAR MULTILAYER PERCEPTRON MODEL ON THIS DATASET
OUT
SPARSITY WITH L1 PENALTY 8080
TEST SCORE WITH L1 PENALTY 08351
EXAMPLE RUN IN 28654 S
IMPORT TIME
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNDATASETS IMPORT FETCHOPENML
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM SKLEARNUTILS IMPORT CHECKRANDOMSTATE
PRINTDOC
 AUTHOR ARTHUR MENSCH ARTHURMENSCHM4XORG
 LICENSE BSD 3 CLAUSE

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TURN DOWN FOR FASTER CONVERGENCE
T0 TIMETIME
TRAINSAMPLES 5000
LOAD DATA FROM HTTPSWWWOPENMLORGD554
X Y FETCHOPENMLMNIST784 VERSION1 RETURNXYTRUE
RANDOMSTATE CHECKRANDOMSTATE0
PERMUTATION RANDOMSTATEPERMUTATIONXSHAPE0
X XPERMUTATION
Y YPERMUTATION
X XRESHAPEXSHAPE0 1
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLIT
X Y TRAINSIZETRAINSAMPLES TESTSIZE10000
SCALER STANDARDSCALER
XTRAIN SCALERFITTRANSFORMXTRAIN
XTEST SCALERTRANSFORMXTEST
TURN UP TOLERANCE FOR FASTER CONVERGENCE
CLF LOGISTICREGRESSIONC50 TRAINSAMPLES
MULTICLASSMULTINOMIAL
PENALTYL1 SOLVERSAGA TOL01
CLFFITXTRAIN YTRAIN
SPARSITY NPMEANCLFCOEF 0 100
SCORE CLFSCOREXTEST YTEST
PRINTBEST C 4F CLFC
PRINTSPARSITY WITH L1 PENALTY 2F SPARSITY
PRINTTEST SCORE WITH L1 PENALTY 4F SCORE
COEF CLFCOEFCOPY
PLTFIGUREFIGSIZE10 5
SCALE NPABSCOEFMAX
FORIINRANGE10
L1PLOT PLTSUBPLOT2 5 I 1
L1PLOTIMSHOWCOEFIRESHAPE28 28 INTERPOLATIONNEAREST
CMAPPLTCMRDBU VMINSCALE VMAXSCALE
L1PLOTSETXTICKS
L1PLOTSETYTICKS
L1PLOTSETXLABELCLASS I I
PLTSUPTITLECLASSIFICATION VECTOR FOR
RUNTIME TIMETIME T0
PRINTEXAMPLE RUN IN 3FS RUNTIME
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 28655 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51822 PLOT MULTICLASS SGD ON THE IRIS DATASET
PLOT DECISION SURFACE OF MULTICLASS SGD ON IRIS DATASET THE HYPERPLANES CORRESPONDING TO THE THREE ONEVERSUSALL
OV A CLASSIFIERS ARE REPRESENTED BY THE DASHED LINES

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
 IMPORT SOME DATA TO PLAY WITH
IRIS DATASETSLOADIRIS
 WE ONLY TAKE THE FIRST TWO FEATURES WE COULD
 AVOID THIS UGLY SLICING BY USING A TWODIM DATASET
X IRISDATA 2
Y IRISTARGET
COLORS BRY
 SHUFFLE
IDX NPARANGEXSHAPE0
NPRANDOMSEED13
NPRANDOMSHUFFLEIDX
X XIDX
Y YIDX
 STANDARDIZE
MEAN XMEANAXIS0
STD XSTDAXIS0
518 GENERALIZED LINEAR MODELS 1169

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X X MEAN STD
H 02 STEP SIZE IN THE MESH
CLF SGDCLASSIFIERALPHA0001 MAXITER100 TOL1E3FITX Y
 CREATE A MESH TO PLOT IN
XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX H
NPARANGEYMIN YMAX H
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
Z CLFPREDICTNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
CS PLTCONTOURFXX YY Z CMAPPLTCMPAIRED
PLTAXISTIGHT
 PLOT ALSO THE TRAINING POINTS
FORI COLOR INZIPCLFCLASSES COLORS
IDX NPWHEREY I
PLTSCATTERXIDX 0 XIDX 1 CCOLOR LABELIRISTARGETNAMESI
CMAPPLTCMPAIRED EDGECOLORBLACK S20
PLTTITLEDECISION SURFACE OF MULTICLASS SGD
PLTAXISTIGHT
 PLOT THE THREE ONEAGAINSTALL CLASSIFIERS
XMIN XMAX PLTXLIM
YMIN YMAX PLTYLIM
COEF CLFCOEF
INTERCEPT CLFINTERCEPT
DEFPLOTHYPERPLANEC COLOR
DEFLINEX0
RETURNX0COEFC 0 INTERCEPTC COEFC 1
PLTPLOTXMIN XMAX LINEXMIN LINEXMAX
LS COLORCOLOR
FORI COLOR INZIPCLFCLASSES COLORS
PLOTHYPERPLANEI COLOR
PLTLEGEND
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0050 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
1170 CHAPTER 5 EXAMPLES

51823 LASSO AND ELASTIC NET FOR SPARSE SIGNALS
ESTIMATES LASSO AND ELASTICNET REGRESSION MODELS ON A MANUALLY GENERATED SPARSE SIGNAL CORRUPTED WITH AN ADDITIVE NOISE ESTIMATED COEFFICIENTS ARE COMPARED WITH THE GROUNDTRUTH
OUT
LASSOALPHA01
R2 ON TEST DATA 0658064
ELASTICNETALPHA01 L1RATIO07
R2 ON TEST DATA 0642515
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNMETRICS IMPORT R2SCORE

 GENERATE SOME SPARSE DATA TO PLAY WITH

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NPRANDOMSEED42
NSAMPLES NFEATURES 50 100
X NPRANDOMRANDNNSAMPLES NFEATURES
 DECREASING COEF W ALTERNATED SIGNS FOR VISUALIZATION
IDX NPARANGENFEATURES
COEF 1 IDXNPEXPIDX 10
COEF10 0 SPARSIFY COEF
Y NPDOTX COEF
 ADD NOISE
Y 001 NPRANDOMNORMALSIZENSAMPLES
 SPLIT DATA IN TRAIN SET AND TEST SET
NSAMPLES XSHAPE0
XTRAIN YTRAIN XNSAMPLES 2 YNSAMPLES 2
XTEST YTEST XNSAMPLES 2 YNSAMPLES 2

 LASSO
FROM SKLEARNLINEARMODEL IMPORT LASSO
ALPHA 01
LASSO LASSOALPHAALPHA
YPREDLASSO LASSOFITXTRAIN YTRAINPREDICTXTEST
R2SCORELASSO R2SCOREYTEST YPREDLASSO
PRINTLASSO
PRINTR2 ON TEST DATA F R2SCORELASSO

 ELASTICNET
FROM SKLEARNLINEARMODEL IMPORT ELASTICNET
ENET ELASTICNETALPHAALPHA L1RATIO07
YPREDENET ENETFITXTRAIN YTRAINPREDICTXTEST
R2SCOREENET R2SCOREYTEST YPREDENET
PRINTENET
PRINTR2 ON TEST DATA F R2SCOREENET
M S   PLTSTEMNPWHEREENETCOEF0 ENETCOEFENETCOEF 0
MARKERFMTX LABELELASTIC NET COEFFICIENTS
PLTSETPM S COLOR2CA02C
M S   PLTSTEMNPWHERELASSOCOEF0 LASSOCOEFLASSOCOEF 0
MARKERFMTX LABELLASSO COEFFICIENTS
PLTSETPM S COLORFF7F0E
PLTSTEMNPWHERECOEF0 COEFCOEF 0 LABELTRUE COEFFICIENTS
MARKERFMTBX
PLTLEGENDLOCBEST
PLTTITLELASSO R2 3F ELASTIC NET R2 3F
 R2SCORELASSO R2SCOREENET
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0071 SECONDS
1172 CHAPTER 5 EXAMPLES

SCIKITLEARN USER GUIDE RELEASE 0213
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51824 THEILSEN REGRESSION
COMPUTES A THEILSEN REGRESSION ON A SYNTHETIC DATASET
SEETHEILSEN ESTIMATOR GENERALIZEDMEDIANBASED ESTIMATOR FOR MORE INFORMATION ON THE REGRESSOR
COMPARED TO THE OLS ORDINARY LEAST SQUARES ESTIMATOR THE THEILSEN ESTIMATOR IS ROBUST AGAINST OUTLIERS IT HAS
A BREAKDOWN POINT OF ABOUT 293 IN CASE OF A SIMPLE LINEAR REGRESSION WHICH MEANS THAT IT CAN TOLERATE ARBITRARY
CORRUPTED DATA OUTLIERS OF UP TO 293 IN THE TWODIMENSIONAL CASE
THE ESTIMATION OF THE MODEL IS DONE BY CALCULATING THE SLOPES AND INTERCEPTS OF A SUBPOPULATION OF ALL POSSIBLE COM
BINATIONS OF P SUBSAMPLE POINTS IF AN INTERCEPT IS FITTED P MUST BE GREATER THAN OR EQUAL TO NFEATURES 1 THE FINAL
SLOPE AND INTERCEPT IS THEN DEFINED AS THE SPATIAL MEDIAN OF THESE SLOPES AND INTERCEPTS
IN CERTAIN CASES THEILSEN PERFORMS BETTER THAN RANSAC WHICH IS ALSO A ROBUST METHOD THIS IS ILLUSTRATED IN THE SECOND
EXAMPLE BELOW WHERE OUTLIERS WITH RESPECT TO THE XAXIS PERTURB RANSAC TUNING THE RESIDUALTHRESHOLD
PARAMETER OF RANSAC REMEDIES THIS BUT IN GENERAL A PRIORI KNOWLEDGE ABOUT THE DATA AND THE NATURE OF THE OUTLIERS
IS NEEDED DUE TO THE COMPUTATIONAL COMPLEXITY OF THEILSEN IT IS RECOMMENDED TO USE IT ONLY FOR SMALL PROBLEMS IN
TERMS OF NUMBER OF SAMPLES AND FEATURES FOR LARGER PROBLEMS THE MAXSUBPOPULATION PARAMETER RESTRICTS THE
MAGNITUDE OF ALL POSSIBLE COMBINATIONS OF P SUBSAMPLE POINTS TO A RANDOMLY CHOSEN SUBSET AND THEREFORE ALSO LIMITS THE
RUNTIME THEREFORE THEILSEN IS APPLICABLE TO LARGER PROBLEMS WITH THE DRAWBACK OF LOSING SOME OF ITS MATHEMATICAL
PROPERTIES SINCE IT THEN WORKS ON A RANDOM SUBSET
•
518 GENERALIZED LINEAR MODELS 1173

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•
 AUTHOR FLORIAN WILHELM  FLORIANWILHELMGMAILCOM
 LICENSE BSD 3 CLAUSE
IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION THEILSENREGRESSOR
FROM SKLEARNLINEARMODEL IMPORT RANSACREGRESSOR
PRINTDOC
ESTIMATORS  OLS LINEARREGRESSION
THEILSEN THEILSENREGRESSORRANDOMSTATE42
RANSAC RANSACREGRESSORRANDOMSTATE42
COLORS  OLS TURQUOISE THEILSEN GOLD RANSAC LIGHTGREEN
LW  2

 OUTLIERS ONLY IN THE Y DIRECTION
NPRANDOMSEED0
NSAMPLES  200
 LINEAR MODEL Y  3 X  N2 01 2
X  NPRANDOMRANDNNSAMPLES
W  3
C  2
NOISE  01 NPRANDOMRANDNNSAMPLES
```

SCIKITLEARN USER GUIDE RELEASE 0213
Y WX C NOISE
 10 OUTLIERS
Y20 20 X20
X X NPNEWAXIS
PLTSCATTERX Y COLORINDIGO MARKERX S40
LINEX NPARRAY3 3
FORNAME ESTIMATOR INESTIMATORS
T0 TIMETIME
ESTIMATORFITX Y
ELAPSEDTIME TIMETIME T0
YPRED ESTIMATORPREDICTLINEXRESHAPE2 1
PLTPLOTLINEX YPRED COLORCOLORSNAME LINEWIDTHLW
LABELSFIT TIME 2FS NAME ELAPSEDTIME
PLTAXISTIGHT
PLTLEGENDLOCUPPER LEFT
PLTTITLECORRUPT Y

 OUTLIERS IN THE X DIRECTION
NPRANDOMSEED0
 LINEAR MODEL Y 3 X N2 01 2
X NPRANDOMRANDNNSAMPLES
NOISE 01 NPRANDOMRANDNNSAMPLES
Y 3X 2 NOISE
 10 OUTLIERS
X20 99
Y20 22
X X NPNEWAXIS
PLTFIGURE
PLTSCATTERX Y COLORINDIGO MARKERX S40
LINEX NPARRAY3 10
FORNAME ESTIMATOR INESTIMATORS
T0 TIMETIME
ESTIMATORFITX Y
ELAPSEDTIME TIMETIME T0
YPRED ESTIMATORPREDICTLINEXRESHAPE2 1
PLTPLOTLINEX YPRED COLORCOLORSNAME LINEWIDTHLW
LABELSFIT TIME 2FS NAME ELAPSEDTIME
PLTAXISTIGHT
PLTLEGENDLOCUPPER LEFT
PLTTITLECORRUPT X
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1359 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
518 GENERALIZED LINEAR MODELS 1175

51825 PLOT MULTINOMIAL AND ONEVSREST LOGISTIC REGRESSION
PLOT DECISION SURFACE OF MULTINOMIAL AND ONEVSREST LOGISTIC REGRESSION THE HYPERPLANES CORRESPONDING TO THE THREE ONEVSREST OVR CLASSIFIERS ARE REPRESENTED BY THE DASHED LINES
•

•

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OUT
TRAINING SCORE  0995 MULTINOMIAL
TRAINING SCORE  0976 OVR
PRINTDOC
 AUTHORS TOM DUPRE LA TOUR TOMDUPRELATOURM4XORG
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKEBLOBS
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
 MAKE 3CLASS DATASET FOR CLASSIFICATION
CENTERS  5 0 0 15 5 1
X Y  MAKEBLOBSNSAMPLES1000 CENTERSCENTERS RANDOMSTATE40
TRANSFORMATION  04 02 04 12
X  NPDOTX TRANSFORMATION
FORMULTICLASS INMULTINOMIAL OVR
CLF  LOGISTICREGRESSIONSOLVERSAG MAXITER100 RANDOMSTATE42
```

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MULTICLASSMULTICLASSFITX Y
 PRINT THE TRAINING SCORES
PRINTTRAINING SCORE 3FS CLFSCOREX Y MULTICLASS
 CREATE A MESH TO PLOT IN
H 02 STEP SIZE IN THE MESH
XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX H
NPARANGEYMIN YMAX H
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
Z CLFPREDICTNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
PLTFIGURE
PLTCONTOURFXX YY Z CMAPPLTCMPAIRED
PLTTITLEDECISION SURFACE OF LOGISTICREGRESSION S MULTICLASS
PLTAXISTIGHT
 PLOT ALSO THE TRAINING POINTS
COLORS BRY
FORI COLOR INZIPCLFCLASSES COLORS
IDX NPWHEREY I
PLTSCATTERXIDX 0 XIDX 1 CCOLOR CMAPPLTCMPAIRED
EDGECOLORBLACK S20
 PLOT THE THREE ONEAGAINSTALL CLASSIFIERS
XMIN XMAX PLTXLIM
YMIN YMAX PLTYLIM
COEF CLFCOEF
INTERCEPT CLFINTERCEPT
DEFPLOTHYPERPLANEC COLOR
DEFLINEX0
RETURNX0COEFC 0 INTERCEPTC COEFC 1
PLTPLOTXMIN XMAX LINEXMIN LINEXMAX
LS COLORCOLOR
FORI COLOR INZIPCLFCLASSES COLORS
PLOTHYPERPLANEI COLOR
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0262 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51826 ROBUST LINEAR ESTIMATOR FITTING
HERE A SINE FUNCTION IS FIT WITH A POLYNOMIAL OF ORDER 3 FOR VALUES CLOSE TO ZERO
ROBUST FITTING IS DEMOED IN DIFFERENT SITUATIONS
1178 CHAPTER 5 EXAMPLES

• NO MEASUREMENT ERRORS ONLY MODELLING ERRORS FITTING A SINE WITH A POLYNOMIAL
• MEASUREMENT ERRORS IN X
• MEASUREMENT ERRORS IN Y
THE MEDIAN ABSOLUTE DEVIATION TO NON CORRUPT NEW DATA IS USED TO JUDGE THE QUALITY OF THE PREDICTION
WHAT WE CAN SEE THAT
• RANSAC IS GOOD FOR STRONG OUTLIERS IN THE Y DIRECTION
• THEILSEN IS GOOD FOR SMALL OUTLIERS BOTH IN DIRECTION X AND Y BUT HAS A BREAK POINT ABOVE WHICH IT PERFORMS WORSE THAN OLS
• THE SCORES OF HUBERREGRESSOR MAY NOT BE COMPARED DIRECTLY TO BOTH THEILSEN AND RANSAC BECAUSE IT DOES NOT ATTEMPT TO COMPLETELY FILTER THE OUTLIERS BUT LESSEN THEIR EFFECT
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FROM MATPLOTLIB IMPORT PYPLOTASPLT
IMPORT NUMPY AS NP
FROM SKLEARNLINEARMODEL IMPORT
518 GENERALIZED LINEAR MODELS 1181

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LINEARREGRESSION THEILSENREGRESSOR RANSACREGRESSOR HUBERREGRESSOR
FROM SKLEARNMETRICS IMPORT MEANSQUAREDERROR
FROM SKLEARNPREPROCESSING IMPORT POLYNOMIALFEATURES
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
NPRANDOMSEED42
X NPRANDOMNORMALSIZE400
Y NPSINX
 MAKE SURE THAT IT X IS 2D
X X NPNEWAXIS
XTEST NPRANDOMNORMALSIZE200
YTEST NPSINXTEST
XTEST XTEST NPNEWAXIS
YERRORS YCOPY
YERRORS3 3
XERRORS XCOPY
XERRORS3 3
YERRORSLARGE YCOPY
YERRORSLARGE3 10
XERRORSLARGE XCOPY
XERRORSLARGE3 10
ESTIMATORS OLS LINEARREGRESSION
THEILSEN THEILSENREGRESSORRANDOMSTATE42
RANSAC RANSACREGRESSORRANDOMSTATE42
HUBERREGRESSOR HUBERREGRESSOR
COLORS OLS TURQUOISE THEILSEN GOLD RANSAC LIGHTGREEN
‘→HUBERREGRESSOR BLACK
LINESTYLE OLS THEILSEN RANSAC HUBERREGRESSOR
LW 3
XPLOT NPLINSPACEXMIN XMAX
FORTITLE THISX THISY IN
MODELING ERRORS ONLY X Y
CORRUPT X SMALL DEVIANTS XERRORS Y
CORRUPT Y SMALL DEVIANTS X YERRORS
CORRUPT X LARGE DEVIANTS XERRORSLARGE Y
CORRUPT Y LARGE DEVIANTS X YERRORSLARGE
PLTFIGUREFIGSIZE5 4
PLTPLOTTHISX 0 THISY B
FORNAME ESTIMATOR INESTIMATORS
MODEL MAKEPIPELINEPOLYNOMIALFEATURES3 ESTIMATOR
MODELFITTHISX THISY
MSE MEANSQUAREDERRORMODELPREDICTXTEST YTEST
YPLOT MODELPREDICTXPLOT NPNEWAXIS
PLTPLOTXPLOT YPLOT COLORCOLORSNAME LINESTYLELINESTYLENAME
LINEWIDTHLW LABEL S ERROR 3F NAME MSE
LEGENDTITLE ERROR OF MEAN NABSOLUTE DEVIATION NTO NONCORRUPT DATA
LEGEND PLTLEGENDLOCUPPER RIGHT FRAMEONFALSE TITLELEGENDTITLE
PROPDICTSIZEXSMALL
1182 CHAPTER 5 EXAMPLES

SCIKITLEARN USER GUIDE RELEASE 0213
PLTXLIM4 102
PLTYLIM2 102
PLTTITLETITLE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3950 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51827 L1 PENALTY AND SPARSITY IN LOGISTIC REGRESSION
COMPARISON OF THE SPARSITY PERCENTAGE OF ZERO COEFFICIENTS OF SOLUTIONS WHEN L1 L2 AND ELASTICNET PENALTY ARE USED FOR DIFFERENT VALUES OF C WE CAN SEE THAT LARGE VALUES OF C GIVE MORE FREEDOM TO THE MODEL CONVERSELY SMALLER VALUES OF C CONSTRAIN THE MODEL MORE IN THE L1 PENALTY CASE THIS LEADS TO SPARSER SOLUTIONS AS EXPECTED THE ELASTICNET PENALTY SPARSITY IS BETWEEN THAT OF L1 AND L2
WE CLASSIFY 8X8 IMAGES OF DIGITS INTO TWO CLASSES 04 AGAINST 59 THE VISUALIZATION SHOWS COEFFICIENTS OF THE MODELS FOR VARYING C
OUT
C100
SPARSITY WITH L1 PENALTY 625
518 GENERALIZED LINEAR MODELS 1183

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SPARSITY WITH ELASTICNET PENALTY 469
SPARSITY WITH L2 PENALTY 469
SCORE WITH L1 PENALTY 090
SCORE WITH ELASTICNET PENALTY 090
SCORE WITH L2 PENALTY 090
C010
SPARSITY WITH L1 PENALTY 2969
SPARSITY WITH ELASTICNET PENALTY 1250
SPARSITY WITH L2 PENALTY 469
SCORE WITH L1 PENALTY 090
SCORE WITH ELASTICNET PENALTY 090
SCORE WITH L2 PENALTY 090
C001
SPARSITY WITH L1 PENALTY 8438
SPARSITY WITH ELASTICNET PENALTY 6875
SPARSITY WITH L2 PENALTY 469
SCORE WITH L1 PENALTY 086
SCORE WITH ELASTICNET PENALTY 088
SCORE WITH L2 PENALTY 089
PRINTDOC
 AUTHORS ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
 MATHIEU BLONDEL MATHIEUMBLONDELORG
 ANDREAS MUELLER AMUELLERAISUNIBONNDE
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
DIGITS DATASETSLOADDIGITS
X Y DIGITSDATA DIGITSTARGET
X STANDARDSCALERFITTRANSFORMX
 CLASSIFY SMALL AGAINST LARGE DIGITS
Y Y 4ASTYPENPINT
L1RATIO 05 L1 WEIGHT IN THE ELASTICNET REGULARIZATION
FIG AXES PLTSUBPLOTS3 3
 SET REGULARIZATION PARAMETER
FORI C AXESROW INENUMERATEZIP1 01 001 AXES
 TURN DOWN TOLERANCE FOR SHORT TRAINING TIME
CLFL1LR LOGISTICREGRESSIONCC PENALTYL1 TOL001 SOLVERSAGA
CLFL2LR LOGISTICREGRESSIONCC PENALTYL2 TOL001 SOLVERSAGA
CLFENLR LOGISTICREGRESSIONCC PENALTYELASTICNET SOLVERSAGA
L1RATIOL1RATIO TOL001

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CLFL1LRFITX Y
CLFL2LRFITX Y
CLFENLRFITX Y
COEFL1LR CLFL1LRCOEFRAVEL
COEFL2LR CLFL2LRCOEFRAVEL
COEFENLR CLFENLRCOEFRAVEL
 COEFL1LR CONTAINS ZEROS DUE TO THE
 L1 SPARSITY INDUCING NORM
SPARSITYL1LR NPMEANCOEFL1LR 0 100
SPARSITYL2LR NPMEANCOEFL2LR 0 100
SPARSITYENLR NPMEANCOEFENLR 0 100
PRINTC2F C
PRINT40 2FFORMATSPARSITY WITH L1 PENALTY SPARSITYL1LR
PRINT40 2FFORMATSPARSITY WITH ELASTICNET PENALTY
SPARSITYENLR
PRINT40 2FFORMATSPARSITY WITH L2 PENALTY SPARSITYL2LR
PRINT40 2FFORMATSCORE WITH L1 PENALTY
CLFL1LRSCOREX Y
PRINT40 2FFORMATSCORE WITH ELASTICNET PENALTY
CLFENLRSCOREX Y
PRINT40 2FFORMATSCORE WITH L2 PENALTY
CLFL2LRSCOREX Y
IFI 0
AXESROW0SETTITLEL1 PENALTY
AXESROW1SETTITLEELASTICNET NL1RATIO S L1RATIO
AXESROW2SETTITLEL2 PENALTY
FORAX COEFS INZIPAXESROW COEFL1LR COEFENLR COEFL2LR
AXIMSHOWNPABSCOEFSRESHAPE8 8 INTERPOLATIONNEAREST
CMAPBINARY VMAX1 VMIN0
AXSETXTICKS
AXSETYTICKS
AXESROW0SETYLABELC S C
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0659 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51828 LASSO AND ELASTIC NET
LASSO AND ELASTIC NET L1 AND L2 PENALISATION IMPLEMENTED USING A COORDINATE DESCENT
THE COEFFICIENTS CAN BE FORCED TO BE POSITIVE

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OUT
COMPUTING REGULARIZATION PATH USING THE LASSO
COMPUTING REGULARIZATION PATH USING THE POSITIVE LASSO
COMPUTING REGULARIZATION PATH USING THE ELASTIC NET
COMPUTING REGULARIZATION PATH USING THE POSITIVE ELASTIC NET
PRINTDOC
AUTHOR ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
LICENSE BSD 3 CLAUSE
FROM ITERTOOLS IMPORT CYCLE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNLINEARMODEL IMPORT LASSOPATH ENETPATH
FROM SKLEARN IMPORT DATASETS
DIABETES DATASETSLOADDIABETES
X DIABETESDATA
Y DIABETESTARGET

SCIKITLEARN USER GUIDE RELEASE 0213
X XSTDAXIS0 STANDARDIZE DATA EASIER TO SET THE L1RATIO PARAMETER
 COMPUTE PATHS
EPS 5E3 THE SMALLER IT IS THE LONGER IS THE PATH
PRINTCOMPUTING REGULARIZATION PATH USING THE LASSO
ALPHASLASSO COEFSLASSO   LASSOPATHX Y EPS FITINTERCEPTFALSE
PRINTCOMPUTING REGULARIZATION PATH USING THE POSITIVE LASSO
ALPHASPOSITIVELASSO COEFSPOSITIVELASSO   LASSOPATH
X Y EPS POSITIVETRUE FITINTERCEPTFALSE
PRINTCOMPUTING REGULARIZATION PATH USING THE ELASTIC NET
ALPHASENET COEFSENET   ENETPATH
X Y EPSEPS L1RATIO08 FITINTERCEPTFALSE
PRINTCOMPUTING REGULARIZATION PATH USING THE POSITIVE ELASTIC NET
ALPHASPOSITIVEENET COEFSPOSITIVEENET   ENETPATH
X Y EPSEPS L1RATIO08 POSITIVETRUE FITINTERCEPTFALSE
 DISPLAY RESULTS
PLTFIGURE1
COLORS CYCLEB R G C K
NEGLOGALPHASLASSO NPLOG10ALPHASLASSO
NEGLOGALPHASENET NPLOG10ALPHASENET
FORCOEFL COEFE C INZIPCOEFSLASSO COEFSENET COLORS
L1 PLTPLOTNEGLOGALPHASLASSO COEFL CC
L2 PLTPLOTNEGLOGALPHASENET COEFE LINESTYLE CC
PLTXLABELLOGALPHA
PLTYLABELCOEFFICIENTS
PLTTITLELASSO AND ELASTICNET PATHS
PLTLEGENDL11 L21 LASSO ELASTICNET LOCLOWER LEFT
PLTAXISTIGHT
PLTFIGURE2
NEGLOGALPHASPOSITIVELASSO NPLOG10ALPHASPOSITIVELASSO
FORCOEFL COEFPL C INZIPCOEFSLASSO COEFSPOSITIVELASSO COLORS
L1 PLTPLOTNEGLOGALPHASLASSO COEFL CC
L2 PLTPLOTNEGLOGALPHASPOSITIVELASSO COEFPL LINESTYLE CC
PLTXLABELLOGALPHA
PLTYLABELCOEFFICIENTS
PLTTITLELASSO AND POSITIVE LASSO
PLTLEGENDL11 L21 LASSO POSITIVE LASSO LOCLOWER LEFT
PLTAXISTIGHT
PLTFIGURE3
NEGLOGALPHASPOSITIVEENET NPLOG10ALPHASPOSITIVEENET
FORCOEFE COEFPE C INZIPCOEFSENET COEFSPOSITIVEENET COLORS
L1 PLTPLOTNEGLOGALPHASENET COEFE CC
L2 PLTPLOTNEGLOGALPHASPOSITIVEENET COEFPE LINESTYLE CC
PLTXLABELLOGALPHA

SCIKITLEARN USER GUIDE RELEASE 0213
PLTYLABELCOEFFICIENTS
PLTTITLEELASTICNET AND POSITIVE ELASTICNET
PLTLEGENDL11 L21 ELASTICNET POSITIVE ELASTICNET
LOCLOWER LEFT
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0232 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51829 AUTOMATIC RELEVANCE DETERMINATION REGRESSION ARD
FIT REGRESSION MODEL WITH BAYESIAN RIDGE REGRESSION
SEEBAYESIAN RIDGE REGRESSION FOR MORE INFORMATION ON THE REGRESSOR
COMPARED TO THE OLS ORDINARY LEAST SQUARES ESTIMATOR THE COEFFICIENT WEIGHTS ARE SLIGHTLY SHIFTED TOWARD ZEROS
WHICH STABILISES THEM
THE HISTOGRAM OF THE ESTIMATED WEIGHTS IS VERY PEAKED AS A SPARSITYINDUCING PRIOR IS IMPLIED ON THE WEIGHTS
THE ESTIMATION OF THE MODEL IS DONE BY ITERATIVELY MAXIMIZING THE MARGINAL LOGLIKELIHOOD OF THE OBSERVATIONS
WE ALSO PLOT PREDICTIONS AND UNCERTAINTIES FOR ARD FOR ONE DIMENSIONAL REGRESSION USING POLYNOMIAL FEATURE EXPAN
SION NOTE THE UNCERTAINTY STARTS GOING UP ON THE RIGHT SIDE OF THE PLOT THIS IS BECAUSE THESE TEST SAMPLES ARE OUTSIDE
OF THE RANGE OF THE TRAINING SAMPLES

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518 GENERALIZED LINEAR MODELS 1193

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPY IMPORT STATS
FROM SKLEARNLINEARMODEL IMPORT ARDREGRESSION LINEARREGRESSION

 GENERATING SIMULATED DATA WITH GAUSSIAN WEIGHTS
 PARAMETERS OF THE EXAMPLE
NPRANDOMSEED0
NSAMPLES NFEATURES  100 100
 CREATE GAUSSIAN DATA
X  NPRANDOMRANDNNSAMPLES NFEATURES
 CREATE WEIGHTS WITH A PRECISION LAMBDA OF 4
LAMBDA  4
W  NPZEROSNFEATURES
 ONLY KEEP 10 WEIGHTS OF INTEREST
RELEVANTFEATURES  NPRANDOMRANDINT0 NFEATURES 10
FORIINRELEVANTFEATURES
WI  STATSNORMRVSLOC0 SCALE1  NPSQRTLAMBDA
 CREATE NOISE WITH A PRECISION ALPHA OF 50
ALPHA  50
```

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NOISE STATSNORMRVSLOC0 SCALE1 NPSQRTALPHA SIZENSAMPLES
 CREATE THE TARGET
Y NPDOTX W NOISE

 FIT THE ARD REGRESSION
CLF ARDREGRESSIONCOMPUTESCORETRUE
CLFFITX Y
OLS LINEARREGRESSION
OLSFITX Y

 PLOT THE TRUE WEIGHTS THE ESTIMATED WEIGHTS THE HISTOGRAM OF THE
 WEIGHTS AND PREDICTIONS WITH STANDARD DEVIATIONS
PLTFIGUREFIGSIZE6 5
PLTTITLEWEIGHTS OF THE MODEL
PLTPLOTCLFCOEF COLORDARKBLUE LINESTYLE LINEWIDTH2
LABELARD ESTIMATE
PLTPLOTOLSCOEF COLORYELLOWGREEN LINESTYLE LINEWIDTH2
LABELOLS ESTIMATE
PLTPLOTW COLORORANGE LINESTYLE LINEWIDTH2 LABELGROUND TRUTH
PLTXLABELFEATURES
PLTYLABELVALUES OF THE WEIGHTS
PLTLEGENDLOC1
PLTFIGUREFIGSIZE6 5
PLTTITLEHISTOGRAM OF THE WEIGHTS
PLTHISTCLFCOEF BINSNFEATURES COLORNAVY LOGTRUE
PLTSCATTERCLFCOEFRELEVANTFEATURES NPFULLLENRELEVANTFEATURES 5
COLORGOLD MARKERO LABELRELEVANT FEATURES
PLTYLABELFEATURES
PLTXLABELVALUES OF THE WEIGHTS
PLTLEGENDLOC1
PLTFIGUREFIGSIZE6 5
PLTTITLEMARGINAL LOGLIKELIHOOD
PLTPLOTCLFSCORES COLORNAVY LINEWIDTH2
PLTYLABELSCORE
PLTXLABELITERATIONS
 PLOTTING SOME PREDICTIONS FOR POLYNOMIAL REGRESSION
DEFFX NOISEAMOUNT
Y NPSQRTX NPSINX
NOISE NPRANDOMNORMAL0 1 LENX
RETURNY NOISEAMOUNT NOISE
DEGREE 10
X NPLINSPACE0 10 100
Y FX NOISEAMOUNT1
CLFPOLY ARDREGRESSIONTHRESHOLDLAMBDA1E5
CLFPOLYFITNPVANDERX DEGREE Y
XPLOT NPLINSPACE0 11 25
YPLOT FXPLOT NOISEAMOUNT0
YMEAN YSTD CLFPOLYPREDICTNPVANDERXPLOT DEGREE RETURNSTDTRUE

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PLTFIGUREFIGSIZE6 5
PLTERRORBARXPLOT YMEAN YSTD COLORNAVY
LABELPOLYNOMIAL ARD LINEWIDTH2
PLTPLOTXPLOT YPLOT COLORGOLD LINEWIDTH2
LABELGROUND TRUTH
PLTYLABELOUTPUT Y
PLTXLABELFEATURE X
PLTLEGENDLOCLOWER LEFT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0293 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51830 BAYESIAN RIDGE REGRESSION
COMPUTES A BAYESIAN RIDGE REGRESSION ON A SYNTHETIC DATASET
SEEBAYESIAN RIDGE REGRESSION FOR MORE INFORMATION ON THE REGRESSOR
COMPARED TO THE OLS ORDINARY LEAST SQUARES ESTIMATOR THE COEFFICIENT WEIGHTS ARE SLIGHTLY SHIFTED TOWARD ZEROS
WHICH STABILISES THEM
AS THE PRIOR ON THE WEIGHTS IS A GAUSSIAN PRIOR THE HISTOGRAM OF THE ESTIMATED WEIGHTS IS GAUSSIAN
THE ESTIMATION OF THE MODEL IS DONE BY ITERATIVELY MAXIMIZING THE MARGINAL LOGLIKELIHOOD OF THE OBSERVATIONS
WE ALSO PLOT PREDICTIONS AND UNCERTAINTIES FOR BAYESIAN RIDGE REGRESSION FOR ONE DIMENSIONAL REGRESSION USING POLY
NOMIAL FEATURE EXPANSION NOTE THE UNCERTAINTY STARTS GOING UP ON THE RIGHT SIDE OF THE PLOT THIS IS BECAUSE THESE TEST
SAMPLES ARE OUTSIDE OF THE RANGE OF THE TRAINING SAMPLES

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SCIKITLEARN USER GUIDE RELEASE 0213

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518 GENERALIZED LINEAR MODELS 1199

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPY IMPORT STATS
FROM SKLEARNLINEARMODEL IMPORT BAYESIANRIDGE LINEARREGRESSION

 GENERATING SIMULATED DATA WITH GAUSSIAN WEIGHTS
NPRANDOMSEED0
NSAMPLES NFEATURES  100 100
X  NPRANDOMRANDNNSAMPLES NFEATURES  CREATE GAUSSIAN DATA
 CREATE WEIGHTS WITH A PRECISION LAMBDA OF 4
LAMBDA  4
W  NPZEROSNFEATURES
 ONLY KEEP 10 WEIGHTS OF INTEREST
RELEVANTFEATURES  NPRANDOMRANDINT0 NFEATURES 10
FORIINRELEVANTFEATURES
WI  STATSNORMRVSLOC0 SCALE1  NPSQRTLAMBDA
 CREATE NOISE WITH A PRECISION ALPHA OF 50
ALPHA  50
NOISE  STATSNORMRVSLOC0 SCALE1  NPSQRTALPHA SIZENSAMPLES
 CREATE THE TARGET
Y  NPDOTX W  NOISE
```

```
 FIT THE BAYESIAN RIDGE REGRESSION AND AN OLS FOR COMPARISON
CLF  BAYESIANRIDGECOMPUTESCORETRUE
CLFFITX Y
OLS  LINEARREGRESSION
OLSFITX Y

 PLOT TRUE WEIGHTS ESTIMATED WEIGHTS HISTOGRAM OF THE WEIGHTS AND
 PREDICTIONS WITH STANDARD DEVIATIONS
LW  2
PLTFIGUREFIGSIZE6 5
PLTTITLEWEIGHTS OF THE MODEL
PLTPLOTCLFCOEF COLORLIGHTGREEN LINEWIDTHLW
LABELBAYESIAN RIDGE ESTIMATE
PLTPLOTW COLORGOLD LINEWIDTHLW LABELGROUND TRUTH
PLTPLOTOLSCOEF COLORNAVY LINESTYLE LABELOLS ESTIMATE
PLTXLABELFEATURES
PLTYLABELVALUES OF THE WEIGHTS
PLTLEGENDLOCBEST PROPDICTSIZE12
PLTFIGUREFIGSIZE6 5
PLTTITLEHISTOGRAM OF THE WEIGHTS
PLTHISTCLFCOEF BINSNFEATURES COLORGOLD LOGTRUE
EDGECOLORBLACK
PLTSCATTERCLFCOEFRELEVANTFEATURES NPFULLLENRELEVANTFEATURES 5
COLORNAVY LABELRELEVANT FEATURES
PLTYLABELFEATURES
PLTXLABELVALUES OF THE WEIGHTS
PLTLEGENDLOCUPPER LEFT
PLTFIGUREFIGSIZE6 5
PLTTITLEMARGINAL LOGLIKELIHOOD
PLTPLOTCLFSCORES COLORNAVY LINEWIDTHLW
PLTYLABELSCORE
PLTXLABELITERATIONS
 PLOTTING SOME PREDICTIONS FOR POLYNOMIAL REGRESSION
DEFFX NOISEAMOUNT
Y  NPSQRTX NPSINX
NOISE  NPRANDOMNORMAL0 1 LENX
RETURNY  NOISEAMOUNT NOISE
DEGREE  10
X  NPLINSPACE0 10 100
Y  FX NOISEAMOUNT01
CLFPOLY  BAYESIANRIDGE
CLFPOLYFITNPVANDERX DEGREE Y
XPLOT  NPLINSPACE0 11 25
YPLOT  FXPLOT NOISEAMOUNT0
YMEAN YSTD  CLFPOLYPREDICTNPVANDERXPLOT DEGREE RETURNSTDTRUE
PLTFIGUREFIGSIZE6 5
PLTERRORBARXPLOT YMEAN YSTD COLORNAVY
```

LABELPOLYNOMIAL BAYESIAN RIDGE REGRESSION LINEWIDTHLW
PLTPLOTXPLOT YPLOT COLORGOLD LINEWIDTHLW
LABELGROUND TRUTH
PLTYLABELOUTPUT Y
PLTXLABELFEATURE X
PLTLEGENDLOCLOWER LEFT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0143 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51831 LASSO MODEL SELECTION CROSSVALIDATION AIC BIC
USE THE AKAIKE INFORMATION CRITERION AIC THE BAYES INFORMATION CRITERION BIC AND CROSSVALIDATION TO SELECT AN OPTIMAL VALUE OF THE REGULARIZATION PARAMETER ALPHA OF THE LASSO ESTIMATOR
RESULTS OBTAINED WITH LASSOLARSIC ARE BASED ON AICBIC CRITERIA
INFORMATIONCRITERION BASED MODEL SELECTION IS VERY FAST BUT IT RELIES ON A PROPER ESTIMATION OF DEGREES OF FREEDOM ARE DERIVED FOR LARGE SAMPLES ASYMPTOTIC RESULTS AND ASSUME THE MODEL IS CORRECT IE THAT THE DATA ARE ACTUALLY GENERATED BY THIS MODEL THEY ALSO TEND TO BREAK WHEN THE PROBLEM IS BADLY CONDITIONED MORE FEATURES THAN SAMPLES
FOR CROSSVALIDATION WE USE 20FOLD WITH 2 ALGORITHMS TO COMPUTE THE LASSO PATH COORDINATE DESCENT AS IMPLEMENTED BY THE LASSOCV CLASS AND LARS LEAST ANGLE REGRESSION AS IMPLEMENTED BY THE LASSOLARSCV CLASS BOTH ALGORITHMS GIVE ROUGHLY THE SAME RESULTS THEY DIFFER WITH REGARDS TO THEIR EXECUTION SPEED AND SOURCES OF NUMERICAL ERRORS
LARS COMPUTES A PATH SOLUTION ONLY FOR EACH KINK IN THE PATH AS A RESULT IT IS VERY EFFICIENT WHEN THERE ARE ONLY OF FEW KINKS WHICH IS THE CASE IF THERE ARE FEW FEATURES OR SAMPLES ALSO IT IS ABLE TO COMPUTE THE FULL PATH WITHOUT SETTING ANY META PARAMETER ON THE OPPOSITE COORDINATE DESCENT COMPUTE THE PATH POINTS ON A PRESPECIFIED GRID HERE WE USE THE DEFAULT THUS IT IS MORE EFFICIENT IF THE NUMBER OF GRID POINTS IS SMALLER THAN THE NUMBER OF KINKS IN THE PATH SUCH A STRATEGY CAN BE INTERESTING IF THE NUMBER OF FEATURES IS REALLY LARGE AND THERE ARE ENOUGH SAMPLES TO SELECT A LARGE AMOUNT IN TERMS OF NUMERICAL ERRORS FOR HEAVILY CORRELATED VARIABLES LARS WILL ACCUMULATE MORE ERRORS WHILE THE COORDINATE DESCENT ALGORITHM WILL ONLY SAMPLE THE PATH ON A GRID
NOTE HOW THE OPTIMAL VALUE OF ALPHA VARIES FOR EACH FOLD THIS ILLUSTRATES WHY NESTEDCROSS VALIDATION IS NECESSARY WHEN TRYING TO EVALUATE THE PERFORMANCE OF A METHOD FOR WHICH A PARAMETER IS CHOSEN BY CROSSVALIDATION THIS CHOICE OF PARAMETER MAY NOT BE OPTIMAL FOR UNSEEN DATA

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•

518 GENERALIZED LINEAR MODELS 1203

•

OUT

COMPUTING REGULARIZATION PATH USING THE COORDINATE DESCENT LASSO

COMPUTING REGULARIZATION PATH USING THE LARS LASSO

PRINTDOC

AUTHOR OLIVIER GRISEL GAEL VAROQUAUX ALEXANDRE GRAMFORT

LICENSE BSD 3 CLAUSE

IMPORT TIME

IMPORT NUMPY AS NP

IMPORT MATPLOTLIBPYPLOT AS PLT

FROM SKLEARNLINEARMODEL IMPORT LASSOCV LASSOLARSCV LASSOLARSIC

FROM SKLEARN IMPORT DATASETS

THIS IS TO AVOID DIVISION BY ZERO WHILE DOING NPLOG10

EPSILON 1E4

DIABETES DATASETSLOADDIABETES

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X DIABETESDATA
Y DIABETESTARGET
RNG NPRANDOMRANDOMSTATE42
X NPCX RNGRANDNXSHAPE0 14 ADD SOME BAD FEATURES
 NORMALIZE DATA AS DONE BY LARS TO ALLOW FOR COMPARISON
X NPSQRTNPSUMX 2 AXIS0

 LASSOLARSIC LEAST ANGLE REGRESSION WITH BICAIC CRITERION
MODELBIC LASSOLARSICCRITERIONBIC
T1 TIMETIME
MODELBICFITX Y
TBIC TIMETIME T1
ALPHABIC MODELBICALPHA
MODELAIC LASSOLARSICCRITERIONAIC
MODELAICFITX Y
ALPHAAIC MODELAICALPHA
DEFPLOTICCRITERIONMODEL NAME COLOR
ALPHA MODELALPHA EPSILON
ALPHAS MODELALPHAS EPSILON
CRITERION MODELCRITERION
PLTPLOTNPLOG10ALPHAS CRITERION COLORCOLOR
LINEWIDTH3 LABEL SCRITERION NAME
PLTAXVLINENPLOG10ALPHA COLORCOLOR LINEWIDTH3
LABELALPHA SESTIMATE NAME
PLTXLABELLOGALPHA
PLTYLABELCRITERION
PLTFIGURE
PLOTICCRITERIONMODELAIC AIC B
PLOTICCRITERIONMODELBIC BIC R
PLTLEGEND
PLTTITLEINFORMATIONCRITERION FOR MODEL SELECTION TRAINING TIME 3FS
 TBIC

 LASSOCV COORDINATE DESCENT
 COMPUTE PATHS
PRINTCOMPUTING REGULARIZATION PATH USING THE COORDINATE DESCENT LASSO
T1 TIMETIME
MODEL LASSOCVCV20FITX Y
TLASSOCV TIMETIME T1
 DISPLAY RESULTS
MLOGALPHAS NPLOG10MODELALPHAS EPSILON
PLTFIGURE
YMIN YMAX 2300 3800
PLTPLOTMLOGALPHAS MODELMSEPATH
PLTPLOTMLOGALPHAS MODELMSEPATHMEANAXIS1 K
LABELAVERAGE ACROSS THE FOLDS LINEWIDTH2

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PLTAXVLINENPLOG10MODELALPHA EPSILON LINESTYLE COLORK
LABELALPHA CV ESTIMATE
PLTLEGEND
PLTXLABELLOGALPHA
PLTYLABELMEAN SQUARE ERROR
PLTTITLEMEAN SQUARE ERROR ON EACH FOLD COORDINATE DESCENT
TRAIN TIME 2FS TLASSOCV
PLTAXISTIGHT
PLTYLIMYMIN YMAX

 LASSOLARSCV LEAST ANGLE REGRESSION
 COMPUTE PATHS
PRINTCOMPUTING REGULARIZATION PATH USING THE LARS LASSO
T1 TIMETIME
MODEL LASSOLARSCVCV20FITX Y
TLASSOLARSCV TIMETIME T1
 DISPLAY RESULTS
MLOGALPHAS NPLOG10MODELCVALPHAS EPSILON
PLTFIGURE
PLTPLOTMLOGALPHAS MODELMSEPATH
PLTPLOTMLOGALPHAS MODELMSEPATHMEANAXIS1 K
LABELAVERAGE ACROSS THE FOLDS LINEWIDTH2
PLTAXVLINENPLOG10MODELALPHA LINESTYLE COLORK
LABELALPHA CV
PLTLEGEND
PLTXLABELLOGALPHA
PLTYLABELMEAN SQUARE ERROR
PLTTITLEMEAN SQUARE ERROR ON EACH FOLD LARS TRAIN TIME 2FS
 TLASSOLARSCV
PLTAXISTIGHT
PLTYLIMYMIN YMAX
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0811 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
51832 MULTICLASS SPARSE LOGISITIC REGRESSION ON NEWGROUPS20
COMPARISON OF MULTINOMIAL LOGISTIC L1 VS ONEVERSUSREST L1 LOGISTIC REGRESSION TO CLASSIFY DOCUMENTS FROM THE NEW GROUPS20 DATASET MULTINOMIAL LOGISTIC REGRESSION YIELDS MORE ACCURATE RESULTS AND IS FASTER TO TRAIN ON THE LARGER SCALE DATASET
HERE WE USE THE L1 SPARSITY THAT TRIMS THE WEIGHTS OF NOT INFORMATIVE FEATURES TO ZERO THIS IS GOOD IF THE GOAL IS TO EXTRACT THE STRONGLY DISCRIMINATIVE VOCABULARY OF EACH CLASS IF THE GOAL IS TO GET THE BEST PREDICTIVE ACCURACY IT IS BETTER TO USE THE NON SPARSITYINDUCING L2 PENALTY INSTEAD

A MORE TRADITIONAL AND POSSIBLY BETTER WAY TO PREDICT ON A SPARSE SUBSET OF INPUT FEATURES WOULD BE TO USE UNIVARIATE FEATURE SELECTION FOLLOWED BY A TRADITIONAL L2PENALISED LOGISTIC REGRESSION MODEL
OUT
DATASET 20NEWSGROUP TRAINSAMPLES9000 NFEATURES130107 NCLASSES20
MODELONE VERSUS REST SOLVERSAGA NUMBER OF EPOCHS 1
MODELONE VERSUS REST SOLVERSAGA NUMBER OF EPOCHS 2
MODELONE VERSUS REST SOLVERSAGA NUMBER OF EPOCHS 4
TEST ACCURACY FOR MODEL OVR 07490
NONZERO COEFFICIENTS FOR MODEL OVR PER CLASS
031743104 036815852 04181174 046115889 024595141 041350581
031281945 027054655 058720899 032972861 04158116 03312658
041888599 041120001 059643217 031666244 034279478 028130692
035278655 024748861
RUN TIME 4 EPOCHS FOR MODEL OVR306
MODELMULTINOMIAL SOLVERSAGA NUMBER OF EPOCHS 1
MODELMULTINOMIAL SOLVERSAGA NUMBER OF EPOCHS 3
MODELMULTINOMIAL SOLVERSAGA NUMBER OF EPOCHS 7
TEST ACCURACY FOR MODEL MULTINOMIAL 07450
NONZERO COEFFICIENTS FOR MODEL MULTINOMIAL PER CLASS
013219888 011452112 013066169 013681047 012066991 015909982
013450468 009146318 007916561 012143851 013911627 010760374
018984374 012143851 017524038 022289346 011605832 007916561
007301682 015141384
RUN TIME 7 EPOCHS FOR MODEL MULTINOMIAL255
EXAMPLE RUN IN 11262 S

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IMPORT TIMEIT
IMPORT WARNINGS
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNDATASETS IMPORT FETCH20NEWSGROUPSVECTORIZED
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNEXCEPTIONS IMPORT CONVERGENCEWARNING
PRINTDOC
 AUTHOR ARTHUR MENSCH
WARNINGSFILTERWARNINGSIGNORE CATEGORYCONVERGENCEWARNING
MODULESKLEARN
T0 TIMEITDEFAULTTIMER
 WE USE SAGA SOLVER
SOLVER SAGA
 TURN DOWN FOR FASTER RUN TIME
NSAMPLES 10000
 MEMORIZED FETCHRCV1 FOR FASTER ACCESS
DATASET FETCH20NEWSGROUPSVECTORIZEDALL
X DATASETDATA
Y DATASETTARGET
X XNSAMPLES
Y YNSAMPLES
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y
RANDOMSTATE42
STRATIFYY
TESTSIZE01
TRAINSAMPLES NFEATURES XTRAINSHAPE
NCLASSES NPUNIQUEYSHAPE0
PRINTDATASET 20NEWSGROUP TRAINSAMPLES I NFEATURES I NCLASSES I
 TRAINSAMPLES NFEATURES NCLASSES
MODELS OVR NAME ONE VERSUS REST ITERS 1 2 4
MULTINOMIAL NAME MULTINOMIAL ITERS 1 3 7
FORMODELINMODELS
 ADD INITIAL CHANCELEVEL VALUES FOR PLOTTING PURPOSE
ACCURACIES 1 NCLASSES
TIMES 0
DENSITIES 1
MODELPARAMS MODELSMODEL

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SMALL NUMBER OF EPOCHS FOR FAST RUNTIME
FORTHISMAXITER INMODELPARAMSITERS
PRINTMODEL S SOLVER S NUMBER OF EPOCHS S
MODELPARAMSNAME SOLVER THISMAXITER
LR LOGISTICREGRESSIONSOLVERSOLVER
MULTICLASSMODEL
C1
PENALTYL1
FITINTERCEPTTRUE
MAXITERTHISMAXITER
RANDOMSTATE42

T1 TIMEITDEFAULTTIMER
LRFITXTRAIN YTRAIN
TRAINTIME TIMEITDEFAULTTIMER T1
YPRED LRPREDICTXTEST
ACCURACY NPSUMYPRED YTEST YTESTSHAPE0
DENSITY NPMEANLRCOEF 0 AXIS1 100
ACCURACIESAPPENDACCURACY
DENSITIESAPPENDDENSITY
TIMESAPPENDTRAINTIME
MODELSMODELTIMES TIMES
MODELSMODELDENSITIES DENSITIES
MODELSMODELACCURACIES ACCURACIES
PRINTTEST ACCURACY FOR MODEL S4F MODEL ACCURACIES1
PRINTNONZERO COEFFICIENTS FOR MODEL S
PER CLASS NS MODEL DENSITIES1
PRINTRUN TIME IEPOCHS FOR MODEL S
2F MODELPARAMSITERS1 MODEL TIMES1
FIG PLTFIGURE
AX FIGADDSUBPLOT111
FORMODELINMODELS
NAME MODELSMODELNAME
TIMES MODELSMODELTIMES
ACCURACIES MODELSMODELACCURACIES
AXPLOTTIMES ACCURACIES MARKERO
LABELMODEL S NAME
AXSETXLABELTRAIN TIME S
AXSETYLABELTEST ACCURACY
AXLEGEND
FIGSUPTITLEMULTINOMIAL VS ONEVSREST LOGISTIC L1 N
DATASET S 20NEWSGROUPS
FIGTIGHTLAYOUT
FIGSUBPLOTSADJUSTTOP085
RUNTIME TIMEITDEFAULTTIMER T0
PRINTEXAMPLE RUN IN 3FS RUNTIME
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 11263 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
1210 CHAPTER 5 EXAMPLES

51833 EARLY STOPPING OF STOCHASTIC GRADIENT DESCENT
STOCHASTIC GRADIENT DESCENT IS AN OPTIMIZATION TECHNIQUE WHICH MINIMIZES A LOSS FUNCTION IN A STOCHASTIC FASHION PERFORMING A GRADIENT DESCENT STEP SAMPLE BY SAMPLE IN PARTICULAR IT IS A VERY EFFICIENT METHOD TO FIT LINEAR MODELS AS A STOCHASTIC METHOD THE LOSS FUNCTION IS NOT NECESSARILY DECREASING AT EACH ITERATION AND CONVERGENCE IS ONLY GUARANTEED IN EXPECTATION FOR THIS REASON MONITORING THE CONVERGENCE ON THE LOSS FUNCTION CAN BE DIFFICULT
ANOTHER APPROACH IS TO MONITOR CONVERGENCE ON A VALIDATION SCORE IN THIS CASE THE INPUT DATA IS SPLIT INTO A TRAINING SET AND A VALIDATION SET THE MODEL IS THEN FITTED ON THE TRAINING SET AND THE STOPPING CRITERION IS BASED ON THE PREDICTION SCORE COMPUTED ON THE VALIDATION SET THIS ENABLES US TO FIND THE LEAST NUMBER OF ITERATIONS WHICH IS SUFFICIENT TO BUILD A MODEL THAT GENERALIZES WELL TO UNSEEN DATA AND REDUCES THE CHANCE OF OVERFITTING THE TRAINING DATA
THIS EARLY STOPPING STRATEGY IS ACTIVATED IF EARLYSTOPPINGTRUE OTHERWISE THE STOPPING CRITERION ONLY USES THE TRAINING LOSS ON THE ENTIRE INPUT DATA TO BETTER CONTROL THE EARLY STOPPING STRATEGY WE CAN SPECIFY A PARAMETER VALIDATIONFRACTION WHICH SET THE FRACTION OF THE INPUT DATASET THAT WE KEEP ASIDE TO COMPUTE THE VALIDATION SCORE THE OPTIMIZATION WILL CONTINUE UNTIL THE VALIDATION SCORE DID NOT IMPROVE BY AT LEAST TOL DURING THE LAST NITERNOCHANGE ITERATIONS THE ACTUAL NUMBER OF ITERATIONS IS AVAILABLE AT THE ATTRIBUTE NITER
THIS EXAMPLE ILLUSTRATES HOW THE EARLY STOPPING CAN USED IN THE SKLEARNLINEARMODELSGDCLASSIFIER MODEL TO ACHIEVE ALMOST THE SAME ACCURACY AS COMPARED TO A MODEL BUILT WITHOUT EARLY STOPPING THIS CAN SIGNIFICANTLY REDUCE TRAINING TIME NOTE THAT SCORES DIFFER BETWEEN THE STOPPING CRITERIA EVEN FROM EARLY ITERATIONS BECAUSE SOME OF THE TRAINING DATA IS HELD OUT WITH THE VALIDATION STOPPING CRITERION
OUT
NO STOPPING CRITERION
TRAINING LOSS
VALIDATION SCORE

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AUTHORS TOM DUPRE LA TOUR

LICENSE BSD 3 CLAUSE

```
IMPORT TIME
IMPORT SYS
IMPORT PANDAS AS PD
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT LINEARMODEL
FROM SKLEARNDATASETS IMPORT FETCHOPENML
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNUTILSTESTING IMPORT IGNOREWARNINGS
FROM SKLEARNEXCEPTIONS IMPORT CONVERGENCEWARNING
FROM SKLEARNUTILS IMPORT SHUFFLE
PRINTDOC
DEFLOADMNISTNSAMPLESNONE CLASS00 CLASS18
LOAD MNIST SELECT TWO CLASSES SHUFFLE AND RETURN ONLY NSAMPLES
 LOAD DATA FROM HTTPOPENMLORGD554
MNIST  FETCHOPENMLMNIST784 VERSION1
 TAKE ONLY TWO CLASSES FOR BINARY CLASSIFICATION
MASK  NPLOGICALORMNISTTARGET  CLASS0 MNISTTARGET  CLASS1
X Y  SHUFFLEMNISTDATAMASK MNISTTARGETMASK RANDOMSTATE42
IFNSAMPLES IS NOTNONE
X Y  XNSAMPLES YNSAMPLES
RETURNX Y
IGNOREWARNINGS CATEGORYCONVERGENCEWARNING
DEFFITANDSCOREESTIMATOR MAXITER XTRAIN XTEST YTRAIN YTEST
FIT THE ESTIMATOR ON THE TRAIN SET AND SCORE IT ON BOTH SETS
ESTIMATORSETPARAMSMAXITERMAXITER
ESTIMATORSETPARAMSRANDOMSTATE0
START  TIMETIME
ESTIMATORFITXTRAIN YTRAIN
FITTIME  TIMETIME  START
NITER  ESTIMATORNITER
TRAINSCORE  ESTIMATORSCOREXTRAIN YTRAIN
TESTSCORE  ESTIMATORSCOREXTEST YTEST
RETURNFITTIME NITER TRAINSCORE TESTSCORE
 DEFINE THE ESTIMATORS TO COMPARE
ESTIMATORDICT
NO STOPPING CRITERION
LINEARMODELSGDCLASSIFIERTOL1E3 NITERNOCHANGE3
```

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TRAINING LOSS
LINEARMODELSGDCLASSIFIEREARLYSTOPPINGFALSE NITERNOCHANGE3
TOL01
VALIDATION SCORE
LINEARMODELSGDCLASSIFIEREARLYSTOPPINGTRUE NITERNOCHANGE3
TOL00001 VALIDATIONFRACTION02

LOAD THE DATASET
X Y LOADMNISTNSAMPLES10000
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y TESTSIZE05
RANDOMSTATE0
RESULTS
FORESTIMATORNAME ESTIMATOR INESTIMATORDICTITEMS
PRINTESTIMATORNAME   END
FORMAXITER INRANGE1 50
PRINT END
SYSSTDOUTFLUSH
FITTIME NITER TRAINSCORE TESTSCORE FITANDSCORE
ESTIMATOR MAXITER XTRAIN XTEST YTRAIN YTEST
RESULTSAPPENDESTIMATORNAME MAXITER FITTIME NITER
TRAINSCORE TESTSCORE
PRINT
TRANSFORM THE RESULTS IN A PANDAS DATAFRAME FOR EASY PLOTTING
COLUMNS
STOPPING CRITERION MAXITER FIT TIME SEC NITER
TRAIN SCORE TEST SCORE

RESULTSDF PDDATAFRAMERESULTS COLUMNSCOLUMNS
DEFINE WHAT TO PLOT XAXIS YAXIS
LINES STOPPING CRITERION
PLOTLIST
MAXITER TRAIN SCORE
MAXITER TEST SCORE
MAXITER NITER
MAXITER FIT TIME SEC

NROWS 2
NCOLS INTNPCEILLENPLOTLIST 2
FIG AXES PLTSUBPLOTSNROWSNROWS NCOLSNCOLS FIGSIZE6 NCOLS
4NROWS
AXES0 0GETSHAREDYAXESJOINAXES0 0 AXES0 1
FORAX XAXIS YAXIS INZIPAXESRAVEL PLOTLIST
FORCRITERION GROUPDF INRESULTSDFGROUPBYLINES
GROUPDFPLOTXXAXIS YYAXIS LABELCRITERION AXAX
AXSETTITLEYAXIS
AXLEGENDTITLELINES
FIGTIGHTLAYOUT
PLTSHOW

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 45461 SECONDS
519 MANIFOLD LEARNING
EXAMPLES CONCERNING THE SKLEARNMANIFOLD MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5191 SWISS ROLL REDUCTION WITH LLE
AN ILLUSTRATION OF SWISS ROLL REDUCTION WITH LOCALLY LINEAR EMBEDDING
OUT
COMPUTING LLE EMBEDDING
DONE RECONSTRUCTION ERROR 732714E08

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AUTHOR FABIAN PEDREGOSA FABIANPEDREGOSAINRIAFR
LICENSE BSD 3 CLAUSE C INRIA 2011
PRINTDOC
IMPORT MATPLOTLIBPYPLOT AS PLT
THIS IMPORT IS NEEDED TO MODIFY THE WAY FIGURE BEHAVES
FROM MPLTOOLKITSMPLOT3D IMPORT AXES3D
AXES3D

LOCALLY LINEAR EMBEDDING OF THE SWISS ROLL
FROM SKLEARN IMPORT MANIFOLD DATASETS
X COLOR DATASETSSAMPLESGENERATORMAKESWISSROLLNSAMPLES1500
PRINTCOMPUTING LLE EMBEDDING
XR ERR MANIFOLDLOCALLYLINEAREMBEDDINGX NNEIGHBORS12
NCOMPONENTS2
PRINTDONE RECONSTRUCTION ERROR G ERR

PLOT RESULT
FIG PLTFIGURE
AX FIGADDSUBPLOT211 PROJECTION3D
AXSCATTERX 0 X 1 X 2 CCOLOR CMAPPLTCMSPECTRAL
AXSETTITLEORIGINAL DATA
AX FIGADDSUBPLOT212
AXSCATTERXR 0 XR 1 CCOLOR CMAPPLTCMSPECTRAL
PLTAXISTIGHT
PLTXTICKS PLTYTICKS
PLTTITLEPROJECTED DATA
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0182 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5192 MULTIDIMENSIONAL SCALING
AN ILLUSTRATION OF THE METRIC AND NONMETRIC MDS ON GENERATED NOISY DATA
THE RECONSTRUCTED POINTS USING THE METRIC MDS AND NON METRIC MDS ARE SLIGHTLY SHIFTED TO AVOID OVERLAPPING
519 MANIFOLD LEARNING 1215

```
SCIKITLEARN USER GUIDE RELEASE 0213
 AUTHOR NELLE VAROQUAUX NELLEVAROQUAUXGMAILCOM
 LICENSE BSD
PRINTDOC
IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM MATPLOTLIBCOLLECTIONS IMPORT LINECOLLECTION
FROM SKLEARN IMPORT MANIFOLD
FROM SKLEARNMETRICS IMPORT EUCLIDEANDISTANCES
FROM SKLEARNDECOMPOSITION IMPORT PCA
NSAMPLES  20
SEED  NPRANDOMRANDOMSTATESEED3
XTRUE  SEEDRANDINT0 20 2 NSAMPLESASTYPENPFLOAT
XTRUE  XTRUERESHAPENSAMPLES 2
 CENTER THE DATA
XTRUE  XTRUEMEAN
SIMILARITIES  EUCLIDEANDISTANCESXTRUE
 ADD NOISE TO THE SIMILARITIES
NOISE  NPRANDOMRANDNSAMPLES NSAMPLES
NOISE  NOISE  NOISET
NOISENPARANGENOISESHAPE0 NPARANGENOISESHAPE0  0
1216 CHAPTER 5 EXAMPLES
```

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SIMILARITIES NOISE
MDS MANIFOLDMDSNCOMPONENTS2 MAXITER3000 EPS1E9 RANDOMSTATESEED
DISSIMILARITYPRECOMPUTED NJOBS1
POS MDSFITSIMILARITIESEMBEDDING
NMDS MANIFOLDMDSNCOMPONENTS2 METRICFALSE MAXITER3000 EPS1E12
DISSIMILARITYPRECOMPUTED RANDOMSTATESEED NJOBS1
NINIT1
NPOS NMDSFITTRANSFORMSIMILARITIES INITPOS
 RESCALE THE DATA
POS NPSQRTXTRUE 2SUM NPSQRTPOS 2SUM
NPOS NPSQRTXTRUE 2SUM NPSQRTNPOS 2SUM
 ROTATE THE DATA
CLF PCANCOMPONENTS2
XTRUE CLFFITTRANSFORMXTRUE
POS CLFFITTRANSFORMPOS
NPOS CLFFITTRANSFORMNPOS
FIG PLTFIGURE1
AX PLTAXES0 0 1 1
S 100
PLTSCATTERXTRUE 0 XTRUE 1 COLORNAVY SS LW0
LABELTRUE POSITION
PLTSCATTERPOS 0 POS 1 COLORTURQUOISE SS LW0 LABELMDS
PLTSCATTERNPOS 0 NPOS 1 COLORDARKORANGE SS LW0 LABELNMDS
PLTLEGENDSCATTERPOINTS1 LOCBEST SHADOWFALSE
SIMILARITIES SIMILARITIESMAX SIMILARITIES 100
SIMILARITIESNPISINFSIMILARITIES 0
 PLOT THE EDGES
STARTIDX ENDIDX NPWHEREPOS
 A SEQUENCE OF LINE0LINE1LINE2 WHERE
 LINEN X0 Y0 X1 Y1 XM YM
SEGMENTS XTRUEI XTRUEJ
FORIINRANGELENPOS FORJINRANGELENPOS
VALUES NPABSSIMILARITIES
LC LINECOLLECTIONSEGMENTS
ZORDER0 CMAPPLTCMBLUES
NORMPLTNORMALIZE0 VALUESMAX
LCSETARRAYSIMILARITIESFLATTEN
LCSETLINEWIDTHSNPFULLLENSEGMENTS 05
AXADDCOLLECTIONLC
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0063 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5193 TSNE THE EFFECT OF VARIOUS PERPLEXITY VALUES ON THE SHAPE
AN ILLUSTRATION OF TSNE ON THE TWO CONCENTRIC CIRCLES AND THE SCURVE DATASETS FOR DIFFERENT PERPLEXITY VALUES
WE OBSERVE A TENDENCY TOWARDS CLEARER SHAPES AS THE PREPLEXITY VALUE INCREASES
THE SIZE THE DISTANCE AND THE SHAPE OF CLUSTERS MAY VARY UPON INITIALIZATION PERPLEXITY VALUES AND DOES NOT ALWAYS CONVEY A MEANING
AS SHOWN BELOW TSNE FOR HIGHER PERPLEXITIES FINDS MEANINGFUL TOPOLOGY OF TWO CONCENTRIC CIRCLES HOWEVER THE SIZE AND THE DISTANCE OF THE CIRCLES VARIES SLIGHTLY FROM THE ORIGINAL CONTRARY TO THE TWO CIRCLES DATASET THE SHAPES VISUALLY DIVERGE FROM SCURVE TOPOLOGY ON THE SCURVE DATASET EVEN FOR LARGER PERPLEXITY VALUES
FOR FURTHER DETAILS “HOW TO USE TSNE EFFECTIVELY” HTTPSDISTILLPUB2016MISREADTSNE PROVIDES A GOOD DISCUSSION OF THE EFFECTS OF VARIOUS PARAMETERS AS WELL AS INTERACTIVE PLOTS TO EXPLORE THOSE EFFECTS
OUT
CIRCLES PERPLEXITY5 IN 089 SEC
CIRCLES PERPLEXITY30 IN 12 SEC
CIRCLES PERPLEXITY50 IN 13 SEC
CIRCLES PERPLEXITY100 IN 18 SEC
SCURVE PERPLEXITY5 IN 092 SEC
SCURVE PERPLEXITY30 IN 12 SEC
SCURVE PERPLEXITY50 IN 14 SEC
SCURVE PERPLEXITY100 IN 19 SEC
UNIFORM GRID PERPLEXITY5 IN 088 SEC
UNIFORM GRID PERPLEXITY30 IN 11 SEC
UNIFORM GRID PERPLEXITY50 IN 11 SEC
UNIFORM GRID PERPLEXITY100 IN 17 SEC

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AUTHOR NARINE KOKHLIKYAN NARINESLICECOM
LICENSE BSD
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBTICKER IMPORT NULLFORMATTER
FROM SKLEARN IMPORT MANIFOLD DATASETS
FROM TIME IMPORT TIME
NSAMPLES 300
NCOMPONENTS 2
FIG SUBPLOTS PLTSUBPLOTS3 5 FIGSIZE15 8
PERPLEXITIES 5 30 50 100
X Y DATASETSMAKECIRCLESNSAMPLESNSAMPLES FACTOR5 NOISE05
RED Y 0
GREEN Y 1
AX SUBPLOTS00
AXSCATTERXRED 0 XRED 1 CR
AXSCATTERXGREEN 0 XGREEN 1 CG
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
FORI PERPLEXITY INENUMERATEPERPLEXITIES
AX SUBPLOTS0I 1
T0 TIME
TSNE MANIFOLDTSNENCOMPONENTSNCOMPONENTS INITRANDOM
RANDOMSTATE0 PERPLEXITYPERPLEXITY
Y TSNEFITTRANSFORMX
T1 TIME
PRINTCIRCLES PERPLEXITY DIN2GSEC PERPLEXITY T1 T0
AXSETTITLEPERPLEXITY D PERPLEXITY
AXSCATTERYRED 0 YRED 1 CR
AXSCATTERYGREEN 0 YGREEN 1 CG
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
AXAXISTIGHT
ANOTHER EXAMPLE USING SCURVE
X COLOR DATASETSSAMPLESGENERATORMAKESCURVENSAMPLES RANDOMSTATE0
AX SUBPLOTS10
AXSCATTERX 0 X 2 CCOLOR
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
FORI PERPLEXITY INENUMERATEPERPLEXITIES
AX SUBPLOTS1I 1
T0 TIME
TSNE MANIFOLDTSNENCOMPONENTSNCOMPONENTS INITRANDOM

SCIKITLEARN USER GUIDE RELEASE 0213
RANDOMSTATE0 PERPLEXITYPERPLEXITY
Y TSNEFITTRANSFORMX
T1 TIME
PRINTSCURVE PERPLEXITY DIN2GSEC PERPLEXITY T1 T0
AXSETTITLEPERPLEXITY D PERPLEXITY
AXSCATTERY 0 Y 1 CCOLOR
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
AXAXISTIGHT
 ANOTHER EXAMPLE USING A 2D UNIFORM GRID
X NPLINSPACE0 1 INTNPSQRTNSAMPLES
XX YY NPMESHGRIDX X
X NPHSTACK
XXRAVELRESHAPE1 1
YYRAVELRESHAPE1 1

COLOR XXRAVEL
AX SUBPLOTS20
AXSCATTERX 0 X 1 CCOLOR
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
FORI PERPLEXITY INENUMERATEPERPLEXITIES
AX SUBPLOTS2I 1
T0 TIME
TSNE MANIFOLDTSNENCOMPONENTSNCOMPONENTS INITRANDOM
RANDOMSTATE0 PERPLEXITYPERPLEXITY
Y TSNEFITTRANSFORMX
T1 TIME
PRINTUNIFORM GRID PERPLEXITY DIN2GSEC PERPLEXITY T1 T0
AXSETTITLEPERPLEXITY D PERPLEXITY
AXSCATTERY 0 Y 1 CCOLOR
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
AXAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 15568 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5194 COMPARISON OF MANIFOLD LEARNING METHODS
AN ILLUSTRATION OF DIMENSIONALITY REDUCTION ON THE SCURVE DATASET WITH VARIOUS MANIFOLD LEARNING METHODS
FOR A DISCUSSION AND COMPARISON OF THESE ALGORITHMS SEE THE MANIFOLD MODULE PAGE
FOR A SIMILAR EXAMPLE WHERE THE METHODS ARE APPLIED TO A SPHERE DATASET SEE MANIFOLD LEARNING METHODS ON A SEVERED SPHERE

NOTE THAT THE PURPOSE OF THE MDS IS TO FIND A LOWDIMENSIONAL REPRESENTATION OF THE DATA HERE 2D IN WHICH THE DISTANCES RESPECT WELL THE DISTANCES IN THE ORIGINAL HIGHDIMENSIONAL SPACE UNLIKE OTHER MANIFOLDLEARNING ALGORITHMS IT DOES NOT SEEKS AN ISOTROPIC REPRESENTATION OF THE DATA IN THE LOWDIMENSIONAL SPACE
OUT
STANDARD 0095 SEC
LTSA 02 SEC
HESSIAN 036 SEC
MODIFIED 02 SEC
ISOMAP 036 SEC
MDS 2 SEC
SPECTRALEMBEDDING 01 SEC
TSNE 6 SEC
AUTHOR JAKE VANDERPLAS VANDERPLASASTROWASHINGTONEDU
PRINTDOC
FROM TIME IMPORT TIME
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MPLTOOLKITSMPLOT3D IMPORT AXES3D
FROM MATPLOTLIBTICKER IMPORT NULLFORMATTER
FROM SKLEARN IMPORT MANIFOLD DATASETS
NEXT LINE TO SILENCE PYFLAKES THIS IMPORT IS NEEDED
AXES3D

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NPOINTS 1000
X COLOR DATASETSSAMPLESGENERATORMAKESCURVENPOINTS RANDOMSTATE0
NNEIGHBORS 10
NCOMPONENTS 2
FIG PLTFIGUREFIGSIZE15 8
PLTSUPTITLEMANIFOLD LEARNING WITH IPOINTS INEIGHBORS
 1000 NNEIGHBORS FONTSIZE14
AX FIGADDSUBPLOT251 PROJECTION3D
AXSCATTERX 0 X 1 X 2 CCOLOR CMAPPLTCMSPECTRAL
AXVIEWINIT4 72
METHODS STANDARD LTSA HESSIAN MODIFIED
LABELS LLE LTSA HESSIAN LLE MODIFIED LLE
FORI METHOD INENUMERATEMETHODS
T0 TIME
Y MANIFOLDLOCALLYLINEAREMBEDDINGNNEIGHBORS NCOMPONENTS
EIGENSOLVERAUTO
METHODMETHODFITTRANSFORMX
T1 TIME
PRINTS2GSEC METHODSI T1 T0
AX FIGADDSUBPLOT252 I
PLTSCATTERY 0 Y 1 CCOLOR CMAPPLTCMSPECTRAL
PLTTITLE S2GSEC LABELSI T1 T0
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
T0 TIME
Y MANIFOLDISOMAPNNEIGHBORS NCOMPONENTSFITTRANSFORMX
T1 TIME
PRINTISOMAP 2GSEC T1 T0
AX FIGADDSUBPLOT257
PLTSCATTERY 0 Y 1 CCOLOR CMAPPLTCMSPECTRAL
PLTTITLEISOMAP 2GSEC T1 T0
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
T0 TIME
MDS MANIFOLDMDSNCOMPONENTS MAXITER100 NINIT1
Y MDSFITTRANSFORMX
T1 TIME
PRINTMDS2GSEC T1 T0
AX FIGADDSUBPLOT258
PLTSCATTERY 0 Y 1 CCOLOR CMAPPLTCMSPECTRAL
PLTTITLEMDS 2GSEC T1 T0
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
T0 TIME

SE MANIFOLDSPECTRALEMBEDDINGNCOMPONENTSNCOMPONENTS
NNEIGHBORSNNEIGHBORS
Y SEFITTRANSFORMX
T1 TIME
PRINTSPECTRALEMBEDDING 2GSEC T1 T0
AX FIGADDSUBPLOT259
PLTSCATTERY 0 Y 1 CCOLOR CMAPPLTCMSPECTRAL
PLTTITLESPECTRALEMBEDDING 2GSEC T1 T0
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
T0 TIME
TSNE MANIFOLDTSNENCOMPONENTSNCOMPONENTS INITPCA RANDOMSTATE0
Y TSNEFITTRANSFORMX
T1 TIME
PRINTTSNE 2GSEC T1 T0
AX FIGADDSUBPLOT2 5 10
PLTSCATTERY 0 Y 1 CCOLOR CMAPPLTCMSPECTRAL
PLTTITLETSNE 2GSEC T1 T0
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 9515 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5195 MANIFOLD LEARNING METHODS ON A SEVERED SPHERE
AN APPLICATION OF THE DIFFERENT MANIFOLD LEARNING TECHNIQUES ON A SPHERICAL DATASET HERE ONE CAN SEE THE USE OF DIMENSIONALITY REDUCTION IN ORDER TO GAIN SOME INTUITION REGARDING THE MANIFOLD LEARNING METHODS REGARDING THE DATASET THE POLES ARE CUT FROM THE SPHERE AS WELL AS A THIN SLICE DOWN ITS SIDE THIS ENABLES THE MANIFOLD LEARNING TECHNIQUES TO ‘SPREAD IT OPEN’ WHILST PROJECTING IT ONTO TWO DIMENSIONS
FOR A SIMILAR EXAMPLE WHERE THE METHODS ARE APPLIED TO THE SCURVE DATASET SEE COMPARISON OF MANIFOLD LEARNING METHODS
NOTE THAT THE PURPOSE OF THE MDS IS TO FIND A LOWDIMENSIONAL REPRESENTATION OF THE DATA HERE 2D IN WHICH THE DISTANCES RESPECT WELL THE DISTANCES IN THE ORIGINAL HIGHDIMENSIONAL SPACE UNLIKE OTHER MANIFOLDLEARNING ALGORITHMS IT DOES NOT SEEKS AN ISOTROPIC REPRESENTATION OF THE DATA IN THE LOWDIMENSIONAL SPACE HERE THE MANIFOLD PROBLEM MATCHES FAIRLY THAT OF REPRESENTING A FLAT MAP OF THE EARTH AS WITH MAP PROJECTION

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OUT
STANDARD 0069 SEC
LTSA 012 SEC
HESSIAN 029 SEC
MODIFIED 016 SEC
ISO 027 SEC
MDS 12 SEC
SPECTRAL EMBEDDING 015 SEC
TSNE 35 SEC
 AUTHOR JAQUES GROBLER JAQUESGROBLERINRIAFR
 LICENSE BSD 3 CLAUSE
PRINTDOC
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MPLTOOLKITSMPLOT3D IMPORT AXES3D
FROM MATPLOTLIBTICKER IMPORT NULLFORMATTER
FROM SKLEARN IMPORT MANIFOLD
FROM SKLEARNUTILS IMPORT CHECKRANDOMSTATE
 NEXT LINE TO SILENCE PYFLAKES
AXES3D
 VARIABLES FOR MANIFOLD LEARNING

```
NNEIGHBORS  10
NSAMPLES  1000
 CREATE OUR SPHERE
RANDOMSTATE  CHECKRANDOMSTATE0
P  RANDOMSTATERANDNSAMPLES 2NPPI  055
T  RANDOMSTATERANDNSAMPLES NPPI
 SEVER THE POLES FROM THE SPHERE
INDICES  T  NPPI  NPPI  8  T  NPPI  8
COLORS  PINDICES
X Y Z  NPSINTINDICES NPCOSPINDICES
NPSINTINDICES NPSINPINDICES
NPCOSTINDICES
 PLOT OUR DATASET
FIG  PLTFIGUREFIGSIZE15 8
PLTSUPTITLEMANIFOLD LEARNING WITH IPOINTS INEIGHBORS
 1000 NNEIGHBORS FONTSIZE14
AX  FIGADDSUBPLOT251 PROJECTION3D
AXSCATTERX Y Z CPINDICES CMAPPLTCMRAINBOW
AXVIEWINIT40 10
SPHEREDATA  NPARRAYX Y ZT
 PERFORM LOCALLY LINEAR EMBEDDING MANIFOLD LEARNING
METHODS  STANDARD LTSA HESSIAN MODIFIED
LABELS  LLE LTSA HESSIAN LLE MODIFIED LLE
FORI METHOD INENUMERATEMETHODS
T0  TIME
TRANSDATA  MANIFOLD
LOCALLYLINEAREMBEDDINGNNEIGHBORS 2
METHODMETHODFITTRANSFORMSPHEREDATAT
T1  TIME
PRINTS2GSEC  METHODSI T1  T0
AX  FIGADDSUBPLOT252  I
PLTSCATTERTRANSDATA0 TRANSDATA1 CCOLORS CMAPPLTCMRAINBOW
PLTTITLE S2GSEC  LABELSI T1  T0
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
 PERFORM ISOMAP MANIFOLD LEARNING
T0  TIME
TRANSDATA  MANIFOLDISOMAPNNEIGHBORS NCOMPONENTS2
FITTRANSFORMSPHEREDATAT
T1  TIME
PRINTS2GSEC  ISO T1  T0
AX  FIGADDSUBPLOT257
PLTSCATTERTRANSDATA0 TRANSDATA1 CCOLORS CMAPPLTCMRAINBOW
PLTTITLE S2GSEC  ISOMAP T1  T0
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
```

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PERFORM MULTIDIMENSIONAL SCALING
T0 TIME
MDS MANIFOLDMDS2 MAXITER100 NINIT1
TRANSDATA MDSFITTRANSFORMSPHEREDATAT
T1 TIME
PRINTMDS2GSEC T1 T0
AX FIGADDSUBPLOT258
PLTSCATTERTRANSDATA0 TRANSDATA1 CCOLORS CMAPPLTCMRAINBOW
PLTTITLEMDS 2GSEC T1 T0
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
PERFORM SPECTRAL EMBEDDING
T0 TIME
SE MANIFOLDSPECTRALEMBEDDINGNCOMPONENTS2
NNEIGHBORSNNEIGHBORS
TRANSDATA SEFITTRANSFORMSPHEREDATAT
T1 TIME
PRINTSPECTRAL EMBEDDING 2GSEC T1 T0
AX FIGADDSUBPLOT259
PLTSCATTERTRANSDATA0 TRANSDATA1 CCOLORS CMAPPLTCMRAINBOW
PLTTITLESPECTRAL EMBEDDING 2GSEC T1 T0
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
PERFORM TDISTRIBUTED STOCHASTIC NEIGHBOR EMBEDDING
T0 TIME
TSNE MANIFOLDTSNENCOMPONENTS2 INITPCA RANDOMSTATE0
TRANSDATA TSNEFITTRANSFORMSPHEREDATAT
T1 TIME
PRINTTSNE 2GSEC T1 T0
AX FIGADDSUBPLOT2 5 10
PLTSCATTERTRANSDATA0 TRANSDATA1 CCOLORS CMAPPLTCMRAINBOW
PLTTITLETSNE 2GSEC T1 T0
AXXAXISSETMAJORFORMATTERNULLFORMATTER
AXYAXISSETMAJORFORMATTERNULLFORMATTER
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 5954 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5196 MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING
ISOMAP
AN ILLUSTRATION OF VARIOUS EMBEDDINGS ON THE DIGITS DATASET
1226 CHAPTER 5 EXAMPLES

THE RANDOMTREESEMBEDDING FROM THE SKLEARNENSEMBLE MODULE IS NOT TECHNICALLY A MANIFOLD EMBEDDING METHOD AS IT LEARN A HIGHDIMENSIONAL REPRESENTATION ON WHICH WE APPLY A DIMENSIONALITY REDUCTION METHOD HOWEVER IT IS OFTEN USEFUL TO CAST A DATASET INTO A REPRESENTATION IN WHICH THE CLASSES ARE LINEARLYSEPARABLE TSNE WILL BE INITIALIZED WITH THE EMBEDDING THAT IS GENERATED BY PCA IN THIS EXAMPLE WHICH IS NOT THE DEFAULT SETTING IT ENSURES GLOBAL STABILITY OF THE EMBEDDING IE THE EMBEDDING DOES NOT DEPEND ON RANDOM INITIALIZATION LINEAR DISCRIMINANT ANALYSIS FROM THE SKLEARNDISCRIMINANTANALYSIS MODULE AND NEIGHBORHOOD COM PONENTS ANALYSIS FROM THE SKLEARNNEIGHBORS MODULE ARE SUPERVISED DIMENSIONALITY REDUCTION METHOD IE THEY MAKE USE OF THE PROVIDED LABELS CONTRARY TO OTHER METHODS

•

•

OUT

COMPUTING RANDOM PROJECTION
COMPUTING PCA PROJECTION
COMPUTING LINEAR DISCRIMINANT ANALYSIS PROJECTION
COMPUTING ISOMAP PROJECTION
DONE
COMPUTING LLE EMBEDDING
DONE RECONSTRUCTION ERROR 163544E06
COMPUTING MODIFIED LLE EMBEDDING
DONE RECONSTRUCTION ERROR 0360652
COMPUTING HESSIAN LLE EMBEDDING
DONE RECONSTRUCTION ERROR 0212801
COMPUTING LTSA EMBEDDING
DONE RECONSTRUCTION ERROR 0212808
COMPUTING MDS EMBEDDING
DONE STRESS 148085982692961
COMPUTING TOTALLY RANDOM TREES EMBEDDING
COMPUTING SPECTRAL EMBEDDING
COMPUTING TSNE EMBEDDING
COMPUTING NCA PROJECTION

```
SCIKITLEARN USER GUIDE RELEASE 0213
 AUTHORS FABIAN PEDREGOSA FABIANPEDREGOSAINRIAFR
 OLIVIER GRISEL OLIVIERGRISELENSTAORG
 MATHIEU BLONDEL MATHIEUMBLONDELORG
 GAEL VAROQUAUX
 LICENSE BSD 3 CLAUSE C INRIA 2011
PRINTDOC
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIB IMPORT OFFSETBOX
FROM SKLEARN IMPORT MANIFOLD DATASETS DECOMPOSITION ENSEMBLE
DISCRIMINANTANALYSIS RANDOMPROJECTION NEIGHBORS
DIGITS  DATASETSLOADDIGITSNCLASS6
X  DIGITSDATA
Y  DIGITSTARGET
NSAMPLES NFEATURES  XSHAPE
NNEIGHBORS  30

 SCALE AND VISUALIZE THE EMBEDDING VECTORS
DEFPLOTEMBEDDINGX TITLENONE
XMIN XMAX  NPMINX 0 NPMAXX 0
X  X  XMIN  XMAX  XMIN
PLTFIGURE
AX  PLTSUBPLOT111
FORIINRANGEXSHAPE0
PLTTEXTXI 0 XI 1 STRYI
COLORPLTCMSET1YI  10
FONTDICTWEIGHT BOLD SIZE 9
IFHASATTROFFSETBOX ANNOTATIONBBOX
 ONLY PRINT THUMBNAILS WITH MATPLOTLIB  10
SHOWNIMAGES  NPARRAY1 1  JUST SOMETHING BIG
FORIINRANGEXSHAPE0
DIST  NPSUMXI  SHOWNIMAGES 2 1
IFNPMINDIST  4E3
 DONT SHOW POINTS THAT ARE TOO CLOSE
CONTINUE
SHOWNIMAGES  NPRSHOWNIMAGES XI
IMAGEBOX  OFFSETBOXANNOTATIONBBOX
OFFSETBOXOFFSETIMAGEDIGITSIMAGESI CMAPPLTCMGRAYR
XI
AXADDARTISTIMAGEBOX
PLTXTICKS PLTYTICKS
IFTITLEIS NOTNONE
PLTTITLETITLE

 PLOT IMAGES OF THE DIGITS
NIMGPERROW  20
IMG  NPZEROS10 NIMGPERROW 10 NIMGPERROW
FORIINRANGENIMGPERROW
519 MANIFOLD LEARNING 1241
```

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IX 10 I 1
FORJINRANGENIMGPERROW
IY 10 J 1
IMGIXIX 8 IYIY 8 XI NIMGPERROW JRESHAPE8 8
PLTIMSHOWIMG CMAPPLTCMBINARY
PLTXTICKS
PLTYTICKS
PLTTITLEA SELECTION FROM THE 64DIMENSIONAL DIGITS DATASET

 RANDOM 2D PROJECTION USING A RANDOM UNITARY MATRIX
PRINTCOMPUTING RANDOM PROJECTION
RP RANDOMPROJECTIONSPARSERANDOMPROJECTIONNCOMPONENTS2 RANDOMSTATE42
XPROJECTED RPFITTRANSFORMX
PLOTEMBEDDINGXPROJECTED RANDOM PROJECTION OF THE DIGITS

 PROJECTION ON TO THE FIRST 2 PRINCIPAL COMPONENTS
PRINTCOMPUTING PCA PROJECTION
T0 TIME
XPCA DECOMPOSITIONTRUNCATEDSVDNCOMPONENTS2FITTRANSFORMX
PLOTEMBEDDINGXPCA
PRINCIPAL COMPONENTS PROJECTION OF THE DIGITS TIME 2FS
TIME T0

 PROJECTION ON TO THE FIRST 2 LINEAR DISCRIMINANT COMPONENTS
PRINTCOMPUTING LINEAR DISCRIMINANT ANALYSIS PROJECTION
X2 XCOPY
X2FLATXSHAPE1 1 001 MAKE X INVERTIBLE
T0 TIME
XLDA DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSISNCOMPONENTS2FIT
‹→TRANSFORMX2 Y
PLOTEMBEDDINGXLDA
LINEAR DISCRIMINANT PROJECTION OF THE DIGITS TIME 2FS
TIME T0

 ISOMAP PROJECTION OF THE DIGITS DATASET
PRINTCOMPUTING ISOMAP PROJECTION
T0 TIME
XISO MANIFOLDISOMAPNNEIGHBORS NCOMPONENTS2FITTRANSFORMX
PRINTDONE
PLOTEMBEDDINGXISO
ISOMAP PROJECTION OF THE DIGITS TIME 2FS
TIME T0

 LOCALLY LINEAR EMBEDDING OF THE DIGITS DATASET
PRINTCOMPUTING LLE EMBEDDING
CLF MANIFOLDLOCALLYLINEAREMBEDDINGNNEIGHBORS NCOMPONENTS2

SCIKITLEARN USER GUIDE RELEASE 0213
METHODSTANDARD
T0 TIME
XLLE CLFFITTRANSFORMX
PRINTDONE RECONSTRUCTION ERROR G CLFRECONSTRUCTIONERROR
PLOTEMBEDDINGXLLE
LOCALLY LINEAR EMBEDDING OF THE DIGITS TIME 2FS
TIME T0

 MODIFIED LOCALLY LINEAR EMBEDDING OF THE DIGITS DATASET
PRINTCOMPUTING MODIFIED LLE EMBEDDING
CLF MANIFOLDLOCALLYLINEAREMBEDDINGNNEIGHBORS NCOMPONENTS2
METHODMODIFIED
T0 TIME
XMLLE CLFFITTRANSFORMX
PRINTDONE RECONSTRUCTION ERROR G CLFRECONSTRUCTIONERROR
PLOTEMBEDDINGXMLLE
MODIFIED LOCALLY LINEAR EMBEDDING OF THE DIGITS TIME 2FS
TIME T0

 HLLE EMBEDDING OF THE DIGITS DATASET
PRINTCOMPUTING HESSIAN LLE EMBEDDING
CLF MANIFOLDLOCALLYLINEAREMBEDDINGNNEIGHBORS NCOMPONENTS2
METHODHESSIAN
T0 TIME
XHLLE CLFFITTRANSFORMX
PRINTDONE RECONSTRUCTION ERROR G CLFRECONSTRUCTIONERROR
PLOTEMBEDDINGXHLLE
HESSIAN LOCALLY LINEAR EMBEDDING OF THE DIGITS TIME 2FS
TIME T0

 LTSA EMBEDDING OF THE DIGITS DATASET
PRINTCOMPUTING LTSA EMBEDDING
CLF MANIFOLDLOCALLYLINEAREMBEDDINGNNEIGHBORS NCOMPONENTS2
METHODLTSA
T0 TIME
XLTSA CLFFITTRANSFORMX
PRINTDONE RECONSTRUCTION ERROR G CLFRECONSTRUCTIONERROR
PLOTEMBEDDINGXLTSA
LOCAL TANGENT SPACE ALIGNMENT OF THE DIGITS TIME 2FS
TIME T0

 MDS EMBEDDING OF THE DIGITS DATASET
PRINTCOMPUTING MDS EMBEDDING
CLF MANIFOLDMDSNCOMPONENTS2 NINIT1 MAXITER100
T0 TIME
XMDS CLFFITTRANSFORMX
PRINTDONE STRESS F CLFSTRESS
PLOTEMBEDDINGXMDS
MDS EMBEDDING OF THE DIGITS TIME 2FS
TIME T0

```
 RANDOM TREES EMBEDDING OF THE DIGITS DATASET
PRINTCOMPUTING TOTALLY RANDOM TREES EMBEDDING
HASHER  ENSEMBLERANDOMTREESEMBEDDINGNESTIMATORS200 RANDOMSTATE0
MAXDEPTH5
T0  TIME
XTRANSFORMED  HASHERFITTRANSFORMX
PCA  DECOMPOSITIONTRUNCATEDSVDNCOMPONENTS2
XREDUCED  PCAFITTRANSFORMXTRANSFORMED
PLOTEMBEDDINGXREDUCED
RANDOM FOREST EMBEDDING OF THE DIGITS TIME 2FS
TIME  T0

 SPECTRAL EMBEDDING OF THE DIGITS DATASET
PRINTCOMPUTING SPECTRAL EMBEDDING
EMBEDDER  MANIFOLDSPECTRALEMBEDDINGNCOMPONENTS2 RANDOMSTATE0
EIGENSOLVERARPACK
T0  TIME
XSE  EMBEDDERFITTRANSFORMX
PLOTEMBEDDINGXSE
SPECTRAL EMBEDDING OF THE DIGITS TIME 2FS
TIME  T0

 TSNE EMBEDDING OF THE DIGITS DATASET
PRINTCOMPUTING TSNE EMBEDDING
TSNE  MANIFOLDTSNENCOMPONENTS2 INITPCA RANDOMSTATE0
T0  TIME
XTSNE  TSNEFITTRANSFORMX
PLOTEMBEDDINGXTSNE
TSNE EMBEDDING OF THE DIGITS TIME 2FS
TIME  T0

 NCA PROJECTION OF THE DIGITS DATASET
PRINTCOMPUTING NCA PROJECTION
NCA  NEIGHBORSNEIGHBORHOODCOMPONENTSANALYSISNCOMPONENTS2 RANDOMSTATE0
T0  TIME
XNCA  NCAFITTRANSFORMX Y
PLOTEMBEDDINGXNCA
NCA EMBEDDING OF THE DIGITS TIME 2FS
TIME  T0
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT  0 MINUTES 17641 SECONDS
```

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5201 DENSITY ESTIMATION FOR A GAUSSIAN MIXTURE
PLOT THE DENSITY ESTIMATION OF A MIXTURE OF TWO GAUSSIANS DATA IS GENERATED FROM TWO GAUSSIANS WITH DIFFERENT CENTERS AND COVARIANCE MATRICES

```
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBCOLORS IMPORT LOGNORM
FROM SKLEARN IMPORT MIXTURE
NSAMPLES  300
 GENERATE RANDOM SAMPLE TWO COMPONENTS
NPRANDOMSEED0
 GENERATE SPHERICAL DATA CENTERED ON 20 20
SHIFTEDGAUSSIAN  NPRANDOMRANDNNSAMPLES 2  NPARRAY20 20
 GENERATE ZERO CENTERED STRETCHED GAUSSIAN DATA
C  NPARRAY0 07 35 7
STRETCHEDGAUSSIAN  NPDOTNPRANDOMRANDNNSAMPLES 2 C
```

```
 CONCATENATE THE TWO DATASETS INTO THE FINAL TRAINING SET
XTRAIN  NPVSTACKSHIFTEDGAUSSIAN STRETCHEDGAUSSIAN
 FIT A GAUSSIAN MIXTURE MODEL WITH TWO COMPONENTS
CLF  MIXTUREGAUSSIANMIXTURENCOMPONENTS2 COVARIANCETYPEFULL
CLFFITXTRAIN
 DISPLAY PREDICTED SCORES BY THE MODEL AS A CONTOUR PLOT
X  NPLINSPACE20 30
Y  NPLINSPACE20 40
X Y  NPMESHGRIDX Y
XX  NPARRAYXRAVEL YRAVELT
Z  CLFSCORESAMPLESXX
Z  ZRESHAPEXSHAPE
CS  PLTCONTOURX Y Z NORMLOGNORMVMIN10 VMAX10000
LEVELSNPLOGSPACE0 3 10
CB  PLTCOLORBARCS SHRINK08 EXTENDBOTH
PLTSCATTERXTRAIN 0 XTRAIN 1 8
PLTTITLENEGATIVE LOGLIKELIHOOD PREDICTED BY A GMM
PLTAXISTIGHT
PLTSHOW
```

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0040 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5202 GAUSSIAN MIXTURE MODEL ELLIPSOIDS

PLOT THE CONFIDENCE ELLIPSOIDS OF A MIXTURE OF TWO GAUSSIANS OBTAINED WITH EXPECTATION MAXIMISATION GAUSSIANMIXTURE CLASS AND VARIATIONAL INFERENCE BAYESIANGAUSSIANMIXTURE CLASS MODELS WITH A DIRICHLET PROCESS PRIOR

BOTH MODELS HAVE ACCESS TO FIVE COMPONENTS WITH WHICH TO FIT THE DATA NOTE THAT THE EXPECTATION MAXIMISATION MODEL WILL NECESSARILY USE ALL FIVE COMPONENTS WHILE THE VARIATIONAL INFERENCE MODEL WILL EFFECTIVELY ONLY USE AS MANY AS ARE NEEDED FOR A GOOD FIT HERE WE CAN SEE THAT THE EXPECTATION MAXIMISATION MODEL SPLITS SOME COMPONENTS ARBITRARILY BECAUSE IT IS TRYING TO FIT TOO MANY COMPONENTS WHILE THE DIRICHLET PROCESS MODEL ADAPTS IT NUMBER OF STATE AUTOMATICALLY

THIS EXAMPLE DOESN’T SHOW IT AS WE’RE IN A LOWDIMENSIONAL SPACE BUT ANOTHER ADVANTAGE OF THE DIRICHLET PROCESS MODEL IS THAT IT CAN FIT FULL COVARIANCE MATRICES EFFECTIVELY EVEN WHEN THERE ARE LESS EXAMPLES PER CLUSTER THAN THERE ARE DIMENSIONS IN THE DATA DUE TO REGULARIZATION PROPERTIES OF THE INFERENCE ALGORITHM

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IMPORT ITERTOOLS
IMPORT NUMPY AS NP
FROM SCIPY IMPORT LINALG
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIB AS MPL
FROM SKLEARN IMPORT MIXTURE
COLORITER ITERTOOLSCYCLENAVY C CORNFLOWERBLUE GOLD
DARKORANGE
DEFPLOTRESULTSX Y MEANS COVARIANCES INDEX TITLE
SPLOT PLTSUBPLOT2 1 1 INDEX
FORI MEAN COVAR COLOR INENUMERATEZIP
MEANS COVARIANCES COLORITER
V W LINALGEIGHCOVAR
V 2NPSQRT2 NPSQRTV
U W0 LINALGNORMW0
 AS THE DP WILL NOT USE EVERY COMPONENT IT HAS ACCESS TO
 UNLESS IT NEEDS IT WE SHOULDNT PLOT THE REDUNDANT
 COMPONENTS
IF NOTNPANYY I
CONTINUE
PLTSCATTERXY I 0 XY I 1 8 COLORCOLOR

SCIKITLEARN USER GUIDE RELEASE 0213
PLOT AN ELLIPSE TO SHOW THE GAUSSIAN COMPONENT
ANGLE NPARCTANU1 U0
ANGLE 180 ANGLE NPPI CONVERT TO DEGREES
ELL MPLPATCHESELLIPSEMEAN V0 V1 180 ANGLE COLORCOLOR
ELLSETCLIPBOXSPLOTBBOX
ELLSETALPHA05
SPLOTADDARTISTELL
PLTXLIM9 5
PLTYLIM3 6
PLTXTICKS
PLTYTICKS
PLTTITLETITLE
NUMBER OF SAMPLES PER COMPONENT
NSAMPLES 500
GENERATE RANDOM SAMPLE TWO COMPONENTS
NPRANDOMSEED0
C NPARRAY0 01 17 4
X NPRNPDOTNPRANDOMRANDNNSAMPLES 2 C
7NPRANDOMRANDNNSAMPLES 2 NPARRAY6 3
FIT A GAUSSIAN MIXTURE WITH EM USING FIVE COMPONENTS
GMM MIXTUREGAUSSIANMIXTURENCOMPONENTS5 COVARIANCETYPEFULLFITX
PLOTRESULTSX GMMPREDICTX GMMMEANS GMMCOVARIANCES 0
GAUSSIAN MIXTURE
FIT A DIRICHLET PROCESS GAUSSIAN MIXTURE USING FIVE COMPONENTS
DPGMM MIXTUREBAYESIANGAUSSIANMIXTURENCOMPONENTS5
COVARIANCETYPEFULLFITX
PLOTRESULTSX DPGMMPREDICTX DPGMMMEANS DPGMMCOVARIANCES 1
BAYESIAN GAUSSIAN MIXTURE WITH A DIRICHLET PROCESS PRIOR
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0138 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5203 GAUSSIAN MIXTURE MODEL SELECTION
THIS EXAMPLE SHOWS THAT MODEL SELECTION CAN BE PERFORMED WITH GAUSSIAN MIXTURE MODELS USING INFORMATIONTHEORETIC CRITERIA BIC MODEL SELECTION CONCERNS BOTH THE COVARIANCE TYPE AND THE NUMBER OF COMPONENTS IN THE MODEL IN THAT CASE AIC ALSO PROVIDES THE RIGHT RESULT NOT SHOWN TO SAVE TIME BUT BIC IS BETTER SUITED IF THE PROBLEM IS TO IDENTIFY THE RIGHT MODEL UNLIKE BAYESIAN PROCEDURES SUCH INFERENCES ARE PRIORFREE
IN THAT CASE THE MODEL WITH 2 COMPONENTS AND FULL COVARIANCE WHICH CORRESPONDS TO THE TRUE GENERATIVE MODEL IS SELECTED

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IMPORT NUMPY AS NP
IMPORT ITERTOOLS
FROM SCIPY IMPORT LINALG
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIB AS MPL
FROM SKLEARN IMPORT MIXTURE
PRINTDOC
 NUMBER OF SAMPLES PER COMPONENT
NSAMPLES 500
 GENERATE RANDOM SAMPLE TWO COMPONENTS
NPRANDOMSEED0
C NPARRAY0 01 17 4
X NPRNPDOTNPRANDOMRANDNNSAMPLES 2 C
7NPRANDOMRANDNNSAMPLES 2 NPARRAY6 3
LOWESTBIC NPINFTY
BIC
NCOMPONENTSRANGE RANGE1 7
CVTYPES SPHERICAL TIED DIAG FULL
FORCVTYPE INCVTYPES
FORNCOMPONENTS INNCOMPONENTSRANGE
520 GAUSSIAN MIXTURE MODELS 1249

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 FIT A GAUSSIAN MIXTURE WITH EM
GMM MIXTUREGAUSSIANMIXTURENCOMPONENTSNCOMPONENTS
COVARIANCETYPECVTYPE
GMMFITX
BICAPPENDGMMBICX
IFBIC1 LOWESTBIC
LOWESTBIC BIC1
BESTGMM GMM
BIC NPARRAYBIC
COLORITER ITERTOOLSCYCLENAVY TURQUOISE CORNFLOWERBLUE
DARKORANGE
CLF BESTGMM
BARS
 PLOT THE BIC SCORES
PLTFIGUREFIGSIZE8 6
SPL PLTSUBPLOT2 1 1
FORI CVTYPE COLOR INENUMERATEZIPCVTYPES COLORITER
XPOS NPARRAYNCOMPONENTSRANGE 2 I 2
BARSAPPENDPLTBARXPOS BICI LENNCOMPONENTSRANGE
I 1 LENNCOMPONENTSRANGE
WIDTH2 COLORCOLOR
PLTXTICKSNCOMPONENTSRANGE
PLTYLIMBICMIN 101 01 BICMAX BICMAX
PLTTITLEBIC SCORE PER MODEL
XPOS NPMODBICARGMIN LENNCOMPONENTSRANGE 65
2NPFLOORBICARGMIN LENNCOMPONENTSRANGE
PLTTEXTXPOS BICMIN 097 03 BICMAX   FONTSIZE14
SPLSETXLABELNUMBER OF COMPONENTS
SPLLEGENDB0 FORBINBARS CVTYPES
 PLOT THE WINNER
SPLOT PLTSUBPLOT2 1 2
Y CLFPREDICTX
FORI MEAN COV COLOR INENUMERATEZIPCLFMEANS CLFCOVARIANCES
COLORITER
V W LINALGEIGHCOV
IF NOTNPANYY I
CONTINUE
PLTSCATTERXY I 0 XY I 1 8 COLORCOLOR
 PLOT AN ELLIPSE TO SHOW THE GAUSSIAN COMPONENT
ANGLE NPARCTAN2W01 W00
ANGLE 180 ANGLE NPPI CONVERT TO DEGREES
V 2NPSQRT2 NPSQRTV
ELL MPLPATCHESELLIPSEMEAN V0 V1 180 ANGLE COLORCOLOR
ELLSETCLIPBOXSPLOTBBOX
ELLSETALPHA5
SPLOTADDARTISTELL
PLTXTICKS
PLTYTICKS
PLTTITLESELECTED GMM FULL MODEL 2 COMPONENTS
PLTSUBPLOTSADJUSTHSPACE35 BOTTOM02
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0207 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5204 GMM COVARIANCES
DEMONSTRATION OF SEVERAL COVARIANCES TYPES FOR GAUSSIAN MIXTURE MODELS
SEEGAUSSIAN MIXTURE MODELS FOR MORE INFORMATION ON THE ESTIMATOR
ALTHOUGH GMM ARE OFTEN USED FOR CLUSTERING WE CAN COMPARE THE OBTAINED CLUSTERS WITH THE ACTUAL CLASSES FROM THE DATASET WE INITIALIZE THE MEANS OF THE GAUSSIANS WITH THE MEANS OF THE CLASSES FROM THE TRAINING SET TO MAKE THIS COMPARISON VALID
WE PLOT PREDICTED LABELS ON BOTH TRAINING AND HELD OUT TEST DATA USING A VARIETY OF GMM COVARIANCE TYPES ON THE IRIS DATASET WE COMPARE GMMS WITH SPHERICAL DIAGONAL FULL AND TIED COVARIANCE MATRICES IN INCREASING ORDER OF PERFORMANCE ALTHOUGH ONE WOULD EXPECT FULL COVARIANCE TO PERFORM BEST IN GENERAL IT IS PRONE TO OVERFITTING ON SMALL DATASETS AND DOES NOT GENERALIZE WELL TO HELD OUT TEST DATA
ON THE PLOTS TRAIN DATA IS SHOWN AS DOTS WHILE TEST DATA IS SHOWN AS CROSSES THE IRIS DATASET IS FOURDIMENSIONAL ONLY THE FIRST TWO DIMENSIONS ARE SHOWN HERE AND THUS SOME POINTS ARE SEPARATED IN OTHER DIMENSIONS

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 AUTHOR RON WEISS RONWEISSGMAILCOM GAEL VAROQUAUX
 MODIFIED BY THIERRY GUILLEMOT THIERRYGUILLEMOTWORKGMAILCOM
 LICENSE BSD 3 CLAUSE
IMPORT MATPLOTLIB AS MPL
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNMIXTURE IMPORT GAUSSIANMIXTURE
FROM SKLEARNMODELSELECTION IMPORT STRATIFIEDKFOLD
PRINTDOC
COLORS NAVY TURQUOISE DARKORANGE
1252 CHAPTER 5 EXAMPLES

```
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DEFMAKEELLIPSESGMM AX
FORN COLOR INENUMERATECOLORS
IFGMMCOVARIANCETYPE  FULL
COVARIANCES  GMMCOVARIANCESN2 2
ELIFGMMCOVARIANCETYPE  TIED
COVARIANCES  GMMCOVARIANCES2 2
ELIFGMMCOVARIANCETYPE  DIAG
COVARIANCES  NPDIAGGMMCOVARIANCESN2
ELIFGMMCOVARIANCETYPE  SPHERICAL
COVARIANCES  NPEYEGMMMEANSSHAPE1 GMMCOVARIANCESN
V W  NPLINALGEIGHCOVARIANCES
U  W0  NPLINALGNORMW0
ANGLE  NPARCTAN2U1 U0
ANGLE  180 ANGLE  NPPI  CONVERT TO DEGREES
V  2NPSQRT2 NPSQRTV
ELL  MPLPATCHESELLIPSEGMMMEANSN 2 V0 V1
180  ANGLE COLORCOLOR
ELLSETCLIPBOXAXBBOX
ELLSETALPHA05
AXADDARTISTELL
AXSETASPECTEQUAL DATALIM
IRIS  DATASETSLOADIRIS
 BREAK UP THE DATASET INTO NONOVERLAPPING TRAINING 75 AND TESTING
 25 SETS
SKF  STRATIFIEDKFOLDNSPLITS4
 ONLY TAKE THE FIRST FOLD
TRAININDEX TESTINDEX  NEXTITERSKFSPLITIRISDATA IRISTARGET
XTRAIN  IRISDATATRAININDEX
YTRAIN  IRISTARGETTRAININDEX
XTEST  IRISDATATESTINDEX
YTEST  IRISTARGETTESTINDEX
NCLASSES  LENNPUNIQUEYTRAIN
 TRY GMMS USING DIFFERENT TYPES OF COVARIANCES
ESTIMATORS  COVTYPE GAUSSIANMIXTURENCOMPONENTSNCLASSES
COVARIANCETYPECOVTYPE MAXITER20 RANDOMSTATE0
FORCOVTYPE INSPHERICAL DIAG TIED FULL
NESTIMATORS  LENESTIMATORS
PLTFIGUREFIGSIZE3 NESTIMATORS  2 6
PLTSUBPLOTSADJUSTBOTTOM01 TOP095 HSPACE15 WSPACE05
LEFT01 RIGHT99
FORINDEX NAME ESTIMATOR INENUMERATEESTIMATORSITEMS
 SINCE WE HAVE CLASS LABELS FOR THE TRAINING DATA WE CAN
 INITIALIZE THE GMM PARAMETERS IN A SUPERVISED MANNER
ESTIMATORMEANSINIT  NPARRAYXTRAINYTRAIN  IMEANAXIS0
FORIINRANGENCLASSES
 TRAIN THE OTHER PARAMETERS USING THE EM ALGORITHM
ESTIMATORFITXTRAIN
```

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H PLTSUBPLOT2 NESTIMATORS 2 INDEX 1
MAKEELLIPSESESTIMATOR H
FORN COLOR INENUMERATECOLORS
DATA IRISDATAIRISTARGET N
PLTSCATTERDATA 0 DATA 1 S08 COLORCOLOR
LABELIRISTARGETNAMESN
 PLOT THE TEST DATA WITH CROSSES
FORN COLOR INENUMERATECOLORS
DATA XTESTYTEST N
PLTSCATTERDATA 0 DATA 1 MARKERX COLORCOLOR
YTRAINPRED ESTIMATORPREDICTXTRAIN
TRAINACCURACY NPMEANYTRAINPREDRAVEL YTRAINRAVEL 100
PLTTEXT005 09 TRAIN ACCURACY 1F TRAINACCURACY
TRANSFORMHTRANSAXES
YTESTPRED ESTIMATORPREDICTXTEST
TESTACCURACY NPMEANYTESTPREDRAVEL YTESTRAVEL 100
PLTTEXT005 08 TEST ACCURACY 1F TESTACCURACY
TRANSFORMHTRANSAXES
PLTXTICKS
PLTYTICKS
PLTTITLENAME
PLTLEGENDSCATTERPOINTS1 LOCLOWER RIGHT PROPDICTSIZE12
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0097 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5205 GAUSSIAN MIXTURE MODEL SINE CURVE
THIS EXAMPLE DEMONSTRATES THE BEHAVIOR OF GAUSSIAN MIXTURE MODELS FIT ON DATA THAT WAS NOT SAMPLED FROM A MIXTURE OF GAUSSIAN RANDOM VARIABLES THE DATASET IS FORMED BY 100 POINTS LOOSELY SPACED FOLLOWING A NOISY SINE CURVE THERE IS THEREFORE NO GROUND TRUTH VALUE FOR THE NUMBER OF GAUSSIAN COMPONENTS
THE FIRST MODEL IS A CLASSICAL GAUSSIAN MIXTURE MODEL WITH 10 COMPONENTS FIT WITH THE EXPECTATIONMAXIMIZATION ALGORITHM
THE SECOND MODEL IS A BAYESIAN GAUSSIAN MIXTURE MODEL WITH A DIRICHLET PROCESS PRIOR FIT WITH VARIATIONAL INFERENCE THE LOW VALUE OF THE CONCENTRATION PRIOR MAKES THE MODEL FAVOR A LOWER NUMBER OF ACTIVE COMPONENTS THIS MODELS “DECIDES” TO FOCUS ITS MODELING POWER ON THE BIG PICTURE OF THE STRUCTURE OF THE DATASET GROUPS OF POINTS WITH ALTERNATING DIRECTIONS MODELED BY NONDIAGONAL COVARIANCE MATRICES THOSE ALTERNATING DIRECTIONS ROUGHLY CAPTURE THE ALTERNATING NATURE OF THE ORIGINAL SINE SIGNAL
THE THIRD MODEL IS ALSO A BAYESIAN GAUSSIAN MIXTURE MODEL WITH A DIRICHLET PROCESS PRIOR BUT THIS TIME THE VALUE OF THE CONCENTRATION PRIOR IS HIGHER GIVING THE MODEL MORE LIBERTY TO MODEL THE FINEGRAINED STRUCTURE OF THE DATA THE RESULT IS A MIXTURE WITH A LARGER NUMBER OF ACTIVE COMPONENTS THAT IS SIMILAR TO THE FIRST MODEL WHERE WE ARBITRARILY DECIDED TO FIX THE NUMBER OF COMPONENTS TO 10

WHICH MODEL IS THE BEST IS A MATTER OF SUBJECTIVE JUDGEMENT DO WE WANT TO FAVOR MODELS THAT ONLY CAPTURE THE BIG PICTURE TO SUMMARIZE AND EXPLAIN MOST OF THE STRUCTURE OF THE DATA WHILE IGNORING THE DETAILS OR DO WE PREFER MODELS THAT CLOSELY FOLLOW THE HIGH DENSITY REGIONS OF THE SIGNAL

THE LAST TWO PANELS SHOW HOW WE CAN SAMPLE FROM THE LAST TWO MODELS THE RESULTING SAMPLES DISTRIBUTIONS DO NOT LOOK EXACTLY LIKE THE ORIGINAL DATA DISTRIBUTION THE DIFFERENCE PRIMARILY STEMS FROM THE APPROXIMATION ERROR WE MADE BY USING A MODEL THAT ASSUMES THAT THE DATA WAS GENERATED BY A FINITE NUMBER OF GAUSSIAN COMPONENTS INSTEAD OF A CONTINUOUS NOISY SINE CURVE

```
IMPORT ITERTOOLS
IMPORT NUMPY AS NP
FROM SCIPY IMPORT LINALG
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIB AS MPL
```

```
SCIKITLEARN USER GUIDE RELEASE 0213
FROM SKLEARN IMPORT MIXTURE
PRINTDOC
COLORITER  ITERTOOLSCYCLENAVY C CORNFLOWERBLUE GOLD
DARKORANGE
DEFPLOTRESULTSX Y MEANS COVARIANCES INDEX TITLE
SPLOT  PLTSUBPLOT5 1 1  INDEX
FORI MEAN COVAR COLOR INENUMERATEZIP
MEANS COVARIANCES COLORITER
V W  LINALGEIGHCOVAR
V  2NPSQRT2 NPSQRTV
U  W0  LINALGNORMW0
 AS THE DP WILL NOT USE EVERY COMPONENT IT HAS ACCESS TO
 UNLESS IT NEEDS IT WE SHOULDNT PLOT THE REDUNDANT
 COMPONENTS
IF NOTNPANYY  I
CONTINUE
PLTSCATTERXY  I 0 XY  I 1 8 COLORCOLOR
 PLOT AN ELLIPSE TO SHOW THE GAUSSIAN COMPONENT
ANGLE  NPARCTANU1  U0
ANGLE  180 ANGLE  NPPI  CONVERT TO DEGREES
ELL  MPLPATCHESELLIPSEMEAN V0 V1 180  ANGLE COLORCOLOR
ELLSETCLIPBOXSPLOTBBOX
ELLSETALPHA05
SPLOTADDARTISTELL
PLTXLIM6 4 NPPI  6
PLTYLIM5 5
PLTTITLETITLE
PLTXTICKS
PLTYTICKS
DEFPLOTSAMPLESX Y NCOMPONENTS INDEX TITLE
PLTSUBPLOT5 1 4  INDEX
FORI COLOR INZIPRANGENCOMPONENTS COLORITER
 AS THE DP WILL NOT USE EVERY COMPONENT IT HAS ACCESS TO
 UNLESS IT NEEDS IT WE SHOULDNT PLOT THE REDUNDANT
 COMPONENTS
IF NOTNPANYY  I
CONTINUE
PLTSCATTERXY  I 0 XY  I 1 8 COLORCOLOR
PLTXLIM6 4 NPPI  6
PLTYLIM5 5
PLTTITLETITLE
PLTXTICKS
PLTYTICKS
 PARAMETERS
NSAMPLES  100
```

```
 GENERATE RANDOM SAMPLE FOLLOWING A SINE CURVE
NPRANDOMSEED0
X  NPZEROSNSAMPLES 2
STEP  4 NPPI  NSAMPLES
FORIINRANGEXSHAPE0
X  ISTEP  6
XI 0  X  NPRANDOMNORMAL0 01
XI 1  3 NPSINX  NPRANDOMNORMAL0 2
PLTFIGUREFIGSIZE10 10
PLTSUBPLOTSADJUSTBOTTOM04 TOP095 HSPACE2 WSPACE05
LEFT03 RIGHT97
 FIT A GAUSSIAN MIXTURE WITH EM USING TEN COMPONENTS
GMM  MIXTUREGAUSSIANMIXTURENCOMPONENTS10 COVARIANCETYPEFULL
MAXITER100FITX
PLOTRESULTSX GMMPREDICTX GMMMEANS GMMCOVARIANCES 0
EXPECTATIONMAXIMIZATION
DPGMM  MIXTUREBAYESIANGAUSSIANMIXTURE
NCOMPONENTS10 COVARIANCETYPEFULL WEIGHTCONCENTRATIONPRIOR1E2
WEIGHTCONCENTRATIONPRIORTYPEDIRICHLETPROCESS
MEANPRECISIONPRIOR1E2 COVARIANCEPRIOR1E0 NPEYE2
INITPARAMSRANDOM MAXITER100 RANDOMSTATE2FITX
PLOTRESULTSX DPGMMPREDICTX DPGMMMEANS DPGMMCOVARIANCES 1
BAYESIAN GAUSSIAN MIXTURE MODELS WITH A DIRICHLET PROCESS PRIOR
RFOR GAMMA0001
XS YS  DPGMMSAMPLENSAMPLES2000
PLOTSAMPLESXS YS DPGMMNCOMPONENTS 0
GAUSSIAN MIXTURE WITH A DIRICHLET PROCESS PRIOR
RFOR GAMMA0001 SAMPLED WITH 2000 SAMPLES
DPGMM  MIXTUREBAYESIANGAUSSIANMIXTURE
NCOMPONENTS10 COVARIANCETYPEFULL WEIGHTCONCENTRATIONPRIOR1E2
WEIGHTCONCENTRATIONPRIORTYPEDIRICHLETPROCESS
MEANPRECISIONPRIOR1E2 COVARIANCEPRIOR1E0 NPEYE2
INITPARAMSKMEANS MAXITER100 RANDOMSTATE2FITX
PLOTRESULTSX DPGMMPREDICTX DPGMMMEANS DPGMMCOVARIANCES 2
BAYESIAN GAUSSIAN MIXTURE MODELS WITH A DIRICHLET PROCESS PRIOR
RFOR GAMMA0100
XS YS  DPGMMSAMPLENSAMPLES2000
PLOTSAMPLESXS YS DPGMMNCOMPONENTS 1
GAUSSIAN MIXTURE WITH A DIRICHLET PROCESS PRIOR
RFOR GAMMA0100 SAMPLED WITH 2000 SAMPLES
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT  0 MINUTES 0301 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
```

5206 CONCENTRATION PRIOR TYPE ANALYSIS OF VARIATION BAYESIAN GAUSSIAN MIXTURE
THIS EXAMPLE PLOTS THE ELLIPSOIDS OBTAINED FROM A TOY DATASET MIXTURE OF THREE GAUSSIANS FIT
TED BY THE BAYESIANGAUSSIANMIXTURE CLASS MODELS WITH A DIRICHLET DISTRIBUTION PRIOR
WEIGHTCONCENTRATIONPRIORTYPEDIRICHLETDISTRIBUTION AND A DIRICHLET PROCESS
PRIOR WEIGHTCONCENTRATIONPRIORTYPEDIRICHLETPROCESS ON EACH FIGURE WE PLOT THE
RESULTS FOR THREE DIFFERENT VALUES OF THE WEIGHT CONCENTRATION PRIOR
THEBAYESIANGAUSSIANMIXTURE CLASS CAN ADAPT ITS NUMBER OF MIXTURE COMPONENTS AUTOMATICALLY THE PARAM
ETERWEIGHTCONCENTRATIONPRIOR HAS A DIRECT LINK WITH THE RESULTING NUMBER OF COMPONENTS WITH NONZERO
WEIGHTS SPECIFYING A LOW VALUE FOR THE CONCENTRATION PRIOR WILL MAKE THE MODEL PUT MOST OF THE WEIGHT ON FEW COM
PONENTS SET THE REMAINING COMPONENTS WEIGHTS VERY CLOSE TO ZERO HIGH VALUES OF THE CONCENTRATION PRIOR WILL ALLOW A
LARGER NUMBER OF COMPONENTS TO BE ACTIVE IN THE MIXTURE
THE DIRICHLET PROCESS PRIOR ALLOWS TO DEFINE AN INFINITE NUMBER OF COMPONENTS AND AUTOMATICALLY SELECTS THE CORRECT
NUMBER OF COMPONENTS IT ACTIVATES A COMPONENT ONLY IF IT IS NECESSARY
ON THE CONTRARY THE CLASSICAL FINITE MIXTURE MODEL WITH A DIRICHLET DISTRIBUTION PRIOR WILL FAVOR MORE UNIFORMLY WEIGHTED
COMPONENTS AND THEREFORE TENDS TO DIVIDE NATURAL CLUSTERS INTO UNNECESSARY SUBCOMPONENTS
•

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•
 AUTHOR THIERRY GUILLEMOT THIERRYGUILLEMOTWORKGMAILCOM
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIB AS MPL
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIBGRIDSPEC AS GRIDSPEC
FROM SKLEARNMIXTURE IMPORT BAYESIANGAUSSIANMIXTURE
PRINTDOC
DEFPLOTELLIPSESAX WEIGHTS MEANS COVARS
FORNINRANGEMEANSSHAPE0
EIGVALS EIGVECS  NPLINALGEIGHCOVARSN
UNITEIGVEC  EIGVECS0  NPLINALGNORMEIGVECS0
ANGLE  NPARCTAN2UNITEIGVEC1 UNITEIGVEC0
 ELLIPSE NEEDS DEGREES
ANGLE  180 ANGLE  NPPI
 EIGENVECTOR NORMALIZATION
EIGVALS  2 NPSQRT2 NPSQRTEIGVALS
ELL  MPLPATCHESELLIPSEMEANSN EIGVALS0 EIGVALS1
180  ANGLE EDGECOLORBLACK
ELLSETCLIPBOXAXBBOX
ELLSETALPHAWEIGHTSN
ELLSETFACECOLOR56B4E9
AXADDARTISTELL
DEFPLOTRESULTSAX1 AX2 ESTIMATOR X Y TITLE PLOTTITLEFALSE
AX1SETTITLETITLE
AX1SCATTERX 0 X 1 S5 MARKERO COLORCOLORSY ALPHA08
AX1SETXLIM2 2
AX1SETYLIM3 3
```

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AX1SETXTICKS
AX1SETYTICKS
PLOTELLIPSESAX1 ESTIMATORWEIGHTS ESTIMATORMEANS
ESTIMATORCOVARIANCES
AX2GETXAXISSETTICKPARAMSDIRECTIONOUT
AX2YAXISGRIDTRUE ALPHA07
FORK WINENUMERATEESTIMATORWEIGHTS
AX2BARK W WIDTH09 COLOR56B4E9 ZORDER3
ALIGNCENTER EDGECOLORBLACK
AX2TEXTK W 0007 1F W100
HORIZONTALALIGNMENTCENTER
AX2SETXLIM6 2 NCOMPONENTS 4
AX2SETYLIM0 11
AX2TICKPARAMSAXISY WHICHBOTH LEFTFALSE
RIGHTFALSE LABELLEFTFALSE
AX2TICKPARAMSAXISX WHICHBOTH TOPFALSE
IFPLOTTITLE
AX1SETYLABELESTIMATED MIXTURES
AX2SETYLABELWEIGHT OF EACH COMPONENT
 PARAMETERS OF THE DATASET
RANDOMSTATE NCOMPONENTS NFEATURES 2 3 2
COLORS NPARRAY0072B2 F0E442 D55E00
COVARS NPARRAY7 0 0 1
5 0 0 1
5 0 0 1
SAMPLES NPARRAY200 500 200
MEANS NPARRAY0 70
0 0
0 70
 MEANPRECISIONPRIOR 08 TO MINIMIZE THE INFLUENCE OF THE PRIOR
ESTIMATORS
FINITE MIXTURE WITH A DIRICHLET DISTRIBUTION NPRIOR AND
RGAMMA0 BAYESIANGAUSSIANMIXTURE
WEIGHTCONCENTRATIONPRIORTYPEDIRICHLETDISTRIBUTION
NCOMPONENTS2 NCOMPONENTS REGCOVAR0 INITPARAMSRANDOM
MAXITER1500 MEANPRECISIONPRIOR8
RANDOMSTATERANDOMSTATE 0001 1 1000
INFINITE MIXTURE WITH A DIRICHLET PROCESS NPRIOR AND RGAMMA0
BAYESIANGAUSSIANMIXTURE
WEIGHTCONCENTRATIONPRIORTYPEDIRICHLETPROCESS
NCOMPONENTS2 NCOMPONENTS REGCOVAR0 INITPARAMSRANDOM
MAXITER1500 MEANPRECISIONPRIOR8
RANDOMSTATERANDOMSTATE 1 1000 100000
 GENERATE DATA
RNG NPRANDOMRANDOMSTATERANDOMSTATE
X NPVSTACK
RNGMULTIVARIATENORMALMEANSJ COVARSJ SAMPLESJ
FORJINRANGENCOMPONENTS
Y NPCONCATENATENPFULLSAMPLESJ J DTYPEINT
FORJINRANGENCOMPONENTS
 PLOT RESULTS IN TWO DIFFERENT FIGURES

SCIKITLEARN USER GUIDE RELEASE 0213
FORTITLE ESTIMATOR CONCENTRATIONSPRIOR INESTIMATORS
PLTFIGUREFIGSIZE47 3 8
PLTSUBPLOTSADJUSTBOTTOM04 TOP090 HSPACE05 WSPACE05
LEFT03 RIGHT99
GS GRIDSPECGRIDSPEC3 LENCONCENTRATIONSPRIOR
FORK CONCENTRATION INENUMERATECONCENTRATIONSPRIOR
ESTIMATORWEIGHTCONCENTRATIONPRIOR CONCENTRATION
ESTIMATORFITX
PLOTRESULTSPLTSUBPLOTGS02 K PLTSUBPLOTGS2 K ESTIMATOR
X Y R S1E TITLE CONCENTRATION
PLOTTITLEK 0
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 6923 SECONDS
521 MODEL SELECTION
EXAMPLES RELATED TO THE SKLEARNMODELSELECTION MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5211 PLOTTING CROSSVALIDATED PREDICTIONS
THIS EXAMPLE SHOWS HOW TO USE CROSSVALPREDICT TO VISUALIZE PREDICTION ERRORS

SCIKITLEARN USER GUIDE RELEASE 0213
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNMODELSELECTION IMPORT CROSSVALPREDICT
FROM SKLEARN IMPORT LINEARMODEL
IMPORT MATPLOTLIBPYPLOT AS PLT
LR LINEARMODELLINEARREGRESSION
BOSTON DATASETSLOADBOSTON
Y BOSTONTARGET
 CROSSVALPREDICT RETURNS AN ARRAY OF THE SAME SIZE AS Y WHERE EACH ENTRY
 IS A PREDICTION OBTAINED BY CROSS VALIDATION
PREDICTED CROSSVALPREDICTLR BOSTONDATA Y CV10
FIG AX PLTSUBPLOTS
AXSCATTERY PREDICTED EDGECOLORS0 0 0
AXPLOTYMIN YMAX YMIN YMAX K LW4
AXSETXLABELMEASURED
AXSETYLABELPREDICTED
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0024 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5212 PLOTTING VALIDATION CURVES

IN THIS PLOT YOU CAN SEE THE TRAINING SCORES AND VALIDATION SCORES OF AN SVM FOR DIFFERENT VALUES OF THE KERNEL PARAMETER GAMMA FOR VERY LOW VALUES OF GAMMA YOU CAN SEE THAT BOTH THE TRAINING SCORE AND THE VALIDATION SCORE ARE LOW THIS IS CALLED UNDERFITTING MEDIUM VALUES OF GAMMA WILL RESULT IN HIGH VALUES FOR BOTH SCORES IE THE CLASSIFIER IS PERFORMING FAIRLY WELL IF GAMMA IS TOO HIGH THE CLASSIFIER WILL OVERFIT WHICH MEANS THAT THE TRAINING SCORE IS GOOD BUT THE VALIDATION SCORE IS POOR

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PRINTDOC
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNDATASETS IMPORT LOADDIGITS
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNMODELSELECTION IMPORT VALIDATIONCURVE
DIGITS  LOADDIGITS
X Y  DIGITSDATA DIGITSTARGET
PARAMRANGE  NPLOGSPACE6 1 5
TRAINSCORES TESTSCORES  VALIDATIONCURVE
SVC X Y PARAMNAMEGAMMA PARAMRANGEPARAMRANGE
CV5 SCORINGACCURACY NJOBS1
TRAINSCORESMEAN  NPMEANTRAINSCORES AXIS1
TRAINSCORESSTD  NPSTDTRAINSCORES AXIS1
```

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TESTSCORESMEAN NPMEANTESTSCORES AXIS1
TESTSCORESSTD NPSTDTESTSCORES AXIS1
PLTTITLEVALIDATION CURVE WITH SVM
PLTXLABELRGAMMA
PLTYLABELSCORE
PLTYLIM00 11
LW 2
PLTSEMILOGXPARAMRANGE TRAINSCORESMEAN LABELTRAINING SCORE
COLORDARKORANGE LWLW
PLTFILLBETWEENPARAMRANGE TRAINSCORESMEAN TRAINSCORESSTD
TRAINSCORESMEAN TRAINSCORESSTD ALPHA02
COLORDARKORANGE LWLW
PLTSEMILOGXPARAMRANGE TESTSCORESMEAN LABELCROSSVALIDATION SCORE
COLORNAVY LWLW
PLTFILLBETWEENPARAMRANGE TESTSCORESMEAN TESTSCORESSTD
TESTSCORESMEAN TESTSCORESSTD ALPHA02
COLORNAVY LWLW
PLTLEGENDLOCBEST
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 13416 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5213 UNDERFITTING VS OVERFITTING
THIS EXAMPLE DEMONSTRATES THE PROBLEMS OF UNDERFITTING AND OVERFITTING AND HOW WE CAN USE LINEAR REGRESSION WITH POLYNOMIAL FEATURES TO APPROXIMATE NONLINEAR FUNCTIONS THE PLOT SHOWS THE FUNCTION THAT WE WANT TO APPROXIMATE WHICH IS A PART OF THE COSINE FUNCTION IN ADDITION THE SAMPLES FROM THE REAL FUNCTION AND THE APPROXIMATIONS OF DIFFERENT MODELS ARE DISPLAYED THE MODELS HAVE POLYNOMIAL FEATURES OF DIFFERENT DEGREES WE CAN SEE THAT A LINEAR FUNCTION POLYNOMIAL WITH DEGREE 1 IS NOT SUFFICIENT TO FIT THE TRAINING SAMPLES THIS IS CALLED UNDERFITTING A POLYNOMIAL OF DEGREE 4 APPROXIMATES THE TRUE FUNCTION ALMOST PERFECTLY HOWEVER FOR HIGHER DEGREES THE MODEL WILL OVERFIT THE TRAINING DATA IE IT LEARNS THE NOISE OF THE TRAINING DATA WE EVALUATE QUANTITATIVELY OVERFITTING UNDERFITTING BY USING CROSSVALIDATION WE CALCULATE THE MEAN SQUARED ERROR MSE ON THE VALIDATION SET THE HIGHER THE LESS LIKELY THE MODEL GENERALIZES CORRECTLY FROM THE TRAINING DATA

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNPIPELINE IMPORT PIPELINE
FROM SKLEARNPREPROCESSING IMPORT POLYNOMIALFEATURES
FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION
FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
DEFTRUEFUNX
RETURNNPCOS15 NPPIX
NPRANDOMSEED0
NSAMPLES 30
DEGREES 1 4 15
X NPSORTNPRANDOMRANDNSAMPLES
Y TRUEFUNX NPRANDOMRANDNNSAMPLES 01
PLTFIGUREFIGSIZE14 5
FORIINRANGELENDEGREES
AX PLTSUBPLOT1 LENDEGREES I 1
PLTSETPAX XTICKS YTICKS
POLYNOMIALFEATURES POLYNOMIALFEATURESDEGREEDEGREESI
INCLUDEBIASFALSE
LINEARREGRESSION LINEARREGRESSION
PIPELINE PIPELINEPOLYNOMIALFEATURES POLYNOMIALFEATURES
LINEARREGRESSION LINEARREGRESSION
PIPELINEFITX NPNEWAXIS Y
 EVALUATE THE MODELS USING CROSSVALIDATION
SCORES CROSSVALSCOREPIPELINE X NPNEWAXIS Y
SCORINGNEGMEANSQUAREDERROR CV10
XTEST NPLINSPACE0 1 100
PLTPLOTXTEST PIPELINEPREDICTXTEST NPNEWAXIS LABELMODEL
PLTPLOTXTEST TRUEFUNXTEST LABELTRUE FUNCTION
PLTSCATTERX Y EDGECOLORB S20 LABELSAMPLES
PLTXLABELX
PLTYLABELY
PLTXLIM0 1
PLTYLIM2 2
PLTLEGENDLOCBEST
PLTTITLEDEGREE NMSE 2E 2EFORMAT
DEGREESI SCORESMEAN SCORESSTD
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0084 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5214 PARAMETER ESTIMATION USING GRID SEARCH WITH CROSSVALIDATION
THIS EXAMPLES SHOWS HOW A CLASSIFIER IS OPTIMIZED BY CROSSVALIDATION WHICH IS DONE USING THE SKLEARN MODELSELECTIONGRIDSEARCHCV OBJECT ON A DEVELOPMENT SET THAT COMPRISES ONLY HALF OF THE AVAILABLE LABELED DATA
THE PERFORMANCE OF THE SELECTED HYPERPARAMETERS AND TRAINED MODEL IS THEN MEASURED ON A DEDICATED EVALUATION SET THAT WAS NOT USED DURING THE MODEL SELECTION STEP
MORE DETAILS ON TOOLS AVAILABLE FOR MODEL SELECTION CAN BE FOUND IN THE SECTIONS ON CROSSVALIDATION EVALUATING ESTIMATOR PERFORMANCE ANDTUNING THE HYPERPARAMETERS OF AN ESTIMATOR
OUT
TUNING HYPERPARAMETERS FOR PRECISION
BEST PARAMETERS SET FOUND ON DEVELOPMENT SET
C 10 GAMMA 0001 KERNEL RBF
GRID SCORES ON DEVELOPMENT SET
0986 0016 FOR C 1 GAMMA 0001 KERNEL RBF
0959 0029 FOR C 1 GAMMA 00001 KERNEL RBF
0988 0017 FOR C 10 GAMMA 0001 KERNEL RBF
0982 0026 FOR C 10 GAMMA 00001 KERNEL RBF
0988 0017 FOR C 100 GAMMA 0001 KERNEL RBF
0982 0025 FOR C 100 GAMMA 00001 KERNEL RBF
0988 0017 FOR C 1000 GAMMA 0001 KERNEL RBF
0982 0025 FOR C 1000 GAMMA 00001 KERNEL RBF
0975 0014 FOR C 1 KERNEL LINEAR
0975 0014 FOR C 10 KERNEL LINEAR
0975 0014 FOR C 100 KERNEL LINEAR
0975 0014 FOR C 1000 KERNEL LINEAR
DETAILED CLASSIFICATION REPORT
THE MODEL IS TRAINED ON THE FULL DEVELOPMENT SET
THE SCORES ARE COMPUTED ON THE FULL EVALUATION SET
PRECISION RECALL F1SCORE SUPPORT
0 100 100 100 89
1 097 100 098 90
2 099 098 098 92
3 100 099 099 93
4 100 100 100 76
5 099 098 099 108
6 099 100 099 89
7 099 100 099 78
8 100 098 099 92
9 099 099 099 92
ACCURACY 099 899
MACRO AVG 099 099 099 899
WEIGHTED AVG 099 099 099 899
TUNING HYPERPARAMETERS FOR RECALL

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BEST PARAMETERS SET FOUND ON DEVELOPMENT SET
C 10 GAMMA 0001 KERNEL RBF
GRID SCORES ON DEVELOPMENT SET
0986 0019 FOR C 1 GAMMA 0001 KERNEL RBF
0957 0029 FOR C 1 GAMMA 00001 KERNEL RBF
0987 0019 FOR C 10 GAMMA 0001 KERNEL RBF
0981 0028 FOR C 10 GAMMA 00001 KERNEL RBF
0987 0019 FOR C 100 GAMMA 0001 KERNEL RBF
0981 0026 FOR C 100 GAMMA 00001 KERNEL RBF
0987 0019 FOR C 1000 GAMMA 0001 KERNEL RBF
0981 0026 FOR C 1000 GAMMA 00001 KERNEL RBF
0972 0012 FOR C 1 KERNEL LINEAR
0972 0012 FOR C 10 KERNEL LINEAR
0972 0012 FOR C 100 KERNEL LINEAR
0972 0012 FOR C 1000 KERNEL LINEAR
DETAILED CLASSIFICATION REPORT
THE MODEL IS TRAINED ON THE FULL DEVELOPMENT SET
THE SCORES ARE COMPUTED ON THE FULL EVALUATION SET
PRECISION RECALL F1SCORE SUPPORT
0 100 100 100 89
1 097 100 098 90
2 099 098 098 92
3 100 099 099 93
4 100 100 100 76
5 099 098 099 108
6 099 100 099 89
7 099 100 099 78
8 100 098 099 92
9 099 099 099 92
ACCURACY 099 899
MACRO AVG 099 099 099 899
WEIGHTED AVG 099 099 099 899
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNMETRICS IMPORT CLASSIFICATIONREPORT
FROM SKLEARNSVM IMPORT SVC
PRINTDOC
 LOADING THE DIGITS DATASET
DIGITS DATASETSLOADDIGITS
521 MODEL SELECTION 1267

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 TO APPLY AN CLASSIFIER ON THIS DATA WE NEED TO FLATTEN THE IMAGE TO
 TURN THE DATA IN A SAMPLES FEATURE MATRIX
NSAMPLES LENDIGITSIMAGES
X DIGITSIMAGESRESHAPENSAMPLES 1
Y DIGITSTARGET
 SPLIT THE DATASET IN TWO EQUAL PARTS
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLIT
X Y TESTSIZE05 RANDOMSTATE0
 SET THE PARAMETERS BY CROSSVALIDATION
TUNEDPARAMETERS KERNEL RBF GAMMA 1E3 1E4
C 1 10 100 1000
KERNEL LINEAR C 1 10 100 1000
SCORES PRECISION RECALL
FORSCOREINSCORES
PRINT TUNING HYPERPARAMETERS FOR S SCORE
PRINT
CLF GRIDSEARCHCVSVC TUNEDPARAMETERS CV5
SCORING SMACRO SCORE
CLFFITXTRAIN YTRAIN
PRINTBEST PARAMETERS SET FOUND ON DEVELOPMENT SET
PRINT
PRINTCLFBESTPARAMS
PRINT
PRINTGRID SCORES ON DEVELOPMENT SET
PRINT
MEANS CLFCVRESULTSMEANTESTSCORE
STDS CLFCVRESULTSSTDTESTSCORE
FORMEAN STD PARAMS INZIPMEANS STDS CLFCVRESULTSPARAMS
PRINT03F003F FORR
 MEAN STD 2 PARAMS
PRINT
PRINTDETAILED CLASSIFICATION REPORT
PRINT
PRINTTHE MODEL IS TRAINED ON THE FULL DEVELOPMENT SET
PRINTTHE SCORES ARE COMPUTED ON THE FULL EVALUATION SET
PRINT
YTRUE YPRED YTEST CLFPREDICTXTEST
PRINTCLASSIFICATIONREPORTYTRUE YPRED
PRINT
 NOTE THE PROBLEM IS TOO EASY THE HYPERPARAMETER PLATEAU IS TOO FLAT AND THE
 OUTPUT MODEL IS THE SAME FOR PRECISION AND RECALL WITH TIES IN QUALITY
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 4344 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5215 TRAIN ERROR VS TEST ERROR
ILLUSTRATION OF HOW THE PERFORMANCE OF AN ESTIMATOR ON UNSEEN DATA TEST DATA IS NOT THE SAME AS THE PERFORMANCE ON TRAINING DATA AS THE REGULARIZATION INCREASES THE PERFORMANCE ON TRAIN DECREASES WHILE THE PERFORMANCE ON TEST IS OPTIMAL WITHIN A RANGE OF VALUES OF THE REGULARIZATION PARAMETER THE EXAMPLE WITH AN ELASTICNET REGRESSION MODEL AND THE PERFORMANCE IS MEASURED USING THE EXPLAINED VARIANCE AKA R2
OUT
OPTIMAL REGULARIZATION PARAMETER 00001314147362611756 7
PRINTDOC
 AUTHOR ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
FROM SKLEARN IMPORT LINEARMODEL

 GENERATE SAMPLE DATA

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NSAMPLESTRAIN NSAMPLESTEST NFEATURES 75 150 500
NPRANDOMSEED0
COEF NPRANDOMRANDNNFEATURES
COEF50 00 ONLY THE TOP 10 FEATURES ARE IMPACTING THE MODEL
X NPRANDOMRANDNNSAMPLESTRAIN NSAMPLESTEST NFEATURES
Y NPDOTX COEF
 SPLIT TRAIN AND TEST DATA
XTRAIN XTEST XNSAMPLESTRAIN XNSAMPLESTRAIN
YTRAIN YTEST YNSAMPLESTRAIN YNSAMPLESTRAIN

 COMPUTE TRAIN AND TEST ERRORS
ALPHAS NPLOGSPACE5 1 60
ENET LINEARMODELELASTICNETL1RATIO07 MAXITER10000
TRAINERRORS LIST
TESTERRORS LIST
FORALPHAINALPHAS
ENETSETPARAMSALPHAALPHA
ENETFITXTRAIN YTRAIN
TRAINERRORSAPPENDENETSCOREXTRAIN YTRAIN
TESTERRORSAPPENDENETSCOREXTEST YTEST
IALPHAOPTIM NPARGMAXTESTERRORS
ALPHAOPTIM ALPHASIALPHAOPTIM
PRINTOPTIMAL REGULARIZATION PARAMETER S ALPHAOPTIM
 ESTIMATE THE COEF ON FULL DATA WITH OPTIMAL REGULARIZATION PARAMETER
ENETSETPARAMSALPHAALPHAOPTIM
COEF ENETFITX YCOEF

 PLOT RESULTS FUNCTIONS
IMPORT MATPLOTLIBPYPLOT AS PLT
PLTSUBPLOT2 1 1
PLTSEMILOGXALPHAS TRAINERRORS LABELTRAIN
PLTSEMILOGXALPHAS TESTERRORS LABELTEST
PLTVLINESALPHAOPTIM PLTYLIM0 NPMAXTESTERRORS COLORK
LINEWIDTH3 LABELOPTIMUM ON TEST
PLTLEGENDLOCLOWER LEFT
PLTYLIM0 12
PLTXLABELREGULARIZATION PARAMETER
PLTYLABELPERFORMANCE
 SHOW ESTIMATED COEF VS TRUE COEF
PLTSUBPLOT2 1 2
PLTPLOTCOEF LABELTRUE COEF
PLTPLOTCOEF LABELESTIMATED COEF
PLTLEGEND
PLTSUBPLOTSADJUST009 004 094 094 026 026
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3507 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
1270 CHAPTER 5 EXAMPLES

5216 RECEIVER OPERATING CHARACTERISTIC ROC WITH CROSS VALIDATION
EXAMPLE OF RECEIVER OPERATING CHARACTERISTIC ROC METRIC TO EVALUATE CLASSIFIER OUTPUT QUALITY USING CROSSVALIDATION
ROC CURVES TYPICALLY FEATURE TRUE POSITIVE RATE ON THE Y AXIS AND FALSE POSITIVE RATE ON THE X AXIS THIS MEANS THAT THE TOP LEFT CORNER OF THE PLOT IS THE “IDEAL” POINT A FALSE POSITIVE RATE OF ZERO AND A TRUE POSITIVE RATE OF ONE THIS IS NOT VERY REALISTIC BUT IT DOES MEAN THAT A LARGER AREA UNDER THE CURVE AUC IS USUALLY BETTER
THE “STEEPNESS” OF ROC CURVES IS ALSO IMPORTANT SINCE IT IS IDEAL TO MAXIMIZE THE TRUE POSITIVE RATE WHILE MINIMIZING THE FALSE POSITIVE RATE
THIS EXAMPLE SHOWS THE ROC RESPONSE OF DIFFERENT DATASETS CREATED FROM KFOLD CROSSVALIDATION TAKING ALL OF THESE CURVES IT IS POSSIBLE TO CALCULATE THE MEAN AREA UNDER CURVE AND SEE THE VARIANCE OF THE CURVE WHEN THE TRAINING SET IS SPLIT INTO DIFFERENT SUBSETS THIS ROUGHLY SHOWS HOW THE CLASSIFIER OUTPUT IS AFFECTED BY CHANGES IN THE TRAINING DATA AND HOW DIFFERENT THE SPLITS GENERATED BY KFOLD CROSSVALIDATION ARE FROM ONE ANOTHER
NOTE
SEE ALSO SKLEARNMETRICSROCAUCSCORE SKLEARNMODELSELECTIONCROSSVALSCORE
RECEIVER OPERATING CHARACTERISTIC ROC
PRINTDOC
IMPORT NUMPY AS NP
FROM SCIPY IMPORT INTERP

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IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT SVM DATASETS
FROM SKLEARNMETRICS IMPORT ROCCURVE AUC
FROM SKLEARNMODELSELECTION IMPORT STRATIFIEDKFOLD

DATA IO AND GENERATION
IMPORT SOME DATA TO PLAY WITH
IRIS DATASETSLOADIRIS
X IRISDATA
Y IRISTARGET
X Y XY 2 YY 2
NSAMPLES NFEATURES XSHAPE
ADD NOISY FEATURES
RANDOMSTATE NPRANDOMRANDOMSTATE0
X NPCX RANDOMSTATERANDNNSAMPLES 200 NFEATURES

CLASSIFICATION AND ROC ANALYSIS
RUN CLASSIFIER WITH CROSSVALIDATION AND PLOT ROC CURVES
CV STRATIFIEDKFOLDNSPLITS6
CLASSIFIER SVMSVCKERNELLINEAR PROBABILITYTRUE
RANDOMSTATERANDOMSTATE
TPRS
AUCS
MEANFPR NPLINSPACE0 1 100
I 0
FORTRAIN TEST INCVSPLITX Y
PROBAS CLASSIFIERFITXTRAIN YTRAINPREDICTPROBAXTEST
COMPUTE ROC CURVE AND AREA THE CURVE
FPR TPR THRESHOLDS ROCCURVEYTEST PROBAS 1
TPRSAPPENDINTERPMEANFPR FPR TPR
TPRS10 00
ROCAUC AUCFPR TPR
AUCSAPPENDROCAUC
PLTPLOTFPR TPR LW1 ALPHA03
LABELROC FOLD DAUC 02F I ROCAUC
I 1
PLTPLOT0 1 0 1 LINESTYLE LW2 COLORR
LABELCHANCE ALPHA8
MEANTPR NPMEANTPRS AXIS0
MEANTPR1 10
MEANAUC AUCMEANFPR MEANTPR
STDAUC NPSTDAUCS
PLTPLOTMEANFPR MEANTPR COLORB
LABELRMEAN ROC AUC 02FPM02F MEANAUC STDAUC
LW2 ALPHA8
STDTPR NPSTDTPRS AXIS0
TPRSUPPER NPMINIMUMMEANTPR STDTPR 1

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TPRSLOWER NPMAXIMUMMEANTPR STDTPR 0
PLTFILLBETWEENMEANFPR TPRSLOWER TPRSUPPER COLORGREY ALPHA2
LABELRPM 1 STD DEV
PLTXLIM005 105
PLTYLIM005 105
PLTXLABELFALSE POSITIVE RATE
PLTYLABELTRUE POSITIVE RATE
PLTTITLERECEIVER OPERATING CHARACTERISTIC EXAMPLE
PLTLEGENDLOCLOWER RIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0245 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5217 COMPARING RANDOMIZED SEARCH AND GRID SEARCH FOR HYPERPARAMETER ESTIMA
TION
COMPARE RANDOMIZED SEARCH AND GRID SEARCH FOR OPTIMIZING HYPERPARAMETERS OF A RANDOM FOREST ALL PARAMETERS THAT INFLUENCE THE LEARNING ARE SEARCHED SIMULTANEOUSLY EXCEPT FOR THE NUMBER OF ESTIMATORS WHICH POSES A TIME QUALITY TRADEOFF
THE RANDOMIZED SEARCH AND THE GRID SEARCH EXPLORE EXACTLY THE SAME SPACE OF PARAMETERS THE RESULT IN PARAMETER SETTINGS IS QUITE SIMILAR WHILE THE RUN TIME FOR RANDOMIZED SEARCH IS DRASTICALLY LOWER
THE PERFORMANCE IS SLIGHTLY WORSE FOR THE RANDOMIZED SEARCH THOUGH THIS IS MOST LIKELY A NOISE EFFECT AND WOULD NOT CARRY OVER TO A HELDOUT TEST SET
NOTE THAT IN PRACTICE ONE WOULD NOT SEARCH OVER THIS MANY DIFFERENT PARAMETERS SIMULTANEOUSLY USING GRID SEARCH BUT PICK ONLY THE ONES DEEMED MOST IMPORTANT
OUT
RANDOMIZEDSEARCHCV TOOK 442 SECONDS FOR 20 CANDIDATES PARAMETER SETTINGS
MODEL WITH RANK 1
MEAN VALIDATION SCORE 0939 STD 0024
PARAMETERS BOOTSTRAP FALSE CRITERION ENTROPY MAXDEPTH NONE MAX
‹→FEATURES 7 MINSAMPLESSPLIT 3
MODEL WITH RANK 2
MEAN VALIDATION SCORE 0933 STD 0022
PARAMETERS BOOTSTRAP FALSE CRITERION GINI MAXDEPTH NONE MAXFEATURES
‹→ 6 MINSAMPLESSPLIT 6
MODEL WITH RANK 3
MEAN VALIDATION SCORE 0930 STD 0031
PARAMETERS BOOTSTRAP TRUE CRITERION GINI MAXDEPTH NONE MAXFEATURES
‹→ 6 MINSAMPLESSPLIT 6
GRIDSEARCHCV TOOK 1324 SECONDS FOR 72 CANDIDATE PARAMETER SETTINGS
MODEL WITH RANK 1
MEAN VALIDATION SCORE 0937 STD 0019
PARAMETERS BOOTSTRAP FALSE CRITERION ENTROPY MAXDEPTH NONE MAX
‹→FEATURES 10 MINSAMPLESSPLIT 2
521 MODEL SELECTION 1273

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MODEL WITH RANK 2
MEAN VALIDATION SCORE 0936 STD 0020
PARAMETERS BOOTSTRAP FALSE CRITERION GINI MAXDEPTH NONE MAXFEATURES
‘→ 10 MINSAMPLESSPLIT 2
MODEL WITH RANK 3
MEAN VALIDATION SCORE 0931 STD 0029
PARAMETERS BOOTSTRAP FALSE CRITERION ENTROPY MAXDEPTH NONE MAX
‘→FEATURES 10 MINSAMPLESSPLIT 3
PRINTDOC
IMPORT NUMPY AS NP
FROM TIME IMPORT TIME
FROM SCIPYSTATS IMPORT RANDINT ASSPRANDINT
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNMODELSELECTION IMPORT RANDOMIZEDSEARCHCV
FROM SKLEARNDATASETS IMPORT LOADDIGITS
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
GET SOME DATA
DIGITS LOADDIGITS
X Y DIGITSDATA DIGITSTARGET
BUILD A CLASSIFIER
CLF RANDOMFORESTCLASSIFIERNESTIMATORS20
UTILITY FUNCTION TO REPORT BEST SCORES
DEFREPORTRESULTS NTOP3
FORIINRANGE1 NTOP 1
CANDIDATES NPFLATNONZERORESULTSRANKTESTSCORE I
FORCANDIDATE INCANDIDATES
PRINTMODEL WITH RANK 0FORMATI
PRINTMEAN VALIDATION SCORE 03F STD 13FFORMAT
RESULTSMEANTESTSCORECANDIDATE
RESULTSSTDTESTSCORECANDIDATE
PRINTPARAMETERS 0FORMATRESULTSPARAMSCANDIDATE
PRINT
SPECIFY PARAMETERS AND DISTRIBUTIONS TO SAMPLE FROM
PARAMDIST MAXDEPTH 3 NONE
MAXFEATURES SPRANDINT1 11
MINSAMPLESSPLIT SPRANDINT2 11
BOOTSTRAP TRUE FALSE
CRITERION GINI ENTROPY
RUN RANDOMIZED SEARCH
NITERSEARCH 20
RANDOMSEARCH RANDOMIZEDSEARCHCVCLF PARAMDISTRIBUTIONSPARAMDIST

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NITERNITERSEARCH CV5 IIDFALSE
START TIME
RANDOMSEARCHFITX Y
PRINTRANDOMIZEDSEARCHCV TOOK 2FSECONDS FOR DCANDIDATES
 PARAMETER SETTINGS TIME START NITERSEARCH
REPORTRANDOMSEARCHCVRESULTS
 USE A FULL GRID OVER ALL PARAMETERS
PARAMGRID MAXDEPTH 3 NONE
MAXFEATURES 1 3 10
MINSAMPLESSPLIT 2 3 10
BOOTSTRAP TRUE FALSE
CRITERION GINI ENTROPY
 RUN GRID SEARCH
GRIDSEARCH GRIDSEARCHCVCLF PARAMGRIDPARAMGRID CV5 IIDFALSE
START TIME
GRIDSEARCHFITX Y
PRINTGRIDSEARCHCV TOOK 2FSECONDS FOR DCANDIDATE PARAMETER SETTINGS
 TIME START LENGRIDSEARCHCVRESULTSPARAMS
REPORTGRIDSEARCHCVRESULTS
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 17712 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5218 NESTED VERSUS NONNESTED CROSSVALIDATION
THIS EXAMPLE COMPARES NONNESTED AND NESTED CROSSVALIDATION STRATEGIES ON A CLASSIFIER OF THE IRIS DATA SET NESTED
CROSSVALIDATION CV IS OFTEN USED TO TRAIN A MODEL IN WHICH HYPERPARAMETERS ALSO NEED TO BE OPTIMIZED NESTED CV
ESTIMATES THE GENERALIZATION ERROR OF THE UNDERLYING MODEL AND ITS HYPERPARAMETER SEARCH CHOOSING THE PARAMETERS
THAT MAXIMIZE NONNESTED CV BIASES THE MODEL TO THE DATASET YIELDING AN OVERLYOPTIMISTIC SCORE
MODEL SELECTION WITHOUT NESTED CV USES THE SAME DATA TO TUNE MODEL PARAMETERS AND EVALUATE MODEL PERFORMANCE
INFORMATION MAY THUS “LEAK” INTO THE MODEL AND OVERFIT THE DATA THE MAGNITUDE OF THIS EFFECT IS PRIMARILY DEPENDENT
ON THE SIZE OF THE DATASET AND THE STABILITY OF THE MODEL SEE CAWLEY AND TALBOT1FOR AN ANALYSIS OF THESE ISSUES
TO AVOID THIS PROBLEM NESTED CV EFFECTIVELY USES A SERIES OF TRAINVALIDATIONTEST SET SPLITS IN THE INNER LOOP
HERE EXECUTED BY GRIDSEARCHCV THE SCORE IS APPROXIMATELY MAXIMIZED BY FITTING A MODEL TO EACH TRAINING
SET AND THEN DIRECTLY MAXIMIZED IN SELECTING HYPERPARAMETERS OVER THE VALIDATION SET IN THE OUTER LOOP HERE IN
CROSSVALSCORE GENERALIZATION ERROR IS ESTIMATED BY AVERAGING TEST SET SCORES OVER SEVERAL DATASET SPLITS
THE EXAMPLE BELOW USES A SUPPORT VECTOR CLASSIFIER WITH A NONLINEAR KERNEL TO BUILD A MODEL WITH OPTIMIZED HYPERPA
RAMETERS BY GRID SEARCH WE COMPARE THE PERFORMANCE OF NONNESTED AND NESTED CV STRATEGIES BY TAKING THE DIFFERENCE
BETWEEN THEIR SCORES
SEE ALSO
•CROSSVALIDATION EVALUATING ESTIMATOR PERFORMANCE
1CAWLEY GC TALBOT NLC ON OVERFITTING IN MODEL SELECTION AND SUBSEQUENT SELECTION BIAS IN PERFORMANCE EVALUATION J MACH LEA
201011 20792107

•TUNING THE HYPERPARAMETERS OF AN ESTIMATOR
REFERENCES
OUT
AVERAGE DIFFERENCE OF 0007581 WITH STD DEV OF 0007833
FROM SKLEARNDATASETS IMPORT LOADIRIS
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV CROSSVALSCORE KFOLD
IMPORT NUMPY AS NP
PRINTDOC
NUMBER OF RANDOM TRIALS
NUMTRIALS 30

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```
 LOAD THE DATASET
IRIS  LOADIRIS
XIRIS  IRISDATA
YIRIS  IRISTARGET
 SET UP POSSIBLE VALUES OF PARAMETERS TO OPTIMIZE OVER
PGRID  C 1 10 100
GAMMA 01 1
 WE WILL USE A SUPPORT VECTOR CLASSIFIER WITH RBF KERNEL
SVM  SVCKERNELRBF
 ARRAYS TO STORE SCORES
NONNESTEDSCORES  NPZEROSNUMTRIALS
NESTEDSCORES  NPZEROSNUMTRIALS
 LOOP FOR EACH TRIAL
FORIINRANGENUMTRIALS
 CHOOSE CROSSVALIDATION TECHNIQUES FOR THE INNER AND OUTER LOOPS
 INDEPENDENTLY OF THE DATASET
 EG GROUPKFOLD LEAVEONEOUT LEAVEONEGROUPOUT ETC
INNERCV  KFOLDNSPLITS4 SHUFFLETRUE RANDOMSTATEI
OUTERCV  KFOLDNSPLITS4 SHUFFLETRUE RANDOMSTATEI
 NONNESTED PARAMETER SEARCH AND SCORING
CLF  GRIDSEARCHCVESTIMATORSVM PARAMGRIDPGRID CVINNERCV
IIDFALSE
CLFFITXIRIS YIRIS
NONNESTEDSCORESI  CLFBESTSCORE
 NESTED CV WITH PARAMETER OPTIMIZATION
NESTEDSCORE  CROSSVALSCORECLF XXIRIS YYIRIS CVOUTERCV
NESTEDSCORESI  NESTEDSCOREMEAN
SCOREDIFFERENCE  NONNESTEDSCORES  NESTEDSCORES
PRINTAVERAGE DIFFERENCE OF 6F WITH STD DEV OF 6F
FORMATSCOREDIFFERENCEMEAN SCOREDIFFERENCESTD
 PLOT SCORES ON EACH TRIAL FOR NESTED AND NONNESTED CV
PLTFIGURE
PLTSUBPLOT211
NONNESTEDSCORESLINE  PLTPLOTNONNESTEDSCORES COLORR
NESTEDLINE  PLTPLOTNESTEDSCORES COLORB
PLTYLABELSCORE FONTSIZE14
PLTLEGENDNONNESTEDSCORESLINE NESTEDLINE
NONNESTED CV NESTED CV
BBOXTOANCHOR0 4 5 0
PLTTITLENONNESTED AND NESTED CROSS VALIDATION ON IRIS DATASET
X5 Y11 FONTSIZE15
 PLOT BAR CHART OF THE DIFFERENCE
PLTSUBPLOT212
DIFFERENCEPLOT  PLTBARRANGENUMTRIALS SCOREDIFFERENCE
PLTXLABELINDIVIDUAL TRIAL
PLTLEGENDDIFFERENCEPLOT
```

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NONNESTED CV NESTED CV SCORE
BBOXTOANCHOR0 1 8 0
PLTYLABELSCORE DIFFERENCE FONTSIZE14
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3447 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5219 DEMONSTRATION OF MULTIMETRIC EVALUATION ON CROSSVALSCORE AND GRID
SEARCHCV
MULTIPLE METRIC PARAMETER SEARCH CAN BE DONE BY SETTING THE SCORING PARAMETER TO A LIST OF METRIC SCORER NAMES OR A
DICT MAPPING THE SCORER NAMES TO THE SCORER CALLABLES
THE SCORES OF ALL THE SCORERS ARE AVAILABLE IN THE CVRESULTS DICT AT KEYS ENDING IN SCORERNAME
MEANTESTPRECISION RANKTESTPRECISION ETC
THEBESTESTIMATOR BESTINDEX BESTSCORE ANDBESTPARAMS CORRESPOND TO THE SCORER KEY
THAT IS SET TO THE REFIT ATTRIBUTE
 AUTHOR RAGHAV RV RVRAGHAV93GMAILCOM
 LICENSE BSD
IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM SKLEARNDATASETS IMPORT MAKEHASTIE102
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNMETRICS IMPORT MAKESCORER
FROM SKLEARNMETRICS IMPORT ACCURACYSCORE
FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
PRINTDOC
RUNNINGGRIDSEARCHCV USING MULTIPLE EVALUATION METRICS
X Y MAKEHASTIE102NSAMPLES8000 RANDOMSTATE42
 THE SCORERS CAN BE EITHER BE ONE OF THE PREDEFINED METRIC STRINGS OR A SCORER
 CALLABLE LIKE THE ONE RETURNED BY MAKESCORER
SCORING AUC ROCAUC ACCURACY MAKESCORERACCURACYSCORE
 SETTING REFITAUC REFITS AN ESTIMATOR ON THE WHOLE DATASET WITH THE
 PARAMETER SETTING THAT HAS THE BEST CROSSVALIDATED AUC SCORE
 THAT ESTIMATOR IS MADE AVAILABLE AT GSBESTESTIMATOR ALONG WITH
 PARAMETERS LIKE GSBESTSCORE GSBESTPARAMS AND
 GSBESTINDEX
GS GRIDSEARCHCVDECISIONTREECLASSIFIERRANDOMSTATE42
PARAMGRIDMINSAMPLESSPLIT RANGE2 403 10
SCORINGSCORING CV5 REFITAUC RETURNTRAINSCORETRUE

```
SCIKITLEARN USER GUIDE RELEASE 0213
GSFITX Y
RESULTS  GSCVRESULTS
PLOTTING THE RESULT
PLTFIGUREFIGSIZE13 13
PLTTITLEGRIDSEARCHCV EVALUATING USING MULTIPLE SCORERS SIMULTANEOUSLY
FONTSIZE16
PLTXLABELMINSAMPLESSPLIT
PLTYLABELSCORE
AX  PLTGCA
AXSETXLIM0 402
AXSETYLIM073 1
 GET THE REGULAR NUMPY ARRAY FROM THE MASKEDARRAY
XAXIS  NPARRAYRESULTSPARAMMINSAMPLESSPLITDATA DTYPEFLOAT
FORSCORER COLOR INZIPSORTEDSCORING G K
FORSAMPLE STYLE INTRAIN  TEST
SAMPLESCOREMEAN  RESULTSMEAN SS  SAMPLE SCORER
SAMPLESCORESTD  RESULTSSTD SS  SAMPLE SCORER
AXFILLBETWEENXAXIS SAMPLESCOREMEAN  SAMPLESCORESTD
SAMPLESCOREMEAN  SAMPLESCORESTD
ALPHA01 IFSAMPLE  TEST ELSE0 COLORCOLOR
AXPLOTXAXIS SAMPLESCOREMEAN STYLE COLORCOLOR
ALPHA1 IFSAMPLE  TEST ELSE07
LABELSS  SCORER SAMPLE
BESTINDEX  NPNONZERORESULTSRANKTEST S  SCORER  100
BESTSCORE  RESULTSMEANTEST S  SCORERBESTINDEX
 PLOT A DOTTED VERTICAL LINE AT THE BEST SCORE FOR THAT SCORER MARKED BY X
AXPLOTXAXISBESTINDEX  2 0 BESTSCORE
LINESTYLE COLORCOLOR MARKERX MARKEREDGEWIDTH3 MS8
 ANNOTATE THE BEST SCORE FOR THAT SCORER
AXANNOTATE 02F  BESTSCORE
XAXISBESTINDEX BESTSCORE  0005
PLTLEGENDLOCBEST
PLTGRIDFALSE
PLTSHOW
521 MODEL SELECTION 1279
```

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 20458 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52110 BALANCE MODEL COMPLEXITY AND CROSSVALIDATED SCORE
THIS EXAMPLE BALANCES MODEL COMPLEXITY AND CROSSVALIDATED SCORE BY FINDING A DECENT ACCURACY WITHIN 1 STANDARD DEVIATION OF THE BEST ACCURACY SCORE WHILE MINIMISING THE NUMBER OF PCA COMPONENTS 1
THE FIGURE SHOWS THE TRADEOFF BETWEEN CROSSVALIDATED SCORE AND THE NUMBER OF PCA COMPONENTS THE BALANCED CASE IS WHEN NCOMPONENTS6 AND ACCURACY080 WHICH FALLS INTO THE RANGE WITHIN 1 STANDARD DEVIATION OF THE BEST ACCURACY SCORE

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1 HASTIE T TIBSHIRANI R„ FRIEDMAN J 2001 MODEL ASSESSMENT AND SELECTION THE ELEMENTS OF STATISTICAL LEARNING PP 219260 NEW YORK NY USA SPRINGER NEW YORK INC
OUT
THE BESTINDEX IS 2
THE NCOMPONENTS SELECTED IS 6
THE CORRESPONDING ACCURACY SCORE IS 080
 AUTHOR WENHAO ZHANG WENHAOZUCLAEDU
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT LOADDIGITS
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNPIPELINE IMPORT PIPELINE
FROM SKLEARNSVM IMPORT LINEARSVC
521 MODEL SELECTION 1281

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DEFLOWERBOUNDCVRESULTS

CALCULATE THE LOWER BOUND WITHIN 1 STANDARD DEVIATION
OF THE BEST MEANTESTSCORES
PARAMETERS

CVRESULTS DICT OF NUMPYMASKED NDARRAYS
SEE ATTRIBUTE CVRESULTS OF GRIDSEARCHCV
RETURNS

FLOAT
LOWER BOUND WITHIN 1 STANDARD DEVIATION OF THE
BEST MEANTESTSCORE

BESTSCOREIDX NPARGMAXCVRESULTSMEANTESTSCORE
RETURNCVRESULTSMEANTESTSCOREBESTSCOREIDX
 CVRESULTSSTDTESTSCOREBESTSCOREIDX
DEFBESTLOWCOMPLEXITYCVRESULTS

BALANCE MODEL COMPLEXITY WITH CROSSVALIDATED SCORE
PARAMETERS

CVRESULTS DICT OF NUMPYMASKED NDARRAYS
SEE ATTRIBUTE CVRESULTS OF GRIDSEARCHCV
RETURN

INT
INDEX OF A MODEL THAT HAS THE FEWEST PCA COMPONENTS
WHILE HAS ITS TEST SCORE WITHIN 1 STANDARD DEVIATION OF THE BEST
MEANTESTSCORE

THRESHOLD LOWERBOUNDCVRESULTS
CANDIDATEIDX NPFLATNONZEROCVRESULTSMEANTESTSCORE THRESHOLD
BESTIDX CANDIDATEIDXCVRESULTSPARAMREDUCEDIMNCOMPONENTS
CANDIDATEIDXARGMIN
RETURNBESTIDX
PIPE PIPELINE
REDUCEDIM PCARANDOMSTATE42
CLASSIFY LINEARSVCRANDOMSTATE42

PARAMGRID
REDUCEDIMNCOMPONENTS 2 4 6 8

GRID GRIDSEARCHCVPIPE CV10 NJOBS1 PARAMGRIDPARAMGRID
SCORINGACCURACY REFITBESTLOWCOMPLEXITY

SCIKITLEARN USER GUIDE RELEASE 0213
DIGITS LOADDIGITS
GRIDFITDIGITSDATA DIGITSTARGET
NCOMPONENTS GRIDCVRESULTSPARAMREDUCEDIMNCOMPONENTS
TESTSCORES GRIDCVRESULTSMEANTESTSCORE
PLTFIGURE
PLTBARNCOMPONENTS TESTSCORES WIDTH13 COLORB
LOWER LOWERBOUNDGRIDCVRESULTS
PLTAXHLINENPMAXTESTSCORES LINESTYLE COLORY
LABELBEST SCORE
PLTAXHLINELOWER LINESTYLE COLOR5 LABELBEST SCORE 1 STD
PLTTITLEBALANCE MODEL COMPLEXITY AND CROSSVALIDATED SCORE
PLTXLABELNUMBER OF PCA COMPONENTS USED
PLTYLABELDIGIT CLASSIFICATION ACCURACY
PLTXTICKSNCOMPONENTSTOLIST
PLTYLIM0 10
PLTLEGENDLOCUPPER LEFT
BESTINDEX GRIDBESTINDEX
PRINTTHE BESTINDEX IS D BESTINDEX
PRINTTHE NCOMPONENTS SELECTED IS D NCOMPONENTSBESTINDEX
PRINTTHE CORRESPONDING ACCURACY SCORE IS 2F
 GRIDCVRESULTSMEANTESTSCOREBESTINDEX
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 16219 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52111 SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
THE DATASET USED IN THIS EXAMPLE IS THE 20 NEWSGROUPS DATASET WHICH WILL BE AUTOMATICALLY DOWNLOADED AND THEN CACHED AND REUSED FOR THE DOCUMENT CLASSIFICATION EXAMPLE
YOU CAN ADJUST THE NUMBER OF CATEGORIES BY GIVING THEIR NAMES TO THE DATASET LOADER OR SETTING THEM TO NONE TO GET THE 20 OF THEM
HERE IS A SAMPLE OUTPUT OF A RUN ON A QUADCORE MACHINE
LOADING 20 NEWSGROUPS DATASET FORCATEGORIES
ALTATHEISM TALKRELIGIONMISC
1427 DOCUMENTS
2 CATEGORIES
PERFORMING GRID SEARCH
PIPELINE VECT TFIDF CLF
PARAMETERS
CLFALPHA 10000000000000001E05 99999999999999995E07
CLFMAXITER 10 50 80
CLFPENALTY L2 ELASTICNET
TFIDFUSEIDF TRUEFALSE
521 MODEL SELECTION 1283

```
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VECTMAXN 1 2
VECTMAXDF 05 075 10
VECTMAXFEATURES  NONE 5000 10000 50000
DONEIN1737030S
BEST SCORE 0940
BEST PARAMETERS SET
CLFALPHA 99999999999999995E07
CLFMAXITER 50
CLFPENALTY ELASTICNET
TFIDFUSEIDF TRUE
VECTMAXN 2
VECTMAXDF 075
VECTMAXFEATURES 50000
 AUTHOR OLIVIER GRISEL OLIVIERGRISELENSTAORG
 PETER PRETTENHOFER PETERPRETTENHOFERGMAILCOM
 MATHIEU BLONDEL MATHIEUMBLONDELORG
 LICENSE BSD 3 CLAUSE
FROM PPRINT IMPORT PPRINT
FROM TIME IMPORT TIME
IMPORT LOGGING
FROM SKLEARNDATASETS IMPORT FETCH20NEWSGROUPS
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT COUNTVECTORIZER
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFTRANSFORMER
FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNPIPELINE IMPORT PIPELINE
PRINTDOC
 DISPLAY PROGRESS LOGS ON STDOUT
LOGGINGBASICCONFIGLEVELLOGGINGINFO
FORMAT ASCTIMES LEVELNAMES MESSAGES

 LOAD SOME CATEGORIES FROM THE TRAINING SET
CATEGORIES
ALTATHEISM
TALKRELIGIONMISC

 UNCOMMENT THE FOLLOWING TO DO THE ANALYSIS ON ALL THE CATEGORIES
CATEGORIES  NONE
PRINTLOADING 20 NEWSGROUPS DATASET FOR CATEGORIES
PRINTCATEGORIES
DATA  FETCH20NEWSGROUPSSUBSETTRAIN CATEGORIESCATEGORIES
PRINTDDOCUMENTS  LENDATAFILENAMES
PRINTDCATEGORIES  LENDATATARGETNAMES
PRINT

 DEFINE A PIPELINE COMBINING A TEXT FEATURE EXTRACTOR WITH A SIMPLE
 CLASSIFIER
PIPELINE  PIPELINE
1284 CHAPTER 5 EXAMPLES
```

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VECT COUNTVECTORIZER
TFIDF TFIDFTRANSFORMER
CLF SGDCLASSIFIERTOL1E3

UNCOMMENTING MORE PARAMETERS WILL GIVE BETTER EXPLORING POWER BUT WILL
INCREASE PROCESSING TIME IN A COMBINATORIAL WAY
PARAMETERS
VECTMAXDF 05 075 10
VECTMAXFEATURES NONE 5000 10000 50000
VECTNGRAMRANGE 1 1 1 2 UNIGRAMS OR BIGRAMS
TFIDFUSEIDF TRUE FALSE
TFIDFNORM L1 L2
CLFMAXITER 20
CLFALPHA 000001 0000001
CLFPENALTY L2 ELASTICNET
CLFMAXITER 10 50 80

IFNAME MAIN
MULTIPROCESSING REQUIRES THE FORK TO HAPPEN IN A MAIN PROTECTED
BLOCK
FIND THE BEST PARAMETERS FOR BOTH THE FEATURE EXTRACTION AND THE
CLASSIFIER
GRIDSEARCH GRIDSEARCHCVPIPELINE PARAMETERS CV5
NJOBS1 VERBOSE1
PRINTPERFORMING GRID SEARCH
PRINTPIPELINE NAME FORNAME INPIPELINESTEPS
PRINTPARAMETERS
PPRINTPARAMETERS
T0 TIME
GRIDSEARCHFITDATADATA DATATARGET
PRINTDONE IN 03FS TIME T0
PRINT
PRINTBEST SCORE 03F GRIDSEARCHBESTSCORE
PRINTBEST PARAMETERS SET
BESTPARAMETERS GRIDSEARCHBESTESTIMATORGETPARAMS
FORPARAMNAME INSORTEDPARAMETERSKEYS
PRINTTSR PARAMNAME BESTPARAMETERSPARAMNAME
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0000 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52112 CONFUSION MATRIX
EXAMPLE OF CONFUSION MATRIX USAGE TO EVALUATE THE QUALITY OF THE OUTPUT OF A CLASSIFIER ON THE IRIS DATA SET THE DIAGONAL ELEMENTS REPRESENT THE NUMBER OF POINTS FOR WHICH THE PREDICTED LABEL IS EQUAL TO THE TRUE LABEL WHILE OFFDIAGONAL ELEMENTS ARE THOSE THAT ARE MISLABELED BY THE CLASSIFIER THE HIGHER THE DIAGONAL VALUES OF THE CONFUSION MATRIX THE BETTER INDICATING MANY CORRECT PREDICTIONS
THE FIGURES SHOW THE CONFUSION MATRIX WITH AND WITHOUT NORMALIZATION BY CLASS SUPPORT SIZE NUMBER OF ELEMENTS IN

EACH CLASS THIS KIND OF NORMALIZATION CAN BE INTERESTING IN CASE OF CLASS IMBALANCE TO HAVE A MORE VISUAL INTERPRETATION OF WHICH CLASS IS BEING MISCLASSIFIED

HERE THE RESULTS ARE NOT AS GOOD AS THEY COULD BE AS OUR CHOICE FOR THE REGULARIZATION PARAMETER C WAS NOT THE BEST IN REAL LIFE APPLICATIONS THIS PARAMETER IS USUALLY CHOSEN USING TUNING THE HYPERPARAMETERS OF AN ESTIMATOR

•

•
OUT
CONFUSION MATRIX WITHOUT NORMALIZATION
13 0 0
 0 10 6
 0 0 9
NORMALIZED CONFUSION MATRIX
1 0 0
0 062 038
0 0 1
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT SVM DATASETS
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNMETRICS IMPORT CONFUSIONMATRIX
FROM SKLEARNUTILSMULTICLASS IMPORT UNIQUELABELS
 IMPORT SOME DATA TO PLAY WITH

SCIKITLEARN USER GUIDE RELEASE 0213
IRIS DATASETSLOADIRIS
X IRISDATA
Y IRISTARGET
CLASSNAMES IRISTARGETNAMES
 SPLIT THE DATA INTO A TRAINING SET AND A TEST SET
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y RANDOMSTATE0
 RUN CLASSIFIER USING A MODEL THAT IS TOO REGULARIZED C TOO LOW TO SEE
 THE IMPACT ON THE RESULTS
CLASSIFIER SVMSVCKERNELLINEAR C001
YPRED CLASSIFIERFITXTRAIN YTRAINPREDICTXTEST
DEFPLOTCONFUSIONMATRIXYTRUE YPRED CLASSES
NORMALIZEFALSE
TITLENONE
CMAPPLTCMBLUES

THIS FUNCTION PRINTS AND PLOTS THE CONFUSION MATRIX
NORMALIZATION CAN BE APPLIED BY SETTING NORMALIZETRUE

IF NOTTITLE
IFNORMALIZE
TITLE NORMALIZED CONFUSION MATRIX
ELSE
TITLE CONFUSION MATRIX WITHOUT NORMALIZATION
 COMPUTE CONFUSION MATRIX
CM CONFUSIONMATRIXYTRUE YPRED
 ONLY USE THE LABELS THAT APPEAR IN THE DATA
CLASSES CLASSESUNIQUELABELSYTRUE YPRED
IFNORMALIZE
CM CMASTYPEFLOAT CMSUMAXIS1 NPNEWAXIS
PRINTNORMALIZED CONFUSION MATRIX
ELSE
PRINTCONFUSION MATRIX WITHOUT NORMALIZATION
PRINTCM
FIG AX PLTSUBPLOTS
IM AXIMSHOWCM INTERPOLATIONNEAREST CMAPCMAP
AXFIGURECOLORBARIM AXAX
 WE WANT TO SHOW ALL TICKS
AXSETXTICKSNPARANGECMSHAPE1
YTICKSNPARANGECMSHAPE0
  AND LABEL THEM WITH THE RESPECTIVE LIST ENTRIES
XTICKLABELSCLASSES YTICKLABELSCLASSES
TITLETITLE
YLABELTRUE LABEL
XLABELPREDICTED LABEL
 ROTATE THE TICK LABELS AND SET THEIR ALIGNMENT
PLTSETPAXGETXTICKLABELS ROTATION45 HARIGHT
ROTATIONMODEANCHOR
 LOOP OVER DATA DIMENSIONS AND CREATE TEXT ANNOTATIONS
FMT 2F IFNORMALIZE ELSED
1288 CHAPTER 5 EXAMPLES

SCIKITLEARN USER GUIDE RELEASE 0213
THRESH CMMAX 2
FORIINRANGECMSHAPE0
FORJINRANGECMSHAPE1
AXTEXTJ I FORMATCMI J FMT
HACENTER VACENTER
COLORWHITE IFCMI J THRESH ELSEBLACK
FIGTIGHTLAYOUT
RETURNAX
NPSETPRINTOPTIONSPRECISION2
 PLOT NONNORMALIZED CONFUSION MATRIX
PLOTCONFUSIONMATRIXYTEST YPRED CLASSESCLASSNAMES
TITLECONFUSION MATRIX WITHOUT NORMALIZATION
 PLOT NORMALIZED CONFUSION MATRIX
PLOTCONFUSIONMATRIXYTEST YPRED CLASSESCLASSNAMES NORMALIZETRUE
TITLENORMALIZED CONFUSION MATRIX
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0217 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52113 VISUALIZING CROSSVALIDATION BEHAVIOR IN SCIKITLEARN
CHOOSING THE RIGHT CROSSVALIDATION OBJECT IS A CRUCIAL PART OF FITTING A MODEL PROPERLY THERE ARE MANY WAYS TO SPLIT DATA INTO TRAINING AND TEST SETS IN ORDER TO AVOID MODEL OVERFITTING TO STANDARDIZE THE NUMBER OF GROUPS IN TEST SETS ETC
THIS EXAMPLE VISUALIZES THE BEHAVIOR OF SEVERAL COMMON SCIKITLEARN OBJECTS FOR COMPARISON
FROM SKLEARNMODELSELECTION IMPORT TIMESERIESSPLIT KFOLD SHUFFLESPLIT
STRATIFIEDKFOLD GROUPSHUFFLESPLIT
GROUPKFOLD STRATIFIEDSHUFFLESPLIT
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBPATCHES IMPORT PATCH
NPRANDOMSEED1338
CMAPDATA PLTCMPAIRED
CMAPCV PLTCMCOOLWARM
NSPLITS 4
VISUALIZE OUR DATA
FIRST WE MUST UNDERSTAND THE STRUCTURE OF OUR DATA IT HAS 100 RANDOMLY GENERATED INPUT DATAPOINTS 3 CLASSES SPLIT UNEVENLY ACROSS DATAPOINTS AND 10 “GROUPS” SPLIT EVENLY ACROSS DATAPOINTS
AS WE’LL SEE SOME CROSSVALIDATION OBJECTS DO SPECIFIC THINGS WITH LABELED DATA OTHERS BEHAVE DIFFERENTLY WITH GROUPED DATA AND OTHERS DO NOT USE THIS INFORMATION
TO BEGIN WE’LL VISUALIZE OUR DATA

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```
 GENERATE THE CLASSGROUP DATA
NPOINTS  100
X  NPRANDOMRANDN100 10
PERCENTILESCLASSES  1 3 6
Y  NPHSTACKII INT100 PERC
FORII PERC INENUMERATEPERCENTILESCLASSES
 EVENLY SPACED GROUPS REPEATED ONCE
GROUPS  NPHSTACKII 10FORIIINRANGE10
DEFVISUALIZEGROUPSCLASSES GROUPS NAME
 VISUALIZE DATASET GROUPS
FIG AX  PLTSUBPLOTS
AXSCATTERRANGELENGROUPS 5 LENGROUPS CGROUPS MARKER
LW50 CMAPCMAPDATA
AXSCATTERRANGELENGROUPS 35 LENGROUPS CCLASSES MARKER
LW50 CMAPCMAPDATA
AXSETYLIM1 5 YTICKS5 35
YTICKLABELSDATA NGROUP DATA NCLASS XLABELSAMPLE INDEX
VISUALIZEGROUPSY GROUPS NO GROUPS
```

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DEFINE A FUNCTION TO VISUALIZE CROSSVALIDATION BEHAVIOR
WE'LL DEFINE A FUNCTION THAT LETS US VISUALIZE THE BEHAVIOR OF EACH CROSSVALIDATION OBJECT WE'LL PERFORM 4 SPLITS OF THE DATA ON EACH SPLIT WE'LL VISUALIZE THE INDICES CHOSEN FOR THE TRAINING SET IN BLUE AND THE TEST SET IN RED
DEFPLOTCVINDICESCV X Y GROUP AX NSPLITS LW10
CREATE A SAMPLE PLOT FOR INDICES OF A CROSSVALIDATION OBJECT
GENERATE THE TRAININGTESTING VISUALIZATIONS FOR EACH CV SPLIT
FORII TR TT INENUMERATECVSPLITXX YY GROUPSGROUP
FILL IN INDICES WITH THE TRAININGTEST GROUPS
INDICES NPARRAYNPNAN LENX
INDICESTT 1
INDICESTR 0
VISUALIZE THE RESULTS
AXSCATTERRANGELENINDICES II 5 LENINDICES
CINDICES MARKER LWLW CMAPCMAPCV
VMIN2 VMAX12
PLOT THE DATA CLASSES AND GROUPS AT THE END
AXSCATTERRANGELENX II 15 LENX
CY MARKER LWLW CMAPCMAPDATA
AXSCATTERRANGELENX II 25 LENX
CGROUP MARKER LWLW CMAPCMAPDATA
FORMATTING
YTICKLABELS LISTRANGENSPLITS CLASS GROUP
AXSETYTICKSNPARANGENSPLITS2 5 YTICKLABELSYTICKLABELS
XLABELSAMPLE INDEX YLABELCV ITERATION
YLIMNSPLITS22 2 XLIM0 100
AXSETTITLEFORMATTYPECVNAME FONTSIZE15
RETURNAX
LET'S SEE HOW IT LOOKS FOR THE KFOLD CROSSVALIDATION OBJECT
FIG AX PLTSUBPLOTS
CV KFOLDNSPLITS
PLOTCVINDICESCV X Y GROUPS AX NSPLITS

AS YOU CAN SEE BY DEFAULT THE KFOLD CROSSVALIDATION ITERATOR DOES NOT TAKE EITHER DATAPOINT CLASS OR GROUP INTO CONSIDERATION WE CAN CHANGE THIS BY USING THE STRATIFIEDKFOLD LIKE SO

```
FIG AX  PLTSUBPLOTS
CV  STRATIFIEDKFOLDNSPLITS
PLOTCVINDICESCV X Y GROUPS AX NSPLITS
```

IN THIS CASE THE CROSSVALIDATION RETAINED THE SAME RATIO OF CLASSES ACROSS EACH CV SPLIT NEXT WE'LL VISUALIZE THIS BEHAVIOR FOR A NUMBER OF CV ITERATORS

VISUALIZE CROSSVALIDATION INDICES FOR MANY CV OBJECTS

LET'S VISUALLY COMPARE THE CROSS VALIDATION BEHAVIOR FOR MANY SCIKITLEARN CROSSVALIDATION OBJECTS BELOW WE WILL LOOP THROUGH SEVERAL COMMON CROSSVALIDATION OBJECTS VISUALIZING THE BEHAVIOR OF EACH

NOTE HOW SOME USE THE GROUPCLASS INFORMATION WHILE OTHERS DO NOT

```
CVS  KFOLD GROUPKFOLD SHUFFLESPLIT STRATIFIEDKFOLD
GROUPSHUFFLESPLIT STRATIFIEDSHUFFLESPLIT TIMESERIESSPLIT
FORCVINCVS
THISCV  CVNSPLITSNSPLITS
FIG AX  PLTSUBPLOTSFIGSIZE6 3
PLOTCVINDICESTHISCV X Y GROUPS AX NSPLITS
AXLEGENDPATCHCOLORCMAPCV8 PATCHCOLORCMAPCV02
TESTING SET TRAINING SET LOC102 8
 MAKE THE LEGEND FIT
PLTTIGHTLAYOUT
FIGSUBPLOTSADJUSTRIGHT7
PLTSHOW
```

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•

•
•

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TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0401 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

52114 RECEIVER OPERATING CHARACTERISTIC ROC

EXAMPLE OF RECEIVER OPERATING CHARACTERISTIC ROC METRIC TO EVALUATE CLASSIFIER OUTPUT QUALITY

ROC CURVES TYPICALLY FEATURE TRUE POSITIVE RATE ON THE Y AXIS AND FALSE POSITIVE RATE ON THE X AXIS THIS MEANS THAT THE TOP LEFT CORNER OF THE PLOT IS THE “IDEAL” POINT A FALSE POSITIVE RATE OF ZERO AND A TRUE POSITIVE RATE OF ONE THIS IS NOT VERY REALISTIC BUT IT DOES MEAN THAT A LARGER AREA UNDER THE CURVE AUC IS USUALLY BETTER

THE “STEEPNESS” OF ROC CURVES IS ALSO IMPORTANT SINCE IT IS IDEAL TO MAXIMIZE THE TRUE POSITIVE RATE WHILE MINIMIZING THE FALSE POSITIVE RATE

MULTICLASS SETTINGS

ROC CURVES ARE TYPICALLY USED IN BINARY CLASSIFICATION TO STUDY THE OUTPUT OF A CLASSIFIER IN ORDER TO EXTEND ROC CURVE AND ROC AREA TO MULTICLASS OR MULTILABEL CLASSIFICATION IT IS NECESSARY TO BINARIZE THE OUTPUT ONE ROC CURVE CAN BE DRAWN PER LABEL BUT ONE CAN ALSO DRAW A ROC CURVE BY CONSIDERING EACH ELEMENT OF THE LABEL INDICATOR MATRIX AS A BINARY PREDICTION MICROAVERAGING

ANOTHER EVALUATION MEASURE FOR MULTICLASS CLASSIFICATION IS MACROAVERAGING WHICH GIVES EQUAL WEIGHT TO THE CLASSI FICATION OF EACH LABEL

NOTE

SEE ALSO SKLEARNMETRICSROCAUCSCORE RECEIVER OPERATING CHARACTERISTIC ROC WITH CROSS VALIDA TION

PRINTDOC

IMPORT NUMPY AS NP

SCIKITLEARN USER GUIDE RELEASE 0213
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM ITERTOOLS IMPORT CYCLE
FROM SKLEARN IMPORT SVM DATASETS
FROM SKLEARNMETRICS IMPORT ROCCURVE AUC
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNPREPROCESSING IMPORT LABELBINARIZE
FROM SKLEARNMULTICLASS IMPORT ONEVSRESTCLASSIFIER
FROM SCIPY IMPORT INTERP
IMPORT SOME DATA TO PLAY WITH
IRIS DATASETSLOADIRIS
X IRISDATA
Y IRISTARGET
BINARIZE THE OUTPUT
Y LABELBINARIZEY CLASSES0 1 2
NCLASSES YSHAPE1
ADD NOISY FEATURES TO MAKE THE PROBLEM HARDER
RANDOMSTATE NPRANDOMRANDOMSTATE0
NSAMPLES NFEATURES XSHAPE
X NPCX RANDOMSTATERANDNNSAMPLES 200 NFEATURES
SHUFFLE AND SPLIT TRAINING AND TEST SETS
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y TESTSIZE5
RANDOMSTATE0
LEARN TO PREDICT EACH CLASS AGAINST THE OTHER
CLASSIFIER ONEVSRESTCLASSIFIERSVMSVCKERNELLINEAR PROBABILITYTRUE
RANDOMSTATERANDOMSTATE
YSCORE CLASSIFIERFITXTRAIN YTRAINDECISIONFUNCTIONXTEST
COMPUTE ROC CURVE AND ROC AREA FOR EACH CLASS
FPR DICT
TPR DICT
ROCAUC DICT
FORIINRANGENCLASSES
FPRI TPRI   ROCCURVEYTEST I YSCORE I
ROCAUCI AUCFPRI TPRI
COMPUTE MICROAVERAGE ROC CURVE AND ROC AREA
FPRMICRO TPRMICRO   ROCCURVEYTESTRAVEL YSCORERAVEL
ROCAUCMICRO AUCFPRMICRO TPRMICRO
PLOT OF A ROC CURVE FOR A SPECIFIC CLASS
PLTFIGURE
LW 2
PLTPLOTFPR2 TPR2 COLORDARKORANGE
LWLW LABELROC CURVE AREA 02F ROCAUC2
PLTPLOT0 1 0 1 COLORNAVY LWLW LINESTYLE
PLTXLIM00 10
PLTYLIM00 105
PLTXLABELFALSE POSITIVE RATE
PLTYLABELTRUE POSITIVE RATE
PLTTITLERECEIVER OPERATING CHARACTERISTIC EXAMPLE
PLTLEGENDLOCLOWER RIGHT

```
PLTSHOW
PLOT ROC CURVES FOR THE MULTICLASS PROBLEM
 COMPUTE MACROAVERAGE ROC CURVE AND ROC AREA
 FIRST AGGREGATE ALL FALSE POSITIVE RATES
ALLFPR  NPUNIQUENPCONCATENATEFPRI FORIINRANGENCLASSES
 THEN INTERPOLATE ALL ROC CURVES AT THIS POINTS
MEANTPR  NPZEROSLIKEALLFPR
FORIINRANGENCLASSES
MEANTPR  INTERPALLFPR FPRI TPRI
 FINALLY AVERAGE IT AND COMPUTE AUC
MEANTPR  NCLASSES
FPRMACRO  ALLFPR
TPRMACRO  MEANTPR
ROCAUCMACRO  AUCFPRMACRO TPRMACRO
 PLOT ALL ROC CURVES
PLTFIGURE
PLTPLOTFPRMICRO TPRMICRO
LABELMICROAVERAGE ROC CURVE AREA  002F
FORMATROCAUCMICRO
```

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COLORDEEPPINK LINESTYLE LINEWIDTH4
PLTPLOTFPRMACRO TPRMACRO
LABELMACROAVERAGE ROC CURVE AREA 002F
FORMATROCAUCMACRO
COLORNAVY LINESTYLE LINEWIDTH4
COLORS CYCLEAQUA DARKORANGE CORNFLOWERBLUE
FORI COLOR INZIPRANGENCLASSES COLORS
PLTPLOTFPRI TPRI COLORCOLOR LWLW
LABELROC CURVE OF CLASS 0 AREA 102F
FORMATI ROCAUCI
PLTPLOT0 1 0 1 K LWLW
PLTXLIM00 10
PLTYLIM00 105
PLTXLABELFALSE POSITIVE RATE
PLTYLABELTRUE POSITIVE RATE
PLTTITLESOME EXTENSION OF RECEIVER OPERATING CHARACTERISTIC TO MULTICLASS
PLTLEGENDLOCLOWER RIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0145 SECONDS
1300 CHAPTER 5 EXAMPLES

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52115 PLOTTING LEARNING CURVES
ON THE LEFT SIDE THE LEARNING CURVE OF A NAIVE BAYES CLASSIFIER IS SHOWN FOR THE DIGITS DATASET NOTE THAT THE TRAINING SCORE AND THE CROSSVALIDATION SCORE ARE BOTH NOT VERY GOOD AT THE END HOWEVER THE SHAPE OF THE CURVE CAN BE FOUND IN MORE COMPLEX DATASETS VERY OFTEN THE TRAINING SCORE IS VERY HIGH AT THE BEGINNING AND DECREASES AND THE CROSS VALIDATION SCORE IS VERY LOW AT THE BEGINNING AND INCREASES ON THE RIGHT SIDE WE SEE THE LEARNING CURVE OF AN SVM WITH RBF KERNEL WE CAN SEE CLEARLY THAT THE TRAINING SCORE IS STILL AROUND THE MAXIMUM AND THE VALIDATION SCORE COULD BE INCREASED WITH MORE TRAINING SAMPLES
•

•

```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNDATASETS IMPORT LOADDIGITS
FROM SKLEARNMODELSELECTION IMPORT LEARNINGCURVE
FROM SKLEARNMODELSELECTION IMPORT SHUFFLESPLIT
DEFPLOTLEARNINGCURVEESTIMATOR TITLE X Y YLIMNONE CVNONE
NJOBSNONE TRAINSIZESNPLINSPACE1 10 5

GENERATE A SIMPLE PLOT OF THE TEST AND TRAINING LEARNING CURVE
PARAMETERS

ESTIMATOR  OBJECT TYPE THAT IMPLEMENTS THE FIT AND PREDICT METHODS
AN OBJECT OF THAT TYPE WHICH IS CLONED FOR EACH VALIDATION
TITLE  STRING
TITLE FOR THE CHART
X  ARRAYLIKE SHAPE NSAMPLES NFEATURES
TRAINING VECTOR WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND
NFEATURES IS THE NUMBER OF FEATURES
```

SCIKITLEARN USER GUIDE RELEASE 0213
Y ARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NFEATURES OPTIONAL
TARGET RELATIVE TO X FOR CLASSIFICATION OR REGRESSION
NONE FOR UNSUPERVISED LEARNING
YLIM TUPLE SHAPE YMIN YMAX OPTIONAL
DEFINES MINIMUM AND MAXIMUM YVALUES PLOTTED
CV INT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL
DETERMINES THE CROSSVALIDATION SPLITTING STRATEGY
POSSIBLE INPUTS FOR CV ARE
 NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
 INTEGER TO SPECIFY THE NUMBER OF FOLDS
 TERMCV SPLITTER
 AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF Y IS BINARY OR MULTICLASS
CLASSSTRATIFIEDKFOLD USED IF THE ESTIMATOR IS NOT A CLASSIFIER
OR IF Y IS NEITHER BINARY NOR MULTICLASS CLASSKFOLD IS USED
REFER REFUSER GUIDE CROSSVALIDATION FOR THE VARIOUS
CROSSVALIDATORS THAT CAN BE USED HERE
NJOBS INT OR NONE OPTIONAL DEFAULTNONE
NUMBER OF JOBS TO RUN IN PARALLEL
NONE MEANS 1 UNLESS IN A OBJJOBLIBPARALLELBACKEND CONTEXT
1 MEANS USING ALL PROCESSORS SEE TERMGLOSSARY NJOBS
FOR MORE DETAILS
TRAINSIZES ARRAYLIKE SHAPE NTICKS DTYPE FLOAT OR INT
RELATIVE OR ABSOLUTE NUMBERS OF TRAINING EXAMPLES THAT WILL BE USED TO
GENERATE THE LEARNING CURVE IF THE DTYPE IS FLOAT IT IS REGARDED AS A
FRACTION OF THE MAXIMUM SIZE OF THE TRAINING SET THAT IS DETERMINED
BY THE SELECTED VALIDATION METHOD IE IT HAS TO BE WITHIN 0 1
OTHERWISE IT IS INTERPRETED AS ABSOLUTE SIZES OF THE TRAINING SETS
NOTE THAT FOR CLASSIFICATION THE NUMBER OF SAMPLES USUALLY HAVE TO
BE BIG ENOUGH TO CONTAIN AT LEAST ONE SAMPLE FROM EACH CLASS
DEFAULT NPLINSPACE01 10 5

PLTFIGURE
PLTTITLETITLE
IFYLIMIS NOTNONE
PLTYLIM YLIM
PLTXLABELTRAINING EXAMPLES
PLTYLABELSCORE
TRAINSIZES TRAINSCORES TESTSCORES LEARNINGCURVE
ESTIMATOR X Y CVCV NJOBSNJOBS TRAINSIZESTRAINSIZES
TRAINSCORESMEAN NPMEANTRAINSCORES AXIS1
TRAINSCORESSTD NPSTDTRAINSCORES AXIS1
TESTSCORESMEAN NPMEANTESTSCORES AXIS1
TESTSCORESSTD NPSTDTESTSCORES AXIS1
PLTGRID
PLTFILLBETWEENTRAINSIZES TRAINSCORESMEAN TRAINSCORESSTD
TRAINSCORESMEAN TRAINSCORESSTD ALPHA01
COLORR
PLTFILLBETWEENTRAINSIZES TESTSCORESMEAN TESTSCORESSTD
TESTSCORESMEAN TESTSCORESSTD ALPHA01 COLORG

PLTPLOTTRAINSIZES TRAINSCORESMEAN O COLORR
LABELTRAINING SCORE
PLTPLOTTRAINSIZES TESTSCORESMEAN O COLORG
LABELCROSSVALIDATION SCORE
PLTLEGENDLOCBEST
RETURNPLT
DIGITS LOADDIGITS
X Y DIGITSDATA DIGITSTARGET
TITLE LEARNING CURVES NAIVE BAYES
 CROSS VALIDATION WITH 100 ITERATIONS TO GET SMOOTHER MEAN TEST AND TRAIN
 SCORE CURVES EACH TIME WITH 20 DATA RANDOMLY SELECTED AS A VALIDATION SET
CV SHUFFLESPLITNSPLITS100 TESTSIZE02 RANDOMSTATE0
ESTIMATOR GAUSSIANNB
PLOTLEARNINGCURVEESTIMATOR TITLE X Y YLIM07 101 CVCV NJOBS4
TITLE RLEARNING CURVES SVM RBF KERNEL GAMMA0001
 SVC IS MORE EXPENSIVE SO WE DO A LOWER NUMBER OF CV ITERATIONS
CV SHUFFLESPLITNSPLITS10 TESTSIZE02 RANDOMSTATE0
ESTIMATOR SVCGAMMA0001
PLOTLEARNINGCURVEESTIMATOR TITLE X Y 07 101 CVCV NJOBS4
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2856 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52116 PRECISIONRECALL
EXAMPLE OF PRECISIONRECALL METRIC TO EVALUATE CLASSIFIER OUTPUT QUALITY
PRECISIONRECALL IS A USEFUL MEASURE OF SUCCESS OF PREDICTION WHEN THE CLASSES ARE VERY IMBALANCED IN INFORMATION RETRIEVAL PRECISION IS A MEASURE OF RESULT RELEVANCY WHILE RECALL IS A MEASURE OF HOW MANY TRULY RELEVANT RESULTS ARE RETURNED
THE PRECISIONRECALL CURVE SHOWS THE TRADEOFF BETWEEN PRECISION AND RECALL FOR DIFFERENT THRESHOLD A HIGH AREA UNDER THE CURVE REPRESENTS BOTH HIGH RECALL AND HIGH PRECISION WHERE HIGH PRECISION RELATES TO A LOW FALSE POSITIVE RATE AND HIGH RECALL RELATES TO A LOW FALSE NEGATIVE RATE HIGH SCORES FOR BOTH SHOW THAT THE CLASSIFIER IS RETURNING ACCURATE RESULTS HIGH PRECISION AS WELL AS RETURNING A MAJORITY OF ALL POSITIVE RESULTS HIGH RECALL
A SYSTEM WITH HIGH RECALL BUT LOW PRECISION RETURNS MANY RESULTS BUT MOST OF ITS PREDICTED LABELS ARE INCORRECT WHEN COMPARED TO THE TRAINING LABELS A SYSTEM WITH HIGH PRECISION BUT LOW RECALL IS JUST THE OPPOSITE RETURNING VERY FEW RESULTS BUT MOST OF ITS PREDICTED LABELS ARE CORRECT WHEN COMPARED TO THE TRAINING LABELS AN IDEAL SYSTEM WITH HIGH PRECISION AND HIGH RECALL WILL RETURN MANY RESULTS WITH ALL RESULTS LABELED CORRECTLY
PRECISION □ IS DEFINED AS THE NUMBER OF TRUE POSITIVES □□ OVER THE NUMBER OF TRUE POSITIVES PLUS THE NUMBER OF FALSE POSITIVES □□
□□□
□□□□

RECALL IS DEFINED AS THE NUMBER OF TRUE POSITIVES OVER THE NUMBER OF TRUE POSITIVES PLUS THE NUMBER OF FALSE NEGATIVES
THESE QUANTITIES ARE ALSO RELATED TO THE 1 SCORE WHICH IS DEFINED AS THE HARMONIC MEAN OF PRECISION AND RECALL
1 2×
NOTE THAT THE PRECISION MAY NOT DECREASE WITH RECALL THE DEFINITION OF PRECISION SHOWS THAT LOWERING THE
THRESHOLD OF A CLASSIFIER MAY INCREASE THE DENOMINATOR BY INCREASING THE NUMBER OF RESULTS RETURNED IF THE THRESHOLD WAS PREVIOUSLY SET TOO HIGH THE NEW RESULTS MAY ALL BE TRUE POSITIVES WHICH WILL INCREASE PRECISION IF THE PREVIOUS THRESHOLD WAS ABOUT RIGHT OR TOO LOW FURTHER LOWERING THE THRESHOLD WILL INTRODUCE FALSE POSITIVES DECREASING PRECISION
RECALL IS DEFINED AS WHERE DOES NOT DEPEND ON THE CLASSIFIER THRESHOLD THIS MEANS THAT LOWERING
THE CLASSIFIER THRESHOLD MAY INCREASE RECALL BY INCREASING THE NUMBER OF TRUE POSITIVE RESULTS IT IS ALSO POSSIBLE THAT LOWERING THE THRESHOLD MAY LEAVE RECALL UNCHANGED WHILE THE PRECISION FLUCTUATES
THE RELATIONSHIP BETWEEN RECALL AND PRECISION CAN BE OBSERVED IN THE STAIRSTEP AREA OF THE PLOT AT THE EDGES OF THESE STEPS A SMALL CHANGE IN THE THRESHOLD CONSIDERABLY REDUCES PRECISION WITH ONLY A MINOR GAIN IN RECALL
AVERAGE PRECISION AP SUMMARIZES SUCH A PLOT AS THE WEIGHTED MEAN OF PRECISIONS ACHIEVED AT EACH THRESHOLD WITH THE INCREASE IN RECALL FROM THE PREVIOUS THRESHOLD USED AS THE WEIGHT
AP∑
−1
WHERE AND ARE THE PRECISION AND RECALL AT THE NTH THRESHOLD A PAIR IS REFERRED TO AS AN OPERATING POINT
AP AND THE TRAPEZOIDAL AREA UNDER THE OPERATING POINTS SKLEARNMETRICSAUC ARE COMMON WAYS TO SUMMARIZE A PRECISIONRECALL CURVE THAT LEAD TO DIFFERENT RESULTS READ MORE IN THE USER GUIDE
PRECISIONRECALL CURVES ARE TYPICALLY USED IN BINARY CLASSIFICATION TO STUDY THE OUTPUT OF A CLASSIFIER IN ORDER TO EXTEND THE PRECISIONRECALL CURVE AND AVERAGE PRECISION TO MULTICLASS OR MULTILABEL CLASSIFICATION IT IS NECESSARY TO BINARIZE THE OUTPUT ONE CURVE CAN BE DRAWN PER LABEL BUT ONE CAN ALSO DRAW A PRECISIONRECALL CURVE BY CONSIDERING EACH ELEMENT OF THE LABEL INDICATOR MATRIX AS A BINARY PREDICTION MICROAVERAGING
NOTE
SEE ALSO SKLEARNMETRICSAVERAGEPRECISIONSCORE SKLEARNMETRICSRECALLSCORE SKLEARNMETRICSPRECISIONSCORE SKLEARNMETRICSF1SCORE
IN BINARY CLASSIFICATION SETTINGS
CREATE SIMPLE DATA
TRY TO DIFFERENTIATE THE TWO FIRST CLASSES OF THE IRIS DATA
FROM SKLEARN IMPORT SVM DATASETS
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
IMPORT NUMPY AS NP
IRIS DATASETSLOADIRIS
X IRISDATA
Y IRISTARGET
 ADD NOISY FEATURES
RANDOMSTATE NPRANDOMRANDOMSTATE0
NSAMPLES NFEATURES XSHAPE

```
X  NPCX RANDOMSTATERANDNNSAMPLES 200 NFEATURES
 LIMIT TO THE TWO FIRST CLASSES AND SPLIT INTO TRAINING AND TEST
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLITXY  2 YY  2
TESTSIZE5
RANDOMSTATERANDOMSTATE
 CREATE A SIMPLE CLASSIFIER
CLASSIFIER  SVMLINEARSVCRANDOMSTATERANDOMSTATE
CLASSIFIERFITXTRAIN YTRAIN
YSCORE  CLASSIFIERDECISIONFUNCTIONXTEST
COMPUTE THE AVERAGE PRECISION SCORE
FROM SKLEARNMETRICS IMPORT AVERAGEPRECISIONSCORE
AVERAGEPRECISION  AVERAGEPRECISIONSCOREYTEST YSCORE
PRINTAVERAGE PRECISIONRECALL SCORE 002FFORMAT
AVERAGEPRECISION
OUT
AVERAGE PRECISIONRECALL SCORE 088
PLOT THE PRECISIONRECALL CURVE
FROM SKLEARNMETRICS IMPORT PRECISIONRECALLCURVE
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM INSPECT IMPORT SIGNATURE
PRECISION RECALL   PRECISIONRECALLCURVEYTEST YSCORE
 IN MATPLOTLIB  15 PLTFILLBETWEEN DOES NOT HAVE A STEP ARGUMENT
STEPKWARGS  STEP POST
IFSTEPINSIGNATUREPLTFILLBETWEENPARAMETERS
ELSE
PLTSTEPRECALL PRECISION COLORB ALPHA02
WHEREPOST
PLTFILLBETWEENRECALL PRECISION ALPHA02 COLORB STEPKWARGS
PLTXLABELRECALL
PLTYLABELPRECISION
PLTYLIM00 105
PLTXLIM00 10
PLTTITLE2CLASS PRECISIONRECALL CURVE AP002FFORMAT
AVERAGEPRECISION
```

SCIKITLEARN USER GUIDE RELEASE 0213
IN MULTILABEL SETTINGS
CREATE MULTILABEL DATA FIT AND PREDICT
WE CREATE A MULTILABEL DATASET TO ILLUSTRATE THE PRECISIONRECALL IN MULTILABEL SETTINGS
FROM SKLEARNPREPROCESSING IMPORT LABELBINARIZE
 USE LABELBINARIZE TO BE MULTILABEL LIKE SETTINGS
Y LABELBINARIZEY CLASSES0 1 2
NCLASSES YSHAPE1
 SPLIT INTO TRAINING AND TEST
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y TESTSIZE5
RANDOMSTATERANDOMSTATE
 WE USE ONEVSRESTCLASSIFIER FOR MULTILABEL PREDICTION
FROM SKLEARNMULTICLASS IMPORT ONEVSRESTCLASSIFIER
 RUN CLASSIFIER
CLASSIFIER ONEVSRESTCLASSIFIERSVMLINEARSVCRANDOMSTATERANDOMSTATE
CLASSIFIERFITXTRAIN YTRAIN
YSCORE CLASSIFIERDECISIONFUNCTIONXTEST
521 MODEL SELECTION 1307

THE AVERAGE PRECISION SCORE IN MULTILABEL SETTINGS
FROM SKLEARNMETRICS IMPORT PRECISIONRECALLCURVE
FROM SKLEARNMETRICS IMPORT AVERAGEPRECISIONSCORE
 FOR EACH CLASS
PRECISION DICT
RECALL DICT
AVERAGEPRECISION DICT
FORIINRANGENCLASSES
PRECISIONI RECALLI   PRECISIONRECALLCURVEYTEST I
YSCORE I
AVERAGEPRECISIONI AVERAGEPRECISIONSCOREYTEST I YSCORE I
 A MICROAVERAGE QUANTIFYING SCORE ON ALL CLASSES JOINTLY
PRECISIONMICRO RECALLMICRO   PRECISIONRECALLCURVEYTESTRAVEL
YSCORERAVEL
AVERAGEPRECISIONMICRO AVERAGEPRECISIONSCOREYTEST YSCORE
AVERAGEMICRO
PRINTAVERAGE PRECISION SCORE MICROAVERAGED OVER ALL CLASSES 002F
FORMATAVERAGEPRECISIONMICRO
OUT
AVERAGE PRECISION SCORE MICROAVERAGED OVER ALL CLASSES 043
PLOT THE MICROAVERAGED PRECISIONRECALL CURVE
PLTFIGURE
PLTSTEPRECALLMICRO PRECISIONMICRO COLORB ALPHA02
WHEREPOST
PLTFILLBETWEENRECALLMICRO PRECISIONMICRO ALPHA02 COLORB
STEPKWARGS
PLTXLABELRECALL
PLTYLABELPRECISION
PLTYLIM00 105
PLTXLIM00 10
PLTTITLE
AVERAGE PRECISION SCORE MICROAVERAGED OVER ALL CLASSES AP002F
FORMATAVERAGEPRECISIONMICRO

SCIKITLEARN USER GUIDE RELEASE 0213
PLOT PRECISIONRECALL CURVE FOR EACH CLASS AND ISOF1 CURVES
FROM ITERTOOLS IMPORT CYCLE
 SETUP PLOT DETAILS
COLORS CYCLENAVY TURQUOISE DARKORANGE CORNFLOWERBLUE TEAL
PLTFIGUREFIGSIZE7 8
FSCORES NPLINSPACE02 08 NUM4
LINES
LABELS
FORFSCORE INFSCORES
X NPLINSPACE001 1
Y FSCORE X 2X FSCORE
L PLTPLOTXY 0 YY 0 COLORGRAY ALPHA02
PLTANNOTATEF1001FFORMATFSCORE XY09 Y45 002
LINESAPPENDL
LABELSAPPENDISOF1 CURVES
L PLTPLOTRECALLMICRO PRECISIONMICRO COLORGOLD LW2
LINESAPPENDL
LABELSAPPENDMICROAVERAGE PRECISIONRECALL AREA 002F
FORMATAVERAGEPRECISIONMICRO
FORI COLOR INZIPRANGENCLASSES COLORS
521 MODEL SELECTION 1309

SCIKITLEARN USER GUIDE RELEASE 0213
L PLTPLOTRECALLI PRECISIONI COLORCOLOR LW2
LINESAPPENDL
LABELSAPPENDPRECISIONRECALL FOR CLASS 0 AREA 102F
FORMATI AVERAGEPRECISIONI
FIG PLTGCF
FIGSUBPLOTSADJUSTBOTTOM025
PLTXLIM00 10
PLTYLIM00 105
PLTXLABELRECALL
PLTYLABELPRECISION
PLTTITLEEXTENSION OF PRECISIONRECALL CURVE TO MULTICLASS
PLTLEGENDLINES LABELS LOC0 38 PROPDICTSIZE14
PLTSHOW
1310 CHAPTER 5 EXAMPLES

SCIKITLEARN USER GUIDE RELEASE 0213
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0064 SECONDS
522 MULTIOUTPUT METHODS
EXAMPLES CONCERNING THE SKLEARNMULTIOUTPUT MODULE
522 MULTIOUTPUT METHODS 1311

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5221 CLASSIFIER CHAIN
EXAMPLE OF USING CLASSIFIER CHAIN ON A MULTILABEL DATASET
FOR THIS EXAMPLE WE WILL USE THE YEAST DATASET WHICH CONTAINS 2417 DATAPOINTS EACH WITH 103 FEATURES AND 14 POSSIBLE LABELS EACH DATA POINT HAS AT LEAST ONE LABEL AS A BASELINE WE FIRST TRAIN A LOGISTIC REGRESSION CLASSIFIER FOR EACH OF THE 14 LABELS TO EVALUATE THE PERFORMANCE OF THESE CLASSIFIERS WE PREDICT ON A HELDOUT TEST SET AND CALCULATE THE JACCARD SCORE FOR EACH SAMPLE
NEXT WE CREATE 10 CLASSIFIER CHAINS EACH CLASSIFIER CHAIN CONTAINS A LOGISTIC REGRESSION MODEL FOR EACH OF THE 14 LABELS THE MODELS IN EACH CHAIN ARE ORDERED RANDOMLY IN ADDITION TO THE 103 FEATURES IN THE DATASET EACH MODEL GETS THE PREDICTIONS OF THE PRECEDING MODELS IN THE CHAIN AS FEATURES NOTE THAT BY DEFAULT AT TRAINING TIME EACH MODEL GETS THE TRUE LABELS AS FEATURES THESE ADDITIONAL FEATURES ALLOW EACH CHAIN TO EXPLOIT CORRELATIONS AMONG THE CLASSES THE JACCARD SIMILARITY SCORE FOR EACH CHAIN TENDS TO BE GREATER THAN THAT OF THE SET INDEPENDENT LOGISTIC MODELS
BECAUSE THE MODELS IN EACH CHAIN ARE ARRANGED RANDOMLY THERE IS SIGNIFICANT VARIATION IN PERFORMANCE AMONG THE CHAINS PRESUMABLY THERE IS AN OPTIMAL ORDERING OF THE CLASSES IN A CHAIN THAT WILL YIELD THE BEST PERFORMANCE HOWEVER WE DO NOT KNOW THAT ORDERING A PRIORI INSTEAD WE CAN CONSTRUCT AN VOTING ENSEMBLE OF CLASSIFIER CHAINS BY AVERAGING THE BINARY PREDICTIONS OF THE CHAINS AND APPLY A THRESHOLD OF 05 THE JACCARD SIMILARITY SCORE OF THE ENSEMBLE IS GREATER THAN THAT OF THE INDEPENDENT MODELS AND TENDS TO EXCEED THE SCORE OF EACH CHAIN IN THE ENSEMBLE ALTHOUGH THIS IS NOT GUARANTEED WITH RANDOMLY ORDERED CHAINS
AUTHOR ADAM KLECZEWSKI
LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT FETCHOPENML

SCIKITLEARN USER GUIDE RELEASE 0213
FROM SKLEARNMULTIOUTPUT IMPORT CLASSIFIERCHAIN
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNMULTICLASS IMPORT ONEVSRESTCLASSIFIER
FROM SKLEARNMETRICS IMPORT JACCARDSCORE
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
PRINTDOC
 LOAD A MULTILABEL DATASET FROM HTTPSWWWOPENMLORGD40597
X Y FETCHOPENMLYEAST VERSION4 RETURNXYTRUE
Y Y TRUE
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y TESTSIZE2
RANDOMSTATE0
 FIT AN INDEPENDENT LOGISTIC REGRESSION MODEL FOR EACH CLASS USING THE
 ONEVSRESTCLASSIFIER WRAPPER
BASELR LOGISTICREGRESSIONSOLVERLBFGS
OVR ONEVSRESTCLASSIFIERBASELR
OVRFITXTRAIN YTRAIN
YPREDOVR OVRPREDICTXTEST
OVRJACCARDSCORE JACCARDSCOREYTEST YPREDOVR AVERAGESAMPLES
 FIT AN ENSEMBLE OF LOGISTIC REGRESSION CLASSIFIER CHAINS AND TAKE THE
 TAKE THE AVERAGE PREDICTION OF ALL THE CHAINS
CHAINS CLASSIFIERCHAINBASELR ORDERRANDOM RANDOMSTATEI
FORIINRANGE10
FORCHAININCHAINS
CHAINFITXTRAIN YTRAIN
YPREDCHAINS NPARRAYCHAINPREDICTXTEST FORCHAININ
CHAINS
CHAINJACCARDSCORES JACCARDSCOREYTEST YPREDCHAIN 5
AVERAGESAMPLES
FORYPREDCHAIN INYPREDCHAINS
YPREDENSEMBLE YPREDCHAINSMEANAXIS0
ENSEMBLEJACCARDSCORE JACCARDSCOREYTEST
YPREDENSEMBLE 5
AVERAGESAMPLES
MODELSCORES OVRJACCARDSCORE CHAINJACCARDSCORES
MODELSCORESAPPENDENSEMBLEJACCARDSCORE
MODELNAMES INDEPENDENT
CHAIN 1
CHAIN 2
CHAIN 3
CHAIN 4
CHAIN 5
CHAIN 6
CHAIN 7
CHAIN 8
CHAIN 9
CHAIN 10
ENSEMBLE
XPOS NPARANGELENMODELNAMES
522 MULTIOUTPUT METHODS 1313

```
 PLOT THE JACCARD SIMILARITY SCORES FOR THE INDEPENDENT MODEL EACH OF THE
 CHAINS AND THE ENSEMBLE NOTE THAT THE VERTICAL AXIS ON THIS PLOT DOES
 NOT BEGIN AT 0
FIG AX  PLTSUBPLOTSFIGSIZE7 4
AXGRIDTRUE
AXSETTITLECLASSIFIER CHAIN ENSEMBLE PERFORMANCE COMPARISON
AXSETXTICKSXPOS
AXSETXTICKLABELSMODELNAMES ROTATIONVERTICAL
AXSETYLABELJACCARD SIMILARITY SCORE
AXSETYLIMMINMODELSCORES 9 MAXMODELSCORES 11
COLORS  R  B LENCHAINJACCARDSCORES  G
AXBARXPOS MODELSCORES ALPHA05 COLORCOLORS
PLTTIGHTLAYOUT
PLTSHOW
```
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 7947 SECONDS

523 NEAREST NEIGHBORS

EXAMPLES CONCERNING THE SKLEARNNEIGHBORS MODULE

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5231 NEAREST NEIGHBORS REGRESSION

DEMONSTRATE THE RESOLUTION OF A REGRESSION PROBLEM USING A KNEAREST NEIGHBOR AND THE INTERPOLATION OF THE TARGET USING BOTH BARYCENTER AND CONSTANT WEIGHTS

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
 AUTHOR ALEXANDRE GRAMFORT ALEXANDREGRAMFORTINRIAFR
 FABIAN PEDREGOSA FABIANPEDREGOSAINRIAFR

 LICENSE BSD 3 CLAUSE C INRIA

 GENERATE SAMPLE DATA
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT NEIGHBORS
NPRANDOMSEED0
X NPSORT5 NPRANDOMRAND40 1 AXIS0
T NPLINSPACE0 5 500 NPNEWAXIS
Y NPSINXRAVEL
 ADD NOISE TO TARGETS
Y5 1 05 NPRANDOMRAND8

 FIT REGRESSION MODEL
NNEIGHBORS 5
523 NEAREST NEIGHBORS 1315

FORI WEIGHTS INENUMERATEUNIFORM DISTANCE
KNN NEIGHBORSKNEIGHBORSREGRESSORNNEIGHBORS WEIGHTSWEIGHTS
Y KNNFITX YPREDICTT
PLTSUBPLOT2 1 I 1
PLTSCATTERX Y CK LABELDATA
PLTPLOTT Y CG LABELPREDICTION
PLTAXISTIGHT
PLTLEGEND
PLTTITLEKNEIGHBORSREGRESSOR K I WEIGHTS   S NNEIGHBORS
WEIGHTS
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0089 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5232 OUTLIER DETECTION WITH LOCAL OUTLIER FACTOR LOF
THE LOCAL OUTLIER FACTOR LOF ALGORITHM IS AN UNSUPERVISED ANOMALY DETECTION METHOD WHICH COMPUTES THE LOCAL DENSITY DEVIATION OF A GIVEN DATA POINT WITH RESPECT TO ITS NEIGHBORS IT CONSIDERS AS OUTLIERS THE SAMPLES THAT HAVE A SUBSTANTIALLY LOWER DENSITY THAN THEIR NEIGHBORS THIS EXAMPLE SHOWS HOW TO USE LOF FOR OUTLIER DETECTION WHICH IS THE DEFAULT USE CASE OF THIS ESTIMATOR IN SCIKITLEARN NOTE THAT WHEN LOF IS USED FOR OUTLIER DETECTION IT HAS NO PREDICT DECISIONFUNCTION AND SCORESAMPLES METHODS SEE USER GUIDE FOR DETAILS ON THE DIFFERENCE BETWEEN OUTLIER DETECTION AND NOVELTY DETECTION AND HOW TO USE LOF FOR NOVELTY DETECTION
THE NUMBER OF NEIGHBORS CONSIDERED PARAMETER NNEIGHBORS IS TYPICALLY SET 1 GREATER THAN THE MINIMUM NUMBER OF SAMPLES A CLUSTER HAS TO CONTAIN SO THAT OTHER SAMPLES CAN BE LOCAL OUTLIERS RELATIVE TO THIS CLUSTER AND 2 SMALLER THAN THE MAXIMUM NUMBER OF CLOSE BY SAMPLES THAT CAN POTENTIALLY BE LOCAL OUTLIERS IN PRACTICE SUCH INFORMATIONS ARE GENERALLY NOT AVAILABLE AND TAKING NNEIGHBORS20 APPEARS TO WORK WELL IN GENERAL

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SCIKITLEARN USER GUIDE RELEASE 0213
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNNEIGHBORS IMPORT LOCALOUTLIERFACTOR
PRINTDOC
NPRANDOMSEED42
 GENERATE TRAIN DATA
XINLIERS  03 NPRANDOMRANDN100 2
XINLIERS  NPRXINLIERS  2 XINLIERS  2
 GENERATE SOME OUTLIERS
XOUTLIERS  NPRANDOMUNIFORMLOW4 HIGH4 SIZE20 2
X  NPRXINLIERS XOUTLIERS
NOUTLIERS  LENXOUTLIERS
GROUNDTRUTH  NPONESLENX DTYPEINT
GROUNDTRUTHNOUTLIERS  1
 FIT THE MODEL FOR OUTLIER DETECTION DEFAULT
CLF  LOCALOUTLIERFACTORNNEIGHBORS20 CONTAMINATION01
 USE FITPREDICT TO COMPUTE THE PREDICTED LABELS OF THE TRAINING SAMPLES
 WHEN LOF IS USED FOR OUTLIER DETECTION THE ESTIMATOR HAS NO PREDICT
 DECISIONFUNCTION AND SCORESAMPLES METHODS
YPRED  CLFFITPREDICTX
523 NEAREST NEIGHBORS 1317
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SCIKITLEARN USER GUIDE RELEASE 0213
NERRORS YPRED GROUNDTRUTHSUM
XSCORES CLFNEGATIVEOUTLIERFACTOR
PLTTITLELOCAL OUTLIER FACTOR LOF
PLTSCATTERX 0 X 1 COLORK S3 LABELDATA POINTS
 PLOT CIRCLES WITH RADIUS PROPORTIONAL TO THE OUTLIER SCORES
RADIUS XSCORESMAX XSCORES XSCORESMAX XSCORESMIN
PLTSCATTERX 0 X 1 S1000 RADIUS EDGECOLORSR
FACECOLORSNONE LABELOUTLIER SCORES
PLTAXISTIGHT
PLTXLIM5 5
PLTYLIM5 5
PLTXLABELPREDICTION ERRORS D NERRORS
LEGEND PLTLEGENDLOCUPPER LEFT
LEGENDLEGENDHANDLES0SIZES 10
LEGENDLEGENDHANDLES1SIZES 20
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0017 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5233 NEAREST NEIGHBORS CLASSIFICATION
SAMPLE USAGE OF NEAREST NEIGHBORS CLASSIFICATION IT WILL PLOT THE DECISION BOUNDARIES FOR EACH CLASS
1318 CHAPTER 5 EXAMPLES

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBCOLORS IMPORT LISTEDCOLORMAP
FROM SKLEARN IMPORT NEIGHBORS DATASETS
NNEIGHBORS  15
 IMPORT SOME DATA TO PLAY WITH
IRIS  DATASETSLOADIRIS
 WE ONLY TAKE THE FIRST TWO FEATURES WE COULD AVOID THIS UGLY
 SLICING BY USING A TWODIM DATASET
X  IRISDATA 2
Y  IRISTARGET
H  02  STEP SIZE IN THE MESH
 CREATE COLOR MAPS
CMAPLIGHT  LISTEDCOLORMAPFFAAAA AAFFAA AAAAFF
CMAPBOLD  LISTEDCOLORMAPFF0000 00FF00 0000FF
FORWEIGHTS INUNIFORM DISTANCE
 WE CREATE AN INSTANCE OF NEIGHBOURS CLASSIFIER AND FIT THE DATA
CLF  NEIGHBORSKNEIGHBORSCLASSIFIERNNEIGHBORS WEIGHTSWEIGHTS
CLFFITX Y
```

SCIKITLEARN USER GUIDE RELEASE 0213
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX H
NPARANGEYMIN YMAX H
Z CLFPREDICTNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
PLTFIGURE
PLTPCOLORMESHXX YY Z CMAPCMAPLIGHT
 PLOT ALSO THE TRAINING POINTS
PLTSCATTERX 0 X 1 CY CMAPCMAPBOLD
EDGECOLORK S20
PLTXLIMXXMIN XXMAX
PLTYLIMYYMIN YYMAX
PLTTITLE3CLASS CLASSIFICATION K I WEIGHTS   S
 NNEIGHBORS WEIGHTS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1416 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5234 NEAREST CENTROID CLASSIFICATION
SAMPLE USAGE OF NEAREST CENTROID CLASSIFICATION IT WILL PLOT THE DECISION BOUNDARIES FOR EACH CLASS
523 NEAREST NEIGHBORS 1321

•

OUT

NONE 08133333333333334

02 082

PRINTDOC

```
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBCOLORS IMPORT LISTEDCOLORMAP
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNNEIGHBORS IMPORT NEARESTCENTROID
NNEIGHBORS  15
 IMPORT SOME DATA TO PLAY WITH
IRIS  DATASETSLOADIRIS
 WE ONLY TAKE THE FIRST TWO FEATURES WE COULD AVOID THIS UGLY
 SLICING BY USING A TWODIM DATASET
X  IRISDATA 2
Y  IRISTARGET
```

SCIKITLEARN USER GUIDE RELEASE 0213
H 02 STEP SIZE IN THE MESH
 CREATE COLOR MAPS
CMAPLIGHT LISTEDCOLORMAPFFAAAA AAFFAA AAAAFF
CMAPBOLD LISTEDCOLORMAPFF0000 00FF00 0000FF
FORSHRINKAGE INNONE 2
 WE CREATE AN INSTANCE OF NEIGHBOURS CLASSIFIER AND FIT THE DATA
CLF NEARESTCENTROIDSHRINKTHRESHOLDSHRINKAGE
CLFFITX Y
YPRED CLFPREDICTX
PRINTSHRINKAGE NPMEANY YPRED
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX H
NPARANGEYMIN YMAX H
Z CLFPREDICTNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
PLTFIGURE
PLTPCOLORMESHXX YY Z CMAPCMAPLIGHT
 PLOT ALSO THE TRAINING POINTS
PLTSCATTERX 0 X 1 CY CMAPCMAPBOLD
EDGECOLORK S20
PLTTITLE3CLASS CLASSIFICATION SHRINKTHRESHOLD R
 SHRINKAGE
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0051 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5235 KERNEL DENSITY ESTIMATION
THIS EXAMPLE SHOWS HOW KERNEL DENSITY ESTIMATION KDE A POWERFUL NONPARAMETRIC DENSITY ESTIMATION TECHNIQUE
CAN BE USED TO LEARN A GENERATIVE MODEL FOR A DATASET WITH THIS GENERATIVE MODEL IN PLACE NEW SAMPLES CAN BE DRAWN
THESE NEW SAMPLES REFLECT THE UNDERLYING MODEL OF THE DATA

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OUT
BEST BANDWIDTH 379269019073225
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT LOADDIGITS
FROM SKLEARNNEIGHBORS IMPORT KERNELDENSITY
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
 LOAD THE DATA
DIGITS LOADDIGITS
 PROJECT THE 64DIMENSIONAL DATA TO A LOWER DIMENSION
PCA PCANCOMPONENTS15 WHITENFALSE
DATA PCAFITTRANSFORMDIGITSDATA
 USE GRID SEARCH CROSSVALIDATION TO OPTIMIZE THE BANDWIDTH
PARAMS BANDWIDTH NPLOGSPACE1 1 20
523 NEAREST NEIGHBORS 1325

```
GRID  GRIDSEARCHCVKERNELDENSITY PARAMS CV5 IIDFALSE
GRIDFITDATA
PRINTBEST BANDWIDTH 0FORMATGRIDBESTESTIMATORBANDWIDTH
 USE THE BEST ESTIMATOR TO COMPUTE THE KERNEL DENSITY ESTIMATE
KDE  GRIDBESTESTIMATOR
 SAMPLE 44 NEW POINTS FROM THE DATA
NEWDATA  KDESAMPLE44 RANDOMSTATE0
NEWDATA  PCAINVERSETRANSFORMNEWDATA
 TURN DATA INTO A 4X11 GRID
NEWDATA  NEWDATARESHAPE4 11 1
REALDATA  DIGITSDATA44RESHAPE4 11 1
 PLOT REAL DIGITS AND RESAMPLED DIGITS
FIG AX  PLTSUBPLOTS9 11 SUBPLOTKWDICTXTICKS YTICKS
FORJINRANGE11
AX4 JSETVISIBLEFALSE
FORIINRANGE4
IM  AXI JIMSHOWREALDATAI JRESHAPE8 8
CMAPPLTCMBINARY INTERPOLATIONNEAREST
IMSETCLIM0 16
IM  AXI  5 JIMSHOWNEWDATAI JRESHAPE8 8
CMAPPLTCMBINARY INTERPOLATIONNEAREST
IMSETCLIM0 16
AX0 5SETTITLESELECTION FROM THE INPUT DATA
AX5 5SETTITLENEW DIGITS DRAWN FROM THE KERNEL DENSITY MODEL
PLTSHOW
```
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 4482 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5236 NOVELTY DETECTION WITH LOCAL OUTLIER FACTOR LOF
THE LOCAL OUTLIER FACTOR LOF ALGORITHM IS AN UNSUPERVISED ANOMALY DETECTION METHOD WHICH COMPUTES THE LOCAL DENSITY DEVIATION OF A GIVEN DATA POINT WITH RESPECT TO ITS NEIGHBORS IT CONSIDERS AS OUTLIERS THE SAMPLES THAT HAVE A SUBSTANTIALLY LOWER DENSITY THAN THEIR NEIGHBORS THIS EXAMPLE SHOWS HOW TO USE LOF FOR NOVELTY DETECTION NOTE THAT WHEN LOF IS USED FOR NOVELTY DETECTION YOU MUST NOT USE PREDICT DECISIONFUNCTION AND SCORESAMPLES ON THE TRAINING SET AS THIS WOULD LEAD TO WRONG RESULTS YOU MUST ONLY USE THESE METHODS ON NEW UNSEEN DATA WHICH ARE NOT IN THE TRAINING SET SEE USER GUIDE FOR DETAILS ON THE DIFFERENCE BETWEEN OUTLIER DETECTION AND NOVELTY DETECTION AND HOW TO USE LOF FOR OUTLIER DETECTION
THE NUMBER OF NEIGHBORS CONSIDERED PARAMETER NNEIGHBORS IS TYPICALLY SET 1 GREATER THAN THE MINIMUM NUMBER OF SAMPLES A CLUSTER HAS TO CONTAIN SO THAT OTHER SAMPLES CAN BE LOCAL OUTLIERS RELATIVE TO THIS CLUSTER AND 2 SMALLER THAN THE MAXIMUM NUMBER OF CLOSE BY SAMPLES THAT CAN POTENTIALLY BE LOCAL OUTLIERS IN PRACTICE SUCH INFORMATIONS ARE GENERALLY NOT AVAILABLE AND TAKING NNEIGHBORS20 APPEARS TO WORK WELL IN GENERAL

```
SCIKITLEARN USER GUIDE RELEASE 0213
IMPORT NUMPY AS NP
IMPORT MATPLOTLIB
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNNEIGHBORS IMPORT LOCALOUTLIERFACTOR
PRINTDOC
NPRANDOMSEED42
XX YY  NPMESHGRIDNPLINSPACE5 5 500 NPLINSPACE5 5 500
 GENERATE NORMAL NOT ABNORMAL TRAINING OBSERVATIONS
X  03 NPRANDOMRANDN100 2
XTRAIN  NPRX  2 X  2
 GENERATE NEW NORMAL NOT ABNORMAL OBSERVATIONS
X  03 NPRANDOMRANDN20 2
XTEST  NPRX  2 X  2
 GENERATE SOME ABNORMAL NOVEL OBSERVATIONS
XOUTLIERS  NPRANDOMUNIFORMLOW4 HIGH4 SIZE20 2
 FIT THE MODEL FOR NOVELTY DETECTION NOVELTYTRUE
CLF  LOCALOUTLIERFACTORNNEIGHBORS20 NOVELTYTRUE CONTAMINATION01
CLFFITXTRAIN
 DO NOT USE PREDICT DECISIONFUNCTION AND SCORESAMPLES ON XTRAIN AS THIS
 WOULD GIVE WRONG RESULTS BUT ONLY ON NEW UNSEEN DATA NOT USED IN XTRAIN
 EG XTEST XOUTLIERS OR THE MESHGRID
YPREDTEST  CLFPREDICTXTEST
523 NEAREST NEIGHBORS 1327
```

SCIKITLEARN USER GUIDE RELEASE 0213
YPREDOUTLIERS CLFPREDICTXOUTLIERS
NERRORTEST YPREDTESTYPREDTEST 1SIZE
NERROROUTLIERS YPREDOUTLIERSYPREDOUTLIERS 1SIZE
 PLOT THE LEARNED FRONTIER THE POINTS AND THE NEAREST VECTORS TO THE PLANE
Z CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
PLTTITLENOVELTY DETECTION WITH LOF
PLTCONTOURFXX YY Z LEVELSNPLINSPACEZMIN 0 7 CMAPPLTCMPUBU
A PLTCONTOURXX YY Z LEVELS0 LINEWIDTHS2 COLORSDARKRED
PLTCONTOURFXX YY Z LEVELS0 ZMAX COLORSPALEVIOLETRED
S 40
B1 PLTSCATTERXTRAIN 0 XTRAIN 1 CWHITE SS EDGECOLORSK
B2 PLTSCATTERXTEST 0 XTEST 1 CBLUEVIOLET SS
EDGECOLORSK
C PLTSCATTERXOUTLIERS 0 XOUTLIERS 1 CGOLD SS
EDGECOLORSK
PLTAXISTIGHT
PLTXLIM5 5
PLTYLIM5 5
PLTLEGENDACOLLECTIONS0 B1 B2 C
LEARNED FRONTIER TRAINING OBSERVATIONS
NEW REGULAR OBSERVATIONS NEW ABNORMAL OBSERVATIONS
LOCUPPER LEFT
PROPMATPLOTLIBFONTMANAGERFONTPROPERTIESSIZE11
PLTXLABEL
ERRORS NOVEL REGULAR D40 ERRORS NOVEL ABNORMAL D40
 NERRORTEST NERROROUTLIERS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0634 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5237 COMPARING NEAREST NEIGHBORS WITH AND WITHOUT NEIGHBORHOOD COMPONENTS
ANALYSIS
AN EXAMPLE COMPARING NEAREST NEIGHBORS CLASSIFICATION WITH AND WITHOUT NEIGHBORHOOD COMPONENTS ANALYSIS
IT WILL PLOT THE CLASS DECISION BOUNDARIES GIVEN BY A NEAREST NEIGHBORS CLASSIFIER WHEN USING THE EUCLIDEAN DISTANCE
ON THE ORIGINAL FEATURES VERSUS USING THE EUCLIDEAN DISTANCE AFTER THE TRANSFORMATION LEARNED BY NEIGHBORHOOD COM
PONENTS ANALYSIS THE LATTER AIMS TO FIND A LINEAR TRANSFORMATION THAT MAXIMISES THE STOCHASTIC NEAREST NEIGHBOR
CLASSIFICATION ACCURACY ON THE TRAINING SET
1328 CHAPTER 5 EXAMPLES

```
•
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBCOLORS IMPORT LISTEDCOLORMAP
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSCLASSIFIER
NEIGHBORHOODCOMPONENTSANALYSIS
FROM SKLEARNPIPELINE IMPORT PIPELINE
PRINTDOC
NNEIGHBORS  1
DATASET  DATASETSLOADIRIS
X Y  DATASETDATA DATASETTARGET
 WE ONLY TAKE TWO FEATURES WE COULD AVOID THIS UGLY
 SLICING BY USING A TWODIM DATASET
X  X 0 2
XTRAIN XTEST YTRAIN YTEST
TRAINTESTSPLITX Y STRATIFYY TESTSIZE07 RANDOMSTATE42
```

SCIKITLEARN USER GUIDE RELEASE 0213
H 01 STEP SIZE IN THE MESH
 CREATE COLOR MAPS
CMAPLIGHT LISTEDCOLORMAPFFAAAA AAFFAA AAAAFF
CMAPBOLD LISTEDCOLORMAPFF0000 00FF00 0000FF
NAMES KNN NCA KNN
CLASSIFIERS PIPELINESCALER STANDARDSCALER
KNN KNEIGHBORSCLASSIFIERNNEIGHBORSNNEIGHBORS

PIPELINESCALER STANDARDSCALER
NCA NEIGHBORHOODCOMPONENTSANALYSIS
KNN KNEIGHBORSCLASSIFIERNNEIGHBORSNNEIGHBORS

XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX H
NPARANGEYMIN YMAX H
FORNAME CLF INZIPNAMES CLASSIFIERS
CLFFITXTRAIN YTRAIN
SCORE CLFSCOREXTEST YTEST
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
Z CLFPREDICTNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
PLTFIGURE
PLTPCOLORMESHXX YY Z CMAPCMAPLIGHT ALPHA8
 PLOT ALSO THE TRAINING AND TESTING POINTS
PLTSCATTERX 0 X 1 CY CMAPCMAPBOLD EDGECOLORK S20
PLTXLIMXXMIN XXMAX
PLTYLIMYYMIN YYMAX
PLTTITLE K FORMATNAME NNEIGHBORS
PLTTEXT09 01 2FFORMATSCORE SIZE15
HACENTER VACENTER TRANSFORMPLTGCATRANSAXES
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 16006 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5238 DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
SAMPLE USAGE OF NEIGHBORHOOD COMPONENTS ANALYSIS FOR DIMENSIONALITY REDUCTION
THIS EXAMPLE COMPARES DIFFERENT LINEAR DIMENSIONALITY REDUCTION METHODS APPLIED ON THE DIGITS DATA SET THE DATA
523 NEAREST NEIGHBORS 1331

SET CONTAINS IMAGES OF DIGITS FROM 0 TO 9 WITH APPROXIMATELY 180 SAMPLES OF EACH CLASS EACH IMAGE IS OF DIMENSION 8X8 64 AND IS REDUCED TO A TWODIMENSIONAL DATA POINT
PRINCIPAL COMPONENT ANALYSIS PCA APPLIED TO THIS DATA IDENTIFIES THE COMBINATION OF ATTRIBUTES PRINCIPAL COMPO NENTS OR DIRECTIONS IN THE FEATURE SPACE THAT ACCOUNT FOR THE MOST VARIANCE IN THE DATA HERE WE PLOT THE DIFFERENT SAMPLES ON THE 2 FIRST PRINCIPAL COMPONENTS
LINEAR DISCRIMINANT ANALYSIS LDA TRIES TO IDENTIFY ATTRIBUTES THAT ACCOUNT FOR THE MOST VARIANCE BETWEEN CLASSES IN PARTICULAR LDA IN CONTRAST TO PCA IS A SUPERVISED METHOD USING KNOWN CLASS LABELS
NEIGHBORHOOD COMPONENTS ANALYSIS NCA TRIES TO FIND A FEATURE SPACE SUCH THAT A STOCHASTIC NEAREST NEIGHBOR ALGO RITHM WILL GIVE THE BEST ACCURACY LIKE LDA IT IS A SUPERVISED METHOD
ONE CAN SEE THAT NCA ENFORCES A CLUSTERING OF THE DATA THAT IS VISUALLY MEANINGFUL DESPITE THE LARGE REDUCTION IN DIMENSION
•

•

LICENSE BSD 3 CLAUSE

```
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNDISCRIMINANTANALYSIS IMPORT LINEARDISCRIMINANTANALYSIS
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSCLASSIFIER
NEIGHBORHOODCOMPONENTSANALYSIS
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
PRINTDOC
NNEIGHBORS  3
RANDOMSTATE  0
 LOAD DIGITS DATASET
DIGITS  DATASETSLOADDIGITS
X Y  DIGITSDATA DIGITSTARGET
 SPLIT INTO TRAINTEST
XTRAIN XTEST YTRAIN YTEST
TRAINTESTSPLITX Y TESTSIZE05 STRATIFYY
RANDOMSTATERANDOMSTATE
```

SCIKITLEARN USER GUIDE RELEASE 0213
DIM LENX0
NCLASSES LENNPUNIQUEY
 REDUCE DIMENSION TO 2 WITH PCA
PCA MAKEPIPELINESTANDARDSCALER
PCANCOMPONENTS2 RANDOMSTATERANDOMSTATE
 REDUCE DIMENSION TO 2 WITH LINEARDISCRIMINANTANALYSIS
LDA MAKEPIPELINESTANDARDSCALER
LINEARDISCRIMINANTANALYSISNCOMPONENTS2
 REDUCE DIMENSION TO 2 WITH NEIGHBORHOODCOMPONENTANALYSIS
NCA MAKEPIPELINESTANDARDSCALER
NEIGHBORHOODCOMPONENTSANALYSISNCOMPONENTS2
RANDOMSTATERANDOMSTATE
 USE A NEAREST NEIGHBOR CLASSIFIER TO EVALUATE THE METHODS
KNN KNEIGHBORSCLASSIFIERNNEIGHBORSNNEIGHBORS
 MAKE A LIST OF THE METHODS TO BE COMPARED
DIMREDUCTIONMETHODS PCA PCA LDA LDA NCA NCA
 PLTFIGURE
FORI NAME MODEL INENUMERATEDIMREDUCTIONMETHODS
PLTFIGURE
 PLTSUBPLOT1 3 I 1 ASPECT1
 FIT THE METHODS MODEL
MODELFITXTRAIN YTRAIN
 FIT A NEAREST NEIGHBOR CLASSIFIER ON THE EMBEDDED TRAINING SET
KNNFITMODELTRANSFORMXTRAIN YTRAIN
 COMPUTE THE NEAREST NEIGHBOR ACCURACY ON THE EMBEDDED TEST SET
ACCKNN KNNSCOREMODELTRANSFORMXTEST YTEST
 EMBED THE DATA SET IN 2 DIMENSIONS USING THE FITTED MODEL
XEMBEDDED MODELTRANSFORMX
 PLOT THE PROJECTED POINTS AND SHOW THE EVALUATION SCORE
PLTSCATTERXEMBEDDED 0 XEMBEDDED 1 CY S30 CMAPSET1
PLTTITLE KNN K NTEST ACCURACY 2FFORMATNAME
NNEIGHBORS
ACCKNN
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 2879 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5239 KERNEL DENSITY ESTIMATE OF SPECIES DISTRIBUTIONS
THIS SHOWS AN EXAMPLE OF A NEIGHBORSBASED QUERY IN PARTICULAR A KERNEL DENSITY ESTIMATE ON GEOSPATIAL DATA USING
A BALL TREE BUILT UPON THE HAVERSINE DISTANCE METRIC – IE DISTANCES OVER POINTS IN LATITUDELONGITUDE THE DATASET
523 NEAREST NEIGHBORS 1335

IS PROVIDED BY PHILLIPS ET AL 2006 IF AVAILABLE THE EXAMPLE USES BASEMAP TO PLOT THE COAST LINES AND NATIONAL BOUNDARIES OF SOUTH AMERICA
THIS EXAMPLE DOES NOT PERFORM ANY LEARNING OVER THE DATA SEE SPECIES DISTRIBUTION MODELING FOR AN EXAMPLE OF CLASSIFICATION BASED ON THE ATTRIBUTES IN THIS DATASET IT SIMPLY SHOWS THE KERNEL DENSITY ESTIMATE OF OBSERVED DATA POINTS IN GEOSPATIAL COORDINATES
THE TWO SPECIES ARE
• “BRADYPUS VARIEGATUS” THE BROWNTHROATED SLOTH
• “MICRORYZOMYS MINUTUS” ALSO KNOWN AS THE FOREST SMALL RICE RAT A RODENT THAT LIVES IN PERU COLOMBIA ECUADOR PERU AND VENEZUELA
REFERENCES
• “MAXIMUM ENTROPY MODELING OF SPECIES GEOGRAPHIC DISTRIBUTIONS” S J PHILLIPS R P ANDERSON R E SCHAPIRE ECOLOGICAL MODELLING 190231259 2006
OUT
```
COMPUTING KDE IN SPHERICAL COORDINATES
PLOT COASTLINES FROM COVERAGE
COMPUTING KDE IN SPHERICAL COORDINATES
PLOT COASTLINES FROM COVERAGE
```

SCIKITLEARN USER GUIDE RELEASE 0213
 AUTHOR JAKE VANDERPLAS JAKEVDPCSWASHINGTONEDU

 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT FETCHSPECIESDISTRIBUTIONS
FROM SKLEARNDATASETSSPECIESDISTRIBUTIONS IMPORT CONSTRUCTGRIDS
FROM SKLEARNNEIGHBORS IMPORT KERNELDENSITY
 IF BASEMAP IS AVAILABLE WELL USE IT
 OTHERWISE WELL IMPROVISE LATER
TRY
FROM MPLTOOLKITSBASEMAP IMPORT BASEMAP
BASEMAP TRUE
EXCEPTIMPORTERROR
BASEMAP FALSE
 GET MATRICESARRAYS OF SPECIES IDS AND LOCATIONS
DATA FETCHSPECIESDISTRIBUTIONS
SPECIESNAMES BRADYPUS VARIEGATUS MICRORYZOMYS MINUTUS
XTRAIN NPVSTACKDATATRAINDD LAT
DATATRAINDD LONGT
YTRAIN NPARRAYDDECODEASCIISTARTSWITHMICRO
FORDINDATATRAINSPECIES DTYPEINT
XTRAIN NPPI 180 CONVERT LATLONG TO RADIANS
 SET UP THE DATA GRID FOR THE CONTOUR PLOT
XGRID YGRID CONSTRUCTGRIDSDATA
X Y NPMESHGRIDXGRID5 YGRID51
LANDREFERENCE DATACOVERAGES65 5
LANDMASK LANDREFERENCE 9999RAVEL
XY NPVSTACKYRAVEL XRAVELT
XY XYLANDMASK
XY NPPI 180
 PLOT MAP OF SOUTH AMERICA WITH DISTRIBUTIONS OF EACH SPECIES
FIG PLTFIGURE
FIGSUBPLOTSADJUSTLEFT005 RIGHT095 WSPACE005
FORIINRANGE2
PLTSUBPLOT1 2 I 1
 CONSTRUCT A KERNEL DENSITY ESTIMATE OF THE DISTRIBUTION
PRINT COMPUTING KDE IN SPHERICAL COORDINATES
KDE KERNELDENSITYBANDWIDTH004 METRICHAVERSINE
KERNELGAUSSIAN ALGORITHMBALLTREE
KDEFITXTRAINYTRAIN I
 EVALUATE ONLY ON THE LAND 9999 INDICATES OCEAN
Z NPFULLLANDMASKSHAPE0 9999 DTYPEINT
ZLANDMASK NPEXPKDESCORESAMPLESXY
Z ZRESHAPEXSHAPE
523 NEAREST NEIGHBORS 1337

```
 PLOT CONTOURS OF THE DENSITY
LEVELS  NPLINSPACE0 ZMAX 25
PLTCONTOURFX Y Z LEVELSLEVELS CMAPPLTCMREDS
IFBASEMAP
PRINT  PLOT COASTLINES USING BASEMAP
M  BASEMAPPROJECTIONCYL LLCRNRLATYMIN
URCRNRLATYMAX LLCRNRLONXMIN
URCRNRLONXMAX RESOLUTIONC
MDRAWCOASTLINES
MDRAWCOUNTRIES
ELSE
PRINT  PLOT COASTLINES FROM COVERAGE
PLTCONTOURX Y LANDREFERENCE
LEVELS9998 COLORSK
LINESTYLESSOLID
PLTXTICKS
PLTYTICKS
PLTTITLESPECIESNAMESI
PLTSHOW
```
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 5470 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52310 NEIGHBORHOOD COMPONENTS ANALYSIS ILLUSTRATION
AN EXAMPLE ILLUSTRATING THE GOAL OF LEARNING A DISTANCE METRIC THAT MAXIMIZES THE NEAREST NEIGHBORS CLASSIFICATION ACCURACY THE EXAMPLE IS SOLELY FOR ILLUSTRATION PURPOSES PLEASE REFER TO THE USER GUIDE FOR MORE INFORMATION

```
•
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
FROM SKLEARNNEIGHBORS IMPORT NEIGHBORHOODCOMPONENTSANALYSIS
FROM MATPLOTLIB IMPORT CM
FROM SKLEARNUTILSFIXES IMPORT LOGSUMEXP
PRINTDOC
NNEIGHBORS  1
RANDOMSTATE  0
 CREATE A TINY DATA SET OF 9 SAMPLES FROM 3 CLASSES
X Y  MAKECLASSIFICATIONNSAMPLES9 NFEATURES2 NINFORMATIVE2
NREDUNDANT0 NCLASSES3 NCLUSTERSPERCLASS1
CLASSSEP10 RANDOMSTATERANDOMSTATE
 PLOT THE POINTS IN THE ORIGINAL SPACE
PLTFIGURE
AX  PLTGCA
 DRAW THE GRAPH NODES
FORIINRANGEXSHAPE0
AXTEXTXI 0 XI 1 STRI VACENTER HACENTER
AXSCATTERXI 0 XI 1 S300 CCMSET1YI ALPHA04
```

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DEFPIX I
DIFFEMBEDDED XI X
DISTEMBEDDED NPEINSUMIJIJI DIFFEMBEDDED
DIFFEMBEDDED
DISTEMBEDDEDI NPINF
 COMPUTE EXPONENTIATED DISTANCES USE THE LOGSUMEXP TRICK TO
 AVOID NUMERICAL INSTABILITIES
EXPDISTEMBEDDED NPEXPDISTEMBEDDED
LOGSUMEXPDISTEMBEDDED
RETURNEXPDISTEMBEDDED
DEFRELATEPOINTX I AX
PTI XI
FORJ PTJ INENUMERATEX
THICKNESS PIX I
IFI J
LINE PTI0 PTJ0 PTI1 PTJ1
AXPLOT LINE CCMSET1YJ
LINEWIDTH5 THICKNESSJ
 WE CONSIDER ONLY POINT 3
I 3
 PLOT BONDS LINKED TO SAMPLE I IN THE ORIGINAL SPACE
RELATEPOINTX I AX
AXSETTITLEORIGINAL POINTS
AXAXESGETXAXISSETVISIBLEFALSE
AXAXESGETYAXISSETVISIBLEFALSE
AXAXISEQUAL
 LEARN AN EMBEDDING WITH NEIGHBORHOODCOMPONENTSANALYSIS
NCA NEIGHBORHOODCOMPONENTSANALYSISMAXITER30 RANDOMSTATERANDOMSTATE
NCA NCAFITX Y
 PLOT THE POINTS AFTER TRANSFORMATION WITH NEIGHBORHOODCOMPONENTSANALYSIS
PLTFIGURE
AX2 PLTGCA
 GET THE EMBEDDING AND FIND THE NEW NEAREST NEIGHBORS
XEMBEDDED NCATRANSFORMX
RELATEPOINTXEMBEDDED I AX2
FORIINRANGELENX
AX2TEXTXEMBEDDEDI 0 XEMBEDDEDI 1 STRI
VACENTER HACENTER
AX2SCATTERXEMBEDDEDI 0 XEMBEDDEDI 1 S300 CCMSET1YI
ALPHA04
 MAKE AXES EQUAL SO THAT BOUNDARIES ARE DISPLAYED CORRECTLY AS CIRCLES
AX2SETTITLENCA EMBEDDING
AX2AXESGETXAXISSETVISIBLEFALSE
AX2AXESGETYAXISSETVISIBLEFALSE
523 NEAREST NEIGHBORS 1341

AX2AXISEQUAL
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0069 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52311 SIMPLE 1D KERNEL DENSITY ESTIMATION
THIS EXAMPLE USES THE SKLEARNNEIGHBORSKERNELDENSITY CLASS TO DEMONSTRATE THE PRINCIPLES OF KERNEL DENSITY ESTIMATION IN ONE DIMENSION
THE FIRST PLOT SHOWS ONE OF THE PROBLEMS WITH USING HISTOGRAMS TO VISUALIZE THE DENSITY OF POINTS IN 1D INTUITIVELY A HISTOGRAM CAN BE THOUGHT OF AS A SCHEME IN WHICH A UNIT “BLOCK” IS STACKED ABOVE EACH POINT ON A REGULAR GRID AS THE TOP TWO PANELS SHOW HOWEVER THE CHOICE OF GRIDDING FOR THESE BLOCKS CAN LEAD TO WILDLY DIVERGENT IDEAS ABOUT THE UNDERLYING SHAPE OF THE DENSITY DISTRIBUTION IF WE INSTEAD CENTER EACH BLOCK ON THE POINT IT REPRESENTS WE GET THE ESTIMATE SHOWN IN THE BOTTOM LEFT PANEL THIS IS A KERNEL DENSITY ESTIMATION WITH A “TOP HAT” KERNEL THIS IDEA CAN BE GENERALIZED TO OTHER KERNEL SHAPES THE BOTTOMRIGHT PANEL OF THE FIRST FIGURE SHOWS A GAUSSIAN KERNEL DENSITY ESTIMATE OVER THE SAME DISTRIBUTION
SCIKITLEARN IMPLEMENTS EFFICIENT KERNEL DENSITY ESTIMATION USING EITHER A BALL TREE OR KD TREE STRUCTURE THROUGH THE SKLEARNNEIGHBORSKERNELDENSITY ESTIMATOR THE AVAILABLE KERNELS ARE SHOWN IN THE SECOND FIGURE OF THIS EXAMPLE
THE THIRD FIGURE COMPARES KERNEL DENSITY ESTIMATES FOR A DISTRIBUTION OF 100 SAMPLES IN 1 DIMENSION THOUGH THIS EXAMPLE USES 1D DISTRIBUTIONS KERNEL DENSITY ESTIMATION IS EASILY AND EFFICIENTLY EXTENSIBLE TO HIGHER DIMENSIONS AS WELL

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SCIKITLEARN USER GUIDE RELEASE 0213

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AUTHOR JAKE VANDERPLAS JAKEVDPCSWASHINGTONEDU

```
IMPORT NUMPY AS NP
IMPORT MATPLOTLIB
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM DISTUTILSVERSION IMPORT LOOSEVERSION
FROM SCIPYSTATS IMPORT NORM
FROM SKLEARNNEIGHBORS IMPORT KERNELDENSITY
 NORMED IS BEING DEPRECATED IN FAVOR OF DENSITY IN HISTOGRAMS
IFLOOSEVERSIONMATPLOTLIBVERSION  21
DENSITYPARAM  DENSITY TRUE
ELSE
DENSITYPARAM  NORMED TRUE

 PLOT THE PROGRESSION OF HISTOGRAMS TO KERNELS
NPRANDOMSEED1
N  20
X  NPCONCATENATENPRANDOMNORMAL0 1 INT03 N
NPRANDOMNORMAL5 1 INT07 N NPNEWAXIS
XPLOT  NPLINSPACE5 10 1000 NPNEWAXIS
BINS  NPLINSPACE5 10 10
FIG AX  PLTSUBPLOTS2 2 SHAREXTRUE SHAREYTRUE
FIGSUBPLOTSADJUSTHSPACE005 WSPACE005
```

523 NEAREST NEIGHBORS 1345

```
 HISTOGRAM 1
AX0 0HISTX 0 BINSBINS FCAAAAFF DENSITYPARAM
AX0 0TEXT35 031 HISTOGRAM
 HISTOGRAM 2
AX0 1HISTX 0 BINSBINS  075 FCAAAAFF DENSITYPARAM
AX0 1TEXT35 031 HISTOGRAM BINS SHIFTED
 TOPHAT KDE
KDE  KERNELDENSITYKERNELTOPHAT BANDWIDTH075FITX
LOGDENS  KDESCORESAMPLESXPLOT
AX1 0FILLXPLOT 0 NPEXPLOGDENS FCAAAAFF
AX1 0TEXT35 031 TOPHAT KERNEL DENSITY
 GAUSSIAN KDE
KDE  KERNELDENSITYKERNELGAUSSIAN BANDWIDTH075FITX
LOGDENS  KDESCORESAMPLESXPLOT
AX1 1FILLXPLOT 0 NPEXPLOGDENS FCAAAAFF
AX1 1TEXT35 031 GAUSSIAN KERNEL DENSITY
FORAXIINAXRAVEL
AXIPLOTX 0 NPFULLXSHAPE0 001 K
AXISETXLIM4 9
AXISETYLIM002 034
FORAXIINAX 0
AXISETYLABELNORMALIZED DENSITY
FORAXIINAX1
AXISETXLABELX

 PLOT ALL AVAILABLE KERNELS
XPLOT  NPLINSPACE6 6 1000 NONE
XSRC  NPZEROS1 1
FIG AX  PLTSUBPLOTS2 3 SHAREXTRUE SHAREYTRUE
FIGSUBPLOTSADJUSTLEFT005 RIGHT095 HSPACE005 WSPACE005
DEFFORMATFUNCX LOC
IFX  0
RETURN0
ELIFX  1
RETURNH
ELIFX  1
RETURNH
ELSE
RETURNIH  X
FORI KERNEL INENUMERATEGAUSSIAN TOPHAT EPANECHNIKOV
EXPONENTIAL LINEAR COSINE
AXI  AXRAVELI
LOGDENS  KERNELDENSITYKERNELKERNELFITXSRCSCORESAMPLESXPLOT
AXIFILLXPLOT 0 NPEXPLOGDENS K FCAAAAFF
AXITEXT26 095 KERNEL
AXIXAXISSETMAJORFORMATTERPLTFUNCFORMATTERFORMATFUNC
```

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AXIXAXISSETMAJORLOCATORPLTMULTIPLELOCATOR1
AXIYAXISSETMAJORLOCATORPLTNULLLOCATOR
AXISETYLIM0 105
AXISETXLIM29 29
AX0 1SETTITLEAVAILABLE KERNELS

PLOT A 1D DENSITY EXAMPLE
N 100
NPRANDOMSEED1
X NPCONCATENATENPRANDOMNORMAL0 1 INT03 N
NPRANDOMNORMAL5 1 INT07 N NPNEWAXIS
XPLOT NPLINSPACE5 10 1000 NPNEWAXIS
TRUEDENS 03 NORM0 1PDFXPLOT 0
 07NORM5 1PDFXPLOT 0
FIG AX PLTSUBPLOTS
AXFILLXPLOT 0 TRUEDENS FCBLACK ALPHA02
LABELINPUT DISTRIBUTION
FORKERNELINGAUSSIAN TOPHAT EPANECHNIKOV
KDE KERNELDENSITYKERNELKERNEL BANDWIDTH05FITX
LOGDENS KDESCORESAMPLESXPLOT
AXPLOTXPLOT 0 NPEXPLOGDENS
LABELKERNEL 0FORMATKERNEL
AXTEXT6 038 N0 POINTSFORMATN
AXLEGENDLOCUPPER LEFT
AXPLOTX 0 0005 001 NPRANDOMRANDOMXSHAPE0 K
AXSETXLIM4 9
AXSETYLIM002 04
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0145 SECONDS
524 NEURAL NETWORKS
EXAMPLES CONCERNING THE SKLEARNNEURALNETWORK MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5241 VISUALIZATION OF MLP WEIGHTS ON MNIST
SOMETIMES LOOKING AT THE LEARNED COEFFICIENTS OF A NEURAL NETWORK CAN PROVIDE INSIGHT INTO THE LEARNING BEHAVIOR FOR EXAMPLE IF WEIGHTS LOOK UNSTRUCTURED MAYBE SOME WERE NOT USED AT ALL OR IF VERY LARGE COEFFICIENTS EXIST MAYBE REGULARIZATION WAS TOO LOW OR THE LEARNING RATE TOO HIGH

THIS EXAMPLE SHOWS HOW TO PLOT SOME OF THE FIRST LAYER WEIGHTS IN A MLPCLASSIFIER TRAINED ON THE MNIST DATASET
THE INPUT DATA CONSISTS OF 28X28 PIXEL HANDWRITTEN DIGITS LEADING TO 784 FEATURES IN THE DATASET THEREFORE THE FIRST LAYER WEIGHT MATRIX HAVE THE SHAPE 784 HIDDENLAYERSIZES0 WE CAN THEREFORE VISUALIZE A SINGLE COLUMN OF THE WEIGHT MATRIX AS A 28X28 PIXEL IMAGE
TO MAKE THE EXAMPLE RUN FASTER WE USE VERY FEW HIDDEN UNITS AND TRAIN ONLY FOR A VERY SHORT TIME TRAINING LONGER WOULD RESULT IN WEIGHTS WITH A MUCH SMOOTHER SPATIAL APPEARANCE
OUT
ITERATION 1 LOSS 032009978
ITERATION 2 LOSS 015347534
ITERATION 3 LOSS 011544755
ITERATION 4 LOSS 009279764
ITERATION 5 LOSS 007889367
ITERATION 6 LOSS 007170497
ITERATION 7 LOSS 006282111
ITERATION 8 LOSS 005530788
ITERATION 9 LOSS 004960484
ITERATION 10 LOSS 004645355
TRAINING SET SCORE 0986800
TEST SET SCORE 0970000

SCIKITLEARN USER GUIDE RELEASE 0213
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT FETCHOPENML
FROM SKLEARNNEURALNETWORK IMPORT MLPCLASSIFIER
PRINTDOC
 LOAD DATA FROM HTTPSWWWOPENMLORGD554
X Y FETCHOPENMLMNIST784 VERSION1 RETURNXYTRUE
X X 255
 RESCALE THE DATA USE THE TRADITIONAL TRAINTEST SPLIT
XTRAIN XTEST X60000 X60000
YTRAIN YTEST Y60000 Y60000
 MLP MLPCLASSIFIERHIDDENLAYERSIZES100 100 MAXITER400 ALPHA1E4
 SOLVERSGD VERBOSE10 TOL1E4 RANDOMSTATE1
MLP MLPCLASSIFIERHIDDENLAYERSIZES50 MAXITER10 ALPHA1E4
SOLVERSGD VERBOSE10 TOL1E4 RANDOMSTATE1
LEARNINGRATEINIT1
MLPFITXTRAIN YTRAIN
PRINTTRAINING SET SCORE F MLPSCOREXTRAIN YTRAIN
PRINTTEST SET SCORE F MLPSCOREXTEST YTEST
FIG AXES PLTSUBPLOTS4 4
 USE GLOBAL MIN MAX TO ENSURE ALL WEIGHTS ARE SHOWN ON THE SAME SCALE
VMIN VMAX MLPCOEFS0MIN MLPCOEFS0MAX
FORCOEF AX INZIPMLPCOEFS0T AXESRAVEL
AXMATSHOWCOEFRESHAPE28 28 CMAPPLTCMGRAY VMIN5 VMIN
VMAX5 VMAX
AXSETXTICKS
AXSETYTICKS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 27631 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5242 RESTRICTED BOLTZMANN MACHINE FEATURES FOR DIGIT CLASSIFICATION
FOR GREYSCALE IMAGE DATA WHERE PIXEL VALUES CAN BE INTERPRETED AS DEGREES OF BLACKNESS ON A WHITE BACKGROUND LIKE HANDWRITTEN DIGIT RECOGNITION THE BERNOULLI RESTRICTED BOLTZMANN MACHINE MODEL BERNOULLIRBM CAN PERFORM EFFECTIVE NONLINEAR FEATURE EXTRACTION
IN ORDER TO LEARN GOOD LATENT REPRESENTATIONS FROM A SMALL DATASET WE ARTIFICIALLY GENERATE MORE LABELED DATA BY PER TURBING THE TRAINING DATA WITH LINEAR SHIFTS OF 1 PIXEL IN EACH DIRECTION
THIS EXAMPLE SHOWS HOW TO BUILD A CLASSIFICATION PIPELINE WITH A BERNOULLIRBM FEATURE EXTRACTOR AND A LOGISTICREGRESSION CLASSIFIER THE HYPERPARAMETERS OF THE ENTIRE MODEL LEARNING RATE HIDDEN LAYER SIZE REGU LARIZATION WERE OPTIMIZED BY GRID SEARCH BUT THE SEARCH IS NOT REPRODUCED HERE BECAUSE OF RUNTIME CONSTRAINTS LOGISTIC REGRESSION ON RAW PIXEL VALUES IS PRESENTED FOR COMPARISON THE EXAMPLE SHOWS THAT THE FEATURES EXTRACTED BY THE BERNOULLIRBM HELP IMPROVE THE CLASSIFICATION ACCURACY

OUT
BERNOULLIRBM ITERATION 1 PSEUDOLIKELIHOOD 2539 TIME 015S
BERNOULLIRBM ITERATION 2 PSEUDOLIKELIHOOD 2372 TIME 034S
BERNOULLIRBM ITERATION 3 PSEUDOLIKELIHOOD 2272 TIME 033S
BERNOULLIRBM ITERATION 4 PSEUDOLIKELIHOOD 2186 TIME 032S
BERNOULLIRBM ITERATION 5 PSEUDOLIKELIHOOD 2166 TIME 035S
BERNOULLIRBM ITERATION 6 PSEUDOLIKELIHOOD 2100 TIME 037S
BERNOULLIRBM ITERATION 7 PSEUDOLIKELIHOOD 2075 TIME 035S
BERNOULLIRBM ITERATION 8 PSEUDOLIKELIHOOD 2052 TIME 034S
BERNOULLIRBM ITERATION 9 PSEUDOLIKELIHOOD 2038 TIME 031S
BERNOULLIRBM ITERATION 10 PSEUDOLIKELIHOOD 2023 TIME 035S
BERNOULLIRBM ITERATION 11 PSEUDOLIKELIHOOD 2002 TIME 034S
BERNOULLIRBM ITERATION 12 PSEUDOLIKELIHOOD 1993 TIME 035S
BERNOULLIRBM ITERATION 13 PSEUDOLIKELIHOOD 1971 TIME 033S
BERNOULLIRBM ITERATION 14 PSEUDOLIKELIHOOD 1969 TIME 033S
BERNOULLIRBM ITERATION 15 PSEUDOLIKELIHOOD 1961 TIME 033S
BERNOULLIRBM ITERATION 16 PSEUDOLIKELIHOOD 1957 TIME 032S
BERNOULLIRBM ITERATION 17 PSEUDOLIKELIHOOD 1936 TIME 033S
BERNOULLIRBM ITERATION 18 PSEUDOLIKELIHOOD 1922 TIME 036S
BERNOULLIRBM ITERATION 19 PSEUDOLIKELIHOOD 1931 TIME 035S
BERNOULLIRBM ITERATION 20 PSEUDOLIKELIHOOD 1921 TIME 034S
LOGISTIC REGRESSION USING RBM FEATURES
PRECISION RECALL F1SCORE SUPPORT
0 099 098 099 174
1 094 095 094 184
2 089 096 092 166
3 093 088 090 194
4 096 094 095 186
5 092 090 091 181
6 098 098 098 207

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7 092 099 096 154
8 087 084 086 182
9 091 091 091 169
ACCURACY 093 1797
MACRO AVG 093 093 093 1797
WEIGHTED AVG 093 093 093 1797
LOGISTIC REGRESSION USING RAW PIXEL FEATURES
PRECISION RECALL F1SCORE SUPPORT
0 090 091 091 174
1 060 058 059 184
2 075 085 080 166
3 078 078 078 194
4 081 084 083 186
5 076 077 077 181
6 091 087 089 207
7 085 088 087 154
8 067 057 062 182
9 075 077 076 169
ACCURACY 078 1797
MACRO AVG 078 078 078 1797
WEIGHTED AVG 078 078 078 1797
PRINTDOC
AUTHORS YANN N DAUPHIN VLAD NICULAE GABRIEL SYNNAEVE
LICENSE BSD
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPYNDIMAGE IMPORT CONVOLVE
FROM SKLEARN IMPORT LINEARMODEL DATASETS METRICS
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNNEURALNETWORK IMPORT BERNOULLIRBM
FROM SKLEARNPIPELINE IMPORT PIPELINE
FROM SKLEARNBASE IMPORT CLONE

SETTING UP
DEFNUDGEDATASETX Y

THIS PRODUCES A DATASET 5 TIMES BIGGER THAN THE ORIGINAL ONE
BY MOVING THE 8X8 IMAGES IN X AROUND BY 1PX TO LEFT RIGHT DOWN UP

DIRECTIONVECTORS
0 1 0
524 NEURAL NETWORKS 1351

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0 0 0
0 0 0
0 0 0
1 0 0
0 0 0
0 0 0
0 0 1
0 0 0
0 0 0
0 0 0
0 1 0
DEFSHIFTX W
RETURNCONVOLVEXRESHAPE8 8 MODECONSTANT WEIGHTSWRAVEL
X NPCONCATENATEX
NPAPPLYALONGAXISSHIFT 1 X VECTOR
FORVECTORINDIRECTIONVECTORS
Y NPCONCATENATEY FORINRANGE5 AXIS0
RETURNX Y
 LOAD DATA
DIGITS DATASETSLOADDIGITS
X NPASARRAYDIGITSDATA FLOAT32
X Y NUDGEDATASETX DIGITSTARGET
X X NPMINX 0 NPMAXX 0 00001 01 SCALING
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLIT
X Y TESTSIZE02 RANDOMSTATE0
 MODELS WE WILL USE
LOGISTIC LINEARMODELLOGISTICREGRESSIONSOLVERNEWTONCG TOL1
MULTICLASSMULTINOMIAL
RBM BERNOULLIRBMRANDOMSTATE0 VERBOSETRUE
RBMFEATURESCLASSIFIER PIPELINE
STEPSRBM RBM LOGISTIC LOGISTIC

 TRAINING
 HYPERPARAMETERS THESE WERE SET BY CROSSVALIDATION
 USING A GRIDSEARCHCV HERE WE ARE NOT PERFORMING CROSSVALIDATION TO
 SAVE TIME
RBMLEARNINGRATE 006
RBMNITER 20
 MORE COMPONENTS TEND TO GIVE BETTER PREDICTION PERFORMANCE BUT LARGER
 FITTING TIME
RBMNCOMPONENTS 100
LOGISTICC 6000
 TRAINING RBMLOGISTIC PIPELINE
RBMFEATURESCLASSIFIERFITXTRAIN YTRAIN

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TRAINING THE LOGISTIC REGRESSION CLASSIFIER DIRECTLY ON THE PIXEL
RAWPIXELCLASSIFIER CLONELOGISTIC
RAWPIXELCLASSIFIERC 100
RAWPIXELCLASSIFIERFITXTRAIN YTRAIN

EVALUATION
YPRED RBMFEATURESCLASSIFIERPREDICTXTEST
PRINTLOGISTIC REGRESSION USING RBM FEATURES NSN
METRICSCLASSIFICATIONREPORTYTEST YPRED
YPRED RAWPIXELCLASSIFIERPREDICTXTEST
PRINTLOGISTIC REGRESSION USING RAW PIXEL FEATURES NSN
METRICSCLASSIFICATIONREPORTYTEST YPRED

PLOTTING
PLTFIGUREFIGSIZE42 4
FORI COMP INENUMERATERBMCOMPONENTS
PLTSUBPLOT10 10 I 1
PLTIMSHOWCOMPRESHAPE8 8 CMAPPLTCMGRAYR
INTERPOLATIONNEAREST
PLTXTICKS
PLTYTICKS
PLTSUPTITLE100 COMPONENTS EXTRACTED BY RBM FONTSIZE16
PLTSUBPLOTSADJUST008 002 092 085 008 023
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 11939 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5243 VARYING REGULARIZATION IN MULTILAYER PERCEPTRON
A COMPARISON OF DIFFERENT VALUES FOR REGULARIZATION PARAMETER ‘ALPHA’ ON SYNTHETIC DATASETS THE PLOT SHOWS THAT DIFFERENT ALPHAS YIELD DIFFERENT DECISION FUNCTIONS
ALPHA IS A PARAMETER FOR REGULARIZATION TERM AKA PENALTY TERM THAT COMBATS OVERFITTING BY CONSTRAINING THE SIZE OF THE WEIGHTS INCREASING ALPHA MAY FIX HIGH VARIANCE A SIGN OF OVERFITTING BY ENCOURAGING SMALLER WEIGHTS RESULTING IN A DECISION BOUNDARY PLOT THAT APPEARS WITH LESSER CURVATURES SIMILARLY DECREASING ALPHA MAY FIX HIGH BIAS A SIGN OF UNDERFITTING BY ENCOURAGING LARGER WEIGHTS POTENTIALLY RESULTING IN A MORE COMPLICATED DECISION BOUNDARY
524 NEURAL NETWORKS 1353

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PRINTDOC
 AUTHOR ISSAM H LARADJI
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM MATPLOTLIBCOLORS IMPORT LISTEDCOLORMAP
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM SKLEARNDATASETS IMPORT MAKEMOONS MAKECIRCLES MAKECLASSIFICATION
FROM SKLEARNNEURALNETWORK IMPORT MLPCLASSIFIER
H 02 STEP SIZE IN THE MESH
ALPHAS NPLOGSPACE5 3 5
NAMES ALPHA   STRI FORIINALPHAS
CLASSIFIERS
FORIINALPHAS
CLASSIFIERSAPPENDMLPCLASSIFIERSOLVERLBFGS ALPHAI RANDOMSTATE1
HIDDENLAYERSIZES100 100
X Y MAKECLASSIFICATIONNFEATURES2 NREDUNDANT0 NINFORMATIVE2
RANDOMSTATE0 NCLUSTERSPERCLASS1
RNG NPRANDOMRANDOMSTATE2
X 2RNGUNIFORMSIZEXSHAPE
LINEARLYSEPARABLE X Y
DATASETS MAKEMOONSNOISE03 RANDOMSTATE0
MAKECIRCLESNOISE02 FACTOR05 RANDOMSTATE1
LINEARLYSEPARABLE
FIGURE PLTFIGUREFIGSIZE17 9

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```
I  1
 ITERATE OVER DATASETS
FORX YINDATASETS
 PREPROCESS DATASET SPLIT INTO TRAINING AND TEST PART
X  STANDARDSCALERFITTRANSFORMX
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLITX Y TESTSIZE4
XMIN XMAX  X 0MIN  5 X 0MAX  5
YMIN YMAX  X 1MIN  5 X 1MAX  5
XX YY  NPMESHGRIDNPARANGEXMIN XMAX H
NPARANGEYMIN YMAX H
 JUST PLOT THE DATASET FIRST
CM  PLTCMRDBU
CMBRIGHT  LISTEDCOLORMAPFF0000 0000FF
AX  PLTSUBPLOTLENDATASETS LENCLASSIFIERS  1 I
 PLOT THE TRAINING POINTS
AXSCATTERXTRAIN 0 XTRAIN 1 CYTRAIN CMAPCMBRIGHT
 AND TESTING POINTS
AXSCATTERXTEST 0 XTEST 1 CYTEST CMAPCMBRIGHT ALPHA06
AXSETXLIMXXMIN XXMAX
AXSETYLIMYYMIN YYMAX
AXSETXTICKS
AXSETYTICKS
I  1
 ITERATE OVER CLASSIFIERS
FORNAME CLF INZIPNAMES CLASSIFIERS
AX  PLTSUBPLOTLENDATASETS LENCLASSIFIERS  1 I
CLFFITXTRAIN YTRAIN
SCORE  CLFSCOREXTEST YTEST
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
IFHASATTRCLF DECISIONFUNCTION
Z  CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
ELSE
Z  CLFPREDICTPROBANPCXXRAVEL YYRAVEL 1
 PUT THE RESULT INTO A COLOR PLOT
Z  ZRESHAPEXXSHAPE
AXCONTOURFXX YY Z CMAPCM ALPHA8
 PLOT ALSO THE TRAINING POINTS
AXSCATTERXTRAIN 0 XTRAIN 1 CYTRAIN CMAPCMBRIGHT
EDGECOLORSBLACK S25
 AND TESTING POINTS
AXSCATTERXTEST 0 XTEST 1 CYTEST CMAPCMBRIGHT
ALPHA06 EDGECOLORSBLACK S25
AXSETXLIMXXMIN XXMAX
AXSETYLIMYYMIN YYMAX
AXSETXTICKS
AXSETYTICKS
AXSETTITLENAME
AXTEXTXXMAX  3 YYMIN  3  2F  SCORELSTRIP0
SIZE15 HORIZONTALALIGNMENTRIGHT
I  1
```

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FIGURESUBPLOTSADJUSTLEFT02 RIGHT98
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 7509 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5244 COMPARE STOCHASTIC LEARNING STRATEGIES FOR MLPCLASSIFIER
THIS EXAMPLE VISUALIZES SOME TRAINING LOSS CURVES FOR DIFFERENT STOCHASTIC LEARNING STRATEGIES INCLUDING SGD AND ADAM BECAUSE OF TIMECONSTRAINTS WE USE SEVERAL SMALL DATASETS FOR WHICH LBFGS MIGHT BE MORE SUITABLE THE GENERAL TREND SHOWN IN THESE EXAMPLES SEEMS TO CARRY OVER TO LARGER DATASETS HOWEVER
NOTE THAT THOSE RESULTS CAN BE HIGHLY DEPENDENT ON THE VALUE OF LEARNINGRATEINIT
OUT
LEARNING ON DATASET IRIS
TRAINING CONSTANT LEARNINGRATE
TRAINING SET SCORE 0980000
TRAINING SET LOSS 0096950
TRAINING CONSTANT WITH MOMENTUM
TRAINING SET SCORE 0980000
TRAINING SET LOSS 0049530
TRAINING CONSTANT WITH NESTEROVS MOMENTUM

SCIKITLEARN USER GUIDE RELEASE 0213
TRAINING SET SCORE 0980000
TRAINING SET LOSS 0049540
TRAINING INVSCALING LEARNINGRATE
TRAINING SET SCORE 0360000
TRAINING SET LOSS 0978444
TRAINING INVSCALING WITH MOMENTUM
TRAINING SET SCORE 0860000
TRAINING SET LOSS 0503452
TRAINING INVSCALING WITH NESTEROVS MOMENTUM
TRAINING SET SCORE 0860000
TRAINING SET LOSS 0504185
TRAINING ADAM
TRAINING SET SCORE 0980000
TRAINING SET LOSS 0045311
LEARNING ON DATASET DIGITS
TRAINING CONSTANT LEARNINGRATE
TRAINING SET SCORE 0956038
TRAINING SET LOSS 0243802
TRAINING CONSTANT WITH MOMENTUM
TRAINING SET SCORE 0992766
TRAINING SET LOSS 0041297
TRAINING CONSTANT WITH NESTEROVS MOMENTUM
TRAINING SET SCORE 0993879
TRAINING SET LOSS 0042898
TRAINING INVSCALING LEARNINGRATE
TRAINING SET SCORE 0638843
TRAINING SET LOSS 1855465
TRAINING INVSCALING WITH MOMENTUM
TRAINING SET SCORE 0912632
TRAINING SET LOSS 0290584
TRAINING INVSCALING WITH NESTEROVS MOMENTUM
TRAINING SET SCORE 0909293
TRAINING SET LOSS 0318387
TRAINING ADAM
TRAINING SET SCORE 0991653
TRAINING SET LOSS 0045934
LEARNING ON DATASET CIRCLES
TRAINING CONSTANT LEARNINGRATE
TRAINING SET SCORE 0840000
TRAINING SET LOSS 0601052
TRAINING CONSTANT WITH MOMENTUM
TRAINING SET SCORE 0940000
TRAINING SET LOSS 0157334
TRAINING CONSTANT WITH NESTEROVS MOMENTUM
TRAINING SET SCORE 0940000
TRAINING SET LOSS 0154453
TRAINING INVSCALING LEARNINGRATE
TRAINING SET SCORE 0500000
TRAINING SET LOSS 0692470
TRAINING INVSCALING WITH MOMENTUM
TRAINING SET SCORE 0500000
TRAINING SET LOSS 0689143
TRAINING INVSCALING WITH NESTEROVS MOMENTUM
TRAINING SET SCORE 0500000
TRAINING SET LOSS 0689751
TRAINING ADAM
524 NEURAL NETWORKS 1357

SCIKITLEARN USER GUIDE RELEASE 0213
TRAINING SET SCORE 0940000
TRAINING SET LOSS 0150527
LEARNING ON DATASET MOONS
TRAINING CONSTANT LEARNINGRATE
TRAINING SET SCORE 0850000
TRAINING SET LOSS 0341523
TRAINING CONSTANT WITH MOMENTUM
TRAINING SET SCORE 0850000
TRAINING SET LOSS 0336188
TRAINING CONSTANT WITH NESTEROVS MOMENTUM
TRAINING SET SCORE 0850000
TRAINING SET LOSS 0335919
TRAINING INVSCALING LEARNINGRATE
TRAINING SET SCORE 0500000
TRAINING SET LOSS 0689015
TRAINING INVSCALING WITH MOMENTUM
TRAINING SET SCORE 0830000
TRAINING SET LOSS 0512595
TRAINING INVSCALING WITH NESTEROVS MOMENTUM
TRAINING SET SCORE 0830000
TRAINING SET LOSS 0513034
TRAINING ADAM
TRAINING SET SCORE 0930000
TRAINING SET LOSS 0170087
PRINTDOC
IMPORT WARNINGS
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNNEURALNETWORK IMPORT MLPCLASSIFIER
FROM SKLEARNPREPROCESSING IMPORT MINMAXSCALER
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNEXCEPTIONS IMPORT CONVERGENCEWARNING
 DIFFERENT LEARNING RATE SCHEDULES AND MOMENTUM PARAMETERS
PARAMS SOLVER SGD LEARNINGRATE CONSTANT MOMENTUM 0
LEARNINGRATEINIT 02
SOLVER SGD LEARNINGRATE CONSTANT MOMENTUM 9
NESTEROVSMOMENTUM FALSE LEARNINGRATEINIT 02
SOLVER SGD LEARNINGRATE CONSTANT MOMENTUM 9
NESTEROVSMOMENTUM TRUE LEARNINGRATEINIT 02
SOLVER SGD LEARNINGRATE INVSCALING MOMENTUM 0
LEARNINGRATEINIT 02
SOLVER SGD LEARNINGRATE INVSCALING MOMENTUM 9
NESTEROVSMOMENTUM TRUE LEARNINGRATEINIT 02
SOLVER SGD LEARNINGRATE INVSCALING MOMENTUM 9
NESTEROVSMOMENTUM FALSE LEARNINGRATEINIT 02
SOLVER ADAM LEARNINGRATEINIT 001
LABELS CONSTANT LEARNINGRATE CONSTANT WITH MOMENTUM

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CONSTANT WITH NESTEROVS MOMENTUM
INVSCALING LEARNINGRATE INVSCALING WITH MOMENTUM
INVSCALING WITH NESTEROVS MOMENTUM ADAM
PLOTARGS C RED LINESTYLE
C GREEN LINESTYLE
C BLUE LINESTYLE
C RED LINESTYLE
C GREEN LINESTYLE
C BLUE LINESTYLE
C BLACK LINESTYLE
DEFPLOTONDATASETX Y AX NAME
 FOR EACH DATASET PLOT LEARNING FOR EACH LEARNING STRATEGY
PRINTNLEARNING ON DATASET S NAME
AXSETTITLENAME
X MINMAXSCALERFITTRANSFORMX
MLPS
IFNAME DIGITS
 DIGITS IS LARGER BUT CONVERGES FAIRLY QUICKLY
MAXITER 15
ELSE
MAXITER 400
FORLABEL PARAM INZIPLABELS PARAMS
PRINTTRAINING S LABEL
MLP MLPCLASSIFIERVERBOSE0 RANDOMSTATE0
MAXITERMAXITER PARAM
 SOME PARAMETER COMBINATIONS WILL NOT CONVERGE AS CAN BE SEEN ON THE
 PLOTS SO THEY ARE IGNORED HERE
WITHWARNINGSCATCHWARNINGS
WARNINGSFILTERWARNINGSIGNORE CATEGORYCONVERGENCEWARNING
MODULESKLEARN
MLPFITX Y
MLPSAPPENDMLP
PRINTTRAINING SET SCORE F MLPSCOREX Y
PRINTTRAINING SET LOSS F MLPLOSS
FORMLP LABEL ARGS INZIPMLPS LABELS PLOTARGS
AXPLOTMLPLOSSCURVE LABELLABEL ARGS
FIG AXES PLTSUBPLOTS2 2 FIGSIZE15 10
 LOAD GENERATE SOME TOY DATASETS
IRIS DATASETSLOADIRIS
DIGITS DATASETSLOADDIGITS
DATASETS IRISDATA IRISTARGET
DIGITSDATA DIGITSTARGET
DATASETSMAKECIRCLESNOISE02 FACTOR05 RANDOMSTATE1
DATASETSMAKEMOONSNOISE03 RANDOMSTATE0
FORAX DATA NAME INZIPAXESRAVEL DATASETS IRIS DIGITS
CIRCLES MOONS
PLOTONDATASET DATA AXAX NAMENAME

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FIGLEGENDAXGETLINES LABELS NCOL3 LOCUPPER CENTER
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 4379 SECONDS
525 PREPROCESSING
EXAMPLES CONCERNING THE SKLEARNPREPROCESSING MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5251 USING FUNCTIONTRANSFORMER TO SELECT COLUMNS
SHOWS HOW TO USE A FUNCTION TRANSFORMER IN A PIPELINE IF YOU KNOW YOUR DATASET'S FIRST PRINCIPLE COMPONENT IS IRRELEVANT FOR A CLASSIFICATION TASK YOU CAN USE THE FUNCTIONTRANSFORMER TO SELECT ALL BUT THE FIRST COLUMN OF THE PCA TRANSFORMED DATA
•

•

```
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT NUMPY AS NP
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
FROM SKLEARNPREPROCESSING IMPORT FUNCTIONTRANSFORMER
DEFGENERATEVECTORSHIFT05 NOISE15
RETURNNPARANGE1000  NPRANDOMRAND1000  SHIFT NOISE
DEFGENERATEDATASET

THIS DATASET IS TWO LINES WITH A SLOPE  1 WHERE ONE HAS
A Y OFFSET OF 100

RETURNNPVSTACK
NPVSTACK
GENERATEVECTOR
GENERATEVECTOR  100
T
NPVSTACK
GENERATEVECTOR
GENERATEVECTOR
T
```

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NPHSTACKNPZEROS1000 NPONES1000
DEFALLBUTFIRSTCOLUMNX
RETURNX 1
DEFDROPFIRSTCOMPONENTX Y

CREATE A PIPELINE WITH PCA AND THE COLUMN SELECTOR AND USE IT TO
TRANSFORM THE DATASET

PIPELINE MAKEPIPELINE
PCA FUNCTIONTRANSFORMERALLBUTFIRSTCOLUMN

XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y
PIPELINEFITXTRAIN YTRAIN
RETURNPIPELINETRANSFORMXTEST YTEST
IFNAME MAIN
X Y GENERATEDATASET
LW 0
PLTFIGURE
PLTSCATTERX 0 X 1 CY LWLW
PLTFIGURE
XTRANSFORMED YTRANSFORMED DROPFIRSTCOMPONENT GENERATEDATASET
PLTSCATTER
XTRANSFORMED 0
NPZEROSLENXTRANSFORMED
CYTRANSFORMED
LWLW
S60

PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0028 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5252 USING KBINSDISCRETIZER TO DISCRETIZE CONTINUOUS FEATURES
THE EXAMPLE COMPARES PREDICTION RESULT OF LINEAR REGRESSION LINEAR MODEL AND DECISION TREE TREE BASED MODEL WITH
AND WITHOUT DISCRETIZATION OF REALVALUED FEATURES
AS IS SHOWN IN THE RESULT BEFORE DISCRETIZATION LINEAR MODEL IS FAST TO BUILD AND RELATIVELY STRAIGHTFORWARD TO INTERPRET
BUT CAN ONLY MODEL LINEAR RELATIONSHIPS WHILE DECISION TREE CAN BUILD A MUCH MORE COMPLEX MODEL OF THE DATA ONE
WAY TO MAKE LINEAR MODEL MORE POWERFUL ON CONTINUOUS DATA IS TO USE DISCRETIZATION ALSO KNOWN AS BINNING IN THE
EXAMPLE WE DISCRETIZE THE FEATURE AND ONEHOT ENCODE THE TRANSFORMED DATA NOTE THAT IF THE BINS ARE NOT REASONABLY
WIDE THERE WOULD APPEAR TO BE A SUBSTANTIALLY INCREASED RISK OF OVERFITTING SO THE DISCRETIZER PARAMETERS SHOULD USUALLY
BE TUNED UNDER CROSS VALIDATION
AFTER DISCRETIZATION LINEAR REGRESSION AND DECISION TREE MAKE EXACTLY THE SAME PREDICTION AS FEATURES ARE CONSTANT
WITHIN EACH BIN ANY MODEL MUST PREDICT THE SAME VALUE FOR ALL POINTS WITHIN A BIN COMPARED WITH THE RESULT BEFORE

DISCRETIZATION LINEAR MODEL BECOME MUCH MORE FLEXIBLE WHILE DECISION TREE GETS MUCH LESS FLEXIBLE NOTE THAT BIN NING FEATURES GENERALLY HAS NO BENEFICIAL EFFECT FOR TREEBASED MODELS AS THESE MODELS CAN LEARN TO SPLIT UP THE DATA ANYWHERE

AUTHOR ANDREAS MÜLLER
HANMIN QIN QINHANMIN2005SINACOM


```
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION
FROM SKLEARNPREPROCESSING IMPORT KBINSDISCRETIZER
FROM SKLEARNTREE IMPORT DECISIONTREEREGRESSOR
PRINTDOC
 CONSTRUCT THE DATASET
RND  NPRANDOMRANDOMSTATE42
X  RNDUNIFORM3 3 SIZE100
Y  NPSINX  RNDNORMALSIZELENX  3
X  XRESHAPE1 1
 TRANSFORM THE DATASET WITH KBINSDISCRETIZER
ENC  KBINSDISCRETIZERNBINS10 ENCODEONEHOT
XBINNED  ENCFITTRANSFORMX
 PREDICT WITH ORIGINAL DATASET
FIG AX1 AX2  PLTSUBPLOTSNCOLS2 SHAREYTRUE FIGSIZE10 4
LINE  NPLINSPACE3 3 1000 ENDPOINTFALSERESHAPE1 1
REG  LINEARREGRESSIONFITX Y
AX1PLOTLINE REGPREDICTLINE LINEWIDTH2 COLORGREEN
LABELLINEAR REGRESSION
REG  DECISIONTREEREGRESSORMINSAMPLESSPLIT3 RANDOMSTATE0FITX Y
AX1PLOTLINE REGPREDICTLINE LINEWIDTH2 COLORRED
LABELDECISION TREE
AX1PLOTX 0 Y O CK
AX1LEGENDLOCBEST
AX1SETYLABELREGRESSION OUTPUT
AX1SETXLABELINPUT FEATURE
AX1SETTITLERESULT BEFORE DISCRETIZATION
```

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PREDICT WITH TRANSFORMED DATASET
LINEBINNED ENCTRANSFORMLINE
REG LINEARREGRESSIONFITXBINNED Y
AX2PLOTLINE REGPREDICTLINEBINNED LINEWIDTH2 COLORGREEN
LINESTYLE LABELLINEAR REGRESSION
REG DECISIONTREEREGRESSORMINSAMPLESSPLIT3
RANDOMSTATE0FITXBINNED Y
AX2PLOTLINE REGPREDICTLINEBINNED LINEWIDTH2 COLORRED
LINESTYLE LABELDECISION TREE
AX2PLOTX 0 Y O CK
AX2VLINESENCBINEDGES0 PLTGCAGETYLIM LINEWIDTH1 ALPHA2
AX2LEGENDLOCBEST
AX2SETXLABELINPUT FEATURE
AX2SETTITLERESULT AFTER DISCRETIZATION
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0122 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5253 DEMONSTRATING THE DIFFERENT STRATEGIES OF KBINSDISCRETIZER
THIS EXAMPLE PRESENTS THE DIFFERENT STRATEGIES IMPLEMENTED IN KBINSDISCRETIZER
• 'UNIFORM' THE DISCRETIZATION IS UNIFORM IN EACH FEATURE WHICH MEANS THAT THE BIN WIDTHS ARE CONSTANT IN EACH DIMENSION
• QUANTILE' THE DISCRETIZATION IS DONE ON THE QUANTILED VALUES WHICH MEANS THAT EACH BIN HAS APPROXIMATELY THE SAME NUMBER OF SAMPLES
• 'KMEANS' THE DISCRETIZATION IS BASED ON THE CENTROIDS OF A KMEANS CLUSTERING PROCEDURE
THE PLOT SHOWS THE REGIONS WHERE THE DISCRETIZED ENCODING IS CONSTANT

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 AUTHOR TOM DUPRÉ LA TOUR
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNPREPROCESSING IMPORT KBINSDISCRETIZER
FROM SKLEARNDATASETS IMPORT MAKEBLOBS
PRINTDOC
STRATEGIES UNIFORM QUANTILE KMEANS
NSAMPLES 200
CENTERS0 NPARRAY0 0 0 5 2 4 8 8
CENTERS1 NPARRAY0 0 3 1
 CONSTRUCT THE DATASETS
RANDOMSTATE 42
XLIST
NPRANDOMRANDOMSTATERANDOMSTATEUNIFORM3 3 SIZENSAMPLES 2
MAKEBLOBSNSAMPLESNSAMPLES 10 NSAMPLES 4 10
NSAMPLES 10 NSAMPLES 4 10
CLUSTERSTD05 CENTERSCENTERS0
RANDOMSTATERANDOMSTATE0
MAKEBLOBSNSAMPLESNSAMPLES 5 NSAMPLES 4 5
CLUSTERSTD05 CENTERSCENTERS1
RANDOMSTATERANDOMSTATE0

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FIGURE PLTFIGUREFIGSIZE14 9
I 1
FORDSCNT X INENUMERATEXLIST
AX PLTSUBPLOTLENXLIST LENSTRATEGIES 1 I
AXSCATTERX 0 X 1 EDGECOLORSK
IFDSCNT 0
AXSETTITLEINPUT DATA SIZE14
XX YY NPMESHGRID
NPLINSPACEX 0MIN X 0MAX 300
NPLINSPACEX 1MIN X 1MAX 300
GRID NPCXXRAVEL YYRAVEL
AXSETXLIMXXMIN XXMAX
AXSETYLIMYYMIN YYMAX
AXSETXTICKS
AXSETYTICKS
I 1
 TRANSFORM THE DATASET WITH KBINSDISCRETIZER
FORSTRATEGY INSTRATEGIES
ENC KBINSDISCRETIZERNBINS4 ENCODEORDINAL STRATEGYSTRATEGY
ENCFITX
GRIDENCODED ENCTRANSFORMGRID
AX PLTSUBPLOTLENXLIST LENSTRATEGIES 1 I
 HORIZONTAL STRIPES
HORIZONTAL GRIDENCODED 0RESHAPEXXSHAPE
AXCONTOURFXX YY HORIZONTAL ALPHA5
 VERTICAL STRIPES
VERTICAL GRIDENCODED 1RESHAPEXXSHAPE
AXCONTOURFXX YY VERTICAL ALPHA5
AXSCATTERX 0 X 1 EDGECOLORSK
AXSETXLIMXXMIN XXMAX
AXSETYLIMYYMIN YYMAX
AXSETXTICKS
AXSETYTICKS
IFDSCNT 0
AXSETTITLESTRATEGY S STRATEGY SIZE14
I 1
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0890 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5254 IMPORTANCE OF FEATURE SCALING
FEATURE SCALING THROUGH STANDARDIZATION OR ZSCORE NORMALIZATION CAN BE AN IMPORTANT PREPROCESSING STEP FOR MANY MACHINE LEARNING ALGORITHMS STANDARDIZATION INVOLVES RESCALING THE FEATURES SUCH THAT THEY HAVE THE PROPERTIES OF A STANDARD NORMAL DISTRIBUTION WITH A MEAN OF ZERO AND A STANDARD DEVIATION OF ONE
WHILE MANY ALGORITHMS SUCH AS SVM KNEAREST NEIGHBORS AND LOGISTIC REGRESSION REQUIRE FEATURES TO BE NORMALIZED INTUITIVELY WE CAN THINK OF PRINCIPLE COMPONENT ANALYSIS PCA AS BEING A PRIME EXAMPLE OF WHEN NORMALIZATION IS IMPORTANT IN PCA WE ARE INTERESTED IN THE COMPONENTS THAT MAXIMIZE THE VARIANCE IF ONE COMPONENT EG HUMAN HEIGHT VARIES LESS THAN ANOTHER EG WEIGHT BECAUSE OF THEIR RESPECTIVE SCALES METERS VS KILOS PCA MIGHT DETERMINE THAT THE DIRECTION OF MAXIMAL VARIANCE MORE CLOSELY CORRESPONDS WITH THE ‘WEIGHT’ AXIS IF THOSE FEATURES ARE NOT SCALED AS A CHANGE IN HEIGHT OF ONE METER CAN BE CONSIDERED MUCH MORE IMPORTANT THAN THE CHANGE IN WEIGHT OF ONE KILOGRAM THIS IS CLEARLY INCORRECT
TO ILLUSTRATE THIS PCA IS PERFORMED COMPARING THE USE OF DATA WITH STANDARDSCALER APPLIED TO UNSCALED DATA
THE RESULTS ARE VISUALIZED AND A CLEAR DIFFERENCE NOTED THE 1ST PRINCIPAL COMPONENT IN THE UNSCALED SET CAN BE SEEN IT CAN BE SEEN THAT FEATURE 13 DOMINATES THE DIRECTION BEING A WHOLE TWO ORDERS OF MAGNITUDE ABOVE THE OTHER FEATURES THIS IS CONTRASTED WHEN OBSERVING THE PRINCIPAL COMPONENT FOR THE SCALED VERSION OF THE DATA IN THE SCALED VERSION THE ORDERS OF MAGNITUDE ARE ROUGHLY THE SAME ACROSS ALL THE FEATURES
THE DATASET USED IS THE WINE DATASET AVAILABLE AT UCI THIS DATASET HAS CONTINUOUS FEATURES THAT ARE HETEROGENEOUS IN SCALE DUE TO DIFFERING PROPERTIES THAT THEY MEASURE IE ALCOHOL CONTENT AND MALIC ACID
THE TRANSFORMED DATA IS THEN USED TO TRAIN A NAIVE BAYES CLASSIFIER AND A CLEAR DIFFERENCE IN PREDICTION ACCURACIES IS OBSERVED WHEREIN THE DATASET WHICH IS SCALED BEFORE PCA VASTLY OUTPERFORMS THE UNSCALED VERSION
OUT

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PREDICTION ACCURACY FOR THE NORMAL TEST DATASET WITH PCA
8148
PREDICTION ACCURACY FOR THE STANDARDIZED TEST DATASET WITH PCA
9815
PC 1 WITHOUT SCALING
 176E03 836E04 155E04 531E03 202E02 102E03 153E03
112E04 631E04 233E03 154E04 743E04 100E00
PC 1 WITH SCALING
 013 026 001 023 016 039 042 028 033 011 03 038
028
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM SKLEARNDECOMPOSITION IMPORT PCA
FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
FROM SKLEARN IMPORT METRICS
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT LOADWINE
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
PRINTDOC
 CODE SOURCE TYLER LANIGAN TYLERLANIGANGMAILCOM
 SEBASTIAN RASCHKA MAILSEBASTIANRASCHKACOM
 LICENSE BSD 3 CLAUSE
RANDOMSTATE 42
FIGSIZE 10 7
FEATURES TARGET LOADWINERETURNXYTRUE
 MAKE A TRAINTEST SPLIT USING 30 TEST SIZE
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITFEATURES TARGET
TESTSIZE030
RANDOMSTATERANDOMSTATE
 FIT TO DATA AND PREDICT USING PIPELINED GNB AND PCA
UNSCALEDCLF MAKEPIPELINEPCANCOMPONENTS2 GAUSSIANNB
UNSCALEDCLFFITXTRAIN YTRAIN
PREDTEST UNSCALEDCLFPREDICTXTEST
 FIT TO DATA AND PREDICT USING PIPELINED SCALING GNB AND PCA
STDCLF MAKEPIPELINESTANDARDSCALER PCANCOMPONENTS2 GAUSSIANNB
STDCLFFITXTRAIN YTRAIN
PREDTESTSTD STDCLFPREDICTXTEST
 SHOW PREDICTION ACCURACIES IN SCALED AND UNSCALED DATA
1368 CHAPTER 5 EXAMPLES

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PRINTNPREDICTION ACCURACY FOR THE NORMAL TEST DATASET WITH PCA
PRINT2 NFORMATMETRICSACCURACYSCOREYTEST PREDTEST
PRINTNPREDICTION ACCURACY FOR THE STANDARDIZED TEST DATASET WITH PCA
PRINT2 NFORMATMETRICSACCURACYSCOREYTEST PREDTESTSTD
 EXTRACT PCA FROM PIPELINE
PCA UNSCALEDCLFNAMEDSTEPSPCA
PCASTD STDCLFNAMEDSTEPSPCA
 SHOW FIRST PRINCIPAL COMPONENTS
PRINTNPC 1 WITHOUT SCALING N PCACOMPONENTS0
PRINTNPC 1 WITH SCALING N PCASTDCOMPONENTS0
 USE PCA WITHOUT AND WITH SCALE ON XTRAIN DATA FOR VISUALIZATION
XTRAINTRANSFORMED PCATRANSFORMXTRAIN
SCALER STDCLFNAMEDSTEPSSTANDARDSCALER
XTRAINSTDTRANSFORMED PCASTDTRANSFORMSCALERTRANSFORMXTRAIN
 VISUALIZE STANDARDIZED VS UNTOUCHED DATASET WITH PCA PERFORMED
FIG AX1 AX2 PLTSUBPLOTSNCOLS2 FIGSIZEFIGSIZE
FORL C M INZIPRANGE0 3 BLUE RED GREEN S O
AX1SCATTERXTRAINTRANSFORMEDYTRAIN L 0
XTRAINTRANSFORMEDYTRAIN L 1
COLORC
LABELCLASS S L
ALPHA05
MARKERM

FORL C M INZIPRANGE0 3 BLUE RED GREEN S O
AX2SCATTERXTRAINSTDTRANSFORMEDYTRAIN L 0
XTRAINSTDTRANSFORMEDYTRAIN L 1
COLORC
LABELCLASS S L
ALPHA05
MARKERM

AX1SETTITLETRAINING DATASET AFTER PCA
AX2SETTITLESTANDARDIZED TRAINING DATASET AFTER PCA
FORAXINAX1 AX2
AXSETXLABEL1ST PRINCIPAL COMPONENT
AXSETYLABEL2ND PRINCIPAL COMPONENT
AXLEGENDLOCUPPER RIGHT
AXGRID
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0109 SECONDS
525 PREPROCESSING 1369

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5255 MAP DATA TO A NORMAL DISTRIBUTION
THIS EXAMPLE DEMONSTRATES THE USE OF THE BOXCOX AND YEOJOHNSON TRANSFORMS THROUGH PREPROCESSING POWERTRANSFORMER TO MAP DATA FROM VARIOUS DISTRIBUTIONS TO A NORMAL DISTRIBUTION
THE POWER TRANSFORM IS USEFUL AS A TRANSFORMATION IN MODELING PROBLEMS WHERE HOMOSCEDASTICITY AND NORMALITY ARE DESIRED BELOW ARE EXAMPLES OF BOXCOX AND YEOJOHNWON APPLIED TO SIX DIFFERENT PROBABILITY DISTRIBUTIONS LOGNORMAL CHISQUARED WEIBULL GAUSSIAN UNIFORM AND BIMODAL
NOTE THAT THE TRANSFORMATIONS SUCCESSFULLY MAP THE DATA TO A NORMAL DISTRIBUTION WHEN APPLIED TO CERTAIN DATASETS BUT ARE INEFFECTIVE WITH OTHERS THIS HIGHLIGHTS THE IMPORTANCE OF VISUALIZING THE DATA BEFORE AND AFTER TRANSFORMATION
ALSO NOTE THAT EVEN THOUGH BOXCOX SEEMS TO PERFORM BETTER THAN YEOJOHNSON FOR LOGNORMAL AND CHISQUARED DISTRIBUTIONS KEEP IN MIND THAT BOXCOX DOES NOT SUPPORT INPUTS WITH NEGATIVE VALUES
FOR COMPARISON WE ALSO ADD THE OUTPUT FROM PREPROCESSINGQUANTILETRANSFORMER IT CAN FORCE ANY ARBITRARY DISTRIBUTION INTO A GAUSSIAN PROVIDED THAT THERE ARE ENOUGH TRAINING SAMPLES THOUSANDS BECAUSE IT IS A NONPARAMETRIC METHOD IT IS HARDER TO INTERPRET THAN THE PARAMETRIC ONES BOXCOX AND YEOJOHNSON ON “SMALL” DATASETS LESS THAN A FEW HUNDRED POINTS THE QUANTILE TRANSFORMER IS PRONE TO OVERFITTING THE USE OF THE POWER TRANSFORM IS THEN RECOMMENDED

SCIKITLEARN USER GUIDE RELEASE 0213
AUTHOR ERIC CHANG ERICCHANG2017UNORTHWESTERNEDU
NICOLAS HUG CONTACTNICOLASHUGCOM
LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
525 PREPROCESSING 1371

```
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNPREPROCESSING IMPORT POWERTRANSFORMER
FROM SKLEARNPREPROCESSING IMPORT QUANTILETRANSFORMER
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
PRINTDOC
NSAMPLES  1000
FONTSIZE  6
BINS  30
RNG  NPRANDOMRANDOMSTATE304
BC  POWERTRANSFORMERMETHODBOXCOX
YJ  POWERTRANSFORMERMETHODYEOJOHNSON
 NQUANTILES IS SET TO THE TRAINING SET SIZE RATHER THAN THE DEFAULT VALUE
 TO AVOID A WARNING BEING RAISED BY THIS EXAMPLE
QT  QUANTILETRANSFORMERNQUANTILES500 OUTPUTDISTRIBUTIONNORMAL
RANDOMSTATERNG
SIZE  NSAMPLES 1
 LOGNORMAL DISTRIBUTION
XLOGNORMAL  RNGLOGNORMALSIZESIZE
 CHISQUARED DISTRIBUTION
DF  3
XCHISQ  RNGCHISQUAREDFDF SIZESIZE
 WEIBULL DISTRIBUTION
A  50
XWEIBULL  RNGWEIBULLAA SIZESIZE
 GAUSSIAN DISTRIBUTION
LOC  100
XGAUSSIAN  RNGNORMALLOCLOC SIZESIZE
 UNIFORM DISTRIBUTION
XUNIFORM  RNGUNIFORMLOW0 HIGH1 SIZESIZE
 BIMODAL DISTRIBUTION
LOCA LOCB  100 105
XA XB  RNGNORMALLOCLOCA SIZESIZE RNGNORMALLOCLOCB SIZESIZE
XBIMODAL  NPCONCATENATEXA XB AXIS0
 CREATE PLOTS
DISTRIBUTIONS
LOGNORMAL XLOGNORMAL
CHISQUARED XCHISQ
WEIBULL XWEIBULL
GAUSSIAN XGAUSSIAN
UNIFORM XUNIFORM
BIMODAL XBIMODAL
```

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COLORS FIREBRICK DARKORANGE GOLDENROD
SEAGREEN ROYALBLUE DARKORCHID
FIG AXES PLTSUBPLOTSNROWS8 NCOLS3 FIGSIZEPLTFIGASPECT2
AXES AXESFLATTEN
AXESIDXS 0 3 6 9 1 4 7 10 2 5 8 11 12 15 18 21
13 16 19 22 14 17 20 23
AXESLIST AXESI AXESJ AXESK AXESL
FORI J K L INAXESIDXS
FORDISTRIBUTION COLOR AXES INZIPDISTRIBUTIONS COLORS AXESLIST
NAME X DISTRIBUTION
XTRAIN XTEST TRAINTESTSPLITX TESTSIZE5
 PERFORM POWER TRANSFORMS AND QUANTILE TRANSFORM
XTRANSBC BCFITXTRAINTRANSFORMXTEST
LMBDABC ROUNDBCLAMBDAS0 2
XTRANSYJ YJFITXTRAINTRANSFORMXTEST
LMBDAYJ ROUNDYJLAMBDAS0 2
XTRANSQT QTFITXTRAINTRANSFORMXTEST
AXORIGINAL AXBC AXYJ AXQT AXES
AXORIGINALHISTXTRAIN COLORCOLOR BINSBINS
AXORIGINALSETTITLENAME FONTSIZEFONTSIZE
AXORIGINALTICKPARAMSAXISBOTH WHICHMAJOR LABELSIZEFONTSIZE
FORAX XTRANS METHNAME LMBDA INZIP
AXBC AXYJ AXQT
XTRANSBC XTRANSYJ XTRANSQT
BOXCOX YEOJOHNSON QUANTILE TRANSFORM
LMBDABC LMBDAYJ NONE
AXHISTXTRANS COLORCOLOR BINSBINS
TITLE AFTER FORMATMETHNAME
IFLMBDAIS NOTNONE
TITLE RNLAMBDA FORMATLMBDA
AXSETTITLETITLE FONTSIZEFONTSIZE
AXTICKPARAMSAXISBOTH WHICHMAJOR LABELSIZEFONTSIZE
AXSETXLIM35 35
PLTTIGHTLAYOUT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1536 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5256 FEATURE DISCRETIZATION
A DEMONSTRATION OF FEATURE DISCRETIZATION ON SYNTHETIC CLASSIFICATION DATASETS FEATURE DISCRETIZATION DECOMPOSES EACH FEATURE INTO A SET OF BINS HERE EQUALLY DISTRIBUTED IN WIDTH THE DISCRETE VALUES ARE THEN ONEHOT ENCODED AND GIVEN TO A LINEAR CLASSIFIER THIS PREPROCESSING ENABLES A NONLINEAR BEHAVIOR EVEN THOUGH THE CLASSIFIER IS LINEAR
525 PREPROCESSING 1373

ON THIS EXAMPLE THE FIRST TWO ROWS REPRESENT LINEARLY NONSEPARABLE DATASETS MOONS AND CONCENTRIC CIRCLES WHILE THE THIRD IS APPROXIMATELY LINEARLY SEPARABLE ON THE TWO LINEARLY NONSEPARABLE DATASETS FEATURE DISCRETIZATION LARGELY INCREASES THE PERFORMANCE OF LINEAR CLASSIFIERS ON THE LINEARLY SEPARABLE DATASET FEATURE DISCRETIZATION DECREASES THE PERFORMANCE OF LINEAR CLASSIFIERS TWO NONLINEAR CLASSIFIERS ARE ALSO SHOWN FOR COMPARISON
THIS EXAMPLE SHOULD BE TAKEN WITH A GRAIN OF SALT AS THE INTUITION CONVEYED DOES NOT NECESSARILY CARRY OVER TO REAL DATASETS PARTICULARLY IN HIGHDIMENSIONAL SPACES DATA CAN MORE EASILY BE SEPARATED LINEARLY MOREOVER USING FEATURE DISCRETIZATION AND ONEHOT ENCODING INCREASES THE NUMBER OF FEATURES WHICH EASILY LEAD TO OVERFITTING WHEN THE NUMBER OF SAMPLES IS SMALL
THE PLOTS SHOW TRAINING POINTS IN SOLID COLORS AND TESTING POINTS SEMITRANSPARENT THE LOWER RIGHT SHOWS THE CLASSIFI CATION ACCURACY ON THE TEST SET
OUT
DATASET 0

LOGISTICREGRESSION 086
LINEARSVC 086
KBINSDISCRETIZER LOGISTICREGRESSION 094
KBINSDISCRETIZER LINEARSVC 092
GRADIENTBOOSTINGCLASSIFIER 090
SVC 094
DATASET 1

LOGISTICREGRESSION 040
LINEARSVC 040
KBINSDISCRETIZER LOGISTICREGRESSION 088
KBINSDISCRETIZER LINEARSVC 086
GRADIENTBOOSTINGCLASSIFIER 080
SVC 084
DATASET 2

LOGISTICREGRESSION 096
LINEARSVC 098
KBINSDISCRETIZER LOGISTICREGRESSION 094
KBINSDISCRETIZER LINEARSVC 084
GRADIENTBOOSTINGCLASSIFIER 094

SCIKITLEARN USER GUIDE RELEASE 0213
SVC 098
 CODE SOURCE TOM DUPRÉ LA TOUR
 ADAPTED FROM PLOTCLASSIFIERCOMPARISON BY GAËL VAROQUAUX AND ANDREAS MÜLLER

 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBCOLORS IMPORT LISTEDCOLORMAP
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM SKLEARNDATASETS IMPORT MAKEMOONS MAKECIRCLES MAKECLASSIFICATION
FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
FROM SKLEARNPREPROCESSING IMPORT KBINSDISCRETIZER
FROM SKLEARNSVM IMPORT SVC LINEARSVC
FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGCLASSIFIER
FROM SKLEARNUTILSTESTING IMPORT IGNOREWARNINGS
FROM SKLEARNEXCEPTIONS IMPORT CONVERGENCEWARNING
PRINTDOC
H 02 STEP SIZE IN THE MESH
DEFGETNAMEESTIMATOR
NAME ESTIMATORCLASSNAME
IFNAME PIPELINE
NAME GETNAMEEST1 FORESTINESTIMATORSTEPS
NAME   JOINNAME
RETURNNAME
 LIST OF ESTIMATOR PARAMGRID WHERE PARAMGRID IS USED IN GRIDSEARCHCV
CLASSIFIERS
LOGISTICREGRESSIONSOLVERLBFGS RANDOMSTATE0
C NPLOGSPACE2 7 10

LINEARSVCRANDOMSTATE0
C NPLOGSPACE2 7 10

MAKEPIPELINE
KBINSDISCRETIZERENCODEONEHOT
LOGISTICREGRESSIONSOLVERLBFGS RANDOMSTATE0
KBINSDISCRETIZERNBINS NPARANGE2 10
LOGISTICREGRESSIONC NPLOGSPACE2 7 10

MAKEPIPELINE
KBINSDISCRETIZERENCODEONEHOT LINEARSVCRANDOMSTATE0
KBINSDISCRETIZERNBINS NPARANGE2 10
LINEARSVCC NPLOGSPACE2 7 10
525 PREPROCESSING 1375

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GRADIENTBOOSTINGCLASSIFIERNESTIMATORS50 RANDOMSTATE0
LEARNINGRATE NPLOGSPACE4 0 10

SVCRANDOMSTATE0 GAMMASCALE
C NPLOGSPACE2 7 10

NAMES GETNAMEE FORE GINCLASSIFIERS
NSAMPLES 100
DATASETS
MAKEMOONSNSAMPLESNSAMPLES NOISE02 RANDOMSTATE0
MAKECIRCLESNSAMPLESNSAMPLES NOISE02 FACTOR05 RANDOMSTATE1
MAKECLASSIFICATIONNSAMPLESNSAMPLES NFEATURES2 NREDUNDANT0
NINFORMATIVE2 RANDOMSTATE2
NCLUSTERSPERCLASS1

FIG AXES PLTSUBPLOTSNROWSLENDATASETS NCOLSLENCLASSIFIERS 1
FIGSIZE21 9
CM PLTCMPIYG
CMBRIGHT LISTEDCOLORMAPB30065 178000
 ITERATE OVER DATASETS
FORDSCNT X Y INENUMERATEDATASETS
PRINTNDATASET DN DSCNT
 PREPROCESS DATASET SPLIT INTO TRAINING AND TEST PART
X STANDARDSCALERFITTRANSFORMX
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLIT
X Y TESTSIZE5 RANDOMSTATE42
 CREATE THE GRID FOR BACKGROUND COLORS
XMIN XMAX X 0MIN 5 X 0MAX 5
YMIN YMAX X 1MIN 5 X 1MAX 5
XX YY NPMESHGRID
NPARANGEXMIN XMAX H NPARANGEYMIN YMAX H
 PLOT THE DATASET FIRST
AX AXESDSCNT 0
IFDSCNT 0
AXSETTITLEINPUT DATA
 PLOT THE TRAINING POINTS
AXSCATTERXTRAIN 0 XTRAIN 1 CYTRAIN CMAPCMBRIGHT
EDGECOLORSK
 AND TESTING POINTS
AXSCATTERXTEST 0 XTEST 1 CYTEST CMAPCMBRIGHT ALPHA06
EDGECOLORSK
AXSETXLIMXXMIN XXMAX
AXSETYLIMYYMIN YYMAX
AXSETXTICKS
AXSETYTICKS
 ITERATE OVER CLASSIFIERS
FORESTIDX NAME ESTIMATOR PARAMGRID IN

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ENUMERATEZIPNAMES CLASSIFIERS
AX AXESDSCNT ESTIDX 1
CLF GRIDSEARCHCVESTIMATORESTIMATOR PARAMGRIDPARAMGRID CV5
IIDFALSE
WITHIGNOREWARNINGSCATEGORYCONVERGENCEWARNING
CLFFITXTRAIN YTRAIN
SCORE CLFSCOREXTEST YTEST
PRINTS2F NAME SCORE
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAX YMIN YMAX
IFHASATTRCLF DECISIONFUNCTION
Z CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
ELSE
Z CLFPREDICTPROBANPCXXRAVEL YYRAVEL 1
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
AXCONTOURFXX YY Z CMAPCM ALPHA8
 PLOT THE TRAINING POINTS
AXSCATTERXTRAIN 0 XTRAIN 1 CYTRAIN CMAPCMBRIGHT
EDGECOLORSK
 AND TESTING POINTS
AXSCATTERXTEST 0 XTEST 1 CYTEST CMAPCMBRIGHT
EDGECOLORSK ALPHA06
AXSETXLIMXXMIN XXMAX
AXSETYLIMYYMIN YYMAX
AXSETXTICKS
AXSETYTICKS
IFDSCNT 0
AXSETTITLENAMEREPLACE   N
AXTEXT095 006 2F SCORELSTRIP0 SIZE15
BBOXDICTBOXSTYLEROUND ALPHA08 FACECOLORWHITE
TRANSFORMAXTRANSAXES HORIZONTALALIGNMENTRIGHT
PLTTIGHTLAYOUT
 ADD SUPTITLES ABOVE THE FIGURE
PLTSUBPLOTSADJUSTTOP090
SUPTITLES
LINEAR CLASSIFIERS
FEATURE DISCRETIZATION AND LINEAR CLASSIFIERS
NONLINEAR CLASSIFIERS

FORI SUPTITLE INZIP1 3 5 SUPTITLES
AX AXES0 I
AXTEXT105 125 SUPTITLE TRANSFORMAXTRANSAXES
HORIZONTALALIGNMENTCENTER SIZEXLARGE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 16451 SECONDS
525 PREPROCESSING 1377

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5257 COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS
FEATURE 0 MEDIAN INCOME IN A BLOCK AND FEATURE 5 NUMBER OF HOUSEHOLDS OF THE CALIFORNIA HOUSING DATASET HAVE VERY DIFFERENT SCALES AND CONTAIN SOME VERY LARGE OUTLIERS THESE TWO CHARACTERISTICS LEAD TO DIFFICULTIES TO VISUALIZE THE DATA AND MORE IMPORTANTLY THEY CAN DEGRADE THE PREDICTIVE PERFORMANCE OF MANY MACHINE LEARNING ALGORITHMS UNSCALED DATA CAN ALSO SLOW DOWN OR EVEN PREVENT THE CONVERGENCE OF MANY GRADIENTBASED ESTIMATORS
INDEED MANY ESTIMATORS ARE DESIGNED WITH THE ASSUMPTION THAT EACH FEATURE TAKES VALUES CLOSE TO ZERO OR MORE IM PORTANTLY THAT ALL FEATURES VARY ON COMPARABLE SCALES IN PARTICULAR METRICBASED AND GRADIENTBASED ESTIMATORS OFTEN ASSUME APPROXIMATELY STANDARDIZED DATA CENTERED FEATURES WITH UNIT VARIANCES A NOTABLE EXCEPTION ARE DECISION TREEBASED ESTIMATORS THAT ARE ROBUST TO ARBITRARY SCALING OF THE DATA
THIS EXAMPLE USES DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS TO BRING THE DATA WITHIN A PREDEFINED RANGE SCALERS ARE LINEAR OR MORE PRECISELY AFFINE TRANSFORMERS AND DIFFER FROM EACH OTHER IN THE WAY TO ESTIMATE THE PARAM ETERS USED TO SHIFT AND SCALE EACH FEATURE
QUANTILETRANSFORMER PROVIDES NONLINEAR TRANSFORMATIONS IN WHICH DISTANCES BETWEEN MARGINAL OUTLIERS AND INLIERS ARE SHRUNK POWERTRANSFORMER PROVIDES NONLINEAR TRANSFORMATIONS IN WHICH DATA IS MAPPED TO A NORMAL DISTRIBUTION TO STABILIZE VARIANCE AND MINIMIZE SKEWNESS
UNLIKE THE PREVIOUS TRANSFORMATIONS NORMALIZATION REFERS TO A PER SAMPLE TRANSFORMATION INSTEAD OF A PER FEATURE TRANSFORMATION
THE FOLLOWING CODE IS A BIT VERBOSE FEEL FREE TO JUMP DIRECTLY TO THE ANALYSIS OF THE RESULTS
AUTHOR RAGHAV RV RVRAGHAV93GMAILCOM
GUILLAUME LEMAITRE GLEMAITRE58GMAILCOM
THOMAS UNTERTHINER
LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIB AS MPL
FROM MATPLOTLIB IMPORT PYPLOTASPLT
FROM MATPLOTLIB IMPORT CM
FROM SKLEARNPREPROCESSING IMPORT MINMAXSCALER
FROM SKLEARNPREPROCESSING IMPORT MINMAXSCALE
FROM SKLEARNPREPROCESSING IMPORT MAXABSSCALER
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM SKLEARNPREPROCESSING IMPORT ROBUSTSCALER
FROM SKLEARNPREPROCESSING IMPORT NORMALIZER
FROM SKLEARNPREPROCESSING IMPORT QUANTILETRANSFORMER
FROM SKLEARNPREPROCESSING IMPORT POWERTRANSFORMER
FROM SKLEARNDATASETS IMPORT FETCHCALIFORNIAHOUSING
PRINTDOC
DATASET FETCHCALIFORNIAHOUSING
XFULL YFULL DATASETDATA DATASETTARGET
TAKE ONLY 2 FEATURES TO MAKE VISUALIZATION EASIER

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FEATURE OF 0 HAS A LONG TAIL DISTRIBUTION
FEATURE 5 HAS A FEW BUT VERY LARGE OUTLIERS
X XFULL 0 5
DISTRIBUTIONS
UNSCALED DATA X
DATA AFTER STANDARD SCALING
STANDARDSCALERFITTRANSFORMX
DATA AFTER MINMAX SCALING
MINMAXSCALERFITTRANSFORMX
DATA AFTER MAXABS SCALING
MAXABSSCALERFITTRANSFORMX
DATA AFTER ROBUST SCALING
ROBUSTSCALERQUANTILERANGE25 75FITTRANSFORMX
DATA AFTER POWER TRANSFORMATION YEOJOHNSON
POWERTRANSFORMERMETHODYEOJOHNSONFITTRANSFORMX
DATA AFTER POWER TRANSFORMATION BOXCOX
POWERTRANSFORMERMETHODBOXCOXFITTRANSFORMX
DATA AFTER QUANTILE TRANSFORMATION GAUSSIAN PDF
QUANTILETRANSFORMEROUTPUTDISTRIBUTIONNORMAL
FITTRANSFORMX
DATA AFTER QUANTILE TRANSFORMATION UNIFORM PDF
QUANTILETRANSFORMEROUTPUTDISTRIBUTIONUNIFORM
FITTRANSFORMX
DATA AFTER SAMPLEWISE L2 NORMALIZING
NORMALIZERFITTRANSFORMX

SCALE THE OUTPUT BETWEEN 0 AND 1 FOR THE COLORBAR
Y MINMAXSCALEYFULL
PLASMA DOES NOT EXIST IN MATPLOTLIB 15
CMAP GETATTRCM PLASMAR CMHOTR
DEFCREATEAXESTITLE FIGSIZE16 6
FIG PLTFIGUREFIGSIZEFIGSIZE
FIGSUPTITLETITLE
DEFINE THE AXIS FOR THE FIRST PLOT
LEFT WIDTH 01 022
BOTTOM HEIGHT 01 07
BOTTOMH HEIGHT 015
LEFTH LEFT WIDTH 002
RECTSCATTER LEFT BOTTOM WIDTH HEIGHT
RECTHISTX LEFT BOTTOMH WIDTH 01
RECTHISTY LEFTH BOTTOM 005 HEIGHT
AXSCATTER PLTAXESRECTSCATTER
AXHISTX PLTAXESRECTHISTX
AXHISTY PLTAXESRECTHISTY
DEFINE THE AXIS FOR THE ZOOMEDIN PLOT
LEFT WIDTH LEFT 02
LEFTH LEFT WIDTH 002
RECTSCATTER LEFT BOTTOM WIDTH HEIGHT
525 PREPROCESSING 1379

SCIKITLEARN USER GUIDE RELEASE 0213
RECTHISTX LEFT BOTTOMH WIDTH 01
RECTHISTY LEFTH BOTTOM 005 HEIGHT
AXSCATTERZOOM PLTAXESRECTSCATTER
AXHISTXZOOM PLTAXESRECTHISTX
AXHISTYZOOM PLTAXESRECTHISTY
 DEFINE THE AXIS FOR THE COLORBAR
LEFT WIDTH WIDTH LEFT 013 001
RECTCOLORBAR LEFT BOTTOM WIDTH HEIGHT
AXCOLORBAR PLTAXESRECTCOLORBAR
RETURNAXSCATTER AXHISTY AXHISTX
AXSCATTERZOOM AXHISTYZOOM AXHISTXZOOM
AXCOLORBAR
DEFPLOTDISTRIBUTIONAXES X Y HISTNBINS50 TITLE
X0LABEL X1LABEL
AX HISTX1 HISTX0 AXES
AXSETTITLETITLE
AXSETXLABELX0LABEL
AXSETYLABELX1LABEL
 THE SCATTER PLOT
COLORS CMAPY
AXSCATTERX 0 X 1 ALPHA05 MARKERO S5 LW0 CCOLORS
 REMOVING THE TOP AND THE RIGHT SPINE FOR AESTHETICS
 MAKE NICE AXIS LAYOUT
AXSPINESTOPSETVISIBLEFALSE
AXSPINESRIGHTSETVISIBLEFALSE
AXGETXAXISTICKBOTTOM
AXGETYAXISTICKLEFT
AXSPINESLEFTSETPOSITIONOUTWARD 10
AXSPINESBOTTOMSETPOSITIONOUTWARD 10
 HISTOGRAM FOR AXIS X1 FEATURE 5
HISTX1SETYLIMAXGETYLIM
HISTX1HISTX 1 BINSHISTNBINS ORIENTATIONHORIZONTAL
COLORGREY ECGREY
HISTX1AXISOFF
 HISTOGRAM FOR AXIS X0 FEATURE 0
HISTX0SETXLIMAXGETXLIM
HISTX0HISTX 0 BINSHISTNBINS ORIENTATIONVERTICAL
COLORGREY ECGREY
HISTX0AXISOFF
TWO PLOTS WILL BE SHOWN FOR EACH SCALERNORMALIZERTRANSFORMER THE LEFT FIGURE WILL SHOW A SCATTER PLOT OF THE FULL DATA SET WHILE THE RIGHT FIGURE WILL EXCLUDE THE EXTREME VALUES CONSIDERING ONLY 99 OF THE DATA SET EXCLUDING MARGINAL OUTLIERS IN ADDITION THE MARGINAL DISTRIBUTIONS FOR EACH FEATURE WILL BE SHOWN ON THE SIDE OF THE SCATTER PLOT
DEFMAKEPLOTITEMIDX
TITLE X DISTRIBUTIONSITEMIDX
AXZOOMOUT AXZOOMIN AXCOLORBAR CREATEAXESTITLE

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AXARR AXZOOMOUT AXZOOMIN
PLOTDISTRIBUTIONAXARR0 X Y HISTNBINS200
X0LABELMEDIAN INCOME
X1LABELNUMBER OF HOUSEHOLDS
TITLEFULL DATA
 ZOOMIN
ZOOMINPERCENTILERANGE 0 99
CUTOFFSX0 NPPERCENTILEX 0 ZOOMINPERCENTILERANGE
CUTOFFSX1 NPPERCENTILEX 1 ZOOMINPERCENTILERANGE
NONOUTLIERSMASK
NPALLX CUTOFFSX00 CUTOFFSX10 AXIS1
NPALLX CUTOFFSX01 CUTOFFSX11 AXIS1
PLOTDISTRIBUTIONAXARR1 XNONOUTLIERSMASK YNONOUTLIERSMASK
HISTNBINS50
X0LABELMEDIAN INCOME
X1LABELNUMBER OF HOUSEHOLDS
TITLEZOOMIN
NORM MPLCOLORSNORMALIZEYFULLMIN YFULLMAX
MPLCOLORBARCOLORBARBASEAXCOLORBAR CMAPCMAP
NORMNORM ORIENTATIONVERTICAL
LABELCOLOR MAPPING FOR VALUES OF Y
ORIGINAL DATA
EACH TRANSFORMATION IS PLOTTED SHOWING TWO TRANSFORMED FEATURES WITH THE LEFT PLOT SHOWING THE ENTIRE DATASET AND THE RIGHT ZOOMEDIN TO SHOW THE DATASET WITHOUT THE MARGINAL OUTLIERS A LARGE MAJORITY OF THE SAMPLES ARE COMPACTED TO A SPECIFIC RANGE 0 10 FOR THE MEDIAN INCOME AND 0 6 FOR THE NUMBER OF HOUSEHOLDS NOTE THAT THERE ARE SOME MARGINAL OUTLIERS SOME BLOCKS HAVE MORE THAN 1200 HOUSEHOLDS THEREFORE A SPECIFIC PREPROCESSING CAN BE VERY BENEFICIAL DEPENDING OF THE APPLICATION IN THE FOLLOWING WE PRESENT SOME INSIGHTS AND BEHAVIORS OF THOSE PREPROCESSING METHODS IN THE PRESENCE OF MARGINAL OUTLIERS
MAKEPLOT0
525 PREPROCESSING 1381

STANDARDSCALER
STANDARDSCALER REMOVES THE MEAN AND SCALES THE DATA TO UNIT VARIANCE HOWEVER THE OUTLIERS HAVE AN INFLUENCE WHEN COMPUTING THE EMPIRICAL MEAN AND STANDARD DEVIATION WHICH SHRINK THE RANGE OF THE FEATURE VALUES AS SHOWN IN THE LEFT FIGURE BELOW NOTE IN PARTICULAR THAT BECAUSE THE OUTLIERS ON EACH FEATURE HAVE DIFFERENT MAGNITUDES THE SPREAD OF THE TRANSFORMED DATA ON EACH FEATURE IS VERY DIFFERENT MOST OF THE DATA LIE IN THE 2 4 RANGE FOR THE TRANSFORMED MEDIAN INCOME FEATURE WHILE THE SAME DATA IS SQUEEZED IN THE SMALLER 02 02 RANGE FOR THE TRANSFORMED NUMBER OF HOUSEHOLDS
STANDARDSCALER THEREFORE CANNOT GUARANTEE BALANCED FEATURE SCALES IN THE PRESENCE OF OUTLIERS
MAKEPLOT1
MINMAXSCALER
MINMAXSCALER RESCALES THE DATA SET SUCH THAT ALL FEATURE VALUES ARE IN THE RANGE 0 1 AS SHOWN IN THE RIGHT PANEL BELOW HOWEVER THIS SCALING COMPRESS ALL INLIERS IN THE NARROW RANGE 0 0005 FOR THE TRANSFORMED NUMBER OF HOUSEHOLDS
ASSTANDARDSCALER MINMAXSCALER IS VERY SENSITIVE TO THE PRESENCE OF OUTLIERS
MAKEPLOT2

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MAXABSSCALER
MAXABSSCALER DIFFERS FROM THE PREVIOUS SCALER SUCH THAT THE ABSOLUTE VALUES ARE MAPPED IN THE RANGE 0 1 ON POSITIVE ONLY DATA THIS SCALER BEHAVES SIMILARLY TO MINMAXSCALER AND THEREFORE ALSO SUFFERS FROM THE PRESENCE OF LARGE OUTLIERS
MAKEPLOT3
ROBUSTSCALER
UNLIKE THE PREVIOUS SCALERS THE CENTERING AND SCALING STATISTICS OF THIS SCALER ARE BASED ON PERCENTILES AND ARE THEREFORE NOT INFLUENCED BY A FEW NUMBER OF VERY LARGE MARGINAL OUTLIERS CONSEQUENTLY THE RESULTING RANGE OF THE TRANSFORMED FEATURE VALUES IS LARGER THAN FOR THE PREVIOUS SCALERS AND MORE IMPORTANTLY ARE APPROXIMATELY SIMILAR FOR BOTH FEATURES MOST OF THE TRANSFORMED VALUES LIE IN A 2 3 RANGE AS SEEN IN THE ZOOMEDIN FIGURE NOTE THAT THE OUTLIERS THEMSELVES ARE STILL PRESENT IN THE TRANSFORMED DATA IF A SEPARATE OUTLIER CLIPPING IS DESIRABLE A NONLINEAR TRANSFORMATION IS REQUIRED SEE BELOW
MAKEPLOT4
POWERTRANSFORMER
POWERTRANSFORMER APPLIES A POWER TRANSFORMATION TO EACH FEATURE TO MAKE THE DATA MORE GAUSSIANLIKE CUR

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RENTLYPOWERTRANSFORMER IMPLEMENTS THE YEOJOHNSON AND BOXCOX TRANSFORMS THE POWER TRANSFORM FINDS
THE OPTIMAL SCALING FACTOR TO STABILIZE VARIANCE AND MIMIMIZE SKEWNESS THROUGH MAXIMUM LIKELIHOOD ESTIMATION BY
DEFAULTPOWERTRANSFORMER ALSO APPLIES ZEROMEAN UNIT VARIANCE NORMALIZATION TO THE TRANSFORMED OUTPUT NOTE
THAT BOXCOX CAN ONLY BE APPLIED TO STRICTLY POSITIVE DATA INCOME AND NUMBER OF HOUSEHOLDS HAPPEN TO BE STRICTLY
POSITIVE BUT IF NEGATIVE VALUES ARE PRESENT THE YEOJOHNSON TRANSFORMED IS TO BE PREFERRED
MAKEPLOT5
MAKEPLOT6
•
•
QUANTILETRANSFORMER GAUSSIAN OUTPUT
QUANTILETRANSFORMER HAS AN ADDITIONAL OUTPUTDISTRIBUTION PARAMETER ALLOWING TO MATCH A GAUSSIAN
DISTRIBUTION INSTEAD OF A UNIFORM DISTRIBUTION NOTE THAT THIS NONPARAMETETRIC TRANSFORMER INTRODUCES SATURATION ARTI
FACTS FOR EXTREME VALUES
MAKEPLOT7

QUANTILETRANSFORMER UNIFORM OUTPUT
QUANTILETRANSFORMER APPLIES A NONLINEAR TRANSFORMATION SUCH THAT THE PROBABILITY DENSITY FUNCTION OF EACH FEATURE WILL BE MAPPED TO A UNIFORM DISTRIBUTION IN THIS CASE ALL THE DATA WILL BE MAPPED IN THE RANGE 0 1 EVEN THE OUTLIERS WHICH CANNOT BE DISTINGUISHED ANYMORE FROM THE INLIERS
ASROBUSTSCALER QUANTILETRANSFORMER IS ROBUST TO OUTLIERS IN THE SENSE THAT ADDING OR REMOVING OUTLIERS IN THE TRAINING SET WILL YIELD APPROXIMATELY THE SAME TRANSFORMATION ON HELD OUT DATA BUT CONTRARY TO ROBUSTSCALER QUANTILETRANSFORMER WILL ALSO AUTOMATICALLY COLLAPSE ANY OUTLIER BY SETTING THEM TO THE A PRIORI DEFINED RANGE BOUNDARIES 0 AND 1
MAKEPLOT8
NORMALIZER
THENORMALIZER RESCALES THE VECTOR FOR EACH SAMPLE TO HAVE UNIT NORM INDEPENDENTLY OF THE DISTRIBUTION OF THE SAMPLES IT CAN BE SEEN ON BOTH FIGURES BELOW WHERE ALL SAMPLES ARE MAPPED ONTO THE UNIT CIRCLE IN OUR EXAMPLE THE TWO SELECTED FEATURES HAVE ONLY POSITIVE VALUES THEREFORE THE TRANSFORMED DATA ONLY LIE IN THE POSITIVE QUADRANT THIS WOULD NOT BE THE CASE IF SOME ORIGINAL FEATURES HAD A MIX OF POSITIVE AND NEGATIVE VALUES

MAKEPLOT9
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 4599 SECONDS
526 SEMI SUPERVISED CLASSIFICATION
EXAMPLES CONCERNING THE SKLEARNSEMISUPERVISED MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5261 DECISION BOUNDARY OF LABEL PROPAGATION VERSUS SVM ON THE IRIS DATASET
COMPARISON FOR DECISION BOUNDARY GENERATED ON IRIS DATASET BETWEEN LABEL PROPAGATION AND SVM
THIS DEMONSTRATES LABEL PROPAGATION LEARNING A GOOD BOUNDARY EVEN WITH A SMALL AMOUNT OF LABELED DATA
1386 CHAPTER 5 EXAMPLES

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PRINTDOC
 AUTHORS CLAY WOOLAM CLAYWOOLAMORG
 LICENSE BSD
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT DATASETS
FROM SKLEARN IMPORT SVM
FROM SKLEARNSEMISUPERVISED IMPORT LABELPROPAGATION
RNG NPRANDOMRANDOMSTATE0
IRIS DATASETSLOADIRIS
X IRISDATA 2
Y IRISTARGET
 STEP SIZE IN THE MESH
H 02
Y30 NPCOPYY
Y30RNGRANDLENY 03 1
Y50 NPCOPYY
Y50RNGRANDLENY 05 1
 WE CREATE AN INSTANCE OF SVM AND FIT OUT DATA WE DO NOT SCALE OUR

```
 DATA SINCE WE WANT TO PLOT THE SUPPORT VECTORS
LS30  LABELPROPAGATIONLABELSPREADINGFITX Y30
Y30
LS50  LABELPROPAGATIONLABELSPREADINGFITX Y50
Y50
LS100  LABELPROPAGATIONLABELSPREADINGFITX Y Y
RBFSVC  SVMSVCKERNELRBF GAMMA5FITX Y Y
 CREATE A MESH TO PLOT IN
XMIN XMAX  X 0MIN  1 X 0MAX  1
YMIN YMAX  X 1MIN  1 X 1MAX  1
XX YY  NPMESHGRIDNPARANGEXMIN XMAX H
NPARANGEYMIN YMAX H
 TITLE FOR THE PLOTS
TITLES  LABEL SPREADING 30  DATA
LABEL SPREADING 50  DATA
LABEL SPREADING 100  DATA
SVC WITH RBF KERNEL
COLORMAP  1 1 1 1 0 0 0 9 1 1 0 0 2 8 6 0
FORI CLF YTRAIN INENUMERATELS30 LS50 LS100 RBFSVC
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
PLTSUBPLOT2 2 I  1
Z  CLFPREDICTNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z  ZRESHAPEXXSHAPE
PLTCONTOURFXX YY Z CMAPPLTCMPAIRED
PLTAXISOFF
 PLOT ALSO THE TRAINING POINTS
COLORS  COLORMAPY FORYINYTRAIN
PLTSCATTERX 0 X 1 CCOLORS EDGECOLORSBLACK
PLTTITLETITLESI
PLTSUPTITLEUNLABELED POINTS ARE COLORED WHITE Y01
PLTSHOW
```
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0915 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5262 LABEL PROPAGATION LEARNING A COMPLEX STRUCTURE
EXAMPLE OF LABELPROPAGATION LEARNING A COMPLEX INTERNAL STRUCTURE TO DEMONSTRATE “MANIFOLD LEARNING” THE OUTER CIRCLE SHOULD BE LABELED “RED” AND THE INNER CIRCLE “BLUE” BECAUSE BOTH LABEL GROUPS LIE INSIDE THEIR OWN DISTINCT SHAPE WE CAN SEE THAT THE LABELS PROPAGATE CORRECTLY AROUND THE CIRCLE

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SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDOC
 AUTHORS CLAY WOOLAM CLAYWOOLAMORG
 ANDREAS MUELLER AMUELLERAISUNIBONNDE
 LICENSE BSD
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNSEMISUPERVISED IMPORT LABELPROPAGATION
FROM SKLEARNDATASETS IMPORT MAKECIRCLES
 GENERATE RING WITH INNER BOX
NSAMPLES  200
X Y  MAKECIRCLESNSAMPLESNSAMPLES SHUFFLEFALSE
OUTER INNER  0 1
LABELS  NPFULLNSAMPLES 1
LABELS0  OUTER
LABELS1  INNER

 LEARN WITH LABELSPREADING
LABELSPREAD  LABELPROPAGATIONLABELSPREADINGKERNELKNN ALPHA08
LABELSPREADFITX LABELS

 PLOT OUTPUT LABELS
OUTPUTLABELS  LABELSPREADTRANSDUCTION
PLTFIGUREFIGSIZE85 4
PLTSUBPLOT1 2 1
PLTSCATTERXLABELS  OUTER 0 XLABELS  OUTER 1 COLORNAVY
MARKERS LW0 LABELOUTER LABELED S10
PLTSCATTERXLABELS  INNER 0 XLABELS  INNER 1 COLORC
MARKERS LW0 LABELINNER LABELED S10
PLTSCATTERXLABELS  1 0 XLABELS  1 1 COLORDARKORANGE
MARKER LABELUNLABELED
PLTLEGENDSCATTERPOINTS1 SHADOWFALSE LOCUPPER RIGHT
PLTTITLERAW DATA 2 CLASSESOUTER AND INNER
526 SEMI SUPERVISED CLASSIFICATION 1389
```

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PLTSUBPLOT1 2 2
OUTPUTLABELARRAY NPASARRAYOUTPUTLABELS
OUTERNUMBERS NPWHEREOUTPUTLABELARRAY OUTER0
INNERNUMBERS NPWHEREOUTPUTLABELARRAY INNER0
PLTSCATTERXOUTERNUMBERS 0 XOUTERNUMBERS 1 COLORNAVY
MARKERS LW0 S10 LABELOUTER LEARNED
PLTSCATTERXINNERNUMBERS 0 XINNERNUMBERS 1 COLORC
MARKERS LW0 S10 LABELINNER LEARNED
PLTLEGENDSCATTERPOINTS1 SHADOWFALSE LOCUPPER RIGHT
PLTTITLELABELS LEARNED WITH LABEL SPREADING KNN
PLTSUBPLOTSADJUSTLEFT007 BOTTOM007 RIGHT093 TOP092
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0031 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5263 LABEL PROPAGATION DIGITS DEMONSTRATING PERFORMANCE
THIS EXAMPLE DEMONSTRATES THE POWER OF SEMISUPERVISED LEARNING BY TRAINING A LABEL SPREADING MODEL TO CLASSIFY
HANDWRITTEN DIGITS WITH SETS OF VERY FEW LABELS
THE HANDWRITTEN DIGIT DATASET HAS 1797 TOTAL POINTS THE MODEL WILL BE TRAINED USING ALL POINTS BUT ONLY 30 WILL BE
LABELED RESULTS IN THE FORM OF A CONFUSION MATRIX AND A SERIES OF METRICS OVER EACH CLASS WILL BE VERY GOOD
AT THE END THE TOP 10 MOST UNCERTAIN PREDICTIONS WILL BE SHOWN

OUT
LABEL SPREADING MODEL 40 LABELED 300 UNLABELED POINTS 340 TOTAL
PRECISION RECALL F1SCORE SUPPORT
0 100 100 100 27
1 082 100 090 37
2 100 086 092 28
3 100 080 089 35
4 092 100 096 24
5 074 094 083 34
6 089 096 092 25
7 094 089 091 35
8 100 068 081 31
9 081 088 084 24
ACCURACY 090 300
MACRO AVG 091 090 090 300
WEIGHTED AVG 091 090 090 300
CONFUSION MATRIX
27 0 0 0 0 0 0 0 0 0
 0 37 0 0 0 0 0 0 0 0
 0 1 24 0 0 0 2 1 0 0
 0 0 0 28 0 5 0 1 0 1
 0 0 0 0 24 0 0 0 0 0
 0 0 0 0 0 32 0 0 0 2

SCIKITLEARN USER GUIDE RELEASE 0213
 0 0 0 0 0 1 24 0 0 0
 0 0 0 0 1 3 0 31 0 0
 0 7 0 0 0 0 1 0 21 2
 0 0 0 0 1 2 0 0 0 21
PRINTDOC
 AUTHORS CLAY WOOLAM CLAYWOOLAMORG
 LICENSE BSD
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPY IMPORT STATS
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNSEMISUPERVISED IMPORT LABELPROPAGATION
FROM SKLEARNMETRICS IMPORT CONFUSIONMATRIX CLASSIFICATIONREPORT
DIGITS DATASETSLOADDIGITS
RNG NPRANDOMRANDOMSTATE2
INDICES NPARANGELENDIGITSDATA
RNGSHUFFLEINDICES
X DIGITSDATAINDICES340
Y DIGITSTARGETINDICES340
IMAGES DIGITSIMAGESINDICES340
NTOTALSAMPLES LENY
NLABELEDPOINTS 40
INDICES NPARANGENTOTALSAMPLES
UNLABELEDSET INDICESNLABELEDPOINTS

 SHUFFLE EVERYTHING AROUND
YTRAIN NPCOPYY
YTRAINUNLABELEDSET 1

 LEARN WITH LABELSPREADING
LPMODEL LABELPROPAGATIONLABELSPREADINGGAMMA25 MAXITER20
LPMODELFITX YTRAIN
PREDICTEDLABELS LPMODELTRANSDUCTIONUNLABELEDSET
TRUELABELS YUNLABELEDSET
CM CONFUSIONMATRIXTRUELABELS PREDICTEDLABELS LABELSLPMODELCLASSES
PRINTLABEL SPREADING MODEL DLABELED DUNLABELED POINTS DTOTAL
NLABELEDPOINTS NTOTALSAMPLES NLABELEDPOINTS NTOTALSAMPLES

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PRINTCLASSIFICATIONREPORTTRUELABELS PREDICTEDLABELS
PRINTCONFUSION MATRIX
PRINTCM

CALCULATE UNCERTAINTY VALUES FOR EACH TRANSDUCED DISTRIBUTION
PREDENTROPIES STATSDISTRIBUTIONSENTROPYLPMODELLABELDISTRIBUTIONST

PICK THE TOP 10 MOST UNCERTAIN LABELS
UNCERTAINTYINDEX NPARGSORTPREDENTROPIES10

PLOT
F PLTFIGUREFIGSIZE7 5
FORINDEX IMAGEINDEX INENUMERATEUNCERTAINTYINDEX
IMAGE IMAGESIMAGEINDEX
SUB FADDSUBPLOT2 5 INDEX 1
SUBIMSHOWIMAGE CMAPPLTCMGRAYR
PLTXTICKS
PLTYTICKS
SUBSETTITLEPREDICT INTRUEI
LPMODELTRANSDUCTIONIMAGEINDEX YIMAGEINDEX
FSUPTITLELEARNING WITH SMALL AMOUNT OF LABELED DATA
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0225 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5264 LABEL PROPAGATION DIGITS ACTIVE LEARNING
DEMONSTRATES AN ACTIVE LEARNING TECHNIQUE TO LEARN HANDWRITTEN DIGITS USING LABEL PROPAGATION
WE START BY TRAINING A LABEL PROPAGATION MODEL WITH ONLY 10 LABELED POINTS THEN WE SELECT THE TOP FIVE MOST UNCERTAIN POINTS TO LABEL NEXT WE TRAIN WITH 15 LABELED POINTS ORIGINAL 10 5 NEW ONES WE REPEAT THIS PROCESS FOUR TIMES TO HAVE A MODEL TRAINED WITH 30 LABELED EXAMPLES NOTE YOU CAN INCREASE THIS TO LABEL MORE THAN 30 BY CHANGING MAXITERATIONS LABELING MORE THAN 30 CAN BE USEFUL TO GET A SENSE FOR THE SPEED OF CONVERGENCE OF THIS ACTIVE LEARNING TECHNIQUE
A PLOT WILL APPEAR SHOWING THE TOP 5 MOST UNCERTAIN DIGITS FOR EACH ITERATION OF TRAINING THESE MAY OR MAY NOT CONTAIN MISTAKES BUT WE WILL TRAIN THE NEXT MODEL WITH THEIR TRUE LABELS
526 SEMI SUPERVISED CLASSIFICATION 1393

OUT
ITERATION 0
LABEL SPREADING MODEL 40 LABELED 290 UNLABELED 330 TOTAL
PRECISION RECALL F1SCORE SUPPORT
0 100 100 100 22
1 078 069 073 26
2 093 093 093 29
3 100 089 094 27
4 092 096 094 23
5 096 070 081 33
6 097 097 097 35
7 094 091 092 33
8 062 089 074 28
9 073 079 076 34
ACCURACY 087 290
MACRO AVG 089 087 087 290
WEIGHTED AVG 088 087 087 290
CONFUSION MATRIX
22 0 0 0 0 0 0 0 0 0
 0 18 2 0 0 0 1 0 5 0
 0 0 27 0 0 0 0 0 2 0
 0 0 0 24 0 0 0 0 3 0

0 1 0 0 22 0 0 0 0 0
0 0 0 0 0 23 0 0 0 10
0 1 0 0 0 0 34 0 0 0
0 0 0 0 0 0 0 30 3 0
0 3 0 0 0 0 0 0 25 0
0 0 0 0 2 1 0 2 2 27
ITERATION 1
LABEL SPREADING MODEL 45 LABELED 285 UNLABELED 330 TOTAL
PRECISION RECALL F1SCORE SUPPORT
0 100 100 100 22
1 079 100 088 22
2 100 093 096 29
3 100 100 100 26
4 092 096 094 23
5 096 070 081 33
6 100 097 099 35
7 094 091 092 33
8 077 086 081 28
9 073 079 076 34
ACCURACY 090 285
MACRO AVG 091 091 091 285
WEIGHTED AVG 091 090 090 285
CONFUSION MATRIX
22 0 0 0 0 0 0 0 0 0
0 22 0 0 0 0 0 0 0 0
0 0 27 0 0 0 0 0 2 0
0 0 0 26 0 0 0 0 0 0
0 1 0 0 22 0 0 0 0 0
0 0 0 0 0 23 0 0 0 10
0 1 0 0 0 0 34 0 0 0
0 0 0 0 0 0 0 30 3 0
0 4 0 0 0 0 0 0 24 0
0 0 0 0 2 1 0 2 2 27
ITERATION 2
LABEL SPREADING MODEL 50 LABELED 280 UNLABELED 330 TOTAL
PRECISION RECALL F1SCORE SUPPORT
0 100 100 100 22
1 085 100 092 22
2 100 100 100 28
3 100 100 100 26
4 087 100 093 20
5 096 070 081 33
6 100 097 099 35
7 094 100 097 32
8 092 086 089 28
9 073 079 076 34
ACCURACY 092 280
MACRO AVG 093 093 093 280
WEIGHTED AVG 093 092 092 280
CONFUSION MATRIX
22 0 0 0 0 0 0 0 0 0
0 22 0 0 0 0 0 0 0 0

0 0 28 0 0 0 0 0 0 0
0 0 0 26 0 0 0 0 0 0
0 0 0 0 20 0 0 0 0 0
0 0 0 0 0 23 0 0 0 10
0 1 0 0 0 0 34 0 0 0
0 0 0 0 0 0 0 32 0 0
0 3 0 0 1 0 0 0 24 0
0 0 0 0 2 1 0 2 2 27
ITERATION 3
LABEL SPREADING MODEL 55 LABELED 275 UNLABELED 330 TOTAL
PRECISION RECALL F1SCORE SUPPORT
0 100 100 100 22
1 085 100 092 22
2 100 100 100 27
3 100 100 100 26
4 087 100 093 20
5 096 087 092 31
6 100 097 099 35
7 100 100 100 31
8 092 086 089 28
9 088 085 086 33
ACCURACY 095 275
MACRO AVG 095 095 095 275
WEIGHTED AVG 095 095 095 275
CONFUSION MATRIX
22 0 0 0 0 0 0 0 0 0
0 22 0 0 0 0 0 0 0 0
0 0 27 0 0 0 0 0 0 0
0 0 0 26 0 0 0 0 0 0
0 0 0 0 20 0 0 0 0 0
0 0 0 0 0 27 0 0 0 4
0 1 0 0 0 0 34 0 0 0
0 0 0 0 0 0 0 31 0 0
0 3 0 0 1 0 0 0 24 0
0 0 0 0 2 1 0 0 2 28
ITERATION 4
LABEL SPREADING MODEL 60 LABELED 270 UNLABELED 330 TOTAL
PRECISION RECALL F1SCORE SUPPORT
0 100 100 100 22
1 096 100 098 22
2 100 096 098 27
3 096 100 098 25
4 086 100 093 19
5 096 087 092 31
6 100 097 099 35
7 100 100 100 31
8 092 096 094 25
9 088 085 086 33
ACCURACY 096 270
MACRO AVG 095 096 096 270
WEIGHTED AVG 096 096 096 270
CONFUSION MATRIX

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```
22 0 0 0 0 0 0 0 0 0
 0 22 0 0 0 0 0 0 0 0
 0 0 26 1 0 0 0 0 0 0
 0 0 0 25 0 0 0 0 0 0
 0 0 0 0 19 0 0 0 0 0
 0 0 0 0 0 27 0 0 0 4
 0 1 0 0 0 0 34 0 0 0
 0 0 0 0 0 0 0 31 0 0
 0 0 0 0 1 0 0 0 24 0
 0 0 0 0 2 1 0 0 2 28
PRINTDOC
 AUTHORS CLAY WOOLAM CLAYWOOLAMORG
 LICENSE BSD
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SCIPY IMPORT STATS
FROM SKLEARN IMPORT DATASETS
FROM SKLEARNSEMISUPERVISED IMPORT LABELPROPAGATION
FROM SKLEARNMETRICS IMPORT CLASSIFICATIONREPORT CONFUSIONMATRIX
DIGITS  DATASETSLOADDIGITS
RNG  NPRANDOMRANDOMSTATE0
INDICES  NPARANGELENDIGITSDATA
RNGSHUFFLEINDICES
X  DIGITSDATAINDICES330
Y  DIGITSTARGETINDICES330
IMAGES  DIGITSIMAGESINDICES330
NTOTALSAMPLES  LENY
NLABELEDPOINTS  40
MAXITERATIONS  5
UNLABELEDINDICES  NPARANGENTOTALSAMPLESNLABELEDPOINTS
F  PLTFIGURE
FORIINRANGEMAXITERATIONS
IFLENUNLABELEDINDICES  0
PRINTNO UNLABELED ITEMS LEFT TO LABEL
BREAK
YTRAIN  NPCOPYY
YTRAINUNLABELEDINDICES  1
LPMODEL  LABELPROPAGATIONLABELSPREADINGGAMMA025 MAXITER20
LPMODELFITX YTRAIN
PREDICTEDLABELS  LPMODELTRANSDUCTIONUNLABELEDINDICES
TRUELABELS  YUNLABELEDINDICES
```

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CM CONFUSIONMATRIXTRUELABELS PREDICTEDLABELS
LABELSLPMODELCLASSES
PRINTITERATION I S I 70
PRINTLABEL SPREADING MODEL DLABELED DUNLABELED DTOTAL
 NLABELEDPOINTS NTOTALSAMPLES NLABELEDPOINTS
NTOTALSAMPLES
PRINTCLASSIFICATIONREPORTTRUELABELS PREDICTEDLABELS
PRINTCONFUSION MATRIX
PRINTCM
 COMPUTE THE ENTROPIES OF TRANSDUCED LABEL DISTRIBUTIONS
PREDENTROPIES STATSDISTRIBUTIONSENTROPY
LPMODELLABELDISTRIBUTIONST
 SELECT UP TO 5 DIGIT EXAMPLES THAT THE CLASSIFIER IS MOST UNCERTAIN ABOUT
UNCERTAINTYINDEX NPARGSORTPREDENTROPIES1
UNCERTAINTYINDEX UNCERTAINTYINDEX
NPIN1DUNCERTAINTYINDEX UNLABELEDINDICES5
 KEEP TRACK OF INDICES THAT WE GET LABELS FOR
DELETEINDICES NPARRAY DTYPEINT
 FOR MORE THAN 5 ITERATIONS VISUALIZE THE GAIN ONLY ON THE FIRST 5
IFI 5
FTEXT05 1 I 1 183
MODELDNNFIT WITH NDLABELS
I 1 I 5 10 SIZE10
FORINDEX IMAGEINDEX INENUMERATEUNCERTAINTYINDEX
IMAGE IMAGESIMAGEINDEX
 FOR MORE THAN 5 ITERATIONS VISUALIZE THE GAIN ONLY ON THE FIRST 5
IFI 5
SUB FADDSUBPLOT5 5 INDEX 1 5 I
SUBIMSHOWIMAGE CMAPPLTCMGRAYR INTERPOLATIONNONE
SUBSETTITLEPREDICT INTRUEI
LPMODELTRANSDUCTIONIMAGEINDEX YIMAGEINDEX SIZE10
SUBAXISOFF
 LABELING 5 POINTS REMOTE FROM LABELED SET
DELETEINDEX NPWHEREUNLABELEDINDICES IMAGEINDEX
DELETEINDICES NPCONCATENATEDELETEINDICES DELETEINDEX
UNLABELEDINDICES NPDELETEUNLABELEDINDICES DELETEINDICES
NLABELEDPOINTS LENUNCERTAINTYINDEX
FSUPTITLEACTIVE LEARNING WITH LABEL PROPAGATION NROWS SHOW 5 MOST
UNCERTAIN LABELS TO LEARN WITH THE NEXT MODEL Y115
PLTSUBPLOTSADJUSTLEFT02 BOTTOM003 RIGHT09 TOP09 WSPACE02
HSPACE085
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0575 SECONDS

527 SUPPORT VECTOR MACHINES
EXAMPLES CONCERNING THE SKLEARNSVM MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5271 NONLINEAR SVM
PERFORM BINARY CLASSIFICATION USING NONLINEAR SVC WITH RBF KERNEL THE TARGET TO PREDICT IS A XOR OF THE INPUTS
THE COLOR MAP ILLUSTRATES THE DECISION FUNCTION LEARNED BY THE SVC
```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT SVM
XX YY  NPMESHGRIDNPLINSPACE3 3 500
NPLINSPACE3 3 500
NPRANDOMSEED0
X  NPRANDOMRANDN300 2
Y  NPLOGICALXORX 0  0 X 1  0
```

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FIT THE MODEL
CLF SVMNUSVCGAMMAAUTO
CLFFITX Y
PLOT THE DECISION FUNCTION FOR EACH DATAPOINT ON THE GRID
Z CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
PLTIMSHOWZ INTERPOLATIONNEAREST
EXTENTXXMIN XXMAX YYMIN YYMAX ASPECTAUTO
ORIGINLOWER CMAPPLTCMPUORR
CONTOURS PLTCONTOURXX YY Z LEVELS0 LINEWIDTHS2
LINESTYLESDASHED
PLTSCATTERX 0 X 1 S30 CY CMAPPLTCMPAIRED
EDGECOLORSK
PLTXTICKS
PLTYTICKS
PLTAXIS3 3 3 3
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1073 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5272 SVM MAXIMUM MARGIN SEPARATING HYPERPLANE
PLOT THE MAXIMUM MARGIN SEPARATING HYPERPLANE WITHIN A TWOCLASS SEPARABLE DATASET USING A SUPPORT VECTOR MACHINE CLASSIFIER WITH LINEAR KERNEL

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT SVM
FROM SKLEARNDATASETS IMPORT MAKEBLOBS
 WE CREATE 40 SEPARABLE POINTS
X Y MAKEBLOBSNSAMPLES40 CENTERS2 RANDOMSTATE6
 FIT THE MODEL DONT REGULARIZE FOR ILLUSTRATION PURPOSES
CLF SVMSVCKERNELLINEAR C1000
CLFFITX Y
PLTSCATTERX 0 X 1 CY S30 CMAPPLTCMPAIRED
 PLOT THE DECISION FUNCTION
AX PLTGCA
XLIM AXGETXLIM
YLIM AXGETYLIM
 CREATE GRID TO EVALUATE MODEL
XX NPLINSPACEXLIM0 XLIM1 30
YY NPLINSPACEYLIM0 YLIM1 30
YY XX NPMESHGRIDYY XX

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XY NPVSTACKXXRAVEL YYRAVELT
Z CLFDECISIONFUNCTIONXYRESHAPEXXSHAPE
 PLOT DECISION BOUNDARY AND MARGINS
AXCONTOURXX YY Z COLORSK LEVELS1 0 1 ALPHA05
LINESTYLES
 PLOT SUPPORT VECTORS
AXSCATTERCLFSUPPORTVECTORS 0 CLFSUPPORTVECTORS 1 S100
LINEWIDTH1 FACECOLORSNONE EDGECOLORSK
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0021 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5273 SVM WITH CUSTOM KERNEL
SIMPLE USAGE OF SUPPORT VECTOR MACHINES TO CLASSIFY A SAMPLE IT WILL PLOT THE DECISION SURFACE AND THE SUPPORT VECTORS
PRINTDOC
IMPORT NUMPY AS NP

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IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT SVM DATASETS
 IMPORT SOME DATA TO PLAY WITH
IRIS DATASETSLOADIRIS
X IRISDATA 2 WE ONLY TAKE THE FIRST TWO FEATURES WE COULD
 AVOID THIS UGLY SLICING BY USING A TWODIM DATASET
Y IRISTARGET
DEFMYKERNELX Y

WE CREATE A CUSTOM KERNEL
2 0
KX Y X   YT
0 1

M NPARRAY2 0 0 10
RETURNNPDOTNPDOTX M YT
H 02 STEP SIZE IN THE MESH
 WE CREATE AN INSTANCE OF SVM AND FIT OUT DATA
CLF SVMSVCKERNELMYKERNEL
CLFFITX Y
 PLOT THE DECISION BOUNDARY FOR THAT WE WILL ASSIGN A COLOR TO EACH
 POINT IN THE MESH XMIN XMAXXYMIN YMAX
XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX H NPARANGEYMIN YMAX H
Z CLFPREDICTNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
PLTPCOLORMESHXX YY Z CMAPPLTCMPAIRED
 PLOT ALSO THE TRAINING POINTS
PLTSCATTERX 0 X 1 CY CMAPPLTCMPAIRED EDGECOLORSK
PLTTITLE3CLASS CLASSIFICATION USING SUPPORT VECTOR MACHINE WITH CUSTOM
 KERNEL
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0110 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5274 SVM WEIGHTED SAMPLES
PLOT DECISION FUNCTION OF A WEIGHTED DATASET WHERE THE SIZE OF POINTS IS PROPORTIONAL TO ITS WEIGHT
THE SAMPLE WEIGHTING RESCALES THE C PARAMETER WHICH MEANS THAT THE CLASSIFIER PUTS MORE EMPHASIS ON GETTING THESE
527 SUPPORT VECTOR MACHINES 1403

POINTS RIGHT THE EFFECT MIGHT OFTEN BE SUBTLE TO EMPHASIZE THE EFFECT HERE WE PARTICULARLY WEIGHT OUTLIERS MAKING THE DEFORMATION OF THE DECISION BOUNDARY VERY VISIBLE

```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT SVM
DEFPLOTDECISIONFUNCTIONCLASSIFIER SAMPLEWEIGHT AXIS TITLE
 PLOT THE DECISION FUNCTION
XX YY  NPMESHGRIDNPLINSPACE4 5 500 NPLINSPACE4 5 500
Z  CLASSIFIERDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
Z  ZRESHAPEXXSHAPE
 PLOT THE LINE THE POINTS AND THE NEAREST VECTORS TO THE PLANE
AXISCONTOURFXX YY Z ALPHA075 CMAPPLTCMBONE
AXISSCATTERX 0 X 1 CY S100 SAMPLEWEIGHT ALPHA09
CMAPPLTCMBONE EDGECOLORSBLACK
AXISAXISOFF
AXISSETTITLETITLE
 WE CREATE 20 POINTS
NPRANDOMSEED0
X  NPRNPRANDOMRANDN10 2  1 1 NPRANDOMRANDN10 2
Y  1 10  1 10
SAMPLEWEIGHTLASTTEN  ABSNPRANDOMRANDNLENX
SAMPLEWEIGHTCONSTANT  NPONESLENX
 AND BIGGER WEIGHTS TO SOME OUTLIERS
SAMPLEWEIGHTLASTTEN15  5
SAMPLEWEIGHTLASTTEN9  15
 FOR REFERENCE FIRST FIT WITHOUT SAMPLE WEIGHTS
 FIT THE MODEL
```

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CLFWEIGHTS SVMSVCGAMMA1
CLFWEIGHTSFITX Y SAMPLEWEIGHTSAMPLEWEIGHTLASTTEN
CLFNOWEIGHTS SVMSVCGAMMA1
CLFNOWEIGHTSFITX Y
FIG AXES PLTSUBPLOTS1 2 FIGSIZE14 6
PLOTDECISIONFUNCTIONCLFNOWEIGHTS SAMPLEWEIGHTCONSTANT AXES0
CONSTANT WEIGHTS
PLOTDECISIONFUNCTIONCLFWEIGHTS SAMPLEWEIGHTLASTTEN AXES1
MODIFIED WEIGHTS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0349 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5275 SVM SEPARATING HYPERPLANE FOR UNBALANCED CLASSES
FIND THE OPTIMAL SEPARATING HYPERPLANE USING AN SVC FOR CLASSES THAT ARE UNBALANCED
WE FIRST FIND THE SEPARATING PLANE WITH A PLAIN SVC AND THEN PLOT DASHED THE SEPARATING HYPERPLANE WITH AUTOMATICALLY
CORRECTION FOR UNBALANCED CLASSES
NOTE THIS EXAMPLE WILL ALSO WORK BY REPLACING SVCKERNELLINEAR WITH
SGDCLASSIFIERLOSSHINGE SETTING THE LOSS PARAMETER OF THE SGDCLASSIFIER EQUAL TOHINGE WILL
YIELD BEHAVIOUR SUCH AS THAT OF A SVC WITH A LINEAR KERNEL
FOR EXAMPLE TRY INSTEAD OF THE SVC
CLF SGDCLASSIFIERNITER100 ALPHA001

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT SVM
FROM SKLEARNDATASETS IMPORT MAKEBLOBS
 WE CREATE TWO CLUSTERS OF RANDOM POINTS
NSAMPLES1 1000
NSAMPLES2 100
CENTERS 00 00 20 20
CLUSTERSSTD 15 05
X Y MAKEBLOBSNSAMPLESNSAMPLES1 NSAMPLES2
CENTERSCENTERS
CLUSTERSTDCLUSTERSSTD
RANDOMSTATE0 SHUFFLEFALSE
 FIT THE MODEL AND GET THE SEPARATING HYPERPLANE
CLF SVMSVCKERNELLINEAR C10
CLFFITX Y
 FIT THE MODEL AND GET THE SEPARATING HYPERPLANE USING WEIGHTED CLASSES
WCLF SVMSVCKERNELLINEAR CLASSWEIGHT1 10
WCLFFITX Y
 PLOT THE SAMPLES

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PLTSCATTERX 0 X 1 CY CMAPPLTCMPAIRED EDGECOLORSK
 PLOT THE DECISION FUNCTIONS FOR BOTH CLASSIFIERS
AX PLTGCA
XLIM AXGETXLIM
YLIM AXGETYLIM
 CREATE GRID TO EVALUATE MODEL
XX NPLINSPACEXLIM0 XLIM1 30
YY NPLINSPACEYLIM0 YLIM1 30
YY XX NPMESHGRIDYY XX
XY NPVSTACKXXRAVEL YYRAVELT
 GET THE SEPARATING HYPERPLANE
Z CLFDECISIONFUNCTIONXYRESHAPEXXSHAPE
 PLOT DECISION BOUNDARY AND MARGINS
A AXCONTOURXX YY Z COLORSK LEVELS0 ALPHA05 LINESTYLES
 GET THE SEPARATING HYPERPLANE FOR WEIGHTED CLASSES
Z WCLFDECISIONFUNCTIONXYRESHAPEXXSHAPE
 PLOT DECISION BOUNDARY AND MARGINS FOR WEIGHTED CLASSES
B AXCONTOURXX YY Z COLORSR LEVELS0 ALPHA05 LINESTYLES
PLTLEGENDACOLLECTIONS0 BCOLLECTIONS0 NON WEIGHTED WEIGHTED
LOCUPPER RIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0034 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5276 SVMKERNELS
THREE DIFFERENT TYPES OF SVMKERNELS ARE DISPLAYED BELOW THE POLYNOMIAL AND RBF ARE ESPECIALLY USEFUL WHEN THE DATAPOINTS ARE NOT LINEARLY SEPARABLE
527 SUPPORT VECTOR MACHINES 1407

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•

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```
PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT SVM
 OUR DATASET AND TARGETS
X  NPC4 7
15 1
14 9
13 12
11 2
12 4
5 12
15 21
1 1

13 8
12 5
2 2
5 24
2 23
0 27
13 21T
Y  0 8  1 8
 FIGURE NUMBER
FIGNUM  1
 FIT THE MODEL
FORKERNELINLINEAR POLY RBF
CLF  SVMSVCKERNELKERNEL GAMMA2
CLFFITX Y
```

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PLOT THE LINE THE POINTS AND THE NEAREST VECTORS TO THE PLANE
PLTFIGUREFIGNUM FIGSIZE4 3
PLTCLF
PLTSCATTERCLFSUPPORTVECTORS 0 CLFSUPPORTVECTORS 1 S80
FACECOLORSNONE ZORDER10 EDGECOLORSK
PLTSCATTERX 0 X 1 CY ZORDER10 CMAPPLTCMPAIRED
EDGECOLORSK
PLTAXISTIGHT
XMIN 3
XMAX 3
YMIN 3
YMAX 3
XX YY NPMGRIDXMINXMAX200J YMINYMAX200J
Z CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
PUT THE RESULT INTO A COLOR PLOT
Z ZRESHAPEXXSHAPE
PLTFIGUREFIGNUM FIGSIZE4 3
PLTPCOLORMESHXX YY Z 0 CMAPPLTCMPAIRED
PLTCONTOURXX YY Z COLORSK K K LINESTYLES
LEVELS5 0 5
PLTXLIMXMIN XMAX
PLTYLIMYMIN YMAX
PLTXTICKS
PLTYTICKS
FIGNUM FIGNUM 1
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0096 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5277 SVMANOVA SVM WITH UNIVARIATE FEATURE SELECTION
THIS EXAMPLE SHOWS HOW TO PERFORM UNIVARIATE FEATURE SELECTION BEFORE RUNNING A SVC SUPPORT VECTOR CLASSIFIER TO IMPROVE THE CLASSIFICATION SCORES WE USE THE IRIS DATASET 4 FEATURES AND ADD 36 NONINFORMATIVE FEATURES WE CAN FIND THAT OUR MODEL ACHIEVES BEST PERFORMANCE WHEN WE SELECT AROUND 10 OF FEATURES

```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT LOADIRIS
FROM SKLEARNFEATURESELECTION IMPORT SELECTPERCENTILE CHI2
FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
FROM SKLEARNPIPELINE IMPORT PIPELINE
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM SKLEARNSVM IMPORT SVC

 IMPORT SOME DATA TO PLAY WITH
X Y  LOADIRISRETURNXYTRUE
 ADD NONINFORMATIVE FEATURES
NPRANDOMSEED0
X  NPHSTACKX 2 NPRANDOMRANDOMXSHAPE0 36

 CREATE A FEATURESELECTION TRANSFORM A SCALER AND AN INSTANCE OF SVM THAT WE
 COMBINE TOGETHER TO HAVE AN FULLBLOWN ESTIMATOR
CLF  PIPELINEANOVA SELECTPERCENTILECHI2
SCALER STANDARDSCALER
SVC SVCGAMMAAUTO
```

```
 PLOT THE CROSSVALIDATION SCORE AS A FUNCTION OF PERCENTILE OF FEATURES
SCOREMEANS  LIST
SCORESTDS  LIST
PERCENTILES  1 3 6 10 15 20 30 40 60 80 100
FORPERCENTILE INPERCENTILES
CLFSETPARAMSANOVAPERCENTILEPERCENTILE
THISSCORES  CROSSVALSCORECLF X Y CV5
SCOREMEANSAPPENDTHISSCORESMEAN
SCORESTDSAPPENDTHISSCORESSTD
PLTERRORBARPERCENTILES SCOREMEANS NPARRAYSCORESTDS
PLTTITLE
PERFORMANCE OF THE SVMANOVA VARYING THE PERCENTILE OF FEATURES SELECTED
PLTXTICKSNPLINSPACE0 100 11 ENDPOINTTRUE
PLTXLABELPERCENTILE
PLTYLABELACCURACY SCORE
PLTAXISTIGHT
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT  0 MINUTES 0199 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5278 SUPPORT VECTOR REGRESSION SVR USING LINEAR AND NONLINEAR KERNELS
TOY EXAMPLE OF 1D REGRESSION USING LINEAR POLYNOMIAL AND RBF KERNELS
1412 CHAPTER 5 EXAMPLES
```

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PRINTDOC
IMPORT NUMPY AS NP
FROM SKLEARNSVM IMPORT SVR
IMPORT MATPLOTLIBPYPLOT AS PLT

GENERATE SAMPLE DATA
X NPSORT5 NPRANDOMRAND40 1 AXIS0
Y NPSINXRAVEL

ADD NOISE TO TARGETS
Y5 3 05 NPRANDOMRAND8

FIT REGRESSION MODEL
SVRRBF SVRKERNELRBF C100 GAMMA01 EPSILON1
SVRLIN SVRKERNELLINEAR C100 GAMMAAUTO
SVRPOLY SVRKERNELPOLY C100 GAMMAAUTO DEGREE3 EPSILON1
COEF01

LOOK AT THE RESULTS
LW 2
SVRS SVRRBF SVRLIN SVRPOLY
KERNELLABEL RBF LINEAR POLYNOMIAL
MODELCOLOR M C G
527 SUPPORT VECTOR MACHINES 1413

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FIG AXES PLTSUBPLOTSNROWS1 NCOLS3 FIGSIZE15 10 SHAREYTRUE
FORIX SVR INENUMERATESVRS
AXESIXPLOTX SVRFITX YPREDICTX COLORMODELCOLORIX LWLW
LABEL MODELFORMATKERNELLABELIX
AXESIXSCATTERXSVRSUPPORT YSVRSUPPORT FACECOLORNONE
EDGECOLORMODELCOLORIX S50
LABEL SUPPORT VECTORSFORMATKERNELLABELIX
AXESIXSCATTERXNPSETDIFF1DNPARANGELENX SVRSUPPORT
YNPSETDIFF1DNPARANGELENX SVRSUPPORT
FACECOLORNONE EDGECOLORK S50
LABELOTHER TRAINING DATA
AXESIXLEGENDLOCUPPER CENTER BBOXTOANCHOR05 11
NCOL1 FANCYBOXTRUE SHADOWTRUE
FIGTEXT05 004 DATA HACENTER VACENTER
FIGTEXT006 05 TARGET HACENTER VACENTER ROTATIONVERTICAL
FIGSUPTITLESUPPORT VECTOR REGRESSION FONTSIZE14
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3104 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5279 SVM MARGINS EXAMPLE
THE PLOTS BELOW ILLUSTRATE THE EFFECT THE PARAMETER CHAS ON THE SEPARATION LINE A LARGE VALUE OF CBASICALLY TELLS OUR MODEL THAT WE DO NOT HAVE THAT MUCH FAITH IN OUR DATA’S DISTRIBUTION AND WILL ONLY CONSIDER POINTS CLOSE TO LINE OF SEPARATION
A SMALL VALUE OF CINCLUDES MOREALL THE OBSERVATIONS ALLOWING THE MARGINS TO BE CALCULATED USING ALL THE DATA IN THE AREA
•

•

```
PRINTDOC
 CODE SOURCE GAËL VAROQUAUX
 MODIFIED FOR DOCUMENTATION BY JAQUES GROBLER
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT SVM
 WE CREATE 40 SEPARABLE POINTS
NPRANDOMSEED0
X  NPRNPRANDOMRANDN20 2  2 2 NPRANDOMRANDN20 2  2 2
Y  0 20  1 20
 FIGURE NUMBER
FIGNUM  1
 FIT THE MODEL
FORNAME PENALTY INUNREG 1 REG 005
CLF  SVMSVCKERNELLINEAR CPENALTY
CLFFITX Y
 GET THE SEPARATING HYPERPLANE
W  CLFCOEF0
A  W0  W1
XX  NPLINSPACE5 5
YY  AXX  CLFINTERCEPT0  W1
 PLOT THE PARALLELS TO THE SEPARATING HYPERPLANE THAT PASS THROUGH THE
 SUPPORT VECTORS MARGIN AWAY FROM HYPERPLANE IN DIRECTION
 PERPENDICULAR TO HYPERPLANE THIS IS SQRT1A2 AWAY VERTICALLY IN
 2D
MARGIN  1  NPSQRTNPSUMCLFCOEF 2
YYDOWN  YY  NPSQRT1  A 2MARGIN
YYUP  YY  NPSQRT1  A 2MARGIN
```

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```
 PLOT THE LINE THE POINTS AND THE NEAREST VECTORS TO THE PLANE
PLTFIGUREFIGNUM FIGSIZE4 3
PLTCLF
PLTPLOTXX YY K
PLTPLOTXX YYDOWN K
PLTPLOTXX YYUP K
PLTSCATTERCLFSUPPORTVECTORS 0 CLFSUPPORTVECTORS 1 S80
FACECOLORSNONE ZORDER10 EDGECOLORSK
PLTSCATTERX 0 X 1 CY ZORDER10 CMAPPLTCMPAIRED
EDGECOLORSK
PLTAXISTIGHT
XMIN  48
XMAX  42
YMIN  6
YMAX  6
XX YY  NPMGRIDXMINXMAX200J YMINYMAX200J
Z  CLFPREDICTNPCXXRAVEL YYRAVEL
 PUT THE RESULT INTO A COLOR PLOT
Z  ZRESHAPEXXSHAPE
PLTFIGUREFIGNUM FIGSIZE4 3
PLTPCOLORMESHXX YY Z CMAPPLTCMPAIRED
PLTXLIMXMIN XMAX
PLTYLIMYMIN YMAX
PLTXTICKS
PLTYTICKS
FIGNUM  FIGNUM  1
PLTSHOW
```

TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0061 SECONDS

NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

52710 ONECLASS SVM WITH NONLINEAR KERNEL RBF

AN EXAMPLE USING A ONECLASS SVM FOR NOVELTY DETECTION

ONECLASS SVM IS AN UNSUPERVISED ALGORITHM THAT LEARNS A DECISION FUNCTION FOR NOVELTY DETECTION CLASSIFYING NEW DATA AS SIMILAR OR DIFFERENT TO THE TRAINING SET

```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
IMPORT MATPLOTLIBFONTMANAGER
FROM SKLEARN IMPORT SVM
XX YY  NPMESHGRIDNPLINSPACE5 5 500 NPLINSPACE5 5 500
 GENERATE TRAIN DATA
X  03 NPRANDOMRANDN100 2
XTRAIN  NPRX  2 X  2
 GENERATE SOME REGULAR NOVEL OBSERVATIONS
X  03 NPRANDOMRANDN20 2
XTEST  NPRX  2 X  2
 GENERATE SOME ABNORMAL NOVEL OBSERVATIONS
XOUTLIERS  NPRANDOMUNIFORMLOW4 HIGH4 SIZE20 2
 FIT THE MODEL
CLF  SVMONECLASSSVMNU01 KERNELRBF GAMMA01
CLFFITXTRAIN
YPREDTRAIN  CLFPREDICTXTRAIN
YPREDTEST  CLFPREDICTXTEST
YPREDOUTLIERS  CLFPREDICTXOUTLIERS
NERRORTRAIN  YPREDTRAINYPREDTRAIN  1SIZE
NERRORTEST  YPREDTESTYPREDTEST  1SIZE
NERROROUTLIERS  YPREDOUTLIERSYPREDOUTLIERS  1SIZE
```

PLOT THE LINE THE POINTS AND THE NEAREST VECTORS TO THE PLANE
Z CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
PLTTITLENOVELTY DETECTION
PLTCONTOURFXX YY Z LEVELSNPLINSPACEZMIN 0 7 CMAPPLTCMPUBU
A PLTCONTOURXX YY Z LEVELS0 LINEWIDTHS2 COLORSDARKRED
PLTCONTOURFXX YY Z LEVELS0 ZMAX COLORSPALEVIOLETRED
S 40
B1 PLTSCATTERXTRAIN 0 XTRAIN 1 CWHITE SS EDGECOLORSK
B2 PLTSCATTERXTEST 0 XTEST 1 CBLUEVIOLET SS
EDGECOLORSK
C PLTSCATTERXOUTLIERS 0 XOUTLIERS 1 CGOLD SS
EDGECOLORSK
PLTAXISTIGHT
PLTXLIM5 5
PLTYLIM5 5
PLTLEGENDACOLLECTIONS0 B1 B2 C
LEARNED FRONTIER TRAINING OBSERVATIONS
NEW REGULAR OBSERVATIONS NEW ABNORMAL OBSERVATIONS
LOCUPPER LEFT
PROPMATPLOTLIBFONTMANAGERFONTPROPERTIESSIZE11
PLTXLABEL
ERROR TRAIN D200 ERRORS NOVEL REGULAR D40
ERRORS NOVEL ABNORMAL D40
 NERRORTRAIN NERRORTEST NERROROUTLIERS
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0196 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52711 PLOT DIFFERENT SVM CLASSIFIERS IN THE IRIS DATASET
COMPARISON OF DIFFERENT LINEAR SVM CLASSIFIERS ON A 2D PROJECTION OF THE IRIS DATASET WE ONLY CONSIDER THE FIRST 2 FEATURES OF THIS DATASET
• SEPAL LENGTH
• SEPAL WIDTH
THIS EXAMPLE SHOWS HOW TO PLOT THE DECISION SURFACE FOR FOUR SVM CLASSIFIERS WITH DIFFERENT KERNELS
THE LINEAR MODELS LINEARSVC ANDSVCKERNELLINEAR YIELD SLIGHTLY DIFFERENT DECISION BOUNDARIES
THIS CAN BE A CONSEQUENCE OF THE FOLLOWING DIFFERENCES
•LINEARSVC MINIMIZES THE SQUARED HINGE LOSS WHILE SVC MINIMIZES THE REGULAR HINGE LOSS
•LINEARSVC USES THE ONEVSALL ALSO KNOWN AS ONEVSREST MULTICLASS REDUCTION WHILE SVC USES THE ONE VSONE MULTICLASS REDUCTION
BOTH LINEAR MODELS HAVE LINEAR DECISION BOUNDARIES INTERSECTING HYPERPLANES WHILE THE NONLINEAR KERNEL MODELS POLYNOMIAL OR GAUSSIAN RBF HAVE MORE FLEXIBLE NONLINEAR DECISION BOUNDARIES WITH SHAPES THAT DEPEND ON THE KIND OF KERNEL AND ITS PARAMETERS

NOTE WHILE PLOTTING THE DECISION FUNCTION OF CLASSIFIERS FOR TOY 2D DATASETS CAN HELP GET AN INTUITIVE UNDERSTANDING OF THEIR RESPECTIVE EXPRESSIVE POWER BE AWARE THAT THOSE INTUITIONS DON’T ALWAYS GENERALIZE TO MORE REALISTIC HIGH DIMENSIONAL PROBLEMS
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARN IMPORT SVM DATASETS
DEFMAKEMESHGRIDX Y H02
CREATE A MESH OF POINTS TO PLOT IN
PARAMETERS

X DATA TO BASE XAXIS MESHGRID ON
Y DATA TO BASE YAXIS MESHGRID ON
H STEPSIZE FOR MESHGRID OPTIONAL
RETURNS

XX YY NDARRAY

XMIN XMAX XMIN 1 XMAX 1
YMIN YMAX YMIN 1 YMAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX H
NPARANGEYMIN YMAX H
RETURNXX YY
DEFPLOTCONTOURSAX CLF XX YY PARAMS
PLOT THE DECISION BOUNDARIES FOR A CLASSIFIER
PARAMETERS

AX MATPLOTLIB AXES OBJECT
CLF A CLASSIFIER
XX MESHGRID NDARRAY
YY MESHGRID NDARRAY
PARAMS DICTIONARY OF PARAMS TO PASS TO CONTOURF OPTIONAL

Z CLFPREDICTNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
OUT AXCONTOURFXX YY Z PARAMS
RETURNOUT
 IMPORT SOME DATA TO PLAY WITH
IRIS DATASETSLOADIRIS
 TAKE THE FIRST TWO FEATURES WE COULD AVOID THIS BY USING A TWODIM DATASET
X IRISDATA 2
Y IRISTARGET
 WE CREATE AN INSTANCE OF SVM AND FIT OUT DATA WE DO NOT SCALE OUR
 DATA SINCE WE WANT TO PLOT THE SUPPORT VECTORS
C 10 SVM REGULARIZATION PARAMETER
MODELS SVMSVCKERNELLINEAR CC
SVMLINEARSVCCC MAXITER10000
SVMSVCKERNELRBF GAMMA07 CC
SVMSVCKERNELPOLY DEGREE3 GAMMAAUTO CC
MODELS CLFFITX Y FORCLFINMODELS
 TITLE FOR THE PLOTS
TITLES SVC WITH LINEAR KERNEL
LINEARSVC LINEAR KERNEL
SVC WITH RBF KERNEL
SVC WITH POLYNOMIAL DEGREE 3 KERNEL
 SETUP 2X2 GRID FOR PLOTTING
FIG SUB PLTSUBPLOTS2 2
PLTSUBPLOTSADJUSTWSPACE04 HSPACE04
X0 X1 X 0 X 1
XX YY MAKEMESHGRIDX0 X1
FORCLF TITLE AX INZIPMODELS TITLES SUBFLATTEN
PLOTCONTOURSAX CLF XX YY
CMAPPLTCMCOOLWARM ALPHA08
AXSCATTERX0 X1 CY CMAPPLTCMCOOLWARM S20 EDGECOLORSK
AXSETXLIMXXMIN XXMAX
AXSETYLIMYYMIN YYMAX

AXSETXLABELSEPAL LENGTH
AXSETYLABELSEPAL WIDTH
AXSETXTICKS
AXSETYTICKS
AXSETTITLETITLE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0481 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52712 SCALING THE REGULARIZATION PARAMETER FOR SVCS
THE FOLLOWING EXAMPLE ILLUSTRATES THE EFFECT OF SCALING THE REGULARIZATION PARAMETER WHEN USING SUPPORT VECTOR MA CHINES FORCLASSIFICATION FOR SVC CLASSIFICATION WE ARE INTERESTED IN A RISK MINIMIZATION FOR THE EQUATION
□Σ
□1□ℒ□□□ □□
 □
WHERE
•□IS USED TO SET THE AMOUNT OF REGULARIZATION
•ℒIS ALOSS FUNCTION OF OUR SAMPLES AND OUR MODEL PARAMETERS
•
IS APENALTY FUNCTION OF OUR MODEL PARAMETERS
IF WE CONSIDER THE LOSS FUNCTION TO BE THE INDIVIDUAL ERROR PER SAMPLE THEN THE DATAFIT TERM OR THE SUM OF THE ERROR FOR EACH SAMPLE WILL INCREASE AS WE ADD MORE SAMPLES THE PENALIZATION TERM HOWEVER WILL NOT INCREASE
WHEN USING FOR EXAMPLE CROSS VALIDATION TO SET THE AMOUNT OF REGULARIZATION WITH C THERE WILL BE A DIFFERENT AMOUNT OF SAMPLES BETWEEN THE MAIN PROBLEM AND THE SMALLER PROBLEMS WITHIN THE FOLDS OF THE CROSS VALIDATION
SINCE OUR LOSS FUNCTION IS DEPENDENT ON THE AMOUNT OF SAMPLES THE LATTER WILL INFLUENCE THE SELECTED VALUE OF C THE QUESTION THAT ARISES IS HOW DO WE OPTIMALLY ADJUST C TO ACCOUNT FOR THE DIFFERENT AMOUNT OF TRAINING SAMPLES
THE FIGURES BELOW ARE USED TO ILLUSTRATE THE EFFECT OF SCALING OUR CTO COMPENSATE FOR THE CHANGE IN THE NUMBER OF SAMPLES IN THE CASE OF USING AN L1PENALTY AS WELL AS THE L2PENALTY
L1PENALTY CASE
IN THEL1CASE THEORY SAYS THAT PREDICTION CONSISTENCY IE THAT UNDER GIVEN HYPOTHESIS THE ESTIMATOR LEARNED PREDICTS AS WELL AS A MODEL KNOWING THE TRUE DISTRIBUTION IS NOT POSSIBLE BECAUSE OF THE BIAS OF THE L1 IT DOES SAY HOWEVER THAT MODEL CONSISTENCY IN TERMS OF FINDING THE RIGHT SET OF NONZERO PARAMETERS AS WELL AS THEIR SIGNS CAN BE ACHIEVED BY SCALINGC1
L2PENALTY CASE
THE THEORY SAYS THAT IN ORDER TO ACHIEVE PREDICTION CONSISTENCY THE PENALTY PARAMETER SHOULD BE KEPT CONSTANT AS THE NUMBER OF SAMPLES GROW

SIMULATIONS
THE TWO FIGURES BELOW PLOT THE VALUES OF CON THEXAXIS AND THE CORRESPONDING CROSSVALIDATION SCORES ON THE YAXIS FOR SEVERAL DIFFERENT FRACTIONS OF A GENERATED DATASET
IN THEL1PENALTY CASE THE CROSSVALIDATIONERROR CORRELATES BEST WITH THE TESTERROR WHEN SCALING OUR CWITH THE NUMBER OF SAMPLES N WHICH CAN BE SEEN IN THE FIRST FIGURE
FOR THEL2PENALTY CASE THE BEST RESULT COMES FROM THE CASE WHERE CIS NOT SCALED
NOTE
TWO SEPARATE DATASETS ARE USED FOR THE TWO DIFFERENT PLOTS THE REASON BEHIND THIS IS THE L1CASE WORKS BETTER ON SPARSE DATA WHILE L2IS BETTER SUITED TO THE NONSPARSE CASE

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PRINTDOC
 AUTHOR ANDREAS MUELLER AMUELLERAISUNIBONNDE
 JAQUES GROBLER JAQUESGROBLERINRIAFR
 LICENSE BSD 3 CLAUSE
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNSVM IMPORT LINEARSVC
FROM SKLEARNMODELSELECTION IMPORT SHUFFLESPLIT

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FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
FROM SKLEARNUTILS IMPORT CHECKRANDOMSTATE
FROM SKLEARN IMPORT DATASETS
RND CHECKRANDOMSTATE1
 SET UP DATASET
NSAMPLES 100
NFEATURES 300
 L1 DATA ONLY 5 INFORMATIVE FEATURES
X1 Y1 DATASETSMAKECLASSIFICATIONNSAMPLESNSAMPLES
NFEATURESNFEATURES NINFORMATIVE5
RANDOMSTATE1
 L2 DATA NON SPARSE BUT LESS FEATURES
Y2 NPSIGN5 RNDRANDNSAMPLES
X2 RNDRANDNNSAMPLES NFEATURES 5 Y2 NPNEWAXIS
X2 5 RNDRANDNNSAMPLES NFEATURES 5
CLFSETS LINEARSVCPENALTYL1 LOSSSQUAREDHINGE DUALFALSE
TOL1E3
NPLOGSPACE23 13 10 X1 Y1
LINEARSVCPENALTYL2 LOSSSQUAREDHINGE DUALTRUE
TOL1E4
NPLOGSPACE45 2 10 X2 Y2
COLORS NAVY CYAN DARKORANGE
LW 2
FORCLF CS X Y INCLFSETS
 SET UP THE PLOT FOR EACH REGRESSOR
FIG AXES PLTSUBPLOTSNROWS2 SHAREYTRUE FIGSIZE9 10
FORK TRAINSIZE INENUMERATENPLINSPACE03 07 31
PARAMGRID DICTCCS
 TO GET NICE CURVE WE NEED A LARGE NUMBER OF ITERATIONS TO
 REDUCE THE VARIANCE
GRID GRIDSEARCHCVCLF REFITFALSE PARAMGRIDPARAMGRID
CVSHUFFLESPLITTRAINSIZETRAINSIZE
TESTSIZE3
NSPLITS250 RANDOMSTATE1
GRIDFITX Y
SCORES GRIDCVRESULTSMEANTESTSCORE
SCALES 1 NO SCALING
NSAMPLES TRAINSIZE 1NSAMPLES

FORAX SCALER NAME INZIPAXES SCALES
AXSETXLABELC
AXSETYLABELCV SCORE
GRIDCS CS FLOATSCALER SCALE THE CS
AXSEMILOGXGRIDCS SCORES LABELFRACTION 2F
TRAINSIZE COLORCOLORSK LWLW
AXSETTITLESCALING S PENALTY S LOSSS
NAME CLFPENALTY CLFLOSS

PLTLEGENDLOCBEST
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 14575 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
52713 RBF SVM PARAMETERS
THIS EXAMPLE ILLUSTRATES THE EFFECT OF THE PARAMETERS GAMMA ANDCOF THE RADIAL BASIS FUNCTION RBF KERNEL SVM
INTUITIVELY THE GAMMA PARAMETER DEFINES HOW FAR THE INFLUENCE OF A SINGLE TRAINING EXAMPLE REACHES WITH LOW VALUES MEANING ‘FAR’ AND HIGH VALUES MEANING ‘CLOSE’ THE GAMMA PARAMETERS CAN BE SEEN AS THE INVERSE OF THE RADIUS OF INFLUENCE OF SAMPLES SELECTED BY THE MODEL AS SUPPORT VECTORS
THECPARAMETER TRADES OFF CORRECT CLASSIFICATION OF TRAINING EXAMPLES AGAINST MAXIMIZATION OF THE DECISION FUNCTION’S MARGIN FOR LARGER VALUES OF C A SMALLER MARGIN WILL BE ACCEPTED IF THE DECISION FUNCTION IS BETTER AT CLASSIFYING ALL TRAINING POINTS CORRECTLY A LOWER CWILL ENCOURAGE A LARGER MARGIN THEREFORE A SIMPLER DECISION FUNCTION AT THE COST OF TRAINING ACCURACY IN OTHER WORDS‘‘C‘‘ BEHAVES AS A REGULARIZATION PARAMETER IN THE SVM
THE FIRST PLOT IS A VISUALIZATION OF THE DECISION FUNCTION FOR A VARIETY OF PARAMETER VALUES ON A SIMPLIFIED CLASSIFICATION PROBLEM INVOLVING ONLY 2 INPUT FEATURES AND 2 POSSIBLE TARGET CLASSES BINARY CLASSIFICATION NOTE THAT THIS KIND OF PLOT IS NOT POSSIBLE TO DO FOR PROBLEMS WITH MORE FEATURES OR TARGET CLASSES
THE SECOND PLOT IS A HEATMAP OF THE CLASSIFIER’S CROSSVALIDATION ACCURACY AS A FUNCTION OF CANDGAMMA FOR THIS EXAMPLE WE EXPLORE A RELATIVELY LARGE GRID FOR ILLUSTRATION PURPOSES IN PRACTICE A LOGARITHMIC GRID FROM 10−3TO103 IS USUALLY SUFFICIENT IF THE BEST PARAMETERS LIE ON THE BOUNDARIES OF THE GRID IT CAN BE EXTENDED IN THAT DIRECTION IN A SUBSEQUENT SEARCH
NOTE THAT THE HEAT MAP PLOT HAS A SPECIAL COLORBAR WITH A MIDPOINT VALUE CLOSE TO THE SCORE VALUES OF THE BEST PERFORMING MODELS SO AS TO MAKE IT EASY TO TELL THEM APART IN THE BLINK OF AN EYE
THE BEHAVIOR OF THE MODEL IS VERY SENSITIVE TO THE GAMMA PARAMETER IF GAMMA IS TOO LARGE THE RADIUS OF THE AREA OF INFLUENCE OF THE SUPPORT VECTORS ONLY INCLUDES THE SUPPORT VECTOR ITSELF AND NO AMOUNT OF REGULARIZATION WITH CWILL BE ABLE TO PREVENT OVERFITTING
WHENGAMMA IS VERY SMALL THE MODEL IS TOO CONSTRAINED AND CANNOT CAPTURE THE COMPLEXITY OR “SHAPE” OF THE DATA THE REGION OF INFLUENCE OF ANY SELECTED SUPPORT VECTOR WOULD INCLUDE THE WHOLE TRAINING SET THE RESULTING MODEL WILL BEHAVE SIMILARLY TO A LINEAR MODEL WITH A SET OF HYPERPLANES THAT SEPARATE THE CENTERS OF HIGH DENSITY OF ANY PAIR OF TWO CLASSES
FOR INTERMEDIATE VALUES WE CAN SEE ON THE SECOND PLOT THAT GOOD MODELS CAN BE FOUND ON A DIAGONAL OF CANDGAMMA SMOOTH MODELS LOWER GAMMA VALUES CAN BE MADE MORE COMPLEX BY INCREASING THE IMPORTANCE OF CLASSIFYING EACH POINT CORRECTLY LARGER CVALUES HENCE THE DIAGONAL OF GOOD PERFORMING MODELS
FINALLY ONE CAN ALSO OBSERVE THAT FOR SOME INTERMEDIATE VALUES OF GAMMA WE GET EQUALLY PERFORMING MODELS WHEN C BECOMES VERY LARGE IT IS NOT NECESSARY TO REGULARIZE BY ENFORCING A LARGER MARGIN THE RADIUS OF THE RBF KERNEL ALONE ACTS AS A GOOD STRUCTURAL REGULARIZER IN PRACTICE THOUGH IT MIGHT STILL BE INTERESTING TO SIMPLIFY THE DECISION FUNCTION WITH A LOWER VALUE OF CSO AS TO FAVOR MODELS THAT USE LESS MEMORY AND THAT ARE FASTER TO PREDICT
WE SHOULD ALSO NOTE THAT SMALL DIFFERENCES IN SCORES RESULTS FROM THE RANDOM SPLITS OF THE CROSSVALIDATION PROCEDURE THOSE SPURIOUS VARIATIONS CAN BE SMOOTHED OUT BY INCREASING THE NUMBER OF CV ITERATIONS NSPLITS AT THE EXPENSE OF COMPUTE TIME INCREASING THE VALUE NUMBER OF CRANGE ANDGAMMARANGE STEPS WILL INCREASE THE RESOLUTION OF THE HYPERPARAMETER HEAT MAP

•

•
OUT
THE BEST PARAMETERS ARE C 10 GAMMA 01 WITH A SCORE OF 097
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM MATPLOTLIBCOLORS IMPORT NORMALIZE
FROM SKLEARNSVM IMPORT SVC
FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
FROM SKLEARNDATASETS IMPORT LOADIRIS
FROM SKLEARNMODELSELECTION IMPORT STRATIFIEDSHUFFLESPLIT
FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
UTILITY FUNCTION TO MOVE THE MIDPOINT OF A COLORMAP TO BE AROUND
THE VALUES OF INTEREST
CLASS MIDPOINTNORMALIZE NORMALIZE

```
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DEFINITSELF VMINNONE VMAXNONE MIDPOINTNONE CLIPFALSE
SELFMIDPOINT  MIDPOINT
NORMALIZEINITSELF VMIN VMAX CLIP
DEFCALLSELF VALUE CLIPNONE
X Y  SELFVMIN SELFMIDPOINT SELFVMAX 0 05 1
RETURNNPMAMASKEDARRAYNPINTERPVALUE X Y

 LOAD AND PREPARE DATA SET

 DATASET FOR GRID SEARCH
IRIS  LOADIRIS
X  IRISDATA
Y  IRISTARGET
 DATASET FOR DECISION FUNCTION VISUALIZATION WE ONLY KEEP THE FIRST TWO
 FEATURES IN X AND SUBSAMPLE THE DATASET TO KEEP ONLY 2 CLASSES AND
 MAKE IT A BINARY CLASSIFICATION PROBLEM
X2D  X 2
X2D  X2DY  0
Y2D  YY  0
Y2D  1
 IT IS USUALLY A GOOD IDEA TO SCALE THE DATA FOR SVM TRAINING
 WE ARE CHEATING A BIT IN THIS EXAMPLE IN SCALING ALL OF THE DATA
 INSTEAD OF FITTING THE TRANSFORMATION ON THE TRAINING SET AND
 JUST APPLYING IT ON THE TEST SET
SCALER  STANDARDSCALER
X  SCALERFITTRANSFORMX
X2D  SCALERFITTRANSFORMX2D

 TRAIN CLASSIFIERS

 FOR AN INITIAL SEARCH A LOGARITHMIC GRID WITH BASIS
 10 IS OFTEN HELPFUL USING A BASIS OF 2 A FINER
 TUNING CAN BE ACHIEVED BUT AT A MUCH HIGHER COST
CRANGE  NPLOGSPACE2 10 13
GAMMARANGE  NPLOGSPACE9 3 13
PARAMGRID  DICTGAMMAGAMMARANGE CCRANGE
CV  STRATIFIEDSHUFFLESPLITNSPLITS5 TESTSIZE02 RANDOMSTATE42
GRID  GRIDSEARCHCVSVC PARAMGRIDPARAMGRID CVCV
GRIDFITX Y
PRINTTHE BEST PARAMETERS ARE SWITH A SCORE OF 02F
 GRIDBESTPARAMS GRIDBESTSCORE
 NOW WE NEED TO FIT A CLASSIFIER FOR ALL PARAMETERS IN THE 2D VERSION
 WE USE A SMALLER SET OF PARAMETERS HERE BECAUSE IT TAKES A WHILE TO TRAIN
C2DRANGE  1E2 1 1E2
GAMMA2DRANGE  1E1 1 1E1
CLASSIFIERS
527 SUPPORT VECTOR MACHINES 1429
```

```
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FORCINC2DRANGE
FORGAMMAINGAMMA2DRANGE
CLF  SVCCC GAMMAGAMMA
CLFFITX2D Y2D
CLASSIFIERSAPPENDC GAMMA CLF

 VISUALIZATION

 DRAW VISUALIZATION OF PARAMETER EFFECTS
PLTFIGUREFIGSIZE8 6
XX YY  NPMESHGRIDNPLINSPACE3 3 200 NPLINSPACE3 3 200
FORK C GAMMA CLF INENUMERATECLASSIFIERS
 EVALUATE DECISION FUNCTION IN A GRID
Z  CLFDECISIONFUNCTIONNPCXXRAVEL YYRAVEL
Z  ZRESHAPEXXSHAPE
 VISUALIZE DECISION FUNCTION FOR THESE PARAMETERS
PLTSUBPLOTLENC2DRANGE LENGAMMA2DRANGE K  1
PLTTITLEGAMMA10 D C10D  NPLOG10GAMMA NPLOG10C
SIZEMEDIUM
 VISUALIZE PARAMETERS EFFECT ON DECISION FUNCTION
PLTPCOLORMESHXX YY Z CMAPPLTCMRDBU
PLTSCATTERX2D 0 X2D 1 CY2D CMAPPLTCMRDBUR
EDGECOLORSK
PLTXTICKS
PLTYTICKS
PLTAXISTIGHT
SCORES  GRIDCVRESULTSMEANTESTSCORERESHAPELENCRANGE
LENGAMMARANGE
 DRAW HEATMAP OF THE VALIDATION ACCURACY AS A FUNCTION OF GAMMA AND C

 THE SCORE ARE ENCODED AS COLORS WITH THE HOT COLORMAP WHICH VARIES FROM DARK
 RED TO BRIGHT YELLOW AS THE MOST INTERESTING SCORES ARE ALL LOCATED IN THE
 092 TO 097 RANGE WE USE A CUSTOM NORMALIZER TO SET THE MIDPOINT TO 092 SO
 AS TO MAKE IT EASIER TO VISUALIZE THE SMALL VARIATIONS OF SCORE VALUES IN THE
 INTERESTING RANGE WHILE NOT BRUTALLY COLLAPSING ALL THE LOW SCORE VALUES TO
 THE SAME COLOR
PLTFIGUREFIGSIZE8 6
PLTSUBPLOTSADJUSTLEFT2 RIGHT095 BOTTOM015 TOP095
PLTIMSHOWSCORES INTERPOLATIONNEAREST CMAPPLTCMHOT
NORMMIDPOINTNORMALIZEVMIN02 MIDPOINT092
PLTXLABELGAMMA
PLTYLABELC
PLTCOLORBAR
PLTXTICKSNPARANGELENGAMMARANGE GAMMARANGE ROTATION45
PLTYTICKSNPARANGELENCRANGE CRANGE
PLTTITLEVALIDATION ACCURACY
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT  0 MINUTES 3597 SECONDS
1430 CHAPTER 5 EXAMPLES
```

528 WORKING WITH TEXT DOCUMENTS
EXAMPLES CONCERNING THE SKLEARNFEATUREEXTRACTIONTEXT MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5281 FEATUREHASHER AND DICTVECTORIZER COMPARISON
COMPARES FEATUREHASHER AND DICTVECTORIZER BY USING BOTH TO VECTORIZE TEXT DOCUMENTS
THE EXAMPLE DEMONSTRATES SYNTAX AND SPEED ONLY IT DOESN’T ACTUALLY DO ANYTHING USEFUL WITH THE EXTRACTED VECTORS
SEE THE EXAMPLE SCRIPTS DOCUMENTCLASSIFICATION20NEWSGROUPSCLUSTERINGPY FOR ACTUAL LEARNING ON TEXT DOCUMENTS
A DISCREPANCY BETWEEN THE NUMBER OF TERMS REPORTED FOR DICTVECTORIZER AND FOR FEATUREHASHER IS TO BE EXPECTED DUE
TO HASH COLLISIONS
OUT
USAGE HOMECIRCLECIPROJECTEXAMPLESTEXTPLOTHASHINGVSDICTVECTORIZERPY N
‹→FEATURESFORHASHING
THE DEFAULT NUMBER OF FEATURES IS 2 18
LOADING 20 NEWSGROUPS TRAINING DATA
3803 DOCUMENTS 6245MB
DICTVECTORIZER
DONE IN 0979095S AT 6378MBS
FOUND 47928 UNIQUE TERMS
FEATUREHASHER ON FREQUENCY DICTS
DONE IN 0816599S AT 7647MBS
FOUND 43873 UNIQUE TERMS
FEATUREHASHER ON RAW TOKENS
DONE IN 0935579S AT 6675MBS
FOUND 43873 UNIQUE TERMS
 AUTHOR LARS BUITINCK
 LICENSE BSD 3 CLAUSE
FROM COLLECTIONS IMPORT DEFAULTDICT
IMPORT RE
IMPORT SYS
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
FROM SKLEARNDATASETS IMPORT FETCH20NEWSGROUPS
FROM SKLEARNFEATUREEXTRACTION IMPORT DICTVECTORIZER FEATUREHASHER

```
DEFNNONZEROCOLUMNSX
RETURNS THE NUMBER OF NONZERO COLUMNS IN A CSR MATRIX X
RETURNLENNPUNIQUEXNONZERO1
DEFTOKENSDOC
EXTRACT TOKENS FROM DOC
THIS USES A SIMPLE REGEX TO BREAK STRINGS INTO TOKENS FOR A MORE
PRINCIPLED APPROACH SEE COUNTVECTORIZER OR TFIDFVECTORIZER

RETURNTOKLOWER FORTOKINREFINDALLRW DOC
DEFTOKENFREQSDOC
EXTRACT A DICT MAPPING TOKENS FROM DOC TO THEIR FREQUENCIES
FREQ  DEFAULTDICTINT
FORTOKINTOKENSDOC
FREQTOK  1
RETURNFREQ
CATEGORIES
ALTATHEISM
COMPGRAPHICS
COMPSYSIBMPCHARDWARE
MISCFORSALE
RECAUTOS
SCISPACE
TALKRELIGIONMISC

 UNCOMMENT THE FOLLOWING LINE TO USE A LARGER SET 11K DOCUMENTS
 CATEGORIES  NONE
PRINTDOC
PRINTUSAGE SNFEATURESFORHASHING  SYSARGV0
PRINT THE DEFAULT NUMBER OF FEATURES IS 2 18
PRINT
TRY
NFEATURES  INTSYSARGV1
EXCEPTINDEXERROR
NFEATURES  2 18
EXCEPTVALUEERROR
PRINTNOT A VALID NUMBER OF FEATURES R  SYSARGV1
SYSEXIT1
PRINTLOADING 20 NEWSGROUPS TRAINING DATA
RAWDATA  FETCH20NEWSGROUPSSUBSETTRAIN CATEGORIESCATEGORIESDATA
DATASIZEMB  SUMLENSENCODEUTF8 FORSINRAWDATA  1E6
PRINTDDOCUMENTS  03FMB  LENRAWDATA DATASIZEMB
PRINT
PRINTDICTVECTORIZER
T0  TIME
VECTORIZER  DICTVECTORIZER
VECTORIZERFITTRANSFORMTOKENFREQSD FORDINRAWDATA
```

SCIKITLEARN USER GUIDE RELEASE 0213
DURATION TIME T0
PRINTDONE IN FS AT03FMBS DURATION DATASIZEMB DURATION
PRINTFOUND DUNIQUE TERMS LENVECTORIZERGETFEATURENAMES
PRINT
PRINTFEATUREHASHER ON FREQUENCY DICTS
T0 TIME
HASHER FEATUREHASHERNFEATURESNFEATURES
X HASHERTRANSFORMTOKENFREQSD FORDINRAWDATA
DURATION TIME T0
PRINTDONE IN FS AT03FMBS DURATION DATASIZEMB DURATION
PRINTFOUND DUNIQUE TERMS NNONZEROCOLUMNSX
PRINT
PRINTFEATUREHASHER ON RAW TOKENS
T0 TIME
HASHER FEATUREHASHERNFEATURESNFEATURES INPUTTYPESTRING
X HASHERTRANSFORMTOKENSD FORDINRAWDATA
DURATION TIME T0
PRINTDONE IN FS AT03FMBS DURATION DATASIZEMB DURATION
PRINTFOUND DUNIQUE TERMS NNONZEROCOLUMNSX
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 3036 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5282 CLUSTERING TEXT DOCUMENTS USING KMEANS
THIS IS AN EXAMPLE SHOWING HOW THE SCIKITLEARN CAN BE USED TO CLUSTER DOCUMENTS BY TOPICS USING A BAGOFWORDS APPROACH THIS EXAMPLE USES A SCIPYSPARSE MATRIX TO STORE THE FEATURES INSTEAD OF STANDARD NUMPY ARRAYS
TWO FEATURE EXTRACTION METHODS CAN BE USED IN THIS EXAMPLE
• TFIDFVECTORIZER USES A INMEMORY VOCABULARY A PYTHON DICT TO MAP THE MOST FREQUENT WORDS TO FEATURES INDICES AND HENCE COMPUTE A WORD OCCURRENCE FREQUENCY SPARSE MATRIX THE WORD FREQUENCIES ARE THEN REWEIGHTED USING THE INVERSE DOCUMENT FREQUENCY IDF VECTOR COLLECTED FEATUREWISE OVER THE CORPUS
• HASHINGVECTORIZER HASHES WORD OCCURRENCES TO A FIXED DIMENSIONAL SPACE POSSIBLY WITH COLLISIONS THE WORD COUNT VECTORS ARE THEN NORMALIZED TO EACH HAVE L2NORM EQUAL TO ONE PROJECTED TO THE EUCLIDEAN UNITBALL WHICH SEEMS TO BE IMPORTANT FOR KMEANS TO WORK IN HIGH DIMENSIONAL SPACE
HASHINGVECTORIZER DOES NOT PROVIDE IDF WEIGHTING AS THIS IS A STATELESS MODEL THE FIT METHOD DOES NOTHING WHEN IDF WEIGHTING IS NEEDED IT CAN BE ADDED BY PIPELINING ITS OUTPUT TO A TFIDFTRANSFORMER INSTANCE
TWO ALGORITHMS ARE DEMOED ORDINARY KMEANS AND ITS MORE SCALABLE COUSIN MINIBATCH KMEANS
ADDITIONALLY LATENT SEMANTIC ANALYSIS CAN ALSO BE USED TO REDUCE DIMENSIONALITY AND DISCOVER LATENT PATTERNS IN THE DATA
IT CAN BE NOTED THAT KMEANS AND MINIBATCH KMEANS ARE VERY SENSITIVE TO FEATURE SCALING AND THAT IN THIS CASE THE IDF WEIGHTING HELPS IMPROVE THE QUALITY OF THE CLUSTERING BY QUITE A LOT AS MEASURED AGAINST THE “GROUND TRUTH” PROVIDED BY THE CLASS LABEL ASSIGNMENTS OF THE 20 NEWSGROUPS DATASET
THIS IMPROVEMENT IS NOT VISIBLE IN THE SILHOUETTE COEFFICIENT WHICH IS SMALL FOR BOTH AS THIS MEASURE SEEM TO SUFFER FROM THE PHENOMENON CALLED “CONCENTRATION OF MEASURE” OR “CURSE OF DIMENSIONALITY” FOR HIGH DIMENSIONAL DATASETS

SUCH AS TEXT DATA OTHER MEASURES SUCH AS VMEASURE AND ADJUSTED RAND INDEX ARE INFORMATION THEORETIC BASED EVAL
UATION SCORES AS THEY ARE ONLY BASED ON CLUSTER ASSIGNMENTS RATHER THAN DISTANCES HENCE NOT AFFECTED BY THE CURSE OF
DIMENSIONALITY
NOTE AS KMEANS IS OPTIMIZING A NONCONVEX OBJECTIVE FUNCTION IT WILL LIKELY END UP IN A LOCAL OPTIMUM SEVERAL RUNS
WITH INDEPENDENT RANDOM INIT MIGHT BE NECESSARY TO GET A GOOD CONVERGENCE
OUT
USAGE PLOTDOCUMENTCLUSTERINGPY OPTIONS
OPTIONS
H HELP SHOW THIS HELP MESSAGE AND EXIT
LSANCOMPONENTS PREPROCESS DOCUMENTS WITH LATENT SEMANTIC ANALYSIS
NOMINIBATCH USE ORDINARY KMEANS ALGORITHM IN BATCH MODE
NOIDF DISABLE INVERSE DOCUMENT FREQUENCY FEATURE WEIGHTING
USEHASHING USE A HASHING FEATURE VECTORIZER
NFEATURESNFEATURES
MAXIMUM NUMBER OF FEATURES DIMENSIONS TO EXTRACT
FROM TEXT
VERBOSE PRINT PROGRESS REPORTS INSIDE KMEANS ALGORITHM
LOADING 20 NEWSGROUPS DATASET FOR CATEGORIES
ALTATHEISM TALKRELIGIONMISC COMPGRAPHICS SCISPACE
3387 DOCUMENTS
4 CATEGORIES
EXTRACTING FEATURES FROM THE TRAINING DATASET USING A SPARSE VECTORIZER
DONE IN 0691398S
NSAMPLES 3387 NFEATURES 10000
CLUSTERING SPARSE DATA WITH MINIBATCHKMEANSBATCHSIZE1000 INITSIZE1000 N
‹→CLUSTERS4 NINIT1
VERBOSEFALSE
DONE IN 0057S
HOMOGENEITY 0359
COMPLETENESS 0440
VMEASURE 0396
ADJUSTED RANDINDEX 0253
SILHOUETTE COEFFICIENT 0007
TOP TERMS PER CLUSTER
CLUSTER 0 HENRY ALASKA TORONTO MOON ZOO SPENCER AURORA SPACE NSMCA ZOOLOGY
CLUSTER 1 COM GRAPHICS UNIVERSITY POSTING HOST NNTP KNOW UK ARTICLE CS
CLUSTER 2 GOD COM SANDVIK PEOPLE KEITH MORALITY SGI KENT LIVESEY JESUS
CLUSTER 3 SPACE NASA ACCESS GOV DIGEX PAT SHUTTLE HST ORBIT NET
AUTHOR PETER PRETTENHOFER PETERPRETTENHOFERGMAILCOM
LARS BUITINCK
LICENSE BSD 3 CLAUSE
FROM SKLEARNDATASETS IMPORT FETCH20NEWSGROUPS
FROM SKLEARNDECOMPOSITION IMPORT TRUNCATEDSVD
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFVECTORIZER
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT HASHINGVECTORIZER

SCIKITLEARN USER GUIDE RELEASE 0213
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFTRANSFORMER
FROM SKLEARNPIPELINE IMPORT MAKEPIPELINE
FROM SKLEARNPREPROCESSING IMPORT NORMALIZER
FROM SKLEARN IMPORT METRICS
FROM SKLEARNCLUSTER IMPORT KMEANS MINIBATCHKMEANS
IMPORT LOGGING
FROM OPTPARSE IMPORT OPTIONPARSER
IMPORT SYS
FROM TIME IMPORT TIME
IMPORT NUMPY AS NP
 DISPLAY PROGRESS LOGS ON STDOUT
LOGGINGBASICCONFIGLEVELLOGGINGINFO
FORMAT ASCTIMES LEVELNAMES MESSAGES
 PARSE COMMANDLINE ARGUMENTS
OP OPTIONPARSER
OPADDOPTIONLSA
DESTNCOMPONENTS TYPEINT
HELPPREPROCESS DOCUMENTS WITH LATENT SEMANTIC ANALYSIS
OPADDOPTIONNOMINIBATCH
ACTIONSTOREFALSE DESTMINIBATCH DEFAULTTRUE
HELPUSE ORDINARY KMEANS ALGORITHM IN BATCH MODE
OPADDOPTIONNOIDF
ACTIONSTOREFALSE DESTUSEIDF DEFAULTTRUE
HELPDISABLE INVERSE DOCUMENT FREQUENCY FEATURE WEIGHTING
OPADDOPTIONUSEHASHING
ACTIONSTORETRUE DEFAULTFALSE
HELPUSE A HASHING FEATURE VECTORIZER
OPADDOPTIONNFEATURES TYPEINT DEFAULT10000
HELPMAXIMUM NUMBER OF FEATURES DIMENSIONS
 TO EXTRACT FROM TEXT
OPADDOPTIONVERBOSE
ACTIONSTORETRUE DESTVERBOSE DEFAULTFALSE
HELPPRINT PROGRESS REPORTS INSIDE KMEANS ALGORITHM
PRINTDOC
OPPRINTHELP
DEFISINTERACTIVE
RETURN NOT HASATTRSYSMODULESMAIN FILE
 WORKAROUND FOR JUPYTER NOTEBOOK AND IPYTHON CONSOLE
ARGV   IFISINTERACTIVE ELSESYSARGV1
OPTS ARGS OPPARSEARGSARGV
IFLENARGS 0
OPERRORTHIS SCRIPT TAKES NO ARGUMENTS
SYSEXIT1

 LOAD SOME CATEGORIES FROM THE TRAINING SET
528 WORKING WITH TEXT DOCUMENTS 1435

CATEGORIES
ALTATHEISM
TALKRELIGIONMISC
COMPGRAPHICS
SCISPACE

 UNCOMMENT THE FOLLOWING TO DO THE ANALYSIS ON ALL THE CATEGORIES
 CATEGORIES NONE
PRINTLOADING 20 NEWSGROUPS DATASET FOR CATEGORIES
PRINTCATEGORIES
DATASET FETCH20NEWSGROUPSSUBSETALL CATEGORIESCATEGORIES
SHUFFLETRUE RANDOMSTATE42
PRINTDDOCUMENTS LENDATASETDATA
PRINTDCATEGORIES LENDATASETTARGETNAMES
PRINT
LABELS DATASETTARGET
TRUEK NPUNIQUELABELSSHAPE0
PRINTEXTRACTING FEATURES FROM THE TRAINING DATASET
USING A SPARSE VECTORIZER
T0 TIME
IFOPTSUSEHASHING
IFOPTSUSEIDF
 PERFORM AN IDF NORMALIZATION ON THE OUTPUT OF HASHINGVECTORIZER
HASHER HASHINGVECTORIZERNFEATURESOPTSNFEATURES
STOPWORDSENGLISH ALTERNATESIGNFALSE
NORMNONE BINARYFALSE
VECTORIZER MAKEPIPELINEHASHER TFIDFTRANSFORMER
ELSE
VECTORIZER HASHINGVECTORIZERNFEATURESOPTSNFEATURES
STOPWORDSENGLISH
ALTERNATESIGNFALSE NORML2
BINARYFALSE
ELSE
VECTORIZER TFIDFVECTORIZERMAXDF05 MAXFEATURESOPTSNFEATURES
MINDF2 STOPWORDSENGLISH
USEIDFOPTSUSEIDF
X VECTORIZERFITTRANSFORMDATASETDATA
PRINTDONE IN FS TIME T0
PRINTNSAMPLES D NFEATURES D XSHAPE
PRINT
IFOPTSNCOMPONENTS
PRINTPERFORMING DIMENSIONALITY REDUCTION USING LSA
T0 TIME
 VECTORIZER RESULTS ARE NORMALIZED WHICH MAKES KMEANS BEHAVE AS
 SPHERICAL KMEANS FOR BETTER RESULTS SINCE LSASVD RESULTS ARE
 NOT NORMALIZED WE HAVE TO REDO THE NORMALIZATION
SVD TRUNCATEDSVDOPTSNCOMPONENTS
NORMALIZER NORMALIZERCOPYFALSE
LSA MAKEPIPELINESVD NORMALIZER
X LSAFITTRANSFORMX

SCIKITLEARN USER GUIDE RELEASE 0213
PRINTDONE IN FS TIME T0
EXPLAINEDVARIANCE SVDEXPLAINEDVARIANCERATIOSUM
PRINTEXPLAINED VARIANCE OF THE SVD STEP FORMAT
INTEXPLAINEDVARIANCE 100
PRINT

 DO THE ACTUAL CLUSTERING
IFOPTSMINIBATCH
KM MINIBATCHKMEANSNCLUSTERSTRUEK INITKMEANS NINIT1
INITSIZE1000 BATCHSIZE1000 VERBOSEOPTSVERBOSE
ELSE
KM KMEANSNCLUSTERSTRUEK INITKMEANS MAXITER100 NINIT1
VERBOSEOPTSVERBOSE
PRINTCLUSTERING SPARSE DATA WITH S KM
T0 TIME
KMFITX
PRINTDONE IN 03FS TIME T0
PRINT
PRINTHOMOGENEITY 03F METRICSHOMOGENEITYSCORELABELS KMLABELS
PRINTCOMPLETENESS 03F METRICSCOMPLETENESSSCORELABELS KMLABELS
PRINTVMEASURE 03F METRICSVMEASURESCORELABELS KMLABELS
PRINTADJUSTED RANDINDEX 3F
 METRICSADJUSTEDRANDSCORELABELS KMLABELS
PRINTSILHOUETTE COEFFICIENT 03F
 METRICSSILHOUETTESCOREX KMLABELS SAMPLESIZE1000
PRINT
IF NOTOPTSUSEHASHING
PRINTTOP TERMS PER CLUSTER
IFOPTSNCOMPONENTS
ORIGINALSPACECENTROIDS SVDINVERSETRANSFORMKMCLUSTERCENTERS
ORDERCENTROIDS ORIGINALSPACECENTROIDSARGSORT 1
ELSE
ORDERCENTROIDS KMCLUSTERCENTERSARGSORT 1
TERMS VECTORIZERGETFEATURENAMES
FORIINRANGETRUEK
PRINTCLUSTER D I END
FORINDINORDERCENTROIDSI 10
PRINTS TERMSIND END
PRINT
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 1137 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE

5283 CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
THIS IS AN EXAMPLE SHOWING HOW SCIKITLEARN CAN BE USED TO CLASSIFY DOCUMENTS BY TOPICS USING A BAGOFWORDS AP
PROACH THIS EXAMPLE USES A SCIPYSPARSE MATRIX TO STORE THE FEATURES AND DEMONSTRATES VARIOUS CLASSIFIERS THAT CAN
EFFICIENTLY HANDLE SPARSE MATRICES
THE DATASET USED IN THIS EXAMPLE IS THE 20 NEWSGROUPS DATASET IT WILL BE AUTOMATICALLY DOWNLOADED THEN CACHED
THE BAR PLOT INDICATES THE ACCURACY TRAINING TIME NORMALIZED AND TEST TIME NORMALIZED OF EACH CLASSIFIER
OUT
USAGE PLOTDOCUMENTCLASSIFICATION20NEWSGROUPSPY OPTIONS
OPTIONS
H HELP SHOW THIS HELP MESSAGE AND EXIT
REPORT PRINT A DETAILED CLASSIFICATION REPORT
CHI2SELECTSELECTCHI2
SELECT SOME NUMBER OF FEATURES USING A CHISQUARED
TEST
CONFUSIONMATRIX PRINT THE CONFUSION MATRIX
TOP10 PRINT TEN MOST DISCRIMINATIVE TERMS PER CLASS FOR
EVERY CLASSIFIER
ALLCATEGORIES WHETHER TO USE ALL CATEGORIES OR NOT
USEHASHING USE A HASHING VECTORIZER
NFEATURESNFEATURES
NFEATURES WHEN USING THE HASHING VECTORIZER
FILTERED REMOVE NEWSGROUP INFORMATION THAT IS EASILY OVERFIT
HEADERS SIGNATURES AND QUOTING

SCIKITLEARN USER GUIDE RELEASE 0213
LOADING 20 NEWSGROUPS DATASET FOR CATEGORIES
ALTATHEISM TALKRELIGIONMISC COMPGRAPHICS SCISPACE
DATA LOADED
2034 DOCUMENTS 3980MB TRAINING SET
1353 DOCUMENTS 2867MB TEST SET
4 CATEGORIES
EXTRACTING FEATURES FROM THE TRAINING DATA USING A SPARSE VECTORIZER
DONE IN 0412178S AT 9655MBS
NSAMPLES 2034 NFEATURES 33809
EXTRACTING FEATURES FROM THE TEST DATA USING THE SAME VECTORIZER
DONE IN 0351330S AT 8162MBS
NSAMPLES 1353 NFEATURES 33809

RIDGE CLASSIFIER

TRAINING
RIDGECLASSIFIERSOLVERSAG TOL001
TRAIN TIME 0132S
TEST TIME 0001S
ACCURACY 0896
DIMENSIONALITY 33809
DENSITY 1000000

PERCEPTRON

TRAINING
PERCEPTRONMAXITER50
TRAIN TIME 0017S
TEST TIME 0002S
ACCURACY 0888
DIMENSIONALITY 33809
DENSITY 0255302

PASSIVEAGGRESSIVE

TRAINING
PASSIVEAGGRESSIVECLASSIFIERMAXITER50
TRAIN TIME 0031S
TEST TIME 0002S
ACCURACY 0904
DIMENSIONALITY 33809
DENSITY 0694674

KNN

TRAINING
KNEIGHBORSCLASSIFIERNNEIGHBORS10
TRAIN TIME 0002S
TEST TIME 0317S
528 WORKING WITH TEXT DOCUMENTS 1439

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ACCURACY 0858

RANDOM FOREST

TRAINING
RANDOMFORESTCLASSIFIERNESTIMATORS100
TRAIN TIME 1671S
TEST TIME 0071S
ACCURACY 0840

L2 PENALTY

TRAINING
LINEARSVCDUALFALSE TOL0001
TRAIN TIME 0145S
TEST TIME 0002S
ACCURACY 0900
DIMENSIONALITY 33809
DENSITY 1000000

TRAINING
SGDCLASSIFIERMAXITER50
TRAIN TIME 0030S
TEST TIME 0002S
ACCURACY 0902
DIMENSIONALITY 33809
DENSITY 0579380

L1 PENALTY

TRAINING
LINEARSVCDUALFALSE PENALTYL1 TOL0001
TRAIN TIME 0301S
TEST TIME 0002S
ACCURACY 0873
DIMENSIONALITY 33809
DENSITY 0005553

TRAINING
SGDCLASSIFIERMAXITER50 PENALTYL1
TRAIN TIME 0093S
TEST TIME 0002S
ACCURACY 0887
DIMENSIONALITY 33809
DENSITY 0022901

ELASTICNET PENALTY

SCIKITLEARN USER GUIDE RELEASE 0213
TRAINING
SGDCLASSIFIERMAXITER50 PENALTYELASTICNET
TRAIN TIME 0252S
TEST TIME 0002S
ACCURACY 0899
DIMENSIONALITY 33809
DENSITY 0187472

NEARESTCENTROID AKA ROCCHIO CLASSIFIER

TRAINING
NEARESTCENTROID
TRAIN TIME 0004S
TEST TIME 0002S
ACCURACY 0855

NAIVE BAYES

TRAINING
MULTINOMIALNBALPHA001
TRAIN TIME 0003S
TEST TIME 0001S
ACCURACY 0899
DIMENSIONALITY 33809
DENSITY 1000000

TRAINING
BERNOULLINBALPHA001
TRAIN TIME 0004S
TEST TIME 0003S
ACCURACY 0884
DIMENSIONALITY 33809
DENSITY 1000000

TRAINING
COMPLEMENTNBALPHA01
TRAIN TIME 0004S
TEST TIME 0001S
ACCURACY 0911
DIMENSIONALITY 33809
DENSITY 1000000

LINEARSVC WITH L1BASED FEATURE SELECTION

TRAINING
PIPELINESTEPSFEATURESELECTION
SELECTFROMMODELESTIMATORLINEARSVCDUALFALSE PENALTYL1
TOL0001
CLASSIFICATION LINEARSVC

SCIKITLEARN USER GUIDE RELEASE 0213
TRAIN TIME 0252S
TEST TIME 0002S
ACCURACY 0880
 AUTHOR PETER PRETTENHOFER PETERPRETTENHOFERGMAILCOM
 OLIVIER GRISEL OLIVIERGRISELENSTAORG
 MATHIEU BLONDEL MATHIEUMBLONDELORG
 LARS BUITINCK
 LICENSE BSD 3 CLAUSE
IMPORT LOGGING
IMPORT NUMPY AS NP
FROM OPTPARSE IMPORT OPTIONPARSER
IMPORT SYS
FROM TIME IMPORT TIME
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT FETCH20NEWSGROUPS
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFVECTORIZER
FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT HASHINGVECTORIZER
FROM SKLEARNFEATURESELECTION IMPORT SELECTFROMMODEL
FROM SKLEARNFEATURESELECTION IMPORT SELECTKBEST CHI2
FROM SKLEARNLINEARMODEL IMPORT RIDGECLASSIFIER
FROM SKLEARNPIPELINE IMPORT PIPELINE
FROM SKLEARNSVM IMPORT LINEARSVC
FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
FROM SKLEARNLINEARMODEL IMPORT PERCEPTRON
FROM SKLEARNLINEARMODEL IMPORT PASSIVEAGGRESSIVECLASSIFIER
FROM SKLEARNNAIVEBAYES IMPORT BERNOULLNB COMPLEMENTNB MULTINOMIALNB
FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSCLASSIFIER
FROM SKLEARNNEIGHBORS IMPORT NEARESTCENTROID
FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER
FROM SKLEARNUTILSEXTMATH IMPORT DENSITY
FROM SKLEARN IMPORT METRICS
 DISPLAY PROGRESS LOGS ON STDOUT
LOGGINGBASICCONFIGLEVELLOGGINGINFO
FORMAT ASCTIMES LEVELNAMES MESSAGES
 PARSE COMMANDLINE ARGUMENTS
OP OPTIONPARSER
OPADDOPTIONREPORT
ACTIONSTORETRUE DESTPRINTREPORT
HELPPRINT A DETAILED CLASSIFICATION REPORT
OPADDOPTIONCHI2SELECT
ACTIONSTORE TYPEINT DESTSELECTCHI2
HELPSELECT SOME NUMBER OF FEATURES USING A CHISQUARED TEST
OPADDOPTIONCONFUSIONMATRIX
ACTIONSTORETRUE DESTPRINTCM
HELPPRINT THE CONFUSION MATRIX
OPADDOPTIONTOP10
ACTIONSTORETRUE DESTPRINTTOP10

SCIKITLEARN USER GUIDE RELEASE 0213
HELPPRINT TEN MOST DISCRIMINATIVE TERMS PER CLASS
 FOR EVERY CLASSIFIER
OPADDOPTIONALLCATEGORIES
ACTIONSTORETRUE DESTALLCATEGORIES
HELPWHETHER TO USE ALL CATEGORIES OR NOT
OPADDOPTIONUSEHASHING
ACTIONSTORETRUE
HELPUSE A HASHING VECTORIZER
OPADDOPTIONNFEATURES
ACTIONSTORE TYPEINT DEFAULT2 16
HELPNFEATURES WHEN USING THE HASHING VECTORIZER
OPADDOPTIONFILTERED
ACTIONSTORETRUE
HELPREMOVE NEWSGROUP INFORMATION THAT IS EASILY OVERFIT
HEADERS SIGNATURES AND QUOTING
DEFISINTERACTIVE
RETURN NOT HASATTRSYSMODULESMAIN FILE
 WORKAROUND FOR JUPYTER NOTEBOOK AND IPYTHON CONSOLE
ARGV   IFISINTERACTIVE ELSESYSARGV1
OPTS ARGS OPPARSEARGSARGV
IFLENARGS 0
OPERRORTHIS SCRIPT TAKES NO ARGUMENTS
SYSEXIT1
PRINTDOC
OPPRINTHELP
PRINT

 LOAD SOME CATEGORIES FROM THE TRAINING SET
IFOPTSALLCATEGORIES
CATEGORIES NONE
ELSE
CATEGORIES
ALTATHEISM
TALKRELIGIONMISC
COMPGRAPHICS
SCISPACE

IFOPTSFILTERED
REMOVE HEADERS FOOTERS QUOTES
ELSE
REMOVE
PRINTLOADING 20 NEWSGROUPS DATASET FOR CATEGORIES
PRINTCATEGORIES IFCATEGORIES ELSEALL
DATATRAIN FETCH20NEWSGROUPSSUBSETTRAIN CATEGORIESCATEGORIES
SHUFFLETRUE RANDOMSTATE42
REMOVEREMOVE
DATATEST FETCH20NEWSGROUPSSUBSETTEST CATEGORIESCATEGORIES

```
SCIKITLEARN USER GUIDE RELEASE 0213
SHUFFLETRUE RANDOMSTATE42
REMOVEREMOVE
PRINTDATA LOADED
 ORDER OF LABELS IN TARGETNAMES CAN BE DIFFERENT FROM CATEGORIES
TARGETNAMES  DATATRAINTARGETNAMES
DEFSIZEMBDOCS
RETURNSUMLENSENCODEUTF8 FORSINDOCS  1E6
DATATRAINSIZEMB  SIZEMBDATATRAINDATA
DATATESTSIZEMB  SIZEMBDATATESTDATA
PRINTDDOCUMENTS  03FMB TRAINING SET
LENDATATRAINDATA DATATRAINSIZEMB
PRINTDDOCUMENTS  03FMB TEST SET
LENDATATESTDATA DATATESTSIZEMB
PRINTDCATEGORIES  LENTARGETNAMES
PRINT
 SPLIT A TRAINING SET AND A TEST SET
YTRAIN YTEST  DATATRAINTARGET DATATESTTARGET
PRINTEXTRACTING FEATURES FROM THE TRAINING DATA USING A SPARSE VECTORIZER
T0  TIME
IFOPTSUSEHASHING
VECTORIZER  HASHINGVECTORIZERSTOPWORDSENGLISH ALTERNATESIGNFALSE
NFEATURESOPTSNFEATURES
XTRAIN  VECTORIZERTRANSFORMDATATRAINDATA
ELSE
VECTORIZER  TFIDFVECTORIZERSUBLINEARTFTRUE MAXDF05
STOPWORDSENGLISH
XTRAIN  VECTORIZERFITTRANSFORMDATATRAINDATA
DURATION  TIME  T0
PRINTDONE IN FS AT03FMBS  DURATION DATATRAINSIZEMB  DURATION
PRINTNSAMPLES D NFEATURES D  XTRAINSHAPE
PRINT
PRINTEXTRACTING FEATURES FROM THE TEST DATA USING THE SAME VECTORIZER
T0  TIME
XTEST  VECTORIZERTRANSFORMDATATESTDATA
DURATION  TIME  T0
PRINTDONE IN FS AT03FMBS  DURATION DATATESTSIZEMB  DURATION
PRINTNSAMPLES D NFEATURES D  XTESTSHAPE
PRINT
 MAPPING FROM INTEGER FEATURE NAME TO ORIGINAL TOKEN STRING
IFOPTSUSEHASHING
FEATURENAMES  NONE
ELSE
FEATURENAMES  VECTORIZERGETFEATURENAMES
IFOPTSSELECTCHI2
PRINTEXTRACTING DBEST FEATURES BY A CHISQUARED TEST
OPTSSELECTCHI2
T0  TIME
1444 CHAPTER 5 EXAMPLES
```

```
SCIKITLEARN USER GUIDE RELEASE 0213
CH2  SELECTKBESTCHI2 KOPTSSELECTCHI2
XTRAIN  CH2FITTRANSFORMXTRAIN YTRAIN
XTEST  CH2TRANSFORMXTEST
IFFEATURENAMES
 KEEP SELECTED FEATURE NAMES
FEATURENAMES  FEATURENAMESI FORI
INCH2GETSUPPORTINDICESTRUE
PRINTDONE IN FS  TIME  T0
PRINT
IFFEATURENAMES
FEATURENAMES  NPASARRAYFEATURENAMES
DEFTRIMS
TRIM STRING TO FIT ON TERMINAL ASSUMING 80COLUMN DISPLAY
RETURNSIFLENS  80 ELSES77

 BENCHMARK CLASSIFIERS
DEFBENCHMARKCLF
PRINT80
PRINTTRAINING
PRINTCLF
T0  TIME
CLFFITXTRAIN YTRAIN
TRAINTIME  TIME  T0
PRINTTRAIN TIME 03FS  TRAINTIME
T0  TIME
PRED  CLFPREDICTXTEST
TESTTIME  TIME  T0
PRINTTEST TIME 03FS  TESTTIME
SCORE  METRICSACCURACYSCOREYTEST PRED
PRINTACCURACY 03F  SCORE
IFHASATTRCLF COEF
PRINTDIMENSIONALITY D  CLFCOEFSHAPE1
PRINTDENSITY F  DENSITYCLFCOEF
IFOPTSPRINTTOP10 ANDFEATURENAMES IS NOTNONE
PRINTTOP 10 KEYWORDS PER CLASS
FORI LABEL INENUMERATETARGETNAMES
TOP10  NPARGSORTCLFCOEFI10
PRINTTRIMSS  LABEL  JOINFEATURENAMESTOP10
PRINT
IFOPTSPRINTREPORT
PRINTCLASSIFICATION REPORT
PRINTMETRICSCLASSIFICATIONREPORTYTEST PRED
TARGETNAMESTARGETNAMES
IFOPTSPRINTCM
PRINTCONFUSION MATRIX
PRINTMETRICSCONFUSIONMATRIXYTEST PRED
528 WORKING WITH TEXT DOCUMENTS 1445
```

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PRINT
CLFDESCR STRCLFSPLIT0
RETURNCLFDESCR SCORE TRAINTIME TESTTIME
RESULTS
FORCLF NAME IN
RIDGECLASSIFIERTOL1E2 SOLVERSAG RIDGE CLASSIFIER
PERCEPTRONMAXITER50 TOL1E3 PERCEPTRON
PASSIVEAGGRESSIVECLASSIFIERMAXITER50 TOL1E3
PASSIVEAGGRESSIVE
KNEIGHBORSCLASSIFIERNNEIGHBORS10 KNN
RANDOMFORESTCLASSIFIERNESTIMATORS100 RANDOM FOREST
PRINT80
PRINTNAME
RESULTSAPPENDBENCHMARKCLF
FORPENALTY INL2 L1
PRINT80
PRINTSPENALTY PENALTYUPPER
 TRAIN LIBLINEAR MODEL
RESULTSAPPENDBENCHMARKLINEARSVCPENALTYPENALTY DUALFALSE
TOL1E3
 TRAIN SGD MODEL
RESULTSAPPENDBENCHMARKSGDCLASSIFIERALPHA0001 MAXITER50
PENALTYPENALTY
 TRAIN SGD WITH ELASTIC NET PENALTY
PRINT80
PRINTELASTICNET PENALTY
RESULTSAPPENDBENCHMARKSGDCLASSIFIERALPHA0001 MAXITER50
PENALTYELASTICNET
 TRAIN NEARESTCENTROID WITHOUT THRESHOLD
PRINT80
PRINTNEARESTCENTROID AKA ROCCHIO CLASSIFIER
RESULTSAPPENDBENCHMARKNEARESTCENTROID
 TRAIN SPARSE NAIVE BAYES CLASSIFIERS
PRINT80
PRINTNAIVE BAYES
RESULTSAPPENDBENCHMARKMULTINOMIALNBALPHA01
RESULTSAPPENDBENCHMARKBERNOULLINBALPHA01
RESULTSAPPENDBENCHMARKCOMPLEMENTNBALPHA1
PRINT80
PRINTLINEARSVC WITH L1BASED FEATURE SELECTION
 THE SMALLER C THE STRONGER THE REGULARIZATION
 THE MORE REGULARIZATION THE MORE SPARSITY
RESULTSAPPENDBENCHMARKPIPELINE
FEATURESELECTION SELECTFROMMODELLINEARSVCPENALTYL1 DUALFALSE
TOL1E3
CLASSIFICATION LINEARSVCPENALTYL2
 MAKE SOME PLOTS
INDICES NPARANGELENRESULTS

SCIKITLEARN USER GUIDE RELEASE 0213
RESULTS XI FORXINRESULTS FORIINRANGE4
CLFNAMES SCORE TRAININGTIME TESTTIME RESULTS
TRAININGTIME NPARRAYTRAININGTIME NPMAXTRAININGTIME
TESTTIME NPARRAYTESTTIME NPMAXTESTTIME
PLTFIGUREFIGSIZE12 8
PLTTITLESCORE
PLTBARHINDICES SCORE 2 LABELSCORE COLORNAVY
PLTBARHINDICES 3 TRAININGTIME 2 LABELTRAINING TIME
COLORC
PLTBARHINDICES 6 TESTTIME 2 LABELTEST TIME COLORDARKORANGE
PLTYTICKS
PLTLEGENDLOCBEST
PLTSUBPLOTSADJUSTLEFT25
PLTSUBPLOTSADJUSTTOP95
PLTSUBPLOTSADJUSTBOTTOM05
FORI CINZIPINDICES CLFNAMES
PLTTEXT3 I C
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 4728 SECONDS
529 DECISION TREES
EXAMPLES CONCERNING THE SKLEARNTREE MODULE
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5291 DECISION TREE REGRESSION
A 1D REGRESSION WITH DECISION TREE
THEDECISION TREES IS USED TO FIT A SINE CURVE WITH ADDITION NOISY OBSERVATION AS A RESULT IT LEARNS LOCAL LINEAR REGRES
SIONS APPROXIMATING THE SINE CURVE
WE CAN SEE THAT IF THE MAXIMUM DEPTH OF THE TREE CONTROLLED BY THE MAXDEPTH PARAMETER IS SET TOO HIGH THE
DECISION TREES LEARN TOO FINE DETAILS OF THE TRAINING DATA AND LEARN FROM THE NOISE IE THEY OVERFIT

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PRINTDOC
 IMPORT THE NECESSARY MODULES AND LIBRARIES
IMPORT NUMPY AS NP
FROM SKLEARNTREE IMPORT DECISIONTREEREGRESSOR
IMPORT MATPLOTLIBPYPLOT AS PLT
 CREATE A RANDOM DATASET
RNG NPRANDOMRANDOMSTATE1
X NPSORT5 RNGRAND80 1 AXIS0
Y NPSINXRAVEL
Y5 3 05 RNGRAND16
 FIT REGRESSION MODEL
REGR1 DECISIONTREEREGRESSORMAXDEPTH2
REGR2 DECISIONTREEREGRESSORMAXDEPTH5
REGR1FITX Y
REGR2FITX Y
 PREDICT
XTEST NPARANGE00 50 001 NPNEWAXIS
Y1 REGR1PREDICTXTEST
Y2 REGR2PREDICTXTEST
 PLOT THE RESULTS
PLTFIGURE
1448 CHAPTER 5 EXAMPLES

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PLTSCATTERX Y S20 EDGECOLORBLACK
CDARKORANGE LABELDATA
PLTPLOTXTEST Y1 COLORCORNFLOWERBLUE
LABELMAXDEPTH2 LINEWIDTH2
PLTPLOTXTEST Y2 COLORYELLOWGREEN LABELMAXDEPTH5 LINEWIDTH2
PLTXLABELDATA
PLTYLABELTARGET
PLTTITLEDECISION TREE REGRESSION
PLTLEGEND
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0124 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5292 MULTIOUTPUT DECISION TREE REGRESSION
AN EXAMPLE TO ILLUSTRATE MULTIOUTPUT REGRESSION WITH DECISION TREE
THEDECISION TREES IS USED TO PREDICT SIMULTANEOUSLY THE NOISY X AND Y OBSERVATIONS OF A CIRCLE GIVEN A SINGLE UNDERLYING
FEATURE AS A RESULT IT LEARNS LOCAL LINEAR REGRESSIONS APPROXIMATING THE CIRCLE
WE CAN SEE THAT IF THE MAXIMUM DEPTH OF THE TREE CONTROLLED BY THE MAXDEPTH PARAMETER IS SET TOO HIGH THE
DECISION TREES LEARN TOO FINE DETAILS OF THE TRAINING DATA AND LEARN FROM THE NOISE IE THEY OVERFIT
529 DECISION TREES 1449

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PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNTREE IMPORT DECISIONTREEREGRESSOR
CREATE A RANDOM DATASET
RNG NPRANDOMRANDOMSTATE1
X NPSORT200 RNGRAND100 1 100 AXIS0
Y NPARRAYNPPI NPSINXRAVEL NPPI NPCOSXRAVELT
Y5   05 RNGRAND20 2
FIT REGRESSION MODEL
REGR1 DECISIONTREEREGRESSORMAXDEPTH2
REGR2 DECISIONTREEREGRESSORMAXDEPTH5
REGR3 DECISIONTREEREGRESSORMAXDEPTH8
REGR1FITX Y
REGR2FITX Y
REGR3FITX Y
PREDICT
XTEST NPARANGE1000 1000 001 NPNEWAXIS
Y1 REGR1PREDICTXTEST
Y2 REGR2PREDICTXTEST
Y3 REGR3PREDICTXTEST

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PLOT THE RESULTS
PLTFIGURE
S 25
PLTSCATTERY 0 Y 1 CNAVY SS
EDGECOLORBLACK LABELDATA
PLTSCATTERY1 0 Y1 1 CCORNFLOWERBLUE SS
EDGECOLORBLACK LABELMAXDEPTH2
PLTSCATTERY2 0 Y2 1 CRED SS
EDGECOLORBLACK LABELMAXDEPTH5
PLTSCATTERY3 0 Y3 1 CORANGE SS
EDGECOLORBLACK LABELMAXDEPTH8
PLTXLIM6 6
PLTYLIM6 6
PLTXLABELTARGET 1
PLTYLABELTARGET 2
PLTTITLEMULTIOUTPUT DECISION TREE REGRESSION
PLTLEGENDLOCBEST
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0109 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5293 PLOT THE DECISION SURFACE OF A DECISION TREE ON THE IRIS DATASET
PLOT THE DECISION SURFACE OF A DECISION TREE TRAINED ON PAIRS OF FEATURES OF THE IRIS DATASET
SEEDECISION TREE FOR MORE INFORMATION ON THE ESTIMATOR
FOR EACH PAIR OF IRIS FEATURES THE DECISION TREE LEARNS DECISION BOUNDARIES MADE OF COMBINATIONS OF SIMPLE THRESHOLDING RULES INFERRED FROM THE TRAINING SAMPLES
WE ALSO SHOW THE TREE STRUCTURE OF A MODEL BUILT ON ALL OF THE FEATURES
529 DECISION TREES 1451

•

```
PRINTDOC
IMPORT NUMPY AS NP
IMPORT MATPLOTLIBPYPLOT AS PLT
FROM SKLEARNDATASETS IMPORT LOADIRIS
FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER PLOTTREE
 PARAMETERS
NCLASSES  3
PLOTCOLORS  RYB
PLOTSTEP  002
 LOAD DATA
IRIS  LOADIRIS
FORPAIRIDX PAIR INENUMERATE0 1 0 2 0 3
1 2 1 3 2 3
 WE ONLY TAKE THE TWO CORRESPONDING FEATURES
X  IRISDATA PAIR
Y  IRISTARGET
 TRAIN
CLF  DECISIONTREECLASSIFIERFITX Y
 PLOT THE DECISION BOUNDARY
PLTSUBPLOT2 3 PAIRIDX  1
```

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XMIN XMAX X 0MIN 1 X 0MAX 1
YMIN YMAX X 1MIN 1 X 1MAX 1
XX YY NPMESHGRIDNPARANGEXMIN XMAX PLOTSTEP
NPARANGEYMIN YMAX PLOTSTEP
PLTTIGHTLAYOUTHPAD05 WPAD05 PAD25
Z CLFPREDICTNPCXXRAVEL YYRAVEL
Z ZRESHAPEXXSHAPE
CS PLTCONTOURFXX YY Z CMAPPLTCMRDYLBU
PLTXLABELIRISFEATURENAMESPAIR0
PLTYLABELIRISFEATURENAMESPAIR1
 PLOT THE TRAINING POINTS
FORI COLOR INZIPRANGENCLASSES PLOTCOLORS
IDX NPWHEREY I
PLTSCATTERXIDX 0 XIDX 1 CCOLOR LABELIRISTARGETNAMESI
CMAPPLTCMRDYLBU EDGECOLORBLACK S15
PLTSUPTITLEDECISION SURFACE OF A DECISION TREE USING PAIRED FEATURES
PLTLEGENDLOCLOWER RIGHT BORDERPAD0 HANDLETEXTPAD0
PLTAXISTIGHT
PLTFIGURE
CLF DECISIONTREECLASSIFIERFITIRISDATA IRISTARGET
PLOTTREECLF FILLEDTRUE
PLTSHOW
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0934 SECONDS
NOTE CLICK HERE TO DOWNLOAD THE FULL EXAMPLE CODE
5294 UNDERSTANDING THE DECISION TREE STRUCTURE
THE DECISION TREE STRUCTURE CAN BE ANALYSED TO GAIN FURTHER INSIGHT ON THE RELATION BETWEEN THE FEATURES AND THE TARGET TO PREDICT IN THIS EXAMPLE WE SHOW HOW TO RETRIEVE
• THE BINARY TREE STRUCTURE
• THE DEPTH OF EACH NODE AND WHETHER OR NOT IT’S A LEAF
• THE NODES THAT WERE REACHED BY A SAMPLE USING THE DECISIONPATH METHOD
• THE LEAF THAT WAS REACHED BY A SAMPLE USING THE APPLY METHOD
• THE RULES THAT WERE USED TO PREDICT A SAMPLE
• THE DECISION PATH SHARED BY A GROUP OF SAMPLES
OUT
THE BINARY TREE STRUCTURE HAS 5 NODES AND HAS THE FOLLOWING TREE STRUCTURE
NODE0 TEST NODE GO TO NODE 1 IF X 3 0800000011920929 ELSE TO NODE 2
NODE1 LEAF NODE
NODE2 TEST NODE GO TO NODE 3 IF X 2 4950000047683716 ELSE TO NODE 4
NODE3 LEAF NODE

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NODE4 LEAF NODE
RULES USED TO PREDICT SAMPLE 0
DECISION ID NODE 0 XTEST0 3 24 0800000011920929
DECISION ID NODE 2 XTEST0 2 51 4950000047683716
THE FOLLOWING SAMPLES 0 1 SHARE THE NODE 0 2 IN THE TREE
IT IS 400 OF ALL NODES
IMPORT NUMPY AS NP
FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
FROM SKLEARNDATASETS IMPORT LOADIRIS
FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
IRIS LOADIRIS
X IRISDATA
Y IRISTARGET
XTRAIN XTEST YTRAIN YTEST TRAINTESTSPLITX Y RANDOMSTATE0
ESTIMATOR DECISIONTREECLASSIFIERMAXLEAFNODES3 RANDOMSTATE0
ESTIMATORFITXTRAIN YTRAIN
 THE DECISION ESTIMATOR HAS AN ATTRIBUTE CALLED TREE WHICH STORES THE ENTIRE
 TREE STRUCTURE AND ALLOWS ACCESS TO LOW LEVEL ATTRIBUTES THE BINARY TREE
 TREE IS REPRESENTED AS A NUMBER OF PARALLEL ARRAYS THE ITH ELEMENT OF EACH
 ARRAY HOLDS INFORMATION ABOUT THE NODE I NODE 0 IS THE TREES ROOT NOTE
 SOME OF THE ARRAYS ONLY APPLY TO EITHER LEAVES OR SPLIT NODES RESP IN THIS
 CASE THE VALUES OF NODES OF THE OTHER TYPE ARE ARBITRARY

 AMONG THOSE ARRAYS WE HAVE
  LEFTCHILD ID OF THE LEFT CHILD OF THE NODE
  RIGHTCHILD ID OF THE RIGHT CHILD OF THE NODE
  FEATURE FEATURE USED FOR SPLITTING THE NODE
  THRESHOLD THRESHOLD VALUE AT THE NODE

 USING THOSE ARRAYS WE CAN PARSE THE TREE STRUCTURE
NNODES ESTIMATORTREENODECOUNT
CHILDRENLEFT ESTIMATORTREECHILDRENLEFT
CHILDRENRIGHT ESTIMATORTREECHILDRENRIGHT
FEATURE ESTIMATORTREEFEATURE
THRESHOLD ESTIMATORTREETHRESHOLD
 THE TREE STRUCTURE CAN BE TRAVERSED TO COMPUTE VARIOUS PROPERTIES SUCH
 AS THE DEPTH OF EACH NODE AND WHETHER OR NOT IT IS A LEAF
NODEDEPTH NPZEROSSHAPENNODES DTYPENPINT64
ISLEAVES NPZEROSSHAPENNODES DTYPEBOOL
STACK 0 1 SEED IS THE ROOT NODE ID AND ITS PARENT DEPTH
WHILELENSTACK 0
NODEID PARENTDEPTH STACKPOP
529 DECISION TREES 1455

SCIKITLEARN USER GUIDE RELEASE 0213
NODEDEPTHNODEID PARENTDEPTH 1
 IF WE HAVE A TEST NODE
IFCHILDRENLEFTNODEID CHILDRENRIGHTNODEID
STACKAPPENDCHILDRENLEFTNODEID PARENTDEPTH 1
STACKAPPENDCHILDRENRIGHTNODEID PARENTDEPTH 1
ELSE
ISLEAVESNODEID TRUE
PRINTTHE BINARY TREE STRUCTURE HAS SNODES AND HAS
THE FOLLOWING TREE STRUCTURE
 NNODES
FORIINRANGENNODES
IFISLEAVESI
PRINTSNODESLEAF NODE NODEDEPTHI T I
ELSE
PRINTSNODESTEST NODE GO TO NODE SIF X S SELSE TO
NODES
 NODEDEPTHI T
I
CHILDRENLEFTI
FEATUREI
THRESHOLDI
CHILDRENRIGHTI

PRINT
 FIRST LETS RETRIEVE THE DECISION PATH OF EACH SAMPLE THE DECISIONPATH
 METHOD ALLOWS TO RETRIEVE THE NODE INDICATOR FUNCTIONS A NON ZERO ELEMENT OF
 INDICATOR MATRIX AT THE POSITION I J INDICATES THAT THE SAMPLE I GOES
 THROUGH THE NODE J
NODEINDICATOR ESTIMATORDECISIONPATHXTEST
 SIMILARLY WE CAN ALSO HAVE THE LEAVES IDS REACHED BY EACH SAMPLE
LEAVEID ESTIMATORAPPLYXTEST
 NOW ITS POSSIBLE TO GET THE TESTS THAT WERE USED TO PREDICT A SAMPLE OR
 A GROUP OF SAMPLES FIRST LETS MAKE IT FOR THE SAMPLE
SAMPLEID 0
NODEINDEX NODEINDICATORINDICESNODEINDICATORINDPTRSAMPLEID
NODEINDICATORINDPTRSAMPLEID 1
PRINTRULES USED TO PREDICT SAMPLE S   SAMPLEID
FORNODEID INNODEINDEX
IFLEAVEIDSAMPLEID NODEID
CONTINUE
IFXTESTSAMPLEID FEATURENODEID THRESHOLDNODEID
THRESHOLDSIGN
ELSE
THRESHOLDSIGN
PRINTDECISION ID NODE S XTEST SS SS S
 NODEID
SAMPLEID

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FEATURENODEID
XTESTSAMPLEID FEATURENODEID
THRESHOLDSIGN
THRESHOLDNODEID
 FOR A GROUP OF SAMPLES WE HAVE THE FOLLOWING COMMON NODE
SAMPLEIDS 0 1
COMMONNODES NODEINDICATORTOARRAYSAMPLEIDSSUMAXIS0
LENSAMPLEIDS
COMMONNODEID NPARANGENNODESCOMMONNODES
PRINTNTHE FOLLOWING SAMPLES SSHARE THE NODE SIN THE TREE
 SAMPLEIDS COMMONNODEID
PRINTIT IS S OF ALL NODES 100 LENCOMMONNODEID NNODES
TOTAL RUNNING TIME OF THE SCRIPT 0 MINUTES 0003 SECONDS
529 DECISION TREES 1457

CHAPTER
SIX
API REFERENCE
THIS IS THE CLASS AND FUNCTION REFERENCE OF SCIKITLEARN PLEASE REFER TO THE FULL USER GUIDE FOR FURTHER DETAILS AS THE CLASS AND FUNCTION RAW SPECIFICATIONS MAY NOT BE ENOUGH TO GIVE FULL GUIDELINES ON THEIR USES FOR REFERENCE ON CONCEPTS REPEATED ACROSS THE API SEE GLOSSARY OF COMMON TERMS AND API ELEMENTS
61SKLEARNBASE BASE CLASSES AND UTILITY FUNCTIONS
BASE CLASSES FOR ALL ESTIMATORS
611 BASE CLASSES
BASEBASEESTIMATOR BASE CLASS FOR ALL ESTIMATORS IN SCIKITLEARN
BASEBICLUSTERMIXIN MIXIN CLASS FOR ALL BICLUSTER ESTIMATORS IN SCIKITLEARN
BASECLASSIFIERMIXIN MIXIN CLASS FOR ALL CLASSIFIERS IN SCIKITLEARN
BASECLUSTERMIXIN MIXIN CLASS FOR ALL CLUSTER ESTIMATORS IN SCIKITLEARN
BASEDENSITYMIXIN MIXIN CLASS FOR ALL DENSITY ESTIMATORS IN SCIKITLEARN
BASEREGRESSORMIXIN MIXIN CLASS FOR ALL REGRESSION ESTIMATORS IN SCIKITLEARN
BASETRANSFORMERMIXIN MIXIN CLASS FOR ALL TRANSFORMERS IN SCIKITLEARN
SKLEARNBASE BASEESTIMATOR
CLASSSKLEARNBASE BASEESTIMATOR
BASE CLASS FOR ALL ESTIMATORS IN SCIKITLEARN
NOTES
ALL ESTIMATORS SHOULD SPECIFY ALL THE PARAMETERS THAT CAN BE SET AT THE CLASS LEVEL IN THEIR INIT AS EXPLICIT KEYWORD ARGUMENTS NO ARGS ORKWARGS
METHODS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

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INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNBASEBASEESTIMATOR
•INDUCTIVE CLUSTERING
•COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
SKLEARNBASE BICLUSTERMIXIN
CLASSSKLEARNBASE BICLUSTERMIXIN
MIXIN CLASS FOR ALL BICLUSTER ESTIMATORS IN SCIKITLEARN
ATTRIBUTES
BICLUSTERS CONVENIENT WAY TO GET ROW AND COLUMN INDICATORS TOGETHER
METHODS
GETINDICES SELF I ROW AND COLUMN INDICES OF THE I'TH BICLUSTER
GETSHAPE SELF I SHAPE OF THE I'TH BICLUSTER
GETSUBMATRIX SELF I DATA RETURNS THE SUBMATRIX CORRESPONDING TO BICLUSTER I
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
BICLUSTERS
CONVENIENT WAY TO GET ROW AND COLUMN INDICATORS TOGETHER
RETURNS THE ROWS ANDCOLUMNS MEMBERS
GETINDICES SELFI
ROW AND COLUMN INDICES OF THE I'TH BICLUSTER

ONLY WORKS IF ROWS ANDCOLUMNS ATTRIBUTES EXIST
PARAMETERS
IINT THE INDEX OF THE CLUSTER
RETURNS
ROWIND NPARRAY DTYPENPINTP INDICES OF ROWS IN THE DATASET THAT BELONG TO THE BICLUSTER
COLIND NPARRAY DTYPENPINTP INDICES OF COLUMNS IN THE DATASET THAT BELONG TO THE BICLUS
TER
GETSHAPE SELFI
SHAPE OF THE I'TH BICLUSTER
PARAMETERS
IINT THE INDEX OF THE CLUSTER
RETURNS
SHAPE INT INT NUMBER OF ROWS AND COLUMNS RESP IN THE BICLUSTER
GETSUBMATRIX SELFIDATA
RETURNS THE SUBMATRIX CORRESPONDING TO BICLUSTER I
PARAMETERS
IINT THE INDEX OF THE CLUSTER
DATA ARRAY THE DATA
RETURNS
SUBMATRIX ARRAY THE SUBMATRIX CORRESPONDING TO BICLUSTER I
NOTES
WORKS WITH SPARSE MATRICES ONLY WORKS IF ROWS ANDCOLUMNS ATTRIBUTES EXIST
SKLEARNBASE CLASSIFIERMIXIN
CLASSSKLEARNBASE CLASSIFIERMIXIN
MIXIN CLASS FOR ALL CLASSIFIERS IN SCIKITLEARN
METHODS
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED

PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SKLEARNBASE CLUSTERMIXIN
CLASSSKLEARNBASE CLUSTERMIXIN
MIXIN CLASS FOR ALL CLUSTER ESTIMATORS IN SCIKITLEARN
METHODS
FITPREDICT SELF X Y PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
FITPREDICT SELFXYNONE
PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES INPUT DATA
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
LABELS NDARRAY SHAPE NSAMPLES CLUSTER LABELS
SKLEARNBASE DENSITYMIXIN
CLASSSKLEARNBASE DENSITYMIXIN
MIXIN CLASS FOR ALL DENSITY ESTIMATORS IN SCIKITLEARN
METHODS
SCORE SELF X Y RETURNS THE SCORE OF THE MODEL ON THE DATA X
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
SCORESELFXYNONE
RETURNS THE SCORE OF THE MODEL ON THE DATA X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES

RETURNS
SCORE FLOAT
SKLEARNBASE REGRESSORMIXIN
CLASSSKLEARNBASE REGRESSORMIXIN
MIXIN CLASS FOR ALL REGRESSION ESTIMATORS IN SCIKITLEARN
METHODS
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SKLEARNBASE TRANSFORMERMIXIN
CLASSSKLEARNBASE TRANSFORMERMIXIN
MIXIN CLASS FOR ALL TRANSFORMERS IN SCIKITLEARN

METHODS
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
EXAMPLES USING SKLEARNBASETRANSFORMERMIXIN
•COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
612 FUNCTIONS
BASECLONE ESTIMATOR SAFE CONSTRUCTS A NEW ESTIMATOR WITH THE SAME PARAMETERS
BASEISCLASSIFIER ESTIMATOR RETURNS TRUE IF THE GIVEN ESTIMATOR IS PROBABLY A CLASSI
FIER
BASEISREGRESSOR ESTIMATOR RETURNS TRUE IF THE GIVEN ESTIMATOR IS PROBABLY A REGRES
SOR
CONFIGCONTEXT NEWCONFIG CONTEXT MANAGER FOR GLOBAL SCIKITLEARN CONFIGURATION
GETCONFIG RETRIEVE CURRENT VALUES FOR CONFIGURATION SET BY
SETCONFIG
SETCONFIG ASSUMEFINITE WORKINGMEMORY SET GLOBAL SCIKITLEARN CONFIGURATION
SHOWVERSIONS PRINT USEFUL DEBUGGING INFORMATION
SKLEARNBASE CLONE
SKLEARNBASE CLONEESTIMATOR SAFETRUE
CONSTRUCTS A NEW ESTIMATOR WITH THE SAME PARAMETERS
CLONE DOES A DEEP COPY OF THE MODEL IN AN ESTIMATOR WITHOUT ACTUALLY COPYING ATTACHED DATA IT YIELDS A NEW
ESTIMATOR WITH THE SAME PARAMETERS THAT HAS NOT BEEN FIT ON ANY DATA
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT OR LIST TUPLE OR SET OF OBJECTS THE ESTIMATOR OR GROUP OF ESTIMATORS
TO BE CLONED
SAFE BOOLEAN OPTIONAL IF SAFE IS FALSE CLONE WILL FALL BACK TO A DEEP COPY ON OBJECTS THAT ARE
NOT ESTIMATORS

SKLEARNBASE ISCLASSIFIER
SKLEARNBASE ISCLASSIFIER ESTIMATOR
RETURNS TRUE IF THE GIVEN ESTIMATOR IS PROBABLY A CLASSIFIER
PARAMETERS
ESTIMATOR OBJECT ESTIMATOR OBJECT TO TEST
RETURNS
OUT BOOL TRUE IF ESTIMATOR IS A CLASSIFIER AND FALSE OTHERWISE
SKLEARNBASE ISREGRESSOR
SKLEARNBASE ISREGRESSOR ESTIMATOR
RETURNS TRUE IF THE GIVEN ESTIMATOR IS PROBABLY A REGRESSOR
PARAMETERS
ESTIMATOR OBJECT ESTIMATOR OBJECT TO TEST
RETURNS
OUT BOOL TRUE IF ESTIMATOR IS A REGRESSOR AND FALSE OTHERWISE
SKLEARN CONFIGCONTEXT
SKLEARN CONFIGCONTEXT NEWCONFIG
CONTEXT MANAGER FOR GLOBAL SCIKITLEARN CONFIGURATION
PARAMETERS
ASSUMEFINITE BOOL OPTIONAL IF TRUE VALIDATION FOR FINITENESS WILL BE SKIPPED SAVING TIME BUT
LEADING TO POTENTIAL CRASHES IF FALSE VALIDATION FOR FINITENESS WILL BE PERFORMED AVOIDING
ERROR GLOBAL DEFAULT FALSE
WORKINGMEMORY INT OPTIONAL IF SET SCIKITLEARN WILL ATTEMPT TO LIMIT THE SIZE OF TEMPORARY
ARRAYS TO THIS NUMBER OF MIB PER JOB WHEN PARALLELISED OFTEN SAVING BOTH COMPUTATION
TIME AND MEMORY ON EXPENSIVE OPERATIONS THAT CAN BE PERFORMED IN CHUNKS GLOBAL DEFAULT
1024
SEE ALSO
SETCONFIG SET GLOBAL SCIKITLEARN CONFIGURATION
GETCONFIG RETRIEVE CURRENT VALUES OF THE GLOBAL CONFIGURATION
NOTES
ALL SETTINGS NOT JUST THOSE PRESENTLY MODIFIED WILL BE RETURNED TO THEIR PREVIOUS VALUES WHEN THE CONTEXT MANAGER
IS EXITED THIS IS NOT THREADSAFE
EXAMPLES

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```
IMPORT SKLEARN
FROM SKLEARNUTILSVALIDATION IMPORT ASSERTALLFINITE
WITH SKLEARNCONFIGCONTEXTASSUMEFINITE TRUE
ASSERTALLFINITEFLOATNAN
WITH SKLEARNCONFIGCONTEXTASSUMEFINITE TRUE
WITH SKLEARNCONFIGCONTEXTASSUMEFINITE FALSE
ASSERTALLFINITEFLOATNAN

TRACEBACK MOST RECENT CALL LAST

VALUEERROR INPUT CONTAINS NAN
```

SKLEARN GETCONFIG
SKLEARN GETCONFIG
RETRIEVE CURRENT VALUES FOR CONFIGURATION SET BY SETCONFIG
RETURNS
CONFIG DICT KEYS ARE PARAMETER NAMES THAT CAN BE PASSED TO SETCONFIG
SEE ALSO
CONFIGCONTEXT CONTEXT MANAGER FOR GLOBAL SCIKITLEARN CONFIGURATION
SETCONFIG SET GLOBAL SCIKITLEARN CONFIGURATION
SKLEARN SETCONFIG
SKLEARN SETCONFIG ASSUMEFINITENONE WORKINGMEMORYNONE PRINTCHANGEDONLYNONE
SET GLOBAL SCIKITLEARN CONFIGURATION
NEW IN VERSION 019
PARAMETERS
ASSUMEFINITE BOOL OPTIONAL IF TRUE VALIDATION FOR FINITENESS WILL BE SKIPPED SAVING TIME BUT
LEADING TO POTENTIAL CRASHES IF FALSE VALIDATION FOR FINITENESS WILL BE PERFORMED AVOIDING
ERROR GLOBAL DEFAULT FALSE
NEW IN VERSION 019
WORKINGMEMORY INT OPTIONAL IF SET SCIKITLEARN WILL ATTEMPT TO LIMIT THE SIZE OF TEMPORARY
ARRAYS TO THIS NUMBER OF MIB PER JOB WHEN PARALLELISED OFTEN SAVING BOTH COMPUTATION
TIME AND MEMORY ON EXPENSIVE OPERATIONS THAT CAN BE PERFORMED IN CHUNKS GLOBAL DEFAULT
1024
NEW IN VERSION 020
PRINTCHANGEDONLY BOOL OPTIONAL IF TRUE ONLY THE PARAMETERS THAT WERE SET TO NONDEFAULT
VALUES WILL BE PRINTED WHEN PRINTING AN ESTIMATOR FOR EXAMPLE PRINTSVC WHILE
TRUE WILL ONLY PRINT ‘SVC’ WHILE THE DEFAULT BEHAVIOUR WOULD BE TO PRINT ‘SVCC10
CACHESIZE200 ’ WITH ALL THE NONCHANGED PARAMETERS
NEW IN VERSION 021
SEE ALSO
CONFIGCONTEXT CONTEXT MANAGER FOR GLOBAL SCIKITLEARN CONFIGURATION

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GETCONFIG RETRIEVE CURRENT VALUES OF THE GLOBAL CONFIGURATION
EXAMPLES USING SKLEARNSETCONFIG
•COMPACT ESTIMATOR REPRESENTATIONS
SKLEARN SHOWVERSIONS
SKLEARN SHOWVERSIONS
PRINT USEFUL DEBUGGING INFORMATION
62SKLEARNCALIBRATION PROBABILITY CALIBRATION
CALIBRATION OF PREDICTED PROBABILITIES
USER GUIDE SEE THE PROBABILITY CALIBRATION SECTION FOR FURTHER DETAILS
CALIBRATIONCALIBRATEDCLASSIFIERCV PROBABILITY CALIBRATION WITH ISOTONIC REGRESSION OR SIGMOID
621SKLEARNCALIBRATION CALIBRATEDCLASSIFIERCV
CLASSSKLEARNCALIBRATION CALIBRATEDCLASSIFIERCV BASEESTIMATORNONE
METHOD'SIGMOID' CV'WARN'
PROBABILITY CALIBRATION WITH ISOTONIC REGRESSION OR SIGMOID
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
WITH THIS CLASS THE BASEESTIMATOR IS FIT ON THE TRAIN SET OF THE CROSSVALIDATION GENERATOR AND THE TEST SET IS USED FOR CALIBRATION THE PROBABILITIES FOR EACH OF THE FOLDS ARE THEN AVERAGED FOR PREDICTION IN CASE THAT CV"PREFIT" IS PASSED TO INIT IT IS ASSUMED THAT BASEESTIMATOR HAS BEEN FITTED ALREADY AND ALL DATA IS USED FOR CALIBRATION NOTE THAT DATA FOR FITTING THE CLASSIFIER AND FOR CALIBRATING IT MUST BE DISJOINT
READ MORE IN THE USER GUIDE
PARAMETERS
BASEESTIMATOR INSTANCE BASEESTIMATOR THE CLASSIFIER WHOSE OUTPUT DECISION FUNCTION NEEDS TO BE CALIBRATED TO OFFER MORE ACCURATE PREDICTPROBA OUTPUTS IF CVPREFIT THE CLASSIFIER MUST HAVE BEEN FIT ALREADY ON DATA
METHOD 'SIGMOID' OR 'ISOTONIC' THE METHOD TO USE FOR CALIBRATION CAN BE 'SIGMOID' WHICH CORRESPONDS TO PLATT'S METHOD OR 'ISOTONIC' WHICH IS A NONPARAMETRIC APPROACH IT IS NOT ADVISED TO USE ISOTONIC CALIBRATION WITH TOO FEW CALIBRATION SAMPLES 1000 SINCE IT TENDS TO OVERFIT USE SIGMOIDS PLATT'S CALIBRATION IN THIS CASE
CVINTEGER CROSSVALIDATION GENERATOR ITERABLE OR "PREFIT" OPTIONAL DETERMINES THE CROSS VALIDATION SPLITTING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES

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FOR INTEGERNONE INPUTS IF YIS BINARY OR MULTICLASS SKLEARNMODELSELECTION
STRATIFIEDKFOLD IS USED IF YIS NEITHER BINARY NOR MULTICLASS SKLEARN
MODELSELECTIONKFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
IF “PREFIT” IS PASSED IT IS ASSUMED THAT BASEESTIMATOR HAS BEEN FITTED ALREADY AND ALL DATA IS
USED FOR CALIBRATION
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
ATTRIBUTES
CLASSES ARRAY SHAPE NCLASSES THE CLASS LABELS
CALIBRATEDCLASSIFIERS LIST LEN EQUAL TO CV OR 1 IF CV “PREFIT” THE LIST OF CALIBRATED
CLASSIFIERS ONE FOR EACH CROSSVALIDATION FOLD WHICH HAS BEEN FITTED ON ALL BUT THE VALIDATION
FOLD AND CALIBRATED ON THE VALIDATION FOLD
REFERENCES
R57CF438D70601 R57CF438D70602 R57CF438D70603 R57CF438D70604
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE CALIBRATED MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT THE TARGET OF NEW SAMPLES
PREDICTPROBA SELF X POSTERIOR PROBABILITIES OF CLASSIFICATION
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFBASEESTIMATORNONE METHOD’SIGMOID’ CV’WARN’
FITSELFXYSAMPLEWEIGHTNONE
FIT THE CALIBRATED MODEL
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED
RETURNS
SELF OBJECT RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS

RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT THE TARGET OF NEW SAMPLES CAN BE DIFFERENT FROM THE PREDICTION OF THE UNCALIBRATED CLASSIFIER
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES THE PREDICTED CLASS
PREDICTPROBA SELFX
POSTERIOR PROBABILITIES OF CLASSIFICATION
THIS FUNCTION RETURNS POSTERIOR PROBABILITIES OF CLASSIFICATION ACCORDING TO EACH CLASS ON AN ARRAY OF TEST VECTORS X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES NCLASSES THE PREDICTED PROBAS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNCALIBRATIONCALIBRATEDCLASSIFIERCV
•PROBABILITY CALIBRATION CURVES
•PROBABILITY CALIBRATION OF CLASSIFIERS
•PROBABILITY CALIBRATION FOR 3CLASS CLASSIFICATION

CALIBRATIONCALIBRATIONCURVE YTRUE
YPROBCOMPUTE TRUE AND PREDICTED PROBABILITIES FOR A CALIBRATION
CURVE
622SKLEARNCALIBRATION CALIBRATIONCURVE
SKLEARNCALIBRATION CALIBRATIONCURVE YTRUE YPROB NORMALIZEFALSE NBINS5 STRAT
EGY'UNIFORM'
COMPUTE TRUE AND PREDICTED PROBABILITIES FOR A CALIBRATION CURVE
THE METHOD ASSUMES THE INPUTS COME FROM A BINARY CLASSIFIER
CALIBRATION CURVES MAY ALSO BE REFERRED TO AS RELIABILITY DIAGRAMS
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAY SHAPE NSAMPLES TRUE TARGETS
YPROB ARRAY SHAPE NSAMPLES PROBABILITIES OF THE POSITIVE CLASS
NORMALIZE BOOL OPTIONAL DEFAULTFALSE WHETHER YPROB NEEDS TO BE NORMALIZED INTO THE BIN
0 1 IE IS NOT A PROPER PROBABILITY IF TRUE THE SMALLEST VALUE IN YPROB IS MAPPED ONTO
0 AND THE LARGEST ONE ONTO 1
NBINS INT NUMBER OF BINS A BIGGER NUMBER REQUIRES MORE DATA BINS WITH NO DATA POINTS
IE WITHOUT CORRESPONDING VALUES IN YPROB WILL NOT BE RETURNED THUS THERE MAY BE FEWER
THAN NBINS IN THE RETURN VALUE
STRATEGY 'UNIFORM' 'QUANTILE' DEFAULT'UNIFORM' STRATEGY USED TO DEFINE THE WIDTHS OF THE
BINS
UNIFORM ALL BINS HAVE IDENTICAL WIDTHS
QUANTILE ALL BINS HAVE THE SAME NUMBER OF POINTS
RETURNS
PROBTRUE ARRAY SHAPE NBINS OR SMALLER THE TRUE PROBABILITY IN EACH BIN FRACTION OF POSI
TIVES
PROBPRED ARRAY SHAPE NBINS OR SMALLER THE MEAN PREDICTED PROBABILITY IN EACH BIN
REFERENCES
ALEXANDRU NICULESCUMIZIL AND RICH CARUANA 2005 PREDICTING GOOD PROBABILITIES WITH SUPERVISED LEARNING
IN PROCEEDINGS OF THE 22ND INTERNATIONAL CONFERENCE ON MACHINE LEARNING ICML SEE SECTION 4 QUALITATIVE
ANALYSIS OF PREDICTIONS
EXAMPLES USING SKLEARNCALIBRATIONCALIBRATIONCURVE
•COMPARISON OF CALIBRATION OF CLASSIFIERS
•PROBABILITY CALIBRATION CURVES

63SKLEARNCLUSTER CLUSTERING
THESKLEARNCLUSTER MODULE GATHERS POPULAR UNSUPERVISED CLUSTERING ALGORITHMS
USER GUIDE SEE THE CLUSTERING SECTION FOR FURTHER DETAILS
631 CLASSES
CLUSTERAFFINITYPROPAGATION DAMPING PERFORM AFFINITY PROPAGATION CLUSTERING OF DATA
CLUSTERAGGLOMERATIVECLUSTERING AGGLOMERATIVE CLUSTERING
CLUSTERBIRCH THRESHOLD BRANCHINGFACTOR IMPLEMENTS THE BIRCH CLUSTERING ALGORITHM
CLUSTERDBSCAN EPS MINSAMPLES METRIC PERFORM DBSCAN CLUSTERING FROM VECTOR ARRAY OR DISTANCE MATRIX
CLUSTEROPTICS MINSAMPLES MAXEPS ESTIMATE CLUSTERING STRUCTURE FROM VECTOR ARRAY
CLUSTERFEATUREAGGLOMERATION NCLUSTERS
AGGLOMERATE FEATURES
CLUSTERKMEANS NCLUSTERS INIT NINIT KMEANS CLUSTERING
CLUSTERMINIBATCHKMEANS NCLUSTERS INIT MINIBATCH KMEANS CLUSTERING
CLUSTERMEANSHIFT BANDWIDTH SEEDS MEAN SHIFT CLUSTERING USING A FLAT KERNEL
CLUSTERSPECTRALCLUSTERING NCLUSTERS APPLY CLUSTERING TO A PROJECTION OF THE NORMALIZED LAPLACIAN
SKLEARNCLUSTER AFFINITYPROPAGATION
CLASSSKLEARNCLUSTER AFFINITYPROPAGATION DAMPING05 MAXITER200 CONVERGENCEITER15 COPYTRUE PREFERENCENONE AFFINITY’EUCLIDEAN’ VERBOSEFALSE
PERFORM AFFINITY PROPAGATION CLUSTERING OF DATA
READ MORE IN THE USER GUIDE
PARAMETERS
DAMPING FLOAT OPTIONAL DEFAULT 05 DAMPING FACTOR BETWEEN 05 AND 1 IS THE EXTENT TO WHICH THE CURRENT VALUE IS MAINTAINED RELATIVE TO INCOMING VALUES WEIGHTED 1 DAMPING THIS IN ORDER TO AVOID NUMERICAL OSCILLATIONS WHEN UPDATING THESE VALUES MESSAGES
MAXITER INT OPTIONAL DEFAULT 200 MAXIMUM NUMBER OF ITERATIONS
CONVERGENCEITER INT OPTIONAL DEFAULT 15 NUMBER OF ITERATIONS WITH NO CHANGE IN THE NUMBER OF ESTIMATED CLUSTERS THAT STOPS THE CONVERGENCE
COPY BOOLEAN OPTIONAL DEFAULT TRUE MAKE A COPY OF INPUT DATA
PREFERENCE ARRAYLIKE SHAPE NSAMPLES OR FLOAT OPTIONAL PREFERENCES FOR EACH POINT POINTS WITH LARGER VALUES OF PREFERENCES ARE MORE LIKELY TO BE CHOSEN AS EXEMPLARS THE NUMBER OF EXEMPLARS IE OF CLUSTERS IS INFLUENCED BY THE INPUT PREFERENCES VALUE IF THE PREFERENCES ARE NOT PASSED AS ARGUMENTS THEY WILL BE SET TO THE MEDIAN OF THE INPUT SIMILARITIES
AFFINITY STRING OPTIONAL DEFAULT‘‘EUCLIDEAN‘‘ WHICH AFFINITY TO USE AT THE MOMENT PRECOMPUTED ANDEUCLIDEAN ARE SUPPORTED EUCLIDEAN USES THE NEGATIVE SQUARED EUCLIDEAN DISTANCE BETWEEN POINTS
VERBOSE BOOLEAN OPTIONAL DEFAULT FALSE WHETHER TO BE VERBOSE
ATTRIBUTES

CLUSTERCENTERSINDICES ARRAY SHAPE NCLUSTERS INDICES OF CLUSTER CENTERS
CLUSTERCENTERS ARRAY SHAPE NCLUSTERS NFEATURES CLUSTER CENTERS IF AFFINITY
PRECOMPUTED
LABELS ARRAY SHAPE NSAMPLES LABELS OF EACH POINT
AFFINITYMATRIX ARRAY SHAPE NSAMPLES NSAMPLES STORES THE AFFINITY MATRIX USED IN FIT
NITER INT NUMBER OF ITERATIONS TAKEN TO CONVERGE
NOTES
FOR AN EXAMPLE SEE EXAMPLESCLUSTERPLOTAFFINITYPROPAGATIONPY
THE ALGORITHMIC COMPLEXITY OF AFFINITY PROPAGATION IS QUADRATIC IN THE NUMBER OF POINTS
WHENFIT DOES NOT CONVERGE CLUSTERCENTERS BECOMES AN EMPTY ARRAY AND ALL TRAINING SAMPLES WILL BE
LABELLED AS1 IN ADDITION PREDICT WILL THEN LABEL EVERY SAMPLE AS 1
WHEN ALL TRAINING SAMPLES HAVE EQUAL SIMILARITIES AND EQUAL PREFERENCES THE ASSIGNMENT OF CLUSTER CENTERS AND
LABELS DEPENDS ON THE PREFERENCE IF THE PREFERENCE IS SMALLER THAN THE SIMILARITIES FIT WILL RESULT IN A SINGLE
CLUSTER CENTER AND LABEL 0FOR EVERY SAMPLE OTHERWISE EVERY TRAINING SAMPLE BECOMES ITS OWN CLUSTER CENTER
AND IS ASSIGNED A UNIQUE LABEL
REFERENCES
BRENDAN J FREY AND DELBERT DUECK “CLUSTERING BY PASSING MESSAGES BETWEEN DATA POINTS” SCIENCE FEB 2007
EXAMPLES
```
 FROM SKLEARNCLUSTER IMPORT AFFINITYPROPAGATION
 IMPORT NUMPY AS NP
X  NPARRAY1 2 1 4 1 0
 4 2 4 4 4 0
CLUSTERING  AFFINITYPROPAGATIONFITX
CLUSTERING
AFFINITYPROPAGATIONAFFINITYEUCLIDEAN CONVERGENCEITER15 COPYTRUE
DAMPING05 MAXITER200 PREFERENCENONE VERBOSEFALSE
CLUSTERINGLABELS
ARRAY0 0 0 1 1 1
CLUSTERINGPREDICT0 0 4 4
ARRAY0 1
CLUSTERINGCLUSTERCENTERS
ARRAY1 2
4 2
```
METHODS
FITSELF X Y CREATE AFFINITY MATRIX FROM NEGATIVE EUCLIDEAN DIS
TANCES THEN APPLY AFFINITY PROPAGATION CLUSTERING
FITPREDICT SELF X Y PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
CONTINUED ON NEXT PAGE

TABLE 614 – CONTINUED FROM PREVIOUS PAGE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT THE CLOSEST CLUSTER EACH SAMPLE IN X BELONGS TO
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFDAMPING05 MAXITER200 CONVERGENCEITER15 COPYTRUE PREFERENCENONE
AFFINITY'EUCLIDEAN' VERBOSEFALSE
FITSELFXYNONE
CREATE AFFINITY MATRIX FROM NEGATIVE EUCLIDEAN DISTANCES THEN APPLY AFFINITY PROPAGATION CLUSTERING
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES OR NSAMPLES NSAMPLES DATA MATRIX OR IF
AFFINITY ISPRECOMPUTED MATRIX OF SIMILARITIES AFFINITIES
YIGNORED
FITPREDICT SELFXYNONE
PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES INPUT DATA
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
LABELS NDARRAY SHAPE NSAMPLES CLUSTER LABELS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT THE CLOSEST CLUSTER EACH SAMPLE IN X BELONGS TO
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA TO PREDICT
RETURNS
LABELS ARRAY SHAPE NSAMPLES INDEX OF THE CLUSTER EACH SAMPLE BELONGS TO
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
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EXAMPLES USING SKLEARNCLUSTERAFFINITYPROPAGATION
•DEMO OF AFFINITY PROPAGATION CLUSTERING ALGORITHM
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
SKLEARNCLUSTER AGGLOMERATIVECLUSTERING
CLASSSKLEARNCLUSTER AGGLOMERATIVECLUSTERING NCLUSTERS2 AFFINITY'EUCLIDEAN' MEM
ORYNONE CONNECTIVITYNONE COM
PUTEFULLTREE'AUTO' LINKAGE'WARD'
POOLINGFUNC'DEPRECATED' DIS
TANCETHRESHOLDNONE
AGGLOMERATIVE CLUSTERING
RECURSIVELY MERGES THE PAIR OF CLUSTERS THAT MINIMALLY INCREASES A GIVEN LINKAGE DISTANCE
READ MORE IN THE USER GUIDE
PARAMETERS
NCLUSTERS INT OR NONE OPTIONAL DEFAULT2 THE NUMBER OF CLUSTERS TO FIND IT MUST BE NONE
IFDISTANCETHRESHOLD IS NOTNONE
AFFINITY STRING OR CALLABLE DEFAULT "EUCLIDEAN" METRIC USED TO COMPUTE THE LINKAGE CAN BE
"EUCLIDEAN" "L1" "L2" "MANHATTAN" "COSINE" OR "PRECOMPUTED" IF LINKAGE IS "WARD"
ONLY "EUCLIDEAN" IS ACCEPTED IF "PRECOMPUTED" A DISTANCE MATRIX INSTEAD OF A SIMILARITY
MATRIX IS NEEDED AS INPUT FOR THE FIT METHOD
MEMORY NONE STR OR OBJECT WITH THE JOBLIBMEMORY INTERFACE OPTIONAL USED TO CACHE THE
OUTPUT OF THE COMPUTATION OF THE TREE BY DEFAULT NO CACHING IS DONE IF A STRING IS GIVEN IT
IS THE PATH TO THE CACHING DIRECTORY
CONNECTIVITY ARRAYLIKE OR CALLABLE OPTIONAL CONNECTIVITY MATRIX DEFINES FOR EACH SAMPLE THE
NEIGHBORING SAMPLES FOLLOWING A GIVEN STRUCTURE OF THE DATA THIS CAN BE A CONNECTIVITY
MATRIX ITSELF OR A CALLABLE THAT TRANSFORMS THE DATA INTO A CONNECTIVITY MATRIX SUCH AS DE
RIVED FROM KNEIGHBORSGRAPH DEFAULT IS NONE IE THE HIERARCHICAL CLUSTERING ALGORITHM IS
UNSTRUCTURED
COMPUTEFULLTREE BOOL OR 'AUTO' OPTIONAL STOP EARLY THE CONSTRUCTION OF THE TREE AT
NCLUSTERS THIS IS USEFUL TO DECREASE COMPUTATION TIME IF THE NUMBER OF CLUSTERS IS NOT SMALL
COMPARED TO THE NUMBER OF SAMPLES THIS OPTION IS USEFUL ONLY WHEN SPECIFYING A CONNEC
TIVITY MATRIX NOTE ALSO THAT WHEN VARYING THE NUMBER OF CLUSTERS AND USING CACHING IT MAY
BE ADVANTAGEOUS TO COMPUTE THE FULL TREE IT MUST BE TRUE IFDISTANCETHRESHOLD IS
NOTNONE
LINKAGE "WARD" "COMPLETE" "AVERAGE" "SINGLE" OPTIONAL DEFAULT"WARD" WHICH LINKAGE
CRITERION TO USE THE LINKAGE CRITERION DETERMINES WHICH DISTANCE TO USE BETWEEN SETS OF
OBSERVATION THE ALGORITHM WILL MERGE THE PAIRS OF CLUSTER THAT MINIMIZE THIS CRITERION
• WARD MINIMIZES THE VARIANCE OF THE CLUSTERS BEING MERGED
• AVERAGE USES THE AVERAGE OF THE DISTANCES OF EACH OBSERVATION OF THE TWO SETS
• COMPLETE OR MAXIMUM LINKAGE USES THE MAXIMUM DISTANCES BETWEEN ALL OBSERVATIONS OF
THE TWO SETS
• SINGLE USES THE MINIMUM OF THE DISTANCES BETWEEN ALL OBSERVATIONS OF THE TWO SETS

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POOLINGFUNC CALLABLE DEFAULT’DEPRECATED’ IGNORED
DEPRECATED SINCE VERSION 020 POOLINGFUNC HAS BEEN DEPRECATED IN 020 AND WILL BE
REMOVED IN 022
DISTANCETHRESHOLD FLOAT OPTIONAL DEFAULTNONE THE LINKAGE DISTANCE THRESHOLD ABOVE
WHICH CLUSTERS WILL NOT BE MERGED IF NOT NONE NCLUSTERS MUST BENONE AND
COMPUTEFULLTREE MUST BETRUE
NEW IN VERSION 021
ATTRIBUTES
NCLUSTERS INT THE NUMBER OF CLUSTERS FOUND BY THE ALGORITHM IF
DISTANCETHRESHOLDNONE IT WILL BE EQUAL TO THE GIVEN NCLUSTERS
LABELS ARRAY NSAMPLES CLUSTER LABELS FOR EACH POINT
NLEAVES INT NUMBER OF LEAVES IN THE HIERARCHICAL TREE
NCONNECTEDCOMPONENTS INT THE ESTIMATED NUMBER OF CONNECTED COMPONENTS IN THE GRAPH
CHILDREN ARRAYLIKE SHAPE NSAMPLES1 2 THE CHILDREN OF EACH NONLEAF NODE VALUES LESS
THAN NSAMPLES CORRESPOND TO LEAVES OF THE TREE WHICH ARE THE ORIGINAL SAMPLES A NODE
IGREATER THAN OR EQUAL TO NSAMPLES IS A NONLEAF NODE AND HAS CHILDREN CHILDRENI
 NSAMPLES ALTERNATIVELY AT THE ITH ITERATION CHILDRENI0 AND CHILDRENI1 ARE
MERGED TO FORM NODE NSAMPLES I
EXAMPLES
 FROM SKLEARNCLUSTER IMPORT AGGLOMERATIVECLUSTERING
 IMPORT NUMPY AS NP
X NPARRAY1 2 1 4 1 0
 4 2 4 4 4 0
CLUSTERING AGGLOMERATIVECLUSTERINGFITX
CLUSTERING
AGGLOMERATIVECLUSTERINGAFFINITYEUCLIDEAN COMPUTEFULLTREEAUTO
CONNECTIVITYNONE DISTANCETHRESHOLDNONE
LINKAGEWARD MEMORYNONE NCLUSTERS2
POOLINGFUNCDEPRECATED
CLUSTERINGLABELS
ARRAY1 1 1 0 0 0
METHODS
FITSELF X Y FIT THE HIERARCHICAL CLUSTERING ON THE DATA
FITPREDICT SELF X Y PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELF NCLUSTERS2 AFFINITY’EUCLIDEAN’ MEMORYNONE CONNECTIVITYNONE
COMPUTEFULLTREE’AUTO’ LINKAGE’WARD’ POOLINGFUNC’DEPRECATED’ DIS
TANCETHRESHOLDNONE
FITSELFXYNONE
FIT THE HIERARCHICAL CLUSTERING ON THE DATA

PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA SHAPE NSAMPLES
NFEATURES OR NSAMPLES NSAMPLES IF AFFINITY'PRECOMPUTED'
YIGNORED
RETURNS
SELF
FITPREDICT SELFXYNONE
PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES INPUT DATA
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
LABELS NDARRAY SHAPE NSAMPLES CLUSTER LABELS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNCLUSTERAGGLOMERATIVECLUSTERING
•AGGLOMERATIVE CLUSTERING WITH AND WITHOUT STRUCTURE
•VARIOUS AGGLOMERATIVE CLUSTERING ON A 2D EMBEDDING OF DIGITS
•A DEMO OF STRUCTURED WARD HIERARCHICAL CLUSTERING ON AN IMAGE OF COINS
•HIERARCHICAL CLUSTERING STRUCTURED VS UNSTRUCTURED WARD
•AGGLOMERATIVE CLUSTERING WITH DIFFERENT METRICS
•INDUCTIVE CLUSTERING
•COMPARING DIFFERENT HIERARCHICAL LINKAGE METHODS ON TOY DATASETS
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS

SKLEARNCLUSTER BIRCH
CLASSSKLEARNCLUSTER BIRCHTHRESHOLD05 BRANCHINGFACTOR50 NCLUSTERS3 COM
PUTELABELSTRUE COPYTRUE
IMPLEMENTS THE BIRCH CLUSTERING ALGORITHM
IT IS A MEMORYEFFICIENT ONLINELEARNING ALGORITHM PROVIDED AS AN ALTERNATIVE TO MINIBATCHKMEANS IT CON
STRUCTS A TREE DATA STRUCTURE WITH THE CLUSTER CENTROIDS BEING READ OFF THE LEAF THESE CAN BE EITHER THE FINAL CLUSTER
CENTROIDS OR CAN BE PROVIDED AS INPUT TO ANOTHER CLUSTERING ALGORITHM SUCH AS AGGLOMERATIVECLUSTERING
READ MORE IN THE USER GUIDE
PARAMETERS
THRESHOLD FLOAT DEFAULT 05 THE RADIUS OF THE SUBCLUSTER OBTAINED BY MERGING A NEW SAMPLE
AND THE CLOSEST SUBCLUSTER SHOULD BE LESSER THAN THE THRESHOLD OTHERWISE A NEW SUBCLUSTER IS
STARTED SETTING THIS VALUE TO BE VERY LOW PROMOTES SPLITTING AND VICEVERSA
BRANCHINGFACTOR INT DEFAULT 50 MAXIMUM NUMBER OF CF SUBCLUSTERS IN EACH NODE IF A NEW
SAMPLES ENTERS SUCH THAT THE NUMBER OF SUBCLUSTERS EXCEED THE BRANCHINGFACTOR THEN THAT
NODE IS SPLIT INTO TWO NODES WITH THE SUBCLUSTERS REDISTRIBUTED IN EACH THE PARENT SUBCLUSTER
OF THAT NODE IS REMOVED AND TWO NEW SUBCLUSTERS ARE ADDED AS PARENTS OF THE 2 SPLIT NODES
NCLUSTERS INT INSTANCE OF SKLEARNCLUSTER MODEL DEFAULT 3 NUMBER OF CLUSTERS AFTER THE FINAL
CLUSTERING STEP WHICH TREATS THE SUBCLUSTERS FROM THE LEAVES AS NEW SAMPLES
•NONE THE FINAL CLUSTERING STEP IS NOT PERFORMED AND THE SUBCLUSTERS ARE RETURNED AS THEY
ARE
•SKLEARNCLUSTER ESTIMATOR IF A MODEL IS PROVIDED THE MODEL IS FIT TREATING THE
SUBCLUSTERS AS NEW SAMPLES AND THE INITIAL DATA IS MAPPED TO THE LABEL OF THE CLOSEST SUB
CLUSTER
•INT THE MODEL FIT IS AGGLOMERATIVECLUSTERING WITHNCLUSTERS SET TO BE
EQUAL TO THE INT
COMPUTELABELS BOOL DEFAULT TRUE WHETHER OR NOT TO COMPUTE LABELS FOR EACH FIT
COPY BOOL DEFAULT TRUE WHETHER OR NOT TO MAKE A COPY OF THE GIVEN DATA IF SET TO FALSE THE
INITIAL DATA WILL BE OVERWRITTEN
ATTRIBUTES
ROOT CFNODE ROOT OF THE CFTREE
DUMMYLEAF CFNODE START POINTER TO ALL THE LEAVES
SUBCLUSTERCENTERS NDARRAY CENTROIDS OF ALL SUBCLUSTERS READ DIRECTLY FROM THE LEAVES
SUBCLUSTERLABELS NDARRAY LABELS ASSIGNED TO THE CENTROIDS OF THE SUBCLUSTERS AFTER THEY ARE
CLUSTERED GLOBALLY
LABELS NDARRAY SHAPE NSAMPLES ARRAY OF LABELS ASSIGNED TO THE INPUT DATA IF PARTIALFIT IS
USED INSTEAD OF FIT THEY ARE ASSIGNED TO THE LAST BATCH OF DATA
NOTES
THE TREE DATA STRUCTURE CONSISTS OF NODES WITH EACH NODE CONSISTING OF A NUMBER OF SUBCLUSTERS THE MAXIMUM
NUMBER OF SUBCLUSTERS IN A NODE IS DETERMINED BY THE BRANCHING FACTOR EACH SUBCLUSTER MAINTAINS A LINEAR SUM
SQUARED SUM AND THE NUMBER OF SAMPLES IN THAT SUBCLUSTER IN ADDITION EACH SUBCLUSTER CAN ALSO HAVE A NODE AS
ITS CHILD IF THE SUBCLUSTER IS NOT A MEMBER OF A LEAF NODE

FOR A NEW POINT ENTERING THE ROOT IT IS MERGED WITH THE SUBCLUSTER CLOSEST TO IT AND THE LINEAR SUM SQUARED SUM AND THE NUMBER OF SAMPLES OF THAT SUBCLUSTER ARE UPDATED THIS IS DONE RECURSIVELY TILL THE PROPERTIES OF THE LEAF NODE ARE UPDATED

REFERENCES

• TIAN ZHANG RAGHU RAMAKRISHNAN MARON LIVNY BIRCH AN EFFICIENT DATA CLUSTERING METHOD FOR LARGE DATABASES HTTPSWWWCSSFUCACOURSECENTRAL459HANPAPERSZHANG96PDF
• ROBERTO PERDISCI JBIRCH JAVA IMPLEMENTATION OF BIRCH CLUSTERING ALGORITHM HTTPSCODEGOOGLECOM ARCHIVEPJBIRCH

EXAMPLES

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 FROM SKLEARNCLUSTER IMPORT BIRCH
X  0 1 03 1 03 1 0 1 03 1 03 1
BRC  BIRCHBRANCHINGFACTOR50 NCLUSTERS NONE THRESHOLD05
COMPUTELABELS TRUE
BRCFITX
BIRCHBRANCHINGFACTOR50 COMPUTELABELSTRUE COPYTRUE NCLUSTERSNONE
THRESHOLD05
BRCPREDICTX
ARRAY0 0 0 1 1 1
```

METHODS

FITSELF X Y BUILD A CF TREE FOR THE INPUT DATA
FITPREDICT SELF X Y PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y ONLINE LEARNING
PREDICT SELF X PREDICT DATA USING THE CENTROIDS OF SUBCLUSTERS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM X INTO SUBCLUSTER CENTROIDS DIMENSION
INIT SELFTHRESHOLD05 BRANCHINGFACTOR50 NCLUSTERS3 COMPUTELABELSTRUE COPYTRUE
FITSELFXYNONE
BUILD A CF TREE FOR THE INPUT DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES INPUT DATA
YIGNORED
FITPREDICT SELFXYNONE
PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES INPUT DATA

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YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
LABELS NDARRAY SHAPE NSAMPLES CLUSTER LABELS
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXNONE YNONE
ONLINE LEARNING PREVENTS REBUILDING OF CFTREE FROM SCRATCH
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NONE INPUT DATA IF X IS NOT
PROVIDED ONLY THE GLOBAL CLUSTERING STEP IS DONE
YIGNORED
PREDICTSELFX
PREDICT DATA USING THE CENTROIDS OF SUBCLUSTERS
AVOID COMPUTATION OF THE ROW NORMS OF X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES INPUT DATA
RETURNS
LABELS NDARRAY SHAPENSAMPLES LABELLED DATA
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
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TRANSFORM SELFX
TRANSFORM X INTO SUBCLUSTER CENTROIDS DIMENSION
EACH DIMENSION REPRESENTS THE DISTANCE FROM THE SAMPLE POINT TO EACH CLUSTER CENTROID
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES INPUT DATA
RETURNS
XTRANS ARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NCLUSTERS TRANSFORMED DATA
EXAMPLES USING SKLEARNCLUSTERBIRCH
•COMPARE BIRCH AND MINIBATCHKMEANS
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
SKLEARNCLUSTER DBSCAN
CLASSSKLEARNCLUSTER DBSCANEPS05 MINSAMPLES5 METRIC'EUCLIDEAN' METRICPARAMSNONE
ALGORITHM'AUTO' LEAFSIZE30 PNONE NJOBSNONE
PERFORM DBSCAN CLUSTERING FROM VECTOR ARRAY OR DISTANCE MATRIX
DBSCAN DENSITYBASED SPATIAL CLUSTERING OF APPLICATIONS WITH NOISE FINDS CORE SAMPLES OF HIGH DENSITY
AND EXPANDS CLUSTERS FROM THEM GOOD FOR DATA WHICH CONTAINS CLUSTERS OF SIMILAR DENSITY
READ MORE IN THE USER GUIDE
PARAMETERS
EPS FLOAT OPTIONAL THE MAXIMUM DISTANCE BETWEEN TWO SAMPLES FOR ONE TO BE CONSIDERED AS
IN THE NEIGHBORHOOD OF THE OTHER THIS IS NOT A MAXIMUM BOUND ON THE DISTANCES OF POINTS
WITHIN A CLUSTER THIS IS THE MOST IMPORTANT DBSCAN PARAMETER TO CHOOSE APPROPRIATELY FOR
YOUR DATA SET AND DISTANCE FUNCTION
MINSAMPLES INT OPTIONAL THE NUMBER OF SAMPLES OR TOTAL WEIGHT IN A NEIGHBORHOOD FOR A
POINT TO BE CONSIDERED AS A CORE POINT THIS INCLUDES THE POINT ITSELF
METRIC STRING OR CALLABLE THE METRIC TO USE WHEN CALCULATING DISTANCE BETWEEN INSTANCES IN
A FEATURE ARRAY IF METRIC IS A STRING OR CALLABLE IT MUST BE ONE OF THE OPTIONS ALLOWED
BYSKLEARNMETRICSPAIRWISEDISTANCES FOR ITS METRIC PARAMETER IF METRIC
IS "PRECOMPUTED" X IS ASSUMED TO BE A DISTANCE MATRIX AND MUST BE SQUARE X MAY BE
A SPARSE MATRIX IN WHICH CASE ONLY "NONZERO" ELEMENTS MAY BE CONSIDERED NEIGHBORS FOR
DBSCAN
NEW IN VERSION 017 METRIC PRECOMPUTED TO ACCEPT PRECOMPUTED SPARSE MATRIX
METRICPARAMS DICT OPTIONAL ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC FUNCTION
NEW IN VERSION 019
ALGORITHM 'AUTO' 'BALLTREE' 'KDTREE' 'BRUTE' OPTIONAL THE ALGORITHM TO BE USED BY THE
NEARESTNEIGHBORS MODULE TO COMPUTE POINTWISE DISTANCES AND FIND NEAREST NEIGHBORS SEE
NEARESTNEIGHBORS MODULE DOCUMENTATION FOR DETAILS
LEAFSIZE INT OPTIONAL DEFAULT 30 LEAF SIZE PASSED TO BALLTREE OR CKDTREE THIS CAN AFFECT
THE SPEED OF THE CONSTRUCTION AND QUERY AS WELL AS THE MEMORY REQUIRED TO STORE THE TREE
THE OPTIMAL VALUE DEPENDS ON THE NATURE OF THE PROBLEM

PFLOAT OPTIONAL THE POWER OF THE MINKOWSKI METRIC TO BE USED TO CALCULATE DISTANCE BETWEEN POINTS
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
ATTRIBUTES
CORESAMPLEINDICES ARRAY SHAPE NCORESAMPLES INDICES OF CORE SAMPLES
COMPONENTS ARRAY SHAPE NCORESAMPLES NFEATURES COPY OF EACH CORE SAMPLE FOUND BY TRAINING
LABELS ARRAY SHAPE NSAMPLES CLUSTER LABELS FOR EACH POINT IN THE DATASET GIVEN TO FIT NOISY SAMPLES ARE GIVEN THE LABEL 1
SEE ALSO
OPTICS A SIMILAR CLUSTERING AT MULTIPLE VALUES OF EPS OUR IMPLEMENTATION IS OPTIMIZED FOR MEMORY USAGE
NOTES
FOR AN EXAMPLE SEE EXAMPLESCLUSTERPLOTDBSCANPY
THIS IMPLEMENTATION BULKCOMPUTES ALL NEIGHBORHOOD QUERIES WHICH INCREASES THE MEMORY COMPLEXITY TO OND WHERE D IS THE AVERAGE NUMBER OF NEIGHBORS WHILE ORIGINAL DBSCAN HAD MEMORY COMPLEXITY ON IT MAY ATTRACT A HIGHER MEMORY COMPLEXITY WHEN QUERYING THESE NEAREST NEIGHBORHOODS DEPENDING ON THE ALGORITHM
ONE WAY TO AVOID THE QUERY COMPLEXITY IS TO PRECOMPUTE SPARSE NEIGHBORHOODS IN CHUNKS USINGNEARESTNEIGHBORSRADIUSNEIGHBORSGRAPH WITHMODEDISTANCE THEN USING METRICPRECOMPUTED HERE
ANOTHER WAY TO REDUCE MEMORY AND COMPUTATION TIME IS TO REMOVE NEARDUPLICATE POINTS AND USE SAMPLEWEIGHT INSTEAD
CLUSTEROPTICS PROVIDES A SIMILAR CLUSTERING WITH LOWER MEMORY USAGE
REFERENCES
ESTER M H P KRIEGEL J SANDER AND X XU “A DENSITYBASED ALGORITHM FOR DISCOVERING CLUSTERS IN LARGE SPATIAL DATABASES WITH NOISE” IN PROCEEDINGS OF THE 2ND INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING PORTLAND OR AAAI PRESS PP 226231 1996
SCHUBERT E SANDER J ESTER M KRIEGEL H P XU X 2017 DBSCAN REVISITED REVISITED WHY AND HOW YOU SHOULD STILL USE DBSCAN ACM TRANSACTIONS ON DATABASE SYSTEMS TODS 423 19
EXAMPLES
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 FROM SKLEARNCLUSTER IMPORT DBSCAN
 IMPORT NUMPY AS NP
X  NPARRAY1 2 2 2 2 3
 8 7 8 8 25 80
CLUSTERING  DBSCANEPS3 MINSAMPLES2FITX
CLUSTERINGLABELS
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ARRAY 0 0 0 1 1 1
CLUSTERING
DBSCANALGORITHMAUTO EPS3 LEAFSIZE30 METRICEUCLIDEAN
METRICPARAMSNONE MINSAMPLES2 NJOBSNONE PNONE
METHODS
FITSELF X Y SAMPLEWEIGHT PERFORM DBSCAN CLUSTERING FROM FEATURES OR DISTANCE
MATRIX
FITPREDICT SELF X Y SAMPLEWEIGHT PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFEPS05 MINSAMPLES5 METRIC'EUCLIDEAN' METRICPARAMSNONE ALGO
RITHM'AUTO' LEAFSIZE30 PNONE NJOBSNONE
FITSELFXYNONE SAMPLEWEIGHTNONE
PERFORM DBSCAN CLUSTERING FROM FEATURES OR DISTANCE MATRIX
PARAMETERS
XARRAY OR SPARSE CSR MATRIX OF SHAPE NSAMPLES NFEATURES OR ARRAY OF SHAPE
NSAMPLES NSAMPLES A FEATURE ARRAY OR ARRAY OF DISTANCES BETWEEN SAMPLES IF
METRICPRECOMPUTED
SAMPLEWEIGHT ARRAY SHAPE NSAMPLES OPTIONAL WEIGHT OF EACH SAMPLE SUCH THAT A
SAMPLE WITH A WEIGHT OF AT LEAST MINSAMPLES IS BY ITSELF A CORE SAMPLE A SAMPLE
WITH NEGATIVE WEIGHT MAY INHIBIT ITS EPSNEIGHBOR FROM BEING CORE NOTE THAT WEIGHTS ARE
ABSOLUTE AND DEFAULT TO 1
YIGNORED
FITPREDICT SELFXYNONE SAMPLEWEIGHTNONE
PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
PARAMETERS
XARRAY OR SPARSE CSR MATRIX OF SHAPE NSAMPLES NFEATURES OR ARRAY OF SHAPE
NSAMPLES NSAMPLES A FEATURE ARRAY OR ARRAY OF DISTANCES BETWEEN SAMPLES IF
METRICPRECOMPUTED
SAMPLEWEIGHT ARRAY SHAPE NSAMPLES OPTIONAL WEIGHT OF EACH SAMPLE SUCH THAT A
SAMPLE WITH A WEIGHT OF AT LEAST MINSAMPLES IS BY ITSELF A CORE SAMPLE A SAMPLE
WITH NEGATIVE WEIGHT MAY INHIBIT ITS EPSNEIGHBOR FROM BEING CORE NOTE THAT WEIGHTS ARE
ABSOLUTE AND DEFAULT TO 1
YIGNORED
RETURNS
YNDARRAY SHAPE NSAMPLES CLUSTER LABELS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS

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PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
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RETURNS
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EXAMPLES USING SKLEARNCLUSTERDBSCAN
•DEMO OF DBSCAN CLUSTERING ALGORITHM
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
SKLEARNCLUSTER OPTICS
CLASSSKLEARNCLUSTER OPTICSMINSAMPLES5 MAXEPSINF METRIC'MINKOWSKI' P2MET
RICPARAMSNONE CLUSTERMETHOD'XI' EPSNONE XI005 PREDE
CESSORCORRECTIONTRUE MINCLUSTERSIZENONE ALGORITHM'AUTO'
LEAFSIZE30 NJOBSNONE
ESTIMATE CLUSTERING STRUCTURE FROM VECTOR ARRAY
OPTICS ORDERING POINTS TO IDENTIFY THE CLUSTERING STRUCTURE CLOSELY RELATED TO DBSCAN FINDS CORE SAMPLE
OF HIGH DENSITY AND EXPANDS CLUSTERS FROM THEM R2C55E37003FE1 UNLIKE DBSCAN KEEPS CLUSTER HIERARCHY
FOR A VARIABLE NEIGHBORHOOD RADIUS BETTER SUITED FOR USAGE ON LARGE DATASETS THAN THE CURRENT SKLEARN IMPLEMEN
TATION OF DBSCAN
CLUSTERS ARE THEN EXTRACTED USING A DBSCANLIKE METHOD CLUSTERMETHOD 'DBSCAN' OR AN AUTOMATIC TECHNIQUE
PROPOSED IN R2C55E37003FE1 CLUSTERMETHOD 'XI'
THIS IMPLEMENTATION DEVIATES FROM THE ORIGINAL OPTICS BY FIRST PERFORMING KNEARESTNEIGHBORHOOD SEARCHES
ON ALL POINTS TO IDENTIFY CORE SIZES THEN COMPUTING ONLY THE DISTANCES TO UNPROCESSED POINTS WHEN CONSTRUCTING
THE CLUSTER ORDER NOTE THAT WE DO NOT EMPLOY A HEAP TO MANAGE THE EXPANSION CANDIDATES SO THE TIME COMPLEXITY
WILL BE ON2
READ MORE IN THE USER GUIDE
PARAMETERS
MINSAMPLES INT 1 OR FLOAT BETWEEN 0 AND 1 DEFAULT5 THE NUMBER OF SAMPLES IN A NEIGH
BORHOOD FOR A POINT TO BE CONSIDERED AS A CORE POINT ALSO UP AND DOWN STEEP REGIONS CAN'T
HAVE MORE THEN MINSAMPLES CONSECUTIVE NONSTEEP POINTS EXPRESSED AS AN ABSOLUTE
NUMBER OR A FRACTION OF THE NUMBER OF SAMPLES ROUNDED TO BE AT LEAST 2
MAXEPS FLOAT OPTIONAL DEFAULTNPINF THE MAXIMUM DISTANCE BETWEEN TWO SAMPLES FOR ONE
TO BE CONSIDERED AS IN THE NEIGHBORHOOD OF THE OTHER DEFAULT VALUE OF NPINF WILL IDENTIFY
CLUSTERS ACROSS ALL SCALES REDUCING MAXEPS WILL RESULT IN SHORTER RUN TIMES
METRIC STRING OR CALLABLE OPTIONAL DEFAULT'MINKOWSKI' METRIC TO USE FOR DISTANCE COMPUTA
TION ANY METRIC FROM SCIKITLEARN OR SCIPYSPATIALDISTANCE CAN BE USED
IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF INSTANCES ROWS AND THE RESULTING
VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS AS INPUT AND RETURN ONE VALUE INDICATING
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THE DISTANCE BETWEEN THEM THIS WORKS FOR SCIPY'S METRICS BUT IS LESS EFFICIENT THAN PASSING THE METRIC NAME AS A STRING IF METRIC IS "PRECOMPUTED" X IS ASSUMED TO BE A DISTANCE MATRIX AND MUST BE SQUARE
VALID VALUES FOR METRIC ARE
• FROM SCIKITLEARN 'CITYBLOCK' 'COSINE' 'EUCLIDEAN' 'L1' 'L2' 'MANHATTAN'
• FROM SCIPYSPATIALDISTANCE 'BRAYCURTIS' 'CANBERRA' 'CHEBYSHEV' 'CORRELATION' 'DICE' 'HAMMING' 'JACCARD' 'KULSINSKI' 'MAHALANOBIS' 'MINKOWSKI' 'ROGERSTANIMOTO' 'RUSSELLRAO' 'SEUCLIDEAN' 'SOKALMICHENER' 'SOKALSNEATH' 'SQEUCLIDEAN' 'YULE'
SEE THE DOCUMENTATION FOR SCIPYSPATIALDISTANCE FOR DETAILS ON THESE METRICS
PINTEGER OPTIONAL DEFAULT2 PARAMETER FOR THE MINKOWSKI METRIC FROM SKLEARN METRICSPAIRWISEDISTANCES WHEN P 1 THIS IS EQUIVALENT TO USING MANHATTANDISTANCE L1 AND EUCLIDEANDISTANCE L2 FOR P 2 FOR ARBITRARY P MINKOWSKIDISTANCE LP IS USED
METRICPARAMS DICT OPTIONAL DEFAULTNONE ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC FUNCTION
CLUSTERMETHOD STRING OPTIONAL DEFAULT'XI' THE EXTRACTION METHOD USED TO EXTRACT CLUSTERS USING THE CALCULATED REACHABILITY AND ORDERING POSSIBLE VALUES ARE "XI" AND "DBSCAN"
EPS FLOAT OPTIONAL DEFAULTNONE THE MAXIMUM DISTANCE BETWEEN TWO SAMPLES FOR ONE TO BE CONSIDERED AS IN THE NEIGHBORHOOD OF THE OTHER BY DEFAULT IT ASSUMES THE SAME VALUE AS MAXEPS USED ONLY WHEN CLUSTERMETHODDBSCAN
XIFLOAT BETWEEN 0 AND 1 OPTIONAL DEFAULT005 DETERMINES THE MINIMUM STEEPNESS ON THE REACHABILITY PLOT THAT CONSTITUTES A CLUSTER BOUNDARY FOR EXAMPLE AN UPWARDS POINT IN THE REACHABILITY PLOT IS DEFINED BY THE RATIO FROM ONE POINT TO ITS SUCCESSOR BEING AT MOST 1XI USED ONLY WHEN CLUSTERMETHODXI
PREDECESSORCORRECTION BOOL OPTIONAL DEFAULTTRUE CORRECT CLUSTERS ACCORDING TO THE PRE DECESSORS CALCULATED BY OPTICS R2C55E37003FE2 THIS PARAMETER HAS MINIMAL EFFECT ON MOST DATASETS USED ONLY WHEN CLUSTERMETHODXI
MINCLUSTERSIZE INT 1 OR FLOAT BETWEEN 0 AND 1 DEFAULTNONE MINIMUM NUMBER OF SAMPLES IN AN OPTICS CLUSTER EXPRESSED AS AN ABSOLUTE NUMBER OR A FRACTION OF THE NUMBER OF SAMPLES ROUNDED TO BE AT LEAST 2 IF NONE THE VALUE OF MINSAMPLES IS USED INSTEAD USED ONLY WHEN CLUSTERMETHODXI
ALGORITHM 'AUTO' 'BALLTREE' 'KDTREE' 'BRUTE' OPTIONAL ALGORITHM USED TO COMPUTE THE NEAREST NEIGHBORS
• 'BALLTREE' WILL USE BALLTREE
• 'KDTREE' WILL USE KDTREE
• 'BRUTE' WILL USE A BRUTEFORCE SEARCH
• 'AUTO' WILL ATTEMPT TO DECIDE THE MOST APPROPRIATE ALGORITHM BASED ON THE VALUES PASSED TOFIT METHOD DEFAULT
NOTE FITTING ON SPARSE INPUT WILL OVERRIDE THE SETTING OF THIS PARAMETER USING BRUTE FORCE
LEAFSIZE INT OPTIONAL DEFAULT30 LEAF SIZE PASSED TO BALLTREE ORKDTREE THIS CAN AFFECT THE SPEED OF THE CONSTRUCTION AND QUERY AS WELL AS THE MEMORY REQUIRED TO STORE THE TREE THE OPTIMAL VALUE DEPENDS ON THE NATURE OF THE PROBLEM

NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS
SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
ATTRIBUTES
LABELS ARRAY SHAPE NSAMPLES CLUSTER LABELS FOR EACH POINT IN THE DATASET GIVEN
TO FIT NOISY SAMPLES AND POINTS WHICH ARE NOT INCLUDED IN A LEAF CLUSTER OF
CLUSTERHIERARCHY ARE LABELED AS 1
REACHABILITY ARRAY SHAPE NSAMPLES REACHABILITY DISTANCES PER SAMPLE INDEXED BY OBJECT
ORDER USECLUSTREACHABILITYCLUSTORDERING TO ACCESS IN CLUSTER ORDER
ORDERING ARRAY SHAPE NSAMPLES THE CLUSTER ORDERED LIST OF SAMPLE INDICES
COREDISTANCES ARRAY SHAPE NSAMPLES DISTANCE AT WHICH EACH SAMPLE BECOMES A CORE
POINT INDEXED BY OBJECT ORDER POINTS WHICH WILL NEVER BE CORE HAVE A DISTANCE OF INF USE
CLUSTCOREDISTANCESCLUSTORDERING TO ACCESS IN CLUSTER ORDER
PREDECESSOR ARRAY SHAPE NSAMPLES POINT THAT A SAMPLE WAS REACHED FROM INDEXED BY
OBJECT ORDER SEED POINTS HAVE A PREDECESSOR OF 1
CLUSTERHIERARCHY ARRAY SHAPE NCLUSTERS 2 THE LIST OF CLUSTERS IN THE FORM OF START
END IN EACH ROW WITH ALL INDICES INCLUSIVE THE CLUSTERS ARE ORDERED ACCORDING
TOEND START ASCENDING SO THAT LARGER CLUSTERS ENCOMPASSING SMALLER CLUSTERS
COME AFTER THOSE SMALLER ONES SINCE LABELS DOES NOT REFLECT THE HIERARCHY USUALLY
LENCLUSTERHIERARCHY NPUNIQUEOPTICSLABELS PLEASE ALSO
NOTE THAT THESE INDICES ARE OF THE ORDERING IEXORDERINGSTARTEND
1FORM A CLUSTER ONLY AVAILABLE WHEN CLUSTERMETHODXI
SEE ALSO
DBSCAN A SIMILAR CLUSTERING FOR A SPECIFIED NEIGHBORHOOD RADIUS EPS OUR IMPLEMENTATION IS OPTIMIZED FOR
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FITPREDICT SELF X Y PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFMINSAMPLES5 MAXEPSINF METRIC’MINKOWSKI’ P2METRICPARAMSNONE
CLUSTERMETHOD’XI’ EPSNONE XI005 PREDECESSORCORRECTIONTRUE
MINCLUSTERSIZENONE ALGORITHM’AUTO’ LEAFSIZE30 NJOBSNONE
FITSELFXYNONE
PERFORM OPTICS CLUSTERING
EXTRACTS AN ORDERED LIST OF POINTS AND REACHABILITY DISTANCES AND PERFORMS INITIAL CLUSTERING USING MAXEPS
DISTANCE SPECIFIED AT OPTICS OBJECT INSTANTIATION
PARAMETERS

XARRAY SHAPE NSAMPLES NFEATURES OR NSAMPLES NSAMPLES IF MET
RIC’PRECOMPUTED’ A FEATURE ARRAY OR ARRAY OF DISTANCES BETWEEN SAMPLES IF MET
RIC’PRECOMPUTED’
YIGNORED
RETURNS
SELF INSTANCE OF OPTICS THE INSTANCE
FITPREDICT SELFXYNONE
PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES INPUT DATA
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
LABELS NDARRAY SHAPE NSAMPLES CLUSTER LABELS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
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DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
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PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
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•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
SKLEARNCLUSTER FEATUREAGGLOMERATION
CLASSSKLEARNCLUSTER FEATUREAGGLOMERATION NCLUSTERS2 AFFINITY’EUCLIDEAN’ MEM
ORYNONE CONNECTIVITYNONE COM
PUTEFULLTREE’AUTO’ LINKAGE’WARD’
POOLINGFUNCFUNCTION MEAN DIS
TANCETHRESHOLDNONE
AGGLOMERATE FEATURES
SIMILAR TO AGGLOMERATIVECLUSTERING BUT RECURSIVELY MERGES FEATURES INSTEAD OF SAMPLES

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READ MORE IN THE USER GUIDE
PARAMETERS
NCLUSTERS INT OR NONE OPTIONAL DEFAULT2 THE NUMBER OF CLUSTERS TO FIND IT MUST BE NONE IFDISTANCETHRESHOLD IS NOTNONE
AFFINITY STRING OR CALLABLE DEFAULT “EUCLIDEAN” METRIC USED TO COMPUTE THE LINKAGE CAN BE “EUCLIDEAN” “L1” “L2” “MANHATTAN” “COSINE” OR ‘PRECOMPUTED’ IF LINKAGE IS “WARD” ONLY “EUCLIDEAN” IS ACCEPTED
MEMORY NONE STR OR OBJECT WITH THE JOBLIBMEMORY INTERFACE OPTIONAL USED TO CACHE THE OUTPUT OF THE COMPUTATION OF THE TREE BY DEFAULT NO CACHING IS DONE IF A STRING IS GIVEN IT IS THE PATH TO THE CACHING DIRECTORY
CONNECTIVITY ARRAYLIKE OR CALLABLE OPTIONAL CONNECTIVITY MATRIX DEFINES FOR EACH FEATURE THE NEIGHBORING FEATURES FOLLOWING A GIVEN STRUCTURE OF THE DATA THIS CAN BE A CONNECTIVITY MATRIX ITSELF OR A CALLABLE THAT TRANSFORMS THE DATA INTO A CONNECTIVITY MATRIX SUCH AS DE RIVED FROM KNEIGHBORSGRAPH DEFAULT IS NONE IE THE HIERARCHICAL CLUSTERING ALGORITHM IS UNSTRUCTURED
COMPUTEFULLTREE BOOL OR ‘AUTO’ OPTIONAL DEFAULT “AUTO” STOP EARLY THE CONSTRUCTION OF THE TREE AT NCLUSTERS THIS IS USEFUL TO DECREASE COMPUTATION TIME IF THE NUMBER OF CLUS TERS IS NOT SMALL COMPARED TO THE NUMBER OF FEATURES THIS OPTION IS USEFUL ONLY WHEN SPECIFYING A CONNECTIVITY MATRIX NOTE ALSO THAT WHEN VARYING THE NUMBER OF CLUSTERS AND USING CACHING IT MAY BE ADVANTAGEOUS TO COMPUTE THE FULL TREE IT MUST BE TRUE IF DISTANCETHRESHOLD IS NOTNONE
LINKAGE “WARD” “COMPLETE” “AVERAGE” “SINGLE” OPTIONAL DEFAULT”WARD” WHICH LINKAGE CRITERION TO USE THE LINKAGE CRITERION DETERMINES WHICH DISTANCE TO USE BETWEEN SETS OF FEATURES THE ALGORITHM WILL MERGE THE PAIRS OF CLUSTER THAT MINIMIZE THIS CRITERION
• WARD MINIMIZES THE VARIANCE OF THE CLUSTERS BEING MERGED
• AVERAGE USES THE AVERAGE OF THE DISTANCES OF EACH FEATURE OF THE TWO SETS
• COMPLETE OR MAXIMUM LINKAGE USES THE MAXIMUM DISTANCES BETWEEN ALL FEATURES OF THE TWO SETS
• SINGLE USES THE MINIMUM OF THE DISTANCES BETWEEN ALL OBSERVATIONS OF THE TWO SETS
POOLINGFUNC CALLABLE DEFAULT NPMEAN THIS COMBINES THE VALUES OF AGGLOMERATED FEATURES INTO A SINGLE VALUE AND SHOULD ACCEPT AN ARRAY OF SHAPE M N AND THE KEYWORD ARGUMENT AXIS1 AND REDUCE IT TO AN ARRAY OF SIZE M
DISTANCETHRESHOLD FLOAT OPTIONAL DEFAULTNONE THE LINKAGE DISTANCE THRESHOLD ABOVE WHICH CLUSTERS WILL NOT BE MERGED IF NOT NONE NCLUSTERS MUST BENONE AND COMPUTEFULLTREE MUST BETRUE
NEW IN VERSION 021
ATTRIBUTES
NCLUSTERS INT THE NUMBER OF CLUSTERS FOUND BY THE ALGORITHM IF DISTANCETHRESHOLDNONE IT WILL BE EQUAL TO THE GIVEN NCLUSTERS
LABELS ARRAYLIKE NFEATURES CLUSTER LABELS FOR EACH FEATURE
NLEAVES INT NUMBER OF LEAVES IN THE HIERARCHICAL TREE
NCONNECTEDCOMPONENTS INT THE ESTIMATED NUMBER OF CONNECTED COMPONENTS IN THE GRAPH
CHILDREN ARRAYLIKE SHAPE NNODES1 2 THE CHILDREN OF EACH NONLEAF NODE VALUES LESS THAN NFEATURES CORRESPOND TO LEAVES OF THE TREE WHICH ARE THE ORIGINAL SAMPLES A NODE

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IGREATER THAN OR EQUAL TO NFEATURES IS A NONLEAF NODE AND HAS CHILDREN CHILDRENI
NFEATURES ALTERNATIVELY AT THE ITH ITERATION CHILDRENI0 AND CHILDRENI1 ARE
MERGED TO FORM NODE NFEATURES I
EXAMPLES
IMPORT NUMPY AS NP
FROM SKLEARN IMPORT DATASETS CLUSTER
DIGITS DATASETSLOADDIGITS
IMAGES DIGITSIMAGES
X NPRESHAPEIMAGES LENIMAGES 1
AGGLO CLUSTERFEATUREAGGLOMERATIONNCLUSTERS32
AGGLOFITX
FEATUREAGGLOMERATIONAFFINITYEUCLIDEAN COMPUTEFULLTREEAUTO
CONNECTIVITYNONE DISTANCETHRESHOLDNONE LINKAGEWARD
MEMORYNONE NCLUSTERS32
POOLINGFUNC
XREDUCED AGGLOTRANSFORMX
XREDUCEDSHAPE
1797 32
METHODS
FITSELF X Y FIT THE HIERARCHICAL CLUSTERING ON THE DATA
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF XRED INVERSE THE TRANSFORMATION
POOLINGFUNC A AXIS DTYPE OUT KEEPDIMS COMPUTE THE ARITHMETIC MEAN ALONG THE SPECIFIED AXIS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM A NEW MATRIX USING THE BUILT CLUSTERING
INIT SELFNCLUSTERS2 AFFINITY'EUCLIDEAN' MEMORYNONE CONNECTIVITYNONE COM
PUTEFULLTREE'AUTO' LINKAGE'WARD' POOLINGFUNCFUNCTION MEAN AT 0X7F3C23DF3400
DISTANCETHRESHOLDNONE
FITSELFXYNONE PARAMS
FIT THE HIERARCHICAL CLUSTERING ON THE DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA
YIGNORED
RETURNS
SELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET

YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFXRED
INVERSE THE TRANSFORMATION RETURN A VECTOR OF SIZE NBFEATURES WITH THE VALUES OF XRED ASSIGNED TO EACH
GROUP OF FEATURES
PARAMETERS
XRED ARRAYLIKE SHAPENSAMPLES NCLUSTERS OR NCLUSTERS THE VALUES TO BE ASSIGNED
TO EACH CLUSTER OF SAMPLES
RETURNS
XARRAY SHAPENSAMPLES NFEATURES OR NFEATURES A VECTOR OF SIZE NSAMPLES WITH
THE VALUES OF XRED ASSIGNED TO EACH OF THE CLUSTER OF SAMPLES
POOLINGFUNC AAXISNONE DTYPENONE OUTNONE KEEPDIMSNO VALUE
COMPUTE THE ARITHMETIC MEAN ALONG THE SPECIFIED AXIS
RETURNS THE AVERAGE OF THE ARRAY ELEMENTS THE AVERAGE IS TAKEN OVER THE FLATTENED ARRAY BY DEFAULT OTHER
WISE OVER THE SPECIFIED AXIS FLOAT64 INTERMEDIATE AND RETURN VALUES ARE USED FOR INTEGER INPUTS
PARAMETERS
AARRAYLIKE ARRAY CONTAINING NUMBERS WHOSE MEAN IS DESIRED IF AIS NOT AN ARRAY A
CONVERSION IS ATTEMPTED
AXIS NONE OR INT OR TUPLE OF INTS OPTIONAL AXIS OR AXES ALONG WHICH THE MEANS ARE COM
PUTED THE DEFAULT IS TO COMPUTE THE MEAN OF THE FLATTENED ARRAY
NEW IN VERSION 170
IF THIS IS A TUPLE OF INTS A MEAN IS PERFORMED OVER MULTIPLE AXES INSTEAD OF A SINGLE AXIS OR
ALL THE AXES AS BEFORE
DTYPE DATATYPE OPTIONAL TYPE TO USE IN COMPUTING THE MEAN FOR INTEGER INPUTS THE
DEFAULT ISFLOAT64 FOR FLOATING POINT INPUTS IT IS THE SAME AS THE INPUT DTYPE
OUT NDARRAY OPTIONAL ALTERNATE OUTPUT ARRAY IN WHICH TO PLACE THE RESULT THE DEFAULT IS
NONE IF PROVIDED IT MUST HAVE THE SAME SHAPE AS THE EXPECTED OUTPUT BUT THE TYPE WILL
BE CAST IF NECESSARY SEE DOCUFUNCS FOR DETAILS
KEEPDIMS BOOL OPTIONAL IF THIS IS SET TO TRUE THE AXES WHICH ARE REDUCED ARE LEFT IN THE
RESULT AS DIMENSIONS WITH SIZE ONE WITH THIS OPTION THE RESULT WILL BROADCAST CORRECTLY
AGAINST THE INPUT ARRAY
IF THE DEFAULT VALUE IS PASSED THEN KEEPDIMS WILL NOT BE PASSED THROUGH TO THE MEAN
METHOD OF SUBCLASSES OF NDARRAY HOWEVER ANY NONDEFAULT VALUE WILL BE IF THE SUB
CLASS’ METHOD DOES NOT IMPLEMENT KEEPDIMS ANY EXCEPTIONS WILL BE RAISED

RETURNS
MNDARRAY SEE DTYPE PARAMETER ABOVE IF OUTNONE RETURNS A NEW ARRAY CONTAINING THE
MEAN VALUES OTHERWISE A REFERENCE TO THE OUTPUT ARRAY IS RETURNED
SEE ALSO
AVERAGE WEIGHTED AVERAGE
STDVARNANMEAN NANSTD NANVAR
NOTES
THE ARITHMETIC MEAN IS THE SUM OF THE ELEMENTS ALONG THE AXIS DIVIDED BY THE NUMBER OF ELEMENTS
NOTE THAT FOR FLOATINGPOINT INPUT THE MEAN IS COMPUTED USING THE SAME PRECISION THE INPUT HAS DEPENDING
ON THE INPUT DATA THIS CAN CAUSE THE RESULTS TO BE INACCURATE ESPECIALLY FOR FLOAT32 SEE EXAMPLE BELOW
SPECIFYING A HIGHERPRECISION ACCUMULATOR USING THE DTYPE KEYWORD CAN ALLEVIATE THIS ISSUE
BY DEFAULT FLOAT16 RESULTS ARE COMPUTED USING FLOAT32 INTERMEDIATES FOR EXTRA PRECISION
EXAMPLES
A NPARRAY1 2 3 4
NPMEANA
25
NPMEANA AXIS0
ARRAY 2 3
NPMEANA AXIS1
ARRAY 15 35
IN SINGLE PRECISION MEAN CAN BE INACCURATE
A NPZEROS2 512 512 DTYPENPFLOAT32
A0 10
A1 01
NPMEANA
054999924
COMPUTING THE MEAN IN FLOAT64 IS MORE ACCURATE
NPMEANA DTYPENPFLOAT64
055000000074505806
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM A NEW MATRIX USING THE BUILT CLUSTERING

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PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES OR NFEATURES A M BY N ARRAY OF M OBSER
VATIONS IN N DIMENSIONS OR A LENGTH M ARRAY OF M ONEDIMENSIONAL OBSERVATIONS
RETURNS
YARRAY SHAPE NSAMPLES NCLUSTERS OR NCLUSTERS THE POOLED VALUES FOR EACH FEATURE
CLUSTER
EXAMPLES USING SKLEARNCLUSTERFEATUREAGGLOMERATION
•FEATURE AGGLOMERATION
•FEATURE AGGLOMERATION VS UNIVARIATE SELECTION
SKLEARNCLUSTER KMEANS
CLASSSKLEARNCLUSTER KMEANSNCLUSTERS8 INIT'KMEANS' NINIT10 MAXITER300
TOL00001 PRECOMPUTEDISTANCES'AUTO' VERBOSE0 RAN
DOMSTATENONE COPYXTRUE NJOBSNONE ALGORITHM'AUTO'
KMEANS CLUSTERING
READ MORE IN THE USER GUIDE
PARAMETERS
NCLUSTERS INT OPTIONAL DEFAULT 8 THE NUMBER OF CLUSTERS TO FORM AS WELL AS THE NUMBER OF
CENTROIDS TO GENERATE
INIT 'KMEANS' 'RANDOM' OR AN NDARRAY METHOD FOR INITIALIZATION DEFAULTS TO 'K
MEANS'
'KMEANS' SELECTS INITIAL CLUSTER CENTERS FOR KMEAN CLUSTERING IN A SMART WAY TO SPEED
UP CONVERGENCE SEE SECTION NOTES IN KINIT FOR MORE DETAILS
'RANDOM' CHOOSE K OBSERVATIONS ROWS AT RANDOM FROM DATA FOR THE INITIAL CENTROIDS
IF AN NDARRAY IS PASSED IT SHOULD BE OF SHAPE NCLUSTERS NFEATURES AND GIVES THE INITIAL
CENTERS
NINIT INT DEFAULT 10 NUMBER OF TIME THE KMEANS ALGORITHM WILL BE RUN WITH DIFFERENT CEN
TROID SEEDS THE FINAL RESULTS WILL BE THE BEST OUTPUT OF NINIT CONSECUTIVE RUNS IN TERMS OF
INERTIA
MAXITER INT DEFAULT 300 MAXIMUM NUMBER OF ITERATIONS OF THE KMEANS ALGORITHM FOR A
SINGLE RUN
TOLFLOAT DEFAULT 1E4 RELATIVE TOLERANCE WITH REGARDS TO INERTIA TO DECLARE CONVERGENCE
PRECOMPUTEDISTANCES 'AUTO' TRUE FALSE PRECOMPUTE DISTANCES FASTER BUT TAKES MORE
MEMORY
'AUTO' DO NOT PRECOMPUTE DISTANCES IF NSAMPLES NCLUSTERS 12 MILLION THIS CORRE
SPONDS TO ABOUT 100MB OVERHEAD PER JOB USING DOUBLE PRECISION
TRUE ALWAYS PRECOMPUTE DISTANCES
FALSE NEVER PRECOMPUTE DISTANCES
VERBOSE INT DEFAULT 0 VERBOSITY MODE
63SKLEARNCLUSTER CLUSTERING 1491

RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR CENTROID INITIALIZATION USE AN INT TO MAKE THE RANDOMNESS DETERMINISTIC SEE
GLOSSARY
COPYX BOOLEAN OPTIONAL WHEN PRECOMPUTING DISTANCES IT IS MORE NUMERICALLY ACCURATE TO
CENTER THE DATA FIRST IF COPYX IS TRUE DEFAULT THEN THE ORIGINAL DATA IS NOT MODIFIED
ENSURING X IS CCONTIGUOUS IF FALSE THE ORIGINAL DATA IS MODIFIED AND PUT BACK BEFORE THE
FUNCTION RETURNS BUT SMALL NUMERICAL DIFFERENCES MAY BE INTRODUCED BY SUBTRACTING AND THEN
ADDING THE DATA MEAN IN THIS CASE IT WILL ALSO NOT ENSURE THAT DATA IS CCONTIGUOUS WHICH
MAY CAUSE A SIGNIFICANT SLOWDOWN
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION
THIS WORKS BY COMPUTING EACH OF THE NINIT RUNS IN PARALLEL
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL
PROCESSORS SEE GLOSSARY FOR MORE DETAILS
ALGORITHM “AUTO” “FULL” OR “ELKAN” DEFAULT”AUTO” KMEANS ALGORITHM TO USE THE CLASSICAL
EMSTYLE ALGORITHM IS “FULL” THE “ELKAN” VARIATION IS MORE EFFICIENT BY USING THE TRIANGLE
INEQUALITY BUT CURRENTLY DOESN’T SUPPORT SPARSE DATA “AUTO” CHOOSES “ELKAN” FOR DENSE DATA
AND “FULL” FOR SPARSE DATA
ATTRIBUTES
CLUSTERCENTERS ARRAY NCLUSTERS NFEATURES COORDINATES OF CLUSTER CENTERS IF THE ALGO
RITHM STOPS BEFORE FULLY CONVERGING SEE TOL ANDMAXITER THESE WILL NOT BE CONSISTENT
WITHLABELS
LABELS LABELS OF EACH POINT
INERTIA FLOAT SUM OF SQUARED DISTANCES OF SAMPLES TO THEIR CLOSEST CLUSTER CENTER
NITER INT NUMBER OF ITERATIONS RUN
SEE ALSO
MINIBATCHKMEANS ALTERNATIVE ONLINE IMPLEMENTATION THAT DOES INCREMENTAL UPDATES OF THE CENTERS POSITIONS
USING MINIBATCHES FOR LARGE SCALE LEARNING SAY NSAMPLES 10K MINIBATCHKMEANS IS PROBABLY MUCH
FASTER THAN THE DEFAULT BATCH IMPLEMENTATION
NOTES
THE KMEANS PROBLEM IS SOLVED USING EITHER LLOYD’S OR ELKAN’S ALGORITHM
THE AVERAGE COMPLEXITY IS GIVEN BY OK N T WERE N IS THE NUMBER OF SAMPLES AND T IS THE NUMBER OF ITERATION
THE WORST CASE COMPLEXITY IS GIVEN BY ONK2P WITH N NSAMPLES P NFEATURES D ARTHUR AND S
VASSILVITSKII ‘HOW SLOW IS THE KMEANS METHOD’ SOCG2006
IN PRACTICE THE KMEANS ALGORITHM IS VERY FAST ONE OF THE FASTEST CLUSTERING ALGORITHMS AVAILABLE BUT IT FALLS IN
LOCAL MINIMA THAT’S WHY IT CAN BE USEFUL TO RESTART IT SEVERAL TIMES
IF THE ALGORITHM STOPS BEFORE FULLY CONVERGING BECAUSE OF TOL ORMAXITER LABELS AND
CLUSTERCENTERS WILL NOT BE CONSISTENT IE THE CLUSTERCENTERS WILL NOT BE THE MEANS OF THE
POINTS IN EACH CLUSTER ALSO THE ESTIMATOR WILL REASSIGN LABELS AFTER THE LAST ITERATION TO MAKE LABELS
CONSISTENT WITH PREDICT ON THE TRAINING SET

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EXAMPLES
FROM SKLEARNCLUSTER IMPORT KMEANS
IMPORT NUMPY AS NP
X NPARRAY1 2 1 4 1 0
10 2 10 4 10 0
KMEANS KMEANSNCLUSTERS2 RANDOMSTATE0FITX
KMEANSLABELS
ARRAY1 1 1 0 0 0 DTYPEINT32
KMEANSPREDICT0 0 12 3
ARRAY1 0 DTYPEINT32
KMEANSCLUSTERCENTERS
ARRAY10 2
1 2
METHODS
FITSELF X Y SAMPLEWEIGHT COMPUTE KMEANS CLUSTERING
FITPREDICT SELF X Y SAMPLEWEIGHT COMPUTE CLUSTER CENTERS AND PREDICT CLUSTER INDEX FOR
EACH SAMPLE
FITTRANSFORM SELF X Y SAMPLEWEIGHT COMPUTE CLUSTERING AND TRANSFORM X TO CLUSTERDISTANCE
SPACE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X SAMPLEWEIGHT PREDICT THE CLOSEST CLUSTER EACH SAMPLE IN X BELONGS TO
SCORE SELF X Y SAMPLEWEIGHT OPPOSITE OF THE VALUE OF X ON THE KMEANS OBJECTIVE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM X TO A CLUSTERDISTANCE SPACE
INIT SELFNCLUSTERS8 INIT'KMEANS' NINIT10 MAXITER300 TOL00001 PRECOM
PUTEDISTANCES'AUTO' VERBOSE0 RANDOMSTATENONE COPYXTRUE NJOBSNONE AL
GORITHM'AUTO'
FITSELFXYNONE SAMPLEWEIGHTNONE
COMPUTE KMEANS CLUSTERING
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPENSAMPLES NFEATURES TRAINING INSTANCES TO CLUSTER
IT MUST BE NOTED THAT THE DATA WILL BE CONVERTED TO C ORDERING WHICH WILL CAUSE A MEMORY
COPY IF THE GIVEN DATA IS NOT CCONTIGUOUS
YIGNORED NOT USED PRESENT HERE FOR API CONSISTENCY BY CONVENTION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
FITPREDICT SELFXYNONE SAMPLEWEIGHTNONE
COMPUTE CLUSTER CENTERS AND PREDICT CLUSTER INDEX FOR EACH SAMPLE
CONVENIENCE METHOD EQUIVALENT TO CALLING FITX FOLLOWED BY PREDICTX
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA TO TRANSFORM
YIGNORED NOT USED PRESENT HERE FOR API CONSISTENCY BY CONVENTION

SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
RETURNS
LABELS ARRAY SHAPE NSAMPLES INDEX OF THE CLUSTER EACH SAMPLE BELONGS TO
FITTRANSFORM SELFXYNONE SAMPLEWEIGHTNONE
COMPUTE CLUSTERING AND TRANSFORM X TO CLUSTERDISTANCE SPACE
EQUIVALENT TO FITXTRANSFORMX BUT MORE EFFICIENTLY IMPLEMENTED
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA TO TRANSFORM
YIGNORED NOT USED PRESENT HERE FOR API CONSISTENCY BY CONVENTION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
RETURNS
XNEW ARRAY SHAPE NSAMPLES K X TRANSFORMED IN THE NEW SPACE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXSAMPLEWEIGHTNONE
PREDICT THE CLOSEST CLUSTER EACH SAMPLE IN X BELONGS TO
IN THE VECTOR QUANTIZATION LITERATURE CLUSTERCENTERS IS CALLED THE CODE BOOK AND EACH VALUE RE
TURNED BYPREDICT IS THE INDEX OF THE CLOSEST CODE IN THE CODE BOOK
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA TO PREDICT
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
RETURNS
LABELS ARRAY SHAPE NSAMPLES INDEX OF THE CLUSTER EACH SAMPLE BELONGS TO
SCORESELFXYNONE SAMPLEWEIGHTNONE
OPPOSITE OF THE VALUE OF X ON THE KMEANS OBJECTIVE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA
YIGNORED NOT USED PRESENT HERE FOR API CONSISTENCY BY CONVENTION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
RETURNS

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SCORE FLOAT OPPOSITE OF THE VALUE OF X ON THE KMEANS OBJECTIVE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM X TO A CLUSTERDISTANCE SPACE
IN THE NEW SPACE EACH DIMENSION IS THE DISTANCE TO THE CLUSTER CENTERS NOTE THAT EVEN IF X IS SPARSE THE
ARRAY RETURNED BY TRANSFORM WILL TYPICALLY BE DENSE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA TO TRANSFORM
RETURNS
XNEW ARRAY SHAPE NSAMPLES K X TRANSFORMED IN THE NEW SPACE
EXAMPLES USING SKLEARNCLUSTERKMEANS
•DEMONSTRATION OF KMEANS ASSUMPTIONS
•VECTOR QUANTIZATION EXAMPLE
•KMEANS CLUSTERING
•COLOR QUANTIZATION USING KMEANS
•EMPIRICAL EVALUATION OF THE IMPACT OF KMEANS INITIALIZATION
•COMPARISON OF THE KMEANS AND MINIBATCHKMEANS CLUSTERING ALGORITHMS
•A DEMO OF KMEANS CLUSTERING ON THE HANDWRITTEN DIGITS DATA
•SELECTING THE NUMBER OF CLUSTERS WITH SILHOUETTE ANALYSIS ON KMEANS CLUSTERING
•CLUSTERING TEXT DOCUMENTS USING KMEANS
SKLEARNCLUSTER MINIBATCHKMEANS
CLASSSKLEARNCLUSTER MINIBATCHKMEANS NCLUSTERS8 INIT'KMEANS' MAXITER100
BATCHSIZE100 VERBOSE0 COMPUTELABELSTRUE
RANDOMSTATENONE TOL00 MAXNOIMPROVEMENT10
INITSIZENONE NINIT3 REASSIGNMENTRATIO001
MINIBATCH KMEANS CLUSTERING
READ MORE IN THE USER GUIDE
PARAMETERS
NCLUSTERS INT OPTIONAL DEFAULT 8 THE NUMBER OF CLUSTERS TO FORM AS WELL AS THE NUMBER OF
CENTROIDS TO GENERATE

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INIT ‘KMEANS’ ‘RANDOM’ OR AN NDARRAY DEFAULT ‘KMEANS’ METHOD FOR INITIALIZATION
DEFAULTS TO ‘KMEANS’
‘KMEANS’ SELECTS INITIAL CLUSTER CENTERS FOR KMEAN CLUSTERING IN A SMART WAY TO SPEED
UP CONVERGENCE SEE SECTION NOTES IN KINIT FOR MORE DETAILS
‘RANDOM’ CHOOSE K OBSERVATIONS ROWS AT RANDOM FROM DATA FOR THE INITIAL CENTROIDS
IF AN NDARRAY IS PASSED IT SHOULD BE OF SHAPE NCLUSTERS NFEATURES AND GIVES THE INITIAL
CENTERS
MAXITER INT OPTIONAL MAXIMUM NUMBER OF ITERATIONS OVER THE COMPLETE DATASET BEFORE STOP
PING INDEPENDENTLY OF ANY EARLY STOPPING CRITERION HEURISTICS
BATCHSIZE INT OPTIONAL DEFAULT 100 SIZE OF THE MINI BATCHES
VERBOSE BOOLEAN OPTIONAL VERBOSITY MODE
COMPUTELABELS BOOLEAN DEFAULTTRUE COMPUTE LABEL ASSIGNMENT AND INERTIA FOR THE COM
PLETE DATASET ONCE THE MINIBATCH OPTIMIZATION HAS CONVERGED IN FIT
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR CENTROID INITIALIZATION AND RANDOM REASSIGNMENT USE AN INT TO MAKE THE RANDOM
NESS DETERMINISTIC SEE GLOSSARY
TOLFLOAT DEFAULT 00 CONTROL EARLY STOPPING BASED ON THE RELATIVE CENTER CHANGES AS MEASURED
BY A SMOOTHED VARIANCENORMALIZED OF THE MEAN CENTER SQUARED POSITION CHANGES THIS
EARLY STOPPING HEURISTICS IS CLOSER TO THE ONE USED FOR THE BATCH VARIANT OF THE ALGORITHMS BUT
INDUCES A SLIGHT COMPUTATIONAL AND MEMORY OVERHEAD OVER THE INERTIA HEURISTIC
TO DISABLE CONVERGENCE DETECTION BASED ON NORMALIZED CENTER CHANGE SET TOL TO 00 DEFAULT
MAXNOIMPROVEMENT INT DEFAULT 10 CONTROL EARLY STOPPING BASED ON THE CONSECUTIVE NUM
BER OF MINI BATCHES THAT DOES NOT YIELD AN IMPROVEMENT ON THE SMOOTHED INERTIA
TO DISABLE CONVERGENCE DETECTION BASED ON INERTIA SET MAXNOIMPROVEMENT TO NONE
INITSIZE INT OPTIONAL DEFAULT 3 BATCHSIZE NUMBER OF SAMPLES TO RANDOMLY SAMPLE FOR
SPEEDING UP THE INITIALIZATION SOMETIMES AT THE EXPENSE OF ACCURACY THE ONLY ALGORITHM
IS INITIALIZED BY RUNNING A BATCH KMEANS ON A RANDOM SUBSET OF THE DATA THIS NEEDS TO BE
LARGER THAN NCLUSTERS
NINIT INT DEFAULT3 NUMBER OF RANDOM INITIALIZATIONS THAT ARE TRIED IN CONTRAST TO KMEANS
THE ALGORITHM IS ONLY RUN ONCE USING THE BEST OF THE NINIT INITIALIZATIONS AS MEASURED BY
INERTIA
REASSIGNMENTRATIO FLOAT DEFAULT 001 CONTROL THE FRACTION OF THE MAXIMUM NUMBER OF
COUNTS FOR A CENTER TO BE REASSIGNED A HIGHER VALUE MEANS THAT LOW COUNT CENTERS ARE MORE
EASILY REASSIGNED WHICH MEANS THAT THE MODEL WILL TAKE LONGER TO CONVERGE BUT SHOULD CON
VERGE IN A BETTER CLUSTERING
ATTRIBUTES
CLUSTERCENTERS ARRAY NCLUSTERS NFEATURES COORDINATES OF CLUSTER CENTERS
LABELS LABELS OF EACH POINT IF COMPUTELABELS IS SET TO TRUE
INERTIA FLOAT THE VALUE OF THE INERTIA CRITERION ASSOCIATED WITH THE CHOSEN PARTITION IF COM
PUTELABELS IS SET TO TRUE THE INERTIA IS DEFINED AS THE SUM OF SQUARE DISTANCES OF SAMPLES
TO THEIR NEAREST NEIGHBOR
SEE ALSO

KMEANS THE CLASSIC IMPLEMENTATION OF THE CLUSTERING METHOD BASED ON THE LLOYD’S ALGORITHM IT CONSUMES THE WHOLE SET OF INPUT DATA AT EACH ITERATION

NOTES

SEE HTTPSWWWEECSTUFTSEDUDSCULLEYPAPERSFASTKMEANSPDF

EXAMPLES

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 FROM SKLEARNCLUSTER IMPORT MINIBATCHKMEANS
 IMPORT NUMPY AS NP
X  NPARRAY1 2 1 4 1 0
 4 2 4 0 4 4
 4 5 0 1 2 2
 3 2 5 5 1 1
 MANUALLY FIT ON BATCHES
KMEANS  MINIBATCHKMEANSNCLUSTERS2
 RANDOMSTATE0
 BATCHSIZE6
KMEANS  KMEANSPARTIALFITX06
KMEANS  KMEANSPARTIALFITX612
KMEANSCLUSTERCENTERS
ARRAY1 1
3 4
KMEANSPREDICT0 0 4 4
ARRAY0 1 DTYPEINT32
 FIT ON THE WHOLE DATA
KMEANS  MINIBATCHKMEANSNCLUSTERS2
 RANDOMSTATE0
 BATCHSIZE6
 MAXITER10FITX
KMEANSCLUSTERCENTERS
ARRAY395918367 240816327
112195122 13902439
KMEANSPREDICT0 0 4 4
ARRAY1 0 DTYPEINT32
```

METHODS

FITSELF X Y SAMPLEWEIGHT COMPUTE THE CENTROIDS ON X BY CHUNKING IT INTO MINI BATCHES

FITPREDICT SELF X Y SAMPLEWEIGHT COMPUTE CLUSTER CENTERS AND PREDICT CLUSTER INDEX FOR EACH SAMPLE

FITTRANSFORM SELF X Y SAMPLEWEIGHT COMPUTE CLUSTERING AND TRANSFORM X TO CLUSTERDISTANCE SPACE

GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR

PARTIALFIT SELF X Y SAMPLEWEIGHT UPDATE K MEANS ESTIMATE ON A SINGLE MINIBATCH X

PREDICT SELF X SAMPLEWEIGHT PREDICT THE CLOSEST CLUSTER EACH SAMPLE IN X BELONGS TO

SCORE SELF X Y SAMPLEWEIGHT OPPOSITE OF THE VALUE OF X ON THE KMEANS OBJECTIVE

SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

TRANSFORM SELF X TRANSFORM X TO A CLUSTERDISTANCE SPACE

INIT SELFNCLUSTERS8 INIT’KMEANS’ MAXITER100 BATCHSIZE100 VERBOSE0
COMPUTELABELSTRUE RANDOMSTATENONE TOL00 MAXNOIMPROVEMENT10
INITSIZENONE NINIT3 REASSIGNMENTRATIO001
FITSELFXYNONE SAMPLEWEIGHTNONE
COMPUTE THE CENTROIDS ON X BY CHUNKING IT INTO MINIBATCHES
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPENSAMPLES NFEATURES TRAINING INSTANCES TO CLUSTER
IT MUST BE NOTED THAT THE DATA WILL BE CONVERTED TO C ORDERING WHICH WILL CAUSE A MEMORY
COPY IF THE GIVEN DATA IS NOT CCONTIGUOUS
YIGNORED NOT USED PRESENT HERE FOR API CONSISTENCY BY CONVENTION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
FITPREDICT SELFXYNONE SAMPLEWEIGHTNONE
COMPUTE CLUSTER CENTERS AND PREDICT CLUSTER INDEX FOR EACH SAMPLE
CONVENIENCE METHOD EQUIVALENT TO CALLING FITX FOLLOWED BY PREDICTX
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA TO TRANSFORM
YIGNORED NOT USED PRESENT HERE FOR API CONSISTENCY BY CONVENTION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
RETURNS
LABELS ARRAY SHAPE NSAMPLES INDEX OF THE CLUSTER EACH SAMPLE BELONGS TO
FITTRANSFORM SELFXYNONE SAMPLEWEIGHTNONE
COMPUTE CLUSTERING AND TRANSFORM X TO CLUSTERDISTANCE SPACE
EQUIVALENT TO FITXTRANSFORMX BUT MORE EFFICIENTLY IMPLEMENTED
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA TO TRANSFORM
YIGNORED NOT USED PRESENT HERE FOR API CONSISTENCY BY CONVENTION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
RETURNS
XNEW ARRAY SHAPE NSAMPLES K X TRANSFORMED IN THE NEW SPACE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYNONE SAMPLEWEIGHTNONE
UPDATE K MEANS ESTIMATE ON A SINGLE MINIBATCH X

PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES COORDINATES OF THE DATA POINTS TO CLUSTER IT
MUST BE NOTED THAT X WILL BE COPIED IF IT IS NOT CCONTIGUOUS
YIGNORED NOT USED PRESENT HERE FOR API CONSISTENCY BY CONVENTION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
PREDICTSELFXSAMPLEWEIGHTNONE
PREDICT THE CLOSEST CLUSTER EACH SAMPLE IN X BELONGS TO
IN THE VECTOR QUANTIZATION LITERATURE CLUSTERCENTERS IS CALLED THE CODE BOOK AND EACH VALUE RE
TURNED BYPREDICT IS THE INDEX OF THE CLOSEST CODE IN THE CODE BOOK
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA TO PREDICT
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
RETURNS
LABELS ARRAY SHAPE NSAMPLES INDEX OF THE CLUSTER EACH SAMPLE BELONGS TO
SCORESELFXYNONE SAMPLEWEIGHTNONE
OPPOSITE OF THE VALUE OF X ON THE KMEANS OBJECTIVE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA
YIGNORED NOT USED PRESENT HERE FOR API CONSISTENCY BY CONVENTION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION
IN X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
RETURNS
SCORE FLOAT OPPOSITE OF THE VALUE OF X ON THE KMEANS OBJECTIVE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM X TO A CLUSTERDISTANCE SPACE
IN THE NEW SPACE EACH DIMENSION IS THE DISTANCE TO THE CLUSTER CENTERS NOTE THAT EVEN IF X IS SPARSE THE
ARRAY RETURNED BY TRANSFORM WILL TYPICALLY BE DENSE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA TO TRANSFORM
RETURNS
XNEW ARRAY SHAPE NSAMPLES K X TRANSFORMED IN THE NEW SPACE

EXAMPLES USING SKLEARNCLUSTERMINIBATCHKMEANS
•BICLUSTERING DOCUMENTS WITH THE SPECTRAL COCLUSTERING ALGORITHM
•ONLINE LEARNING OF A DICTIONARY OF PARTS OF FACES
•COMPARE BIRCH AND MINIBATCHKMEANS
•EMPIRICAL EVALUATION OF THE IMPACT OF KMEANS INITIALIZATION
•COMPARISON OF THE KMEANS AND MINIBATCHKMEANS CLUSTERING ALGORITHMS
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
•FACES DATASET DECOMPOSITIONS
•CLUSTERING TEXT DOCUMENTS USING KMEANS
SKLEARNCLUSTER MEANSHIFT
CLASSSKLEARNCLUSTER MEANSHIFT BANDWIDTHNONE SEEDSNONE BINSEEDINGFALSE
MINBINFREQ1 CLUSTERALLTRUE NJOBSNONE
MEAN SHIFT CLUSTERING USING A FLAT KERNEL
MEAN SHIFT CLUSTERING AIMS TO DISCOVER “BLOBS” IN A SMOOTH DENSITY OF SAMPLES IT IS A CENTROIDBASED ALGO
RITHM WHICH WORKS BY UPDATING CANDIDATES FOR CENTROIDS TO BE THE MEAN OF THE POINTS WITHIN A GIVEN REGION
THESE CANDIDATES ARE THEN FILTERED IN A POSTPROCESSING STAGE TO ELIMINATE NEARDUPLICATES TO FORM THE FINAL SET OF
CENTROIDS
SEEDING IS PERFORMED USING A BINNING TECHNIQUE FOR SCALABILITY
READ MORE IN THE USER GUIDE
PARAMETERS
BANDWIDTH FLOAT OPTIONAL BANDWIDTH USED IN THE RBF KERNEL
IF NOT GIVEN THE BANDWIDTH IS ESTIMATED USING SKLEARNCLUSTERESTIMATEBANDWIDTH SEE THE
DOCUMENTATION FOR THAT FUNCTION FOR HINTS ON SCALABILITY SEE ALSO THE NOTES BELOW
SEEDS ARRAY SHAPENSAMPLES NFEATURES OPTIONAL SEEDS USED TO INITIALIZE KERNELS IF NOT
SET THE SEEDS ARE CALCULATED BY CLUSTERINGGETBINSEEDS WITH BANDWIDTH AS THE GRID SIZE AND
DEFAULT VALUES FOR OTHER PARAMETERS
BINSEEDING BOOLEAN OPTIONAL IF TRUE INITIAL KERNEL LOCATIONS ARE NOT LOCATIONS OF ALL POINTS
BUT RATHER THE LOCATION OF THE DISCRETIZED VERSION OF POINTS WHERE POINTS ARE BINNED ONTO A
GRID WHOSE COARSENESS CORRESPONDS TO THE BANDWIDTH SETTING THIS OPTION TO TRUE WILL SPEED
UP THE ALGORITHM BECAUSE FEWER SEEDS WILL BE INITIALIZED DEFAULT VALUE FALSE IGNORED IF
SEEDS ARGUMENT IS NOT NONE
MINBINFREQ INT OPTIONAL TO SPEED UP THE ALGORITHM ACCEPT ONLY THOSE BINS WITH AT LEAST
MINBINFREQ POINTS AS SEEDS IF NOT DEFINED SET TO 1
CLUSTERALL BOOLEAN DEFAULT TRUE IF TRUE THEN ALL POINTS ARE CLUSTERED EVEN THOSE ORPHANS THAT
ARE NOT WITHIN ANY KERNEL ORPHANS ARE ASSIGNED TO THE NEAREST KERNEL IF FALSE THEN ORPHANS
ARE GIVEN CLUSTER LABEL 1
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION
THIS WORKS BY COMPUTING EACH OF THE NINIT RUNS IN PARALLEL
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL
PROCESSORS SEE GLOSSARY FOR MORE DETAILS

ATTRIBUTES
CLUSTERCENTERS ARRAY NCLUSTERS NFEATURES COORDINATES OF CLUSTER CENTERS
LABELS LABELS OF EACH POINT
NOTES
SCALABILITY
BECAUSE THIS IMPLEMENTATION USES A FLAT KERNEL AND A BALL TREE TO LOOK UP MEMBERS OF EACH KERNEL THE COMPLEXITY WILL TEND TOWARDS OTNLOGN IN LOWER DIMENSIONS WITH N THE NUMBER OF SAMPLES AND T THE NUMBER OF POINTS IN HIGHER DIMENSIONS THE COMPLEXITY WILL TEND TOWARDS OTN2
SCALABILITY CAN BE BOOSTED BY USING FEWER SEEDS FOR EXAMPLE BY USING A HIGHER VALUE OF MINBINFREQ IN THE GETBINSEEDS FUNCTION
NOTE THAT THE ESTIMATEBANDWIDTH FUNCTION IS MUCH LESS SCALABLE THAN THE MEAN SHIFT ALGORITHM AND WILL BE THE BOTTLENECK IF IT IS USED
REFERENCES
DORIN COMANICIU AND PETER MEER “MEAN SHIFT A ROBUST APPROACH TOWARD FEATURE SPACE ANALYSIS” IEEE TRANS ACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE 2002 PP 603619
EXAMPLES
```
 FROM SKLEARNCLUSTER IMPORT MEANSHIFT
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 1 0
 4 7 3 5 3 6
CLUSTERING  MEANSHIFTBANDWIDTH2FITX
CLUSTERINGLABELS
ARRAY1 1 1 0 0 0
CLUSTERINGPREDICT0 0 5 5
ARRAY1 0
CLUSTERING
MEANSHIFTBANDWIDTH2 BINSEEDINGFALSE CLUSTERALLTRUE MINBINFREQ1
NJOBSNONE SEEDSNONE
```
METHODS
FITSELF X Y PERFORM CLUSTERING
FITPREDICT SELF X Y PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT THE CLOSEST CLUSTER EACH SAMPLE IN X BELONGS TO
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFBANDWIDTHNONE SEEDSNONE BINSEEDINGFALSE MINBINFREQ1 CLUSTERALLTRUE NJOBSNONE
FITSELFXYNONE

PERFORM CLUSTERING
PARAMETERS
XARRAYLIKE SHAPENSAMPLES NFEATURES SAMPLES TO CLUSTER
YIGNORED
FITPREDICT SELFXYNONE
PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES INPUT DATA
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
LABELS NDARRAY SHAPE NSAMPLES CLUSTER LABELS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT THE CLOSEST CLUSTER EACH SAMPLE IN X BELONGS TO
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPENSAMPLES NFEATURES NEW DATA TO PREDICT
RETURNS
LABELS ARRAY SHAPE NSAMPLES INDEX OF THE CLUSTER EACH SAMPLE BELONGS TO
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNCLUSTERMEANSHIFT
•A DEMO OF THE MEANSHIFT CLUSTERING ALGORITHM
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS

SKLEARNCLUSTER SPECTRALCLUSTERING
CLASSSKLEARNCLUSTER SPECTRALCLUSTERING NCLUSTERS8 EIGENSOLVERNONE RAN
DOMSTATENONE NINIT10 GAMMA10 AFFIN
ITY'RBF' NNEIGHBORS10 EIGENTOL00 AS
SIGNLABELS'KMEANS' DEGREE3 COEF01 KER
NELPARAMSNONE NJOBSNONE
APPLY CLUSTERING TO A PROJECTION OF THE NORMALIZED LAPLACIAN
IN PRACTICE SPECTRAL CLUSTERING IS VERY USEFUL WHEN THE STRUCTURE OF THE INDIVIDUAL CLUSTERS IS HIGHLY NONCONVEX
OR MORE GENERALLY WHEN A MEASURE OF THE CENTER AND SPREAD OF THE CLUSTER IS NOT A SUITABLE DESCRIPTION OF THE
COMPLETE CLUSTER FOR INSTANCE WHEN CLUSTERS ARE NESTED CIRCLES ON THE 2D PLANE
IF AFFINITY IS THE ADJACENCY MATRIX OF A GRAPH THIS METHOD CAN BE USED TO FIND NORMALIZED GRAPH CUTS
WHEN CALLING FIT AN AFFINITY MATRIX IS CONSTRUCTED USING EITHER KERNEL FUNCTION SUCH THE GAUSSIAN AKA RBF
KERNEL OF THE EUCLIDEAN DISTANCED DX X
NPEXPGAMMA DXX2
OR A KNEAREST NEIGHBORS CONNECTIVITY MATRIX
ALTERNATIVELY USING PRECOMPUTED A USERPROVIDED AFFINITY MATRIX CAN BE USED
READ MORE IN THE USER GUIDE
PARAMETERS
NCLUSTERS INTEGER OPTIONAL THE DIMENSION OF THE PROJECTION SUBSPACE
EIGENSOLVER NONE 'ARPACK' 'LOBPCG' OR 'AMG' THE EIGENVALUE DECOMPOSITION STRATEGY TO
USE AMG REQUIRES PYAMG TO BE INSTALLED IT CAN BE FASTER ON VERY LARGE SPARSE PROBLEMS
BUT MAY ALSO LEAD TO INSTABILITIES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT A PSEUDO RANDOM NUMBER
GENERATOR USED FOR THE INITIALIZATION OF THE LOBPCG EIGEN VECTORS DECOMPOSITION WHEN
EIGENSOLVERAMG AND BY THE KMEANS INITIALIZATION USE AN INT TO MAKE THE RAN
DOMNESS DETERMINISTIC SEE GLOSSARY
NINIT INT OPTIONAL DEFAULT 10 NUMBER OF TIME THE KMEANS ALGORITHM WILL BE RUN WITH DIF
FERENT CENTROID SEEDS THE FINAL RESULTS WILL BE THE BEST OUTPUT OF NINIT CONSECUTIVE RUNS IN
TERMS OF INERTIA
GAMMA FLOAT DEFAULT10 KERNEL COEFFICIENT FOR RBF POLY SIGMOID LAPLACIAN AND CHI2 KERNELS
IGNORED FOR AFFINITYNEARESTNEIGHBORS
AFFINITY STRING ARRAYLIKE OR CALLABLE DEFAULT 'RBF' IF A STRING THIS MAY BE ONE OF 'NEAR
ESTNEIGHBORS' 'PRECOMPUTED' 'RBF' OR ONE OF THE KERNELS SUPPORTED BY SKLEARN
METRICSPAIRWISEKERNELS
ONLY KERNELS THAT PRODUCE SIMILARITY SCORES NONNEGATIVE VALUES THAT INCREASE WITH SIMILAR
ITY SHOULD BE USED THIS PROPERTY IS NOT CHECKED BY THE CLUSTERING ALGORITHM
NNEIGHBORS INTEGER NUMBER OF NEIGHBORS TO USE WHEN CONSTRUCTING THE AFFINITY MATRIX USING
THE NEAREST NEIGHBORS METHOD IGNORED FOR AFFINITYRBF
EIGENTOL FLOAT OPTIONAL DEFAULT 00 STOPPING CRITERION FOR EIGENDECOMPOSITION OF THE LAPLA
CIAN MATRIX WHEN EIGENSOLVERARPACK
ASSIGNLABELS 'KMEANS' 'DISCRETIZE' DEFAULT 'KMEANS' THE STRATEGY TO USE TO ASSIGN LABELS
IN THE EMBEDDING SPACE THERE ARE TWO WAYS TO ASSIGN LABELS AFTER THE LAPLACIAN EMBEDDING

KMEANS CAN BE APPLIED AND IS A POPULAR CHOICE BUT IT CAN ALSO BE SENSITIVE TO INITIALIZATION
DISCRETIZATION IS ANOTHER APPROACH WHICH IS LESS SENSITIVE TO RANDOM INITIALIZATION
DEGREE FLOAT DEFAULT3 DEGREE OF THE POLYNOMIAL KERNEL IGNORED BY OTHER KERNELS
COEF0 FLOAT DEFAULT1 ZERO COEFFICIENT FOR POLYNOMIAL AND SIGMOID KERNELS IGNORED BY OTHER
KERNELS
KERNELPARAMS DICTIONARY OF STRING TO ANY OPTIONAL PARAMETERS KEYWORD ARGUMENTS AND
VALUES FOR KERNEL PASSED AS CALLABLE OBJECT IGNORED BY OTHER KERNELS
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS
1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
ATTRIBUTES
AFFINITYMATRIX ARRAYLIKE SHAPE NSAMPLES NSAMPLES AFFINITY MATRIX USED FOR CLUSTER
ING AVAILABLE ONLY IF AFTER CALLING FIT
LABELS LABELS OF EACH POINT
NOTES
IF YOU HAVE AN AFFINITY MATRIX SUCH AS A DISTANCE MATRIX FOR WHICH 0 MEANS IDENTICAL ELEMENTS AND HIGH VALUES
MEANS VERY DISSIMILAR ELEMENTS IT CAN BE TRANSFORMED IN A SIMILARITY MATRIX THAT IS WELL SUITED FOR THE ALGORITHM
BY APPLYING THE GAUSSIAN RBF HEAT KERNEL
NPEXP DISTMATRIX 2 2 DELTA2
WHEREDELTA IS A FREE PARAMETER REPRESENTING THE WIDTH OF THE GAUSSIAN KERNEL
ANOTHER ALTERNATIVE IS TO TAKE A SYMMETRIC VERSION OF THE K NEAREST NEIGHBORS CONNECTIVITY MATRIX OF THE POINTS
IF THE PYAMG PACKAGE IS INSTALLED IT IS USED THIS GREATLY SPEEDS UP COMPUTATION
REFERENCES
• NORMALIZED CUTS AND IMAGE SEGMENTATION 2000 JIANBO SHI JITENDRA MALIK HTTPCITESEERISTPSUEDU
VIEWDOCSUMMARYDOI10111602324
• A TUTORIAL ON SPECTRAL CLUSTERING 2007 ULRIKE VON LUXBURG HTTPCITESEERXISTPSUEDUVIEWDOC
SUMMARYDOI10111659323
• MULTICLASS SPECTRAL CLUSTERING 2003 STELLA X YU JIANBO SHI HTTPSWWW1ICSIBERKELEYEDUSTELLAYU
PUBLICATIONDOC2003KWAYICCV PDF
EXAMPLES
```
 FROM SKLEARNCLUSTER IMPORT SPECTRALCLUSTERING
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 1 0
 4 7 3 5 3 6
CLUSTERING  SPECTRALCLUSTERINGNCLUSTERS2
 ASSIGNLABELSDISCRETIZE
 RANDOMSTATE0FITX
CLUSTERINGLABELS
```

SCIKITLEARN USER GUIDE RELEASE 0213
ARRAY1 1 1 0 0 0
CLUSTERING
SPECTRALCLUSTERINGAFFINITYRBF ASSIGNLABELSDISCRETIZE COEF01
DEGREE3 EIGENSOLVERNONE EIGENTOL00 GAMMA10
KERNELPARAMSNONE NCLUSTERS2 NINIT10 NJOBSNONE
NNEIGHBORS10 RANDOMSTATE0
METHODS
FITSELF X Y CREATES AN AFFINITY MATRIX FOR X USING THE SELECTED AFFIN
ITY THEN APPLIES SPECTRAL CLUSTERING TO THIS AFFINITY MA
TRIX
FITPREDICT SELF X Y PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNCLUSTERS8 EIGENSOLVERNONE RANDOMSTATENONE NINIT10 GAMMA10 AFFIN
ITY'RBF' NNEIGHBORS10 EIGENTOL00 ASSIGNLABELS'KMEANS' DEGREE3 COEF01
KERNELPARAMSNONE NJOBSNONE
FITSELFXYNONE
CREATES AN AFFINITY MATRIX FOR X USING THE SELECTED AFFINITY THEN APPLIES SPECTRAL CLUSTERING TO THIS AFFINITY
MATRIX
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES OR IF AFFIN
ITY'PRECOMPUTED' A PRECOMPUTED AFFINITY MATRIX OF SHAPE NSAMPLES NSAMPLES
YIGNORED
FITPREDICT SELFXYNONE
PERFORMS CLUSTERING ON X AND RETURNS CLUSTER LABELS
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES INPUT DATA
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
LABELS NDARRAY SHAPE NSAMPLES CLUSTER LABELS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
63SKLEARNCLUSTER CLUSTERING 1505

THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNCLUSTERSPECTRALCLUSTERING
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
632 FUNCTIONS
CLUSTERAFFINITYPROPAGATION S PERFORM AFFINITY PROPAGATION CLUSTERING OF DATA
CLUSTERCLUSTEROPTICSDBSCAN REACHABILITY
PERFORMS DBSCAN EXTRACTION FOR AN ARBITRARY EPSILON
CLUSTERCLUSTEROPTICSXI REACHABILITY AUTOMATICALLY EXTRACT CLUSTERS ACCORDING TO THE XISTEEP METHOD
CLUSTERCOMPUTEOPTICSGRAPH X
MINSAMPLES COMPUTES THE OPTICS REACHABILITY GRAPH
CLUSTERDBSCAN X EPS MINSAMPLES PERFORM DBSCAN CLUSTERING FROM VECTOR ARRAY OR DISTANCE MATRIX
CLUSTERESTIMATEBANDWIDTH X QUANTILE ESTIMATE THE BANDWIDTH TO USE WITH THE MEANSHIFT ALGO RITHM
CLUSTERKMEANS X NCLUSTERS KMEANS CLUSTERING ALGORITHM
CLUSTERMEANSHIFT X BANDWIDTH SEEDS PERFORM MEAN SHIFT CLUSTERING OF DATA USING A FLAT KERNEL
CLUSTERSPECTRALCLUSTERING AFFINITY APPLY CLUSTERING TO A PROJECTION OF THE NORMALIZED LAPLA CIAN
CLUSTERWARDTREE X CONNECTIVITY WARD CLUSTERING BASED ON A FEATURE MATRIX
SKLEARNCLUSTER AFFINITYPROPAGATION
SKLEARNCLUSTER AFFINITYPROPAGATION S PREFERENCENONE CONVERGENCEITER15 MAXITER200 DAMPING05 COPYTRUE VER BOSEFALSE RETURNNITERFALSE
PERFORM AFFINITY PROPAGATION CLUSTERING OF DATA
READ MORE IN THE USER GUIDE
PARAMETERS
SARRAYLIKE SHAPE NSAMPLES NSAMPLES MATRIX OF SIMILARITIES BETWEEN POINTS
PREFERENCE ARRAYLIKE SHAPE NSAMPLES OR FLOAT OPTIONAL PREFERENCES FOR EACH POINT POINTS WITH LARGER VALUES OF PREFERENCES ARE MORE LIKELY TO BE CHOSEN AS EXEMPLARS THE NUMBER OF EXEMPLARS IE OF CLUSTERS IS INFLUENCED BY THE INPUT PREFERENCES VALUE IF THE PREFERENCES ARE NOT PASSED AS ARGUMENTS THEY WILL BE SET TO THE MEDIAN OF THE INPUT SIMILARITIES RESULTING IN A MODERATE NUMBER OF CLUSTERS FOR A SMALLER AMOUNT OF CLUSTERS THIS CAN BE SET TO THE MINIMUM VALUE OF THE SIMILARITIES
CONVERGENCEITER INT OPTIONAL DEFAULT 15 NUMBER OF ITERATIONS WITH NO CHANGE IN THE NUMBER OF ESTIMATED CLUSTERS THAT STOPS THE CONVERGENCE
MAXITER INT OPTIONAL DEFAULT 200 MAXIMUM NUMBER OF ITERATIONS

DAMPING FLOAT OPTIONAL DEFAULT 05 DAMPING FACTOR BETWEEN 05 AND 1
COPY BOOLEAN OPTIONAL DEFAULT TRUE IF COPY IS FALSE THE AFFINITY MATRIX IS MODIFIED INPLACE
BY THE ALGORITHM FOR MEMORY EFFICIENCY
VERBOSE BOOLEAN OPTIONAL DEFAULT FALSE THE VERBOSITY LEVEL
RETURNNITER BOOL DEFAULT FALSE WHETHER OR NOT TO RETURN THE NUMBER OF ITERATIONS
RETURNS
CLUSTERCENTERSINDICES ARRAY SHAPE NCLUSTERS INDEX OF CLUSTERS CENTERS
LABELS ARRAY SHAPE NSAMPLES CLUSTER LABELS FOR EACH POINT
NITER INT NUMBER OF ITERATIONS RUN RETURNED ONLY IF RETURNNITER IS SET TO TRUE
NOTES
FOR AN EXAMPLE SEE EXAMPLESCLUSTERPLOTAFFINITYPROPAGATIONPY
WHEN THE ALGORITHM DOES NOT CONVERGE IT RETURNS AN EMPTY ARRAY AS CLUSTERCENTERINDICES AND1AS
LABEL FOR EACH TRAINING SAMPLE
WHEN ALL TRAINING SAMPLES HAVE EQUAL SIMILARITIES AND EQUAL PREFERENCES THE ASSIGNMENT OF CLUSTER CENTERS AND
LABELS DEPENDS ON THE PREFERENCE IF THE PREFERENCE IS SMALLER THAN THE SIMILARITIES A SINGLE CLUSTER CENTER AND
LABEL0FOR EVERY SAMPLE WILL BE RETURNED OTHERWISE EVERY TRAINING SAMPLE BECOMES ITS OWN CLUSTER CENTER AND
IS ASSIGNED A UNIQUE LABEL
REFERENCES
BRENDAN J FREY AND DELBERT DUECK “CLUSTERING BY PASSING MESSAGES BETWEEN DATA POINTS” SCIENCE FEB 2007
EXAMPLES USING SKLEARNCLUSTERAFFINITYPROPAGATION
•VISUALIZING THE STOCK MARKET STRUCTURE
SKLEARNCLUSTER CLUSTEROPTICSDBSCAN
SKLEARNCLUSTER CLUSTEROPTICSDBSCAN REACHABILITY COREDISTANCES ORDERING EPS
PERFORMS DBSCAN EXTRACTION FOR AN ARBITRARY EPSILON
EXTRACTING THE CLUSTERS RUNS IN LINEAR TIME NOTE THAT THIS RESULTS IN LABELS WHICH ARE CLOSE TO A DBSCAN
WITH SIMILAR SETTINGS AND EPS ONLY IFEPS IS CLOSE TOMAXEPS
PARAMETERS
REACHABILITY ARRAY SHAPE NSAMPLES REACHABILITY DISTANCES CALCULATED BY OPTICS
REACHABILITY
COREDISTANCES ARRAY SHAPE NSAMPLES DISTANCES AT WHICH POINTS BECOME CORE
COREDISTANCES
ORDERING ARRAY SHAPE NSAMPLES OPTICS ORDERED POINT INDICES ORDERING
EPS FLOAT DBSCAN EPS PARAMETER MUST BE SET TO MAXEPS RESULTS WILL BE CLOSE TO
DBSCAN ALGORITHM IF EPS ANDMAXEPS ARE CLOSE TO ONE ANOTHER

RETURNS
LABELS ARRAY SHAPE NSAMPLES THE ESTIMATED LABELS
EXAMPLES USING SKLEARNCLUSTERCLUSTEROPTICSDBSCAN
•DEMO OF OPTICS CLUSTERING ALGORITHM
SKLEARNCLUSTER CLUSTEROPTICSXI
SKLEARNCLUSTER CLUSTEROPTICSXI REACHABILITY PREDECESSOR ORDERING MINSAMPLES
MINCLUSTERSIZENONE XI005 PREDECES
SORCORRECTIONTRUE
AUTOMATICALLY EXTRACT CLUSTERS ACCORDING TO THE XISTEEP METHOD
PARAMETERS
REACHABILITY ARRAY SHAPE NSAMPLES REACHABILITY DISTANCES CALCULATED BY OPTICS
REACHABILITY
PREDECESSOR ARRAY SHAPE NSAMPLES PREDECESSORS CALCULATED BY OPTICS
ORDERING ARRAY SHAPE NSAMPLES OPTICS ORDERED POINT INDICES ORDERING
MINSAMPLES INT 1 OR FLOAT BETWEEN 0 AND 1 THE SAME AS THE MINSAMPLES GIVEN TO OPTICS
UP AND DOWN STEEP REGIONS CAN'T HAVE MORE THEN MINSAMPLES CONSECUTIVE NONSTEEP
POINTS EXPRESSED AS AN ABSOLUTE NUMBER OR A FRACTION OF THE NUMBER OF SAMPLES ROUNDED TO
BE AT LEAST 2
MINCLUSTERSIZE INT 1 OR FLOAT BETWEEN 0 AND 1 DEFAULTNONE MINIMUM NUMBER OF SAM
PLES IN AN OPTICS CLUSTER EXPRESSED AS AN ABSOLUTE NUMBER OR A FRACTION OF THE NUMBER OF
SAMPLES ROUNDED TO BE AT LEAST 2 IF NONE THE VALUE OF MINSAMPLES IS USED INSTEAD
XIFLOAT BETWEEN 0 AND 1 OPTIONAL DEFAULT005 DETERMINES THE MINIMUM STEEPNESS ON THE
REACHABILITY PLOT THAT CONSTITUTES A CLUSTER BOUNDARY FOR EXAMPLE AN UPWARDS POINT IN THE
REACHABILITY PLOT IS DEFINED BY THE RATIO FROM ONE POINT TO ITS SUCCESSOR BEING AT MOST 1XI
PREDECESSORCORRECTION BOOL OPTIONAL DEFAULTTRUE CORRECT CLUSTERS BASED ON THE CALCU
LATED PREDECESSORS
RETURNS
LABELS ARRAY SHAPE NSAMPLES THE LABELS ASSIGNED TO SAMPLES POINTS WHICH ARE NOT INCLUDED
IN ANY CLUSTER ARE LABELED AS 1
CLUSTERS ARRAY SHAPE NCLUSTERS 2 THE LIST OF CLUSTERS IN THE FORM OF START END
IN EACH ROW WITH ALL INDICES INCLUSIVE THE CLUSTERS ARE ORDERED ACCORDING TO END
START ASCENDING SO THAT LARGER CLUSTERS ENCOMPASSING SMALLER CLUSTERS COME AF
TER SUCH NESTED SMALLER CLUSTERS SINCE LABELS DOES NOT REFLECT THE HIERARCHY USUALLY
LENCLUSTERS NPUNIQUELABELS
SKLEARNCLUSTER COMPUTEOPTICSGRAPH
SKLEARNCLUSTER COMPUTEOPTICSGRAPH XMINSAMPLES MAXEPS METRIC PMETRICPARAMS AL
GORITHM LEAFSIZE NJOBS
COMPUTES THE OPTICS REACHABILITY GRAPH
READ MORE IN THE USER GUIDE

PARAMETERS
XARRAY SHAPE NSAMPLES NFEATURES OR NSAMPLES NSAMPLES IF METRIC'PRECOMPUTED'
A FEATURE ARRAY OR ARRAY OF DISTANCES BETWEEN SAMPLES IF METRIC'PRECOMPUTED'
MINSAMPLES INT 1 OR FLOAT BETWEEN 0 AND 1 THE NUMBER OF SAMPLES IN A NEIGHBORHOOD FOR A
POINT TO BE CONSIDERED AS A CORE POINT EXPRESSED AS AN ABSOLUTE NUMBER OR A FRACTION OF THE
NUMBER OF SAMPLES ROUNDED TO BE AT LEAST 2
MAXEPS FLOAT OPTIONAL DEFAULTNPINF THE MAXIMUM DISTANCE BETWEEN TWO SAMPLES FOR ONE
TO BE CONSIDERED AS IN THE NEIGHBORHOOD OF THE OTHER DEFAULT VALUE OF NPINF WILL IDENTIFY
CLUSTERS ACROSS ALL SCALES REDUCING MAXEPS WILL RESULT IN SHORTER RUN TIMES
METRIC STRING OR CALLABLE OPTIONAL DEFAULT'MINKOWSKI' METRIC TO USE FOR DISTANCE COMPUTA
TION ANY METRIC FROM SCIKITLEARN OR SCIPYSPATIALDISTANCE CAN BE USED
IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF INSTANCES ROWS AND THE RESULTING
VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS AS INPUT AND RETURN ONE VALUE INDICATING
THE DISTANCE BETWEEN THEM THIS WORKS FOR SCIPY'S METRICS BUT IS LESS EFFICIENT THAN PASSING
THE METRIC NAME AS A STRING IF METRIC IS "PRECOMPUTED" X IS ASSUMED TO BE A DISTANCE MATRIX
AND MUST BE SQUARE
VALID VALUES FOR METRIC ARE
• FROM SCIKITLEARN 'CITYBLOCK' 'COSINE' 'EUCLIDEAN' 'L1' 'L2' 'MANHATTAN'
• FROM SCIPYSPATIALDISTANCE 'BRAYCURTIS' 'CANBERRA' 'CHEBYSHEV' 'CORRELATION' 'DICE'
'HAMMING' 'JACCARD' 'KULSINSKI' 'MAHALANOBIS' 'MINKOWSKI' 'ROGERSTANIMOTO' 'RUS
SELLRAO' 'SEUCLIDEAN' 'SOKALMICHENER' 'SOKALSNEATH' 'SQEUCLIDEAN' 'YULE'
SEE THE DOCUMENTATION FOR SCIPYSPATIALDISTANCE FOR DETAILS ON THESE METRICS
PINTEGER OPTIONAL DEFAULT2 PARAMETER FOR THE MINKOWSKI METRIC FROM SKLEARN
METRICSPAIRWISEDISTANCES WHEN P 1 THIS IS EQUIVALENT TO USING MANHAT
TANDISTANCE L1 AND EUCLIDEANDISTANCE L2 FOR P 2 FOR ARBITRARY P MINKOWSKIDISTANCE
LP IS USED
METRICPARAMS DICT OPTIONAL DEFAULTNONE ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC
FUNCTION
ALGORITHM 'AUTO' 'BALLTREE' 'KDTREE' 'BRUTE' OPTIONAL ALGORITHM USED TO COMPUTE THE
NEAREST NEIGHBORS
• 'BALLTREE' WILL USE BALLTREE
• 'KDTREE' WILL USE KDTREE
• 'BRUTE' WILL USE A BRUTEFORCE SEARCH
• 'AUTO' WILL ATTEMPT TO DECIDE THE MOST APPROPRIATE ALGORITHM BASED ON THE VALUES PASSED
TOFIT METHOD DEFAULT
NOTE FITTING ON SPARSE INPUT WILL OVERRIDE THE SETTING OF THIS PARAMETER USING BRUTE FORCE
LEAFSIZE INT OPTIONAL DEFAULT30 LEAF SIZE PASSED TO BALLTREE ORKDTREE THIS CAN
AFFECT THE SPEED OF THE CONSTRUCTION AND QUERY AS WELL AS THE MEMORY REQUIRED TO STORE THE
TREE THE OPTIMAL VALUE DEPENDS ON THE NATURE OF THE PROBLEM
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS
SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RETURNS

ORDERING ARRAY SHAPE NSAMPLES THE CLUSTER ORDERED LIST OF SAMPLE INDICES
COREDISTANCES ARRAY SHAPE NSAMPLES DISTANCE AT WHICH EACH SAMPLE BECOMES A CORE
POINT INDEXED BY OBJECT ORDER POINTS WHICH WILL NEVER BE CORE HAVE A DISTANCE OF INF USE
CLUSTCOREDISTANCESCLUSTORDERING TO ACCESS IN CLUSTER ORDER
REACHABILITY ARRAY SHAPE NSAMPLES REACHABILITY DISTANCES PER SAMPLE INDEXED BY OBJECT
ORDER USECLUSTREACHABILITYCLUSTORDERING TO ACCESS IN CLUSTER ORDER
PREDECESSOR ARRAY SHAPE NSAMPLES POINT THAT A SAMPLE WAS REACHED FROM INDEXED BY
OBJECT ORDER SEED POINTS HAVE A PREDECESSOR OF 1
REFERENCES
1
SKLEARNCLUSTER DBSCAN
SKLEARNCLUSTER DBSCANXEPS05 MINSAMPLES5 METRIC’MINKOWSKI’ METRICPARAMSNONE AL
GORITHM’AUTO’ LEAFSIZE30 P2SAMPLEWEIGHTNONE NJOBSNONE
PERFORM DBSCAN CLUSTERING FROM VECTOR ARRAY OR DISTANCE MATRIX
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY OR SPARSE CSR MATRIX OF SHAPE NSAMPLES NFEATURES OR ARRAY OF SHAPE
NSAMPLES NSAMPLES A FEATURE ARRAY OR ARRAY OF DISTANCES BETWEEN SAMPLES IF
METRICPRECOMPUTED
EPS FLOAT OPTIONAL THE MAXIMUM DISTANCE BETWEEN TWO SAMPLES FOR ONE TO BE CONSIDERED AS
IN THE NEIGHBORHOOD OF THE OTHER THIS IS NOT A MAXIMUM BOUND ON THE DISTANCES OF POINTS
WITHIN A CLUSTER THIS IS THE MOST IMPORTANT DBSCAN PARAMETER TO CHOOSE APPROPRIATELY FOR
YOUR DATA SET AND DISTANCE FUNCTION
MINSAMPLES INT OPTIONAL THE NUMBER OF SAMPLES OR TOTAL WEIGHT IN A NEIGHBORHOOD FOR A
POINT TO BE CONSIDERED AS A CORE POINT THIS INCLUDES THE POINT ITSELF
METRIC STRING OR CALLABLE THE METRIC TO USE WHEN CALCULATING DISTANCE BETWEEN INSTANCES IN
A FEATURE ARRAY IF METRIC IS A STRING OR CALLABLE IT MUST BE ONE OF THE OPTIONS ALLOWED
BYSKLEARNMETRICSPAIRWISEDISTANCES FOR ITS METRIC PARAMETER IF METRIC
IS “PRECOMPUTED” X IS ASSUMED TO BE A DISTANCE MATRIX AND MUST BE SQUARE X MAY BE
A SPARSE MATRIX IN WHICH CASE ONLY “NONZERO” ELEMENTS MAY BE CONSIDERED NEIGHBORS FOR
DBSCAN
METRICPARAMS DICT OPTIONAL ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC FUNCTION
NEW IN VERSION 019
ALGORITHM ‘AUTO’ ‘BALLTREE’ ‘KDTREE’ ‘BRUTE’ OPTIONAL THE ALGORITHM TO BE USED BY THE
NEARESTNEIGHBORS MODULE TO COMPUTE POINTWISE DISTANCES AND FIND NEAREST NEIGHBORS SEE
NEARESTNEIGHBORS MODULE DOCUMENTATION FOR DETAILS
LEAFSIZE INT OPTIONAL DEFAULT 30 LEAF SIZE PASSED TO BALLTREE OR CKDTREE THIS CAN AFFECT
THE SPEED OF THE CONSTRUCTION AND QUERY AS WELL AS THE MEMORY REQUIRED TO STORE THE TREE
THE OPTIMAL VALUE DEPENDS ON THE NATURE OF THE PROBLEM
PFLOAT OPTIONAL THE POWER OF THE MINKOWSKI METRIC TO BE USED TO CALCULATE DISTANCE BETWEEN
POINTS

SAMPLEWEIGHT ARRAY SHAPE NSAMPLES OPTIONAL WEIGHT OF EACH SAMPLE SUCH THAT A SAMPLE
WITH A WEIGHT OF AT LEAST MINSAMPLES IS BY ITSELF A CORE SAMPLE A SAMPLE WITH NEGATIVE
WEIGHT MAY INHIBIT ITS EPSNEIGHBOR FROM BEING CORE NOTE THAT WEIGHTS ARE ABSOLUTE AND
DEFAULT TO 1
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS
SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RETURNS
CORESAMPLES ARRAY NCORESAMPLES INDICES OF CORE SAMPLES
LABELS ARRAY NSAMPLES CLUSTER LABELS FOR EACH POINT NOISY SAMPLES ARE GIVEN THE LABEL 1
SEE ALSO
DBSCAN AN ESTIMATOR INTERFACE FOR THIS CLUSTERING ALGORITHM
OPTICS A SIMILAR ESTIMATOR INTERFACE CLUSTERING AT MULTIPLE VALUES OF EPS OUR IMPLEMENTATION IS OPTIMIZED
FOR MEMORY USAGE
NOTES
FOR AN EXAMPLE SEE EXAMPLESCLUSTERPLOTDBSCANPY
THIS IMPLEMENTATION BULKCOMPUTES ALL NEIGHBORHOOD QUERIES WHICH INCREASES THE MEMORY COMPLEXITY TO
OND WHERE D IS THE AVERAGE NUMBER OF NEIGHBORS WHILE ORIGINAL DBSCAN HAD MEMORY COMPLEXITY ON
IT MAY ATTRACT A HIGHER MEMORY COMPLEXITY WHEN QUERYING THESE NEAREST NEIGHBORHOODS DEPENDING ON THE
ALGORITHM
ONE WAY TO AVOID THE QUERY COMPLEXITY IS TO PRECOMPUTE SPARSE NEIGHBORHOODS IN CHUNKS
USINGNEARESTNEIGHBORSRADIUSNEIGHBORSGRAPH WITHMODEDISTANCE THEN USING
METRICPRECOMPUTED HERE
ANOTHER WAY TO REDUCE MEMORY AND COMPUTATION TIME IS TO REMOVE NEARDUPLICATE POINTS AND USE
SAMPLEWEIGHT INSTEAD
CLUSTEROPTICS PROVIDES A SIMILAR CLUSTERING WITH LOWER MEMORY USAGE
REFERENCES
ESTER M H P KRIEGEL J SANDER AND X XU “A DENSITYBASED ALGORITHM FOR DISCOVERING CLUSTERS IN LARGE
SPATIAL DATABASES WITH NOISE” IN PROCEEDINGS OF THE 2ND INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY
AND DATA MINING PORTLAND OR AAAI PRESS PP 226231 1996
SCHUBERT E SANDER J ESTER M KRIEGEL H P XU X 2017 DBSCAN REVISITED REVISITED WHY AND HOW
YOU SHOULD STILL USE DBSCAN ACM TRANSACTIONS ON DATABASE SYSTEMS TODS 423 19
SKLEARNCLUSTER ESTIMATEBANDWIDTH
SKLEARNCLUSTER ESTIMATEBANDWIDTH XQUANTILE03 NSAMPLESNONE RANDOMSTATE0
NJOBSNONE
ESTIMATE THE BANDWIDTH TO USE WITH THE MEANSHIFT ALGORITHM
THAT THIS FUNCTION TAKES TIME AT LEAST QUADRATIC IN NSAMPLES FOR LARGE DATASETS IT’S WISE TO SET THAT PARAMETER
TO A SMALL VALUE

SCIKITLEARN USER GUIDE RELEASE 0213
PARAMETERS
XARRAYLIKE SHAPENSAMPLES NFEATURES INPUT POINTS
QUANTILE FLOAT DEFAULT 03 SHOULD BE BETWEEN 0 1 05 MEANS THAT THE MEDIAN OF ALL PAIRWISE
DISTANCES IS USED
NSAMPLES INT OPTIONAL THE NUMBER OF SAMPLES TO USE IF NOT GIVEN ALL SAMPLES ARE USED
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT THE GENERATOR USED TO RANDOMLY
SELECT THE SAMPLES FROM INPUT POINTS FOR BANDWIDTH ESTIMATION USE AN INT TO MAKE THE
RANDOMNESS DETERMINISTIC SEE GLOSSARY
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS
SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RETURNS
BANDWIDTH FLOAT THE BANDWIDTH PARAMETER
EXAMPLES USING SKLEARNCLUSTERESTIMATEBANDWIDTH
•A DEMO OF THE MEANSHIFT CLUSTERING ALGORITHM
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
SKLEARNCLUSTER KMEANS
SKLEARNCLUSTER KMEANSXNCLUSTERS SAMPLEWEIGHTNONE INIT’KMEANS’ PRECOM
PUTEDISTANCES’AUTO’ NINIT10 MAXITER300 VERBOSEFALSE
TOL00001 RANDOMSTATENONE COPYXTRUE NJOBSNONE ALGO
RITHM’AUTO’ RETURNNITERFALSE
KMEANS CLUSTERING ALGORITHM
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE OBSERVATIONS TO CLUSTER IT
MUST BE NOTED THAT THE DATA WILL BE CONVERTED TO C ORDERING WHICH WILL CAUSE A MEMORY
COPY IF THE GIVEN DATA IS NOT CCONTIGUOUS
NCLUSTERS INT THE NUMBER OF CLUSTERS TO FORM AS WELL AS THE NUMBER OF CENTROIDS TO GENERATE
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL THE WEIGHTS FOR EACH OBSERVATION IN
X IF NONE ALL OBSERVATIONS ARE ASSIGNED EQUAL WEIGHT DEFAULT NONE
INIT ‘KMEANS’ ‘RANDOM’ OR NDARRAY OR A CALLABLE OPTIONAL METHOD FOR INITIALIZATION
DEFAULT TO ‘KMEANS’
‘KMEANS’ SELECTS INITIAL CLUSTER CENTERS FOR KMEAN CLUSTERING IN A SMART WAY TO SPEED
UP CONVERGENCE SEE SECTION NOTES IN KINIT FOR MORE DETAILS
‘RANDOM’ CHOOSE K OBSERVATIONS ROWS AT RANDOM FROM DATA FOR THE INITIAL CENTROIDS
IF AN NDARRAY IS PASSED IT SHOULD BE OF SHAPE NCLUSTERS NFEATURES AND GIVES THE INITIAL
CENTERS
IF A CALLABLE IS PASSED IT SHOULD TAKE ARGUMENTS X K AND AND A RANDOM STATE AND RETURN AN
INITIALIZATION

PRECOMPUTEDISTANCES ‘AUTO’ TRUE FALSE PRECOMPUTE DISTANCES FASTER BUT TAKES MORE MEMORY
‘AUTO’ DO NOT PRECOMPUTE DISTANCES IF NSAMPLES NCLUSTERS 12 MILLION THIS CORRE SPONDS TO ABOUT 100MB OVERHEAD PER JOB USING DOUBLE PRECISION
TRUE ALWAYS PRECOMPUTE DISTANCES
FALSE NEVER PRECOMPUTE DISTANCES
NINIT INT OPTIONAL DEFAULT 10 NUMBER OF TIME THE KMEANS ALGORITHM WILL BE RUN WITH DIF FERENT CENTROID SEEDS THE FINAL RESULTS WILL BE THE BEST OUTPUT OF NINIT CONSECUTIVE RUNS IN TERMS OF INERTIA
MAXITER INT OPTIONAL DEFAULT 300 MAXIMUM NUMBER OF ITERATIONS OF THE KMEANS ALGORITHM TO RUN
VERBOSE BOOLEAN OPTIONAL VERBOSITY MODE
TOLFLOAT OPTIONAL THE RELATIVE INCREMENT IN THE RESULTS BEFORE DECLARING CONVERGENCE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN ERATION FOR CENTROID INITIALIZATION USE AN INT TO MAKE THE RANDOMNESS DETERMINISTIC SEE GLOSSARY
COPYX BOOLEAN OPTIONAL WHEN PRECOMPUTING DISTANCES IT IS MORE NUMERICALLY ACCURATE TO CENTER THE DATA FIRST IF COPYX IS TRUE DEFAULT THEN THE ORIGINAL DATA IS NOT MODIFIED ENSURING X IS CCONTIGUOUS IF FALSE THE ORIGINAL DATA IS MODIFIED AND PUT BACK BEFORE THE FUNCTION RETURNS BUT SMALL NUMERICAL DIFFERENCES MAY BE INTRODUCED BY SUBTRACTING AND THEN ADDING THE DATA MEAN IN THIS CASE IT WILL ALSO NOT ENSURE THAT DATA IS CCONTIGUOUS WHICH MAY CAUSE A SIGNIFICANT SLOWDOWN
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION THIS WORKS BY COMPUTING EACH OF THE NINIT RUNS IN PARALLEL
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
ALGORITHM “AUTO” “FULL” OR “ELKAN” DEFAULT”AUTO” KMEANS ALGORITHM TO USE THE CLASSICAL EMSTYLE ALGORITHM IS “FULL” THE “ELKAN” VARIATION IS MORE EFFICIENT BY USING THE TRIANGLE INEQUALITY BUT CURRENTLY DOESN’T SUPPORT SPARSE DATA “AUTO” CHOOSES “ELKAN” FOR DENSE DATA AND “FULL” FOR SPARSE DATA
RETURNNITER BOOL OPTIONAL WHETHER OR NOT TO RETURN THE NUMBER OF ITERATIONS
RETURNS
CENTROID FLOAT NDARRAY WITH SHAPE K NFEATURES CENTROIDS FOUND AT THE LAST ITERATION OF K MEANS
LABEL INTEGER NDARRAY WITH SHAPE NSAMPLES LABELI IS THE CODE OR INDEX OF THE CENTROID THE I’TH OBSERVATION IS CLOSEST TO
INERTIA FLOAT THE FINAL VALUE OF THE INERTIA CRITERION SUM OF SQUARED DISTANCES TO THE CLOSEST CENTROID FOR ALL OBSERVATIONS IN THE TRAINING SET
BESTNITER INT NUMBER OF ITERATIONS CORRESPONDING TO THE BEST RESULTS RETURNED ONLY IF RETURNNITER IS SET TO TRUE

SKLEARNCLUSTER MEANSHIFT
SKLEARNCLUSTER MEANSHIFT X BANDWIDTHNONE SEEDSNONE BINSEEDINGFALSE
MINBINFREQ1 CLUSTERALLTRUE MAXITER300 NJOBSNONE
PERFORM MEAN SHIFT CLUSTERING OF DATA USING A FLAT KERNEL
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPENSAMPLES NFEATURES INPUT DATA
BANDWIDTH FLOAT OPTIONAL KERNEL BANDWIDTH
IF BANDWIDTH IS NOT GIVEN IT IS DETERMINED USING A HEURISTIC BASED ON THE MEDIAN OF
ALL PAIRWISE DISTANCES THIS WILL TAKE QUADRATIC TIME IN THE NUMBER OF SAMPLES THE
SKLEARNCLUSTERESTIMATEBANDWIDTH FUNCTION CAN BE USED TO DO THIS MORE EFFICIENTLY
SEEDS ARRAYLIKE SHAPENSEEDS NFEATURES OR NONE POINT USED AS INITIAL KERNEL LOCA
TIONS IF NONE AND BINSEEDINGFALSE EACH DATA POINT IS USED AS A SEED IF NONE AND
BINSEEDINGTRUE SEE BINSEEDING
BINSEEDING BOOLEAN DEFAULTFALSE IF TRUE INITIAL KERNEL LOCATIONS ARE NOT LOCATIONS OF ALL
POINTS BUT RATHER THE LOCATION OF THE DISCRETIZED VERSION OF POINTS WHERE POINTS ARE BINNED
ONTO A GRID WHOSE COARSENESS CORRESPONDS TO THE BANDWIDTH SETTING THIS OPTION TO TRUE WILL
SPEED UP THE ALGORITHM BECAUSE FEWER SEEDS WILL BE INITIALIZED IGNORED IF SEEDS ARGUMENT IS
NOT NONE
MINBINFREQ INT DEFAULT1 TO SPEED UP THE ALGORITHM ACCEPT ONLY THOSE BINS WITH AT LEAST
MINBINFREQ POINTS AS SEEDS
CLUSTERALL BOOLEAN DEFAULT TRUE IF TRUE THEN ALL POINTS ARE CLUSTERED EVEN THOSE ORPHANS THAT
ARE NOT WITHIN ANY KERNEL ORPHANS ARE ASSIGNED TO THE NEAREST KERNEL IF FALSE THEN ORPHANS
ARE GIVEN CLUSTER LABEL 1
MAXITER INT DEFAULT 300 MAXIMUM NUMBER OF ITERATIONS PER SEED POINT BEFORE THE CLUSTERING
OPERATION TERMINATES FOR THAT SEED POINT IF HAS NOT CONVERGED YET
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION
THIS WORKS BY COMPUTING EACH OF THE NINIT RUNS IN PARALLEL
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL
PROCESSORS SEE GLOSSARY FOR MORE DETAILS
NEW IN VERSION 017 PARALLEL EXECUTION USING NJOBS
RETURNS
CLUSTERCENTERS ARRAY SHAPENCLUSTERS NFEATURES COORDINATES OF CLUSTER CENTERS
LABELS ARRAY SHAPENSAMPLES CLUSTER LABELS FOR EACH POINT
NOTES
FOR AN EXAMPLE SEE EXAMPLESCLUSTERPLOTMEANSHIFTPY

SKLEARNCLUSTER SPECTRALCLUSTERING
SKLEARNCLUSTER SPECTRALCLUSTERING AFFINITY NCLUSTERS8 NCOMPONENTSNONE
EIGENSOLVERNONE RANDOMSTATENONE NINIT10
EIGENTOL00 ASSIGNLABELS‘KMEANS’
APPLY CLUSTERING TO A PROJECTION OF THE NORMALIZED LAPLACIAN
IN PRACTICE SPECTRAL CLUSTERING IS VERY USEFUL WHEN THE STRUCTURE OF THE INDIVIDUAL CLUSTERS IS HIGHLY NONCONVEX
OR MORE GENERALLY WHEN A MEASURE OF THE CENTER AND SPREAD OF THE CLUSTER IS NOT A SUITABLE DESCRIPTION OF THE
COMPLETE CLUSTER FOR INSTANCE WHEN CLUSTERS ARE NESTED CIRCLES ON THE 2D PLANE
IF AFFINITY IS THE ADJACENCY MATRIX OF A GRAPH THIS METHOD CAN BE USED TO FIND NORMALIZED GRAPH CUTS
READ MORE IN THE USER GUIDE
PARAMETERS
AFFINITY ARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NSAMPLES THE AFFINITY MATRIX DE
SCRIBING THE RELATIONSHIP OF THE SAMPLES TO EMBED MUST BE SYMMETRIC
POSSIBLE EXAMPLES
• ADJACENCY MATRIX OF A GRAPH
• HEAT KERNEL OF THE PAIRWISE DISTANCE MATRIX OF THE SAMPLES
• SYMMETRIC KNEAREST NEIGHBOURS CONNECTIVITY MATRIX OF THE SAMPLES
NCLUSTERS INTEGER OPTIONAL NUMBER OF CLUSTERS TO EXTRACT
NCOMPONENTS INTEGER OPTIONAL DEFAULT IS NCLUSTERS NUMBER OF EIGEN VECTORS TO USE FOR THE
SPECTRAL EMBEDDING
EIGENSOLVER NONE ‘ARPACK’ ‘LOBPCG’ OR ‘AMG’ THE EIGENVALUE DECOMPOSITION STRATEGY TO
USE AMG REQUIRES PYAMG TO BE INSTALLED IT CAN BE FASTER ON VERY LARGE SPARSE PROBLEMS
BUT MAY ALSO LEAD TO INSTABILITIES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT A PSEUDO RANDOM NUMBER GENER
ATOR USED FOR THE INITIALIZATION OF THE LOBPCG EIGEN VECTORS DECOMPOSITION WHEN EIGENSOLVER
‘AMG’ AND BY THE KMEANS INITIALIZATION USE AN INT TO MAKE THE RANDOMNESS DETERMIN
ISTIC SEE GLOSSARY
NINIT INT OPTIONAL DEFAULT 10 NUMBER OF TIME THE KMEANS ALGORITHM WILL BE RUN WITH DIF
FERENT CENTROID SEEDS THE FINAL RESULTS WILL BE THE BEST OUTPUT OF NINIT CONSECUTIVE RUNS IN
TERMS OF INERTIA
EIGENTOL FLOAT OPTIONAL DEFAULT 00 STOPPING CRITERION FOR EIGENDECOMPOSITION OF THE LAPLA
CIAN MATRIX WHEN USING ARPACK EIGENSOLVER
ASSIGNLABELS ‘KMEANS’ ‘DISCRETIZE’ DEFAULT ‘KMEANS’ THE STRATEGY TO USE TO ASSIGN LABELS
IN THE EMBEDDING SPACE THERE ARE TWO WAYS TO ASSIGN LABELS AFTER THE LAPLACIAN EMBEDDING
KMEANS CAN BE APPLIED AND IS A POPULAR CHOICE BUT IT CAN ALSO BE SENSITIVE TO INITIALIZATION
DISCRETIZATION IS ANOTHER APPROACH WHICH IS LESS SENSITIVE TO RANDOM INITIALIZATION SEE THE
‘MULTICLASS SPECTRAL CLUSTERING’ PAPER REFERENCED BELOW FOR MORE DETAILS ON THE DISCRETIZATION
APPROACH
RETURNS
LABELS ARRAY OF INTEGERS SHAPE NSAMPLES THE LABELS OF THE CLUSTERS

NOTES
THE GRAPH SHOULD CONTAIN ONLY ONE CONNECT COMPONENT ELSEWHERE THE RESULTS MAKE LITTLE SENSE
THIS ALGORITHM SOLVES THE NORMALIZED CUT FOR K2 IT IS A NORMALIZED SPECTRAL CLUSTERING
REFERENCES
• NORMALIZED CUTS AND IMAGE SEGMENTATION 2000 JIANBO SHI JITENDRA MALIK HTTPCITESEERISTPSUEDU
VIEWDOCSUMMARYDOI10111602324
• A TUTORIAL ON SPECTRAL CLUSTERING 2007 ULRIKE VON LUXBURG HTTPCITESEERXISTPSUEDUVIEWDOC
SUMMARYDOI10111659323
• MULTICLASS SPECTRAL CLUSTERING 2003 STELLA X YU JIANBO SHI HTTPSWWW1ICSIBERKELEYEDUSTELLAYU
PUBLICATIONDOC2003KWAYICCV PDF
EXAMPLES USING SKLEARNCLUSTERSPECTRALCLUSTERING
•SEGMENTING THE PICTURE OF GREEK COINS IN REGIONS
•SPECTRAL CLUSTERING FOR IMAGE SEGMENTATION
SKLEARNCLUSTER WARDTREE
SKLEARNCLUSTER WARDTREE XCONNECTIVITYNONE NCLUSTERSNONE RETURNDISTANCEFALSE
WARD CLUSTERING BASED ON A FEATURE MATRIX
RECURSIVELY MERGES THE PAIR OF CLUSTERS THAT MINIMALLY INCREASES WITHINCLUSTER VARIANCE
THE INERTIA MATRIX USES A HEAPQBASED REPRESENTATION
THIS IS THE STRUCTURED VERSION THAT TAKES INTO ACCOUNT SOME TOPOLOGICAL STRUCTURE BETWEEN SAMPLES
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY SHAPE NSAMPLES NFEATURES FEATURE MATRIX REPRESENTING NSAMPLES SAMPLES TO BE
CLUSTERED
CONNECTIVITY SPARSE MATRIX OPTIONAL CONNECTIVITY MATRIX DEFINES FOR EACH SAMPLE THE NEIGH
BORING SAMPLES FOLLOWING A GIVEN STRUCTURE OF THE DATA THE MATRIX IS ASSUMED TO BE SYM
METRIC AND ONLY THE UPPER TRIANGULAR HALF IS USED DEFAULT IS NONE IE THE WARD ALGORITHM IS
UNSTRUCTURED
NCLUSTERS INT OPTIONAL STOP EARLY THE CONSTRUCTION OF THE TREE AT NCLUSTERS THIS IS USEFUL
TO DECREASE COMPUTATION TIME IF THE NUMBER OF CLUSTERS IS NOT SMALL COMPARED TO THE NUMBER
OF SAMPLES IN THIS CASE THE COMPLETE TREE IS NOT COMPUTED THUS THE ‘CHILDREN’ OUTPUT IS OF
LIMITED USE AND THE ‘PARENTS’ OUTPUT SHOULD RATHER BE USED THIS OPTION IS VALID ONLY WHEN
SPECIFYING A CONNECTIVITY MATRIX
RETURNDISTANCE BOOL OPTIONAL IF TRUE RETURN THE DISTANCE BETWEEN THE CLUSTERS
RETURNS

CHILDREN 2D ARRAY SHAPE NNODES1 2 THE CHILDREN OF EACH NONLEAF NODE VALUES LESS
THAN NSAMPLES CORRESPOND TO LEAVES OF THE TREE WHICH ARE THE ORIGINAL SAMPLES A NODE
IGREATER THAN OR EQUAL TO NSAMPLES IS A NONLEAF NODE AND HAS CHILDREN CHILDRENI
NSAMPLES ALTERNATIVELY AT THE ITH ITERATION CHILDRENI0 AND CHILDRENI1 ARE
MERGED TO FORM NODE NSAMPLES I
NCONNECTEDCOMPONENTS INT THE NUMBER OF CONNECTED COMPONENTS IN THE GRAPH
NLEAVES INT THE NUMBER OF LEAVES IN THE TREE
PARENTS 1D ARRAY SHAPE NNODES OR NONE THE PARENT OF EACH NODE ONLY RETURNED WHEN A
CONNECTIVITY MATRIX IS SPECIFIED ELSEWHERE ‘NONE’ IS RETURNED
DISTANCES 1D ARRAY SHAPE NNODES1 ONLY RETURNED IF RETURNDISTANCE IS SET TO TRUE FOR
COMPATIBILITY THE DISTANCES BETWEEN THE CENTERS OF THE NODES DISTANCESI COR
RESPONDS TO A WEIGHTED EUCLIDEAN DISTANCE BETWEEN THE NODES CHILDRENI 1 AND
CHILDRENI 2 IF THE NODES REFER TO LEAVES OF THE TREE THEN DISTANCESI IS
THEIR UNWEIGHTED EUCLIDEAN DISTANCE DISTANCES ARE UPDATED IN THE FOLLOWING WAY FROM
SCIPYHIERARCHYLINKAGE
THE NEW ENTRY □□ □IS COMPUTED AS FOLLOWS
□□ □ √
□□
□□□ □2□□
□□□ □2−□
□□□ □2
WHERE □IS THE NEWLY JOINED CLUSTER CONSISTING OF CLUSTERS □AND□□IS AN UNUSED CLUSTER IN
THE FOREST □□□□ ANDIS THE CARDINALITY OF ITS ARGUMENT THIS IS ALSO KNOWN
AS THE INCREMENTAL ALGORITHM
64SKLEARNCLUSTERBICLUSTER BICLUSTERING
SPECTRAL BICLUSTERING ALGORITHMS
AUTHORS KEMAL EREN LICENSE BSD 3 CLAUSE
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SPECTRALCOCLUSTERING NCLUSTERS SPECTRAL COCLUSTERING ALGORITHM DHILLON 2001
SKLEARNCLUSTERBICLUSTER SPECTRALBICLUSTERING
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PARTITIONS ROWS AND COLUMNS UNDER THE ASSUMPTION THAT THE DATA HAS AN UNDERLYING CHECKERBOARD STRUCTURE FOR INSTANCE IF THERE ARE TWO ROW PARTITIONS AND THREE COLUMN PARTITIONS EACH ROW WILL BELONG TO THREE BICLUSTERS AND EACH COLUMN WILL BELONG TO TWO BICLUSTERS THE OUTER PRODUCT OF THE CORRESPONDING ROW AND COLUMN LABEL VECTORS GIVES THIS CHECKERBOARD STRUCTURE

READ MORE IN THE USER GUIDE

PARAMETERS

NCLUSTERS INTEGER OR TUPLE NROWCLUSTERS NCOLUMNCLUSTERS THE NUMBER OF ROW AND COL UMN CLUSTERS IN THE CHECKERBOARD STRUCTURE

METHOD STRING OPTIONAL DEFAULT 'BISTOCHASTIC' METHOD OF NORMALIZING AND CONVERTING SIN GULAR VECTORS INTO BICLUSTERS MAY BE ONE OF 'SCALE' 'BISTOCHASTIC' OR 'LOG' THE AUTHORS RECOMMEND USING 'LOG' IF THE DATA IS SPARSE HOWEVER LOG NORMALIZATION WILL NOT WORK WHICH IS WHY THE DEFAULT IS 'BISTOCHASTIC' CAUTION IF METHODLOG THE DATA MUST NOT BE SPARSE

NCOMPONENTS INTEGER OPTIONAL DEFAULT 6 NUMBER OF SINGULAR VECTORS TO CHECK

NBEST INTEGER OPTIONAL DEFAULT 3 NUMBER OF BEST SINGULAR VECTORS TO WHICH TO PROJECT THE DATA FOR CLUSTERING

SVDMETHOD STRING OPTIONAL DEFAULT 'RANDOMIZED' SELECTS THE ALGORITHM FOR FINDING SINGU LAR VECTORS MAY BE 'RANDOMIZED' OR 'ARPACK' IF 'RANDOMIZED' USES SKLEARNUTILS EXTMATHRANDOMIZEDSVD WHICH MAY BE FASTER FOR LARGE MATRICES IF 'ARPACK' USES SCIPYSPARSELINALGSVDS WHICH IS MORE ACCURATE BUT POSSIBLY SLOWER IN SOME CASES

NSVDVECS INT OPTIONAL DEFAULT NONE NUMBER OF VECTORS TO USE IN CALCULATING THE SVD CORRESPONDS TO NCV WHENSVDMETHODARPACK ANDNOVERSAMPLES WHEN SVDMETHOD IS 'RANDOMIZED'

MINIBATCH BOOL OPTIONAL DEFAULT FALSE WHETHER TO USE MINIBATCH KMEANS WHICH IS FASTER BUT MAY GET DIFFERENT RESULTS

INIT 'KMEANS' 'RANDOM' OR AN NDARRAY METHOD FOR INITIALIZATION OF KMEANS ALGORITHM DEFAULTS TO 'KMEANS'

NINIT INT OPTIONAL DEFAULT 10 NUMBER OF RANDOM INITIALIZATIONS THAT ARE TRIED WITH THE K MEANS ALGORITHM

IF MINIBATCH KMEANS IS USED THE BEST INITIALIZATION IS CHOSEN AND THE ALGORITHM RUNS ONCE OTHERWISE THE ALGORITHM IS RUN FOR EACH INITIALIZATION AND THE BEST SOLUTION CHOSEN

NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION THIS WORKS BY BREAKING DOWN THE PAIRWISE MATRIX INTO NJOBS EVEN SLICES AND COMPUTING THEM IN PARALLEL

NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS

RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT USED FOR RANDOMIZING THE SINGULAR VALUE DECOMPOSITION AND THE KMEANS INITIALIZATION USE AN INT TO MAKE THE RANDOMNESS DETERMINISTIC SEE GLOSSARY

ATTRIBUTES

ROWS ARRAYLIKE SHAPE NROWCLUSTERS NROWS RESULTS OF THE CLUSTERING ROWSI R IS TRUE IF CLUSTER ICONTAINS ROW R AVAILABLE ONLY AFTER CALLING FIT

COLUMNS ARRAYLIKE SHAPE NCOLUMNCLUSTERS NCOLUMNS RESULTS OF THE CLUSTERING LIKE ROWS

ROWLABELS ARRAYLIKE SHAPE NROWS ROW PARTITION LABELS
COLUMNLABELS ARRAYLIKE SHAPE NCOLS COLUMN PARTITION LABELS
REFERENCES
• KLUGER YUVAL ET AL 2003 SPECTRAL BICLUSTERING OF MICROARRAY DATA COCLUSTERING GENES AND CONDITIONS
EXAMPLES
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 FROM SKLEARNCLUSTER IMPORT SPECTRALBICLUSTERING
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 1 0
 4 7 3 5 3 6
CLUSTERING  SPECTRALBICLUSTERINGNCLUSTERS2 RANDOMSTATE0FITX
CLUSTERINGROWLABELS
ARRAY1 1 1 0 0 0 DTYPEINT32
CLUSTERINGCOLUMNLABELS
ARRAY0 1 DTYPEINT32
CLUSTERING
SPECTRALBICLUSTERINGINITKMEANS METHODBISTOCHASTIC
MINIBATCHFALSE NBEST3 NCLUSTERS2 NCOMPONENTS6
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SVDMETHODRANDOMIZED
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GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSHAPE SELF I SHAPE OF THE I’TH BICLUSTER
GETSUBMATRIX SELF I DATA RETURNS THE SUBMATRIX CORRESPONDING TO BICLUSTER I
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INIT SELF NCLUSTERS3 METHOD’BISTOCHASTIC’ NCOMPONENTS6 NBEST3
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ONLY WORKS IF ROWS ANDCOLUMNS ATTRIBUTES EXIST
PARAMETERS
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ROWIND NPARRAY DTYPENPINTP INDICES OF ROWS IN THE DATASET THAT BELONG TO THE BICLUSTER
COLIND NPARRAY DTYPENPINTP INDICES OF COLUMNS IN THE DATASET THAT BELONG TO THE BICLUS
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GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
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DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
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CLUSTERS ROWS AND COLUMNS OF AN ARRAY XTO SOLVE THE RELAXED NORMALIZED CUT OF THE BIPARTITE GRAPH CREATED FROM
XAS FOLLOWS THE EDGE BETWEEN ROW VERTEX IAND COLUMN VERTEX JHAS WEIGHT XI J
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LAR VECTORS MAY BE 'RANDOMIZED' OR 'ARPACK' IF 'RANDOMIZED' USE SKLEARNUTILS
EXTMATHRANDOMIZEDSVD WHICH MAY BE FASTER FOR LARGE MATRICES IF 'ARPACK' USE
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IF MINIBATCH KMEANS IS USED THE BEST INITIALIZATION IS CHOSEN AND THE ALGORITHM RUNS ONCE
OTHERWISE THE ALGORITHM IS RUN FOR EACH INITIALIZATION AND THE BEST SOLUTION CHOSEN
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION
THIS WORKS BY BREAKING DOWN THE PAIRWISE MATRIX INTO NJOBS EVEN SLICES AND COMPUTING
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• DHILLON INDERJIT S 2001 COCLUSTERING DOCUMENTS AND WORDS USING BIPARTITE SPECTRAL GRAPH PARTITIONING
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IMPORT NUMPY AS NP
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CLUSTERING SPECTRALCOCLUSTERINGNCLUSTERS2 RANDOMSTATE0FITX
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65SKLEARNCOMPOSE COMPOSITE ESTIMATORS
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IN ADDITION TO ITS CURRENT CONTENTS THIS MODULE WILL EVENTUALLY BE HOME TO REFURBISHED VERSIONS OF PIPELINE AND FEA
TUREUNION
USER GUIDE SEE THE PIPELINES AND COMPOSITE ESTIMATORS SECTION FOR FURTHER DETAILS
COMPOSECOLUMNTRANSFORMER TRANSFORMERS APPLIES TRANSFORMERS TO COLUMNS OF AN ARRAY OR PANDAS
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COMPOSETRANSFORMEDTARGETREGRESSOR METAESTIMATOR TO REGRESS ON A TRANSFORMED TARGET
651SKLEARNCOMPOSE COLUMNTRANSFORMER
CLASSSKLEARNCOMPOSE COLUMNTRANSFORMER TRANSFORMERS REMAINDER‘DROP’
SPARSETHRESHOLD03 NJOBSNONE TRANS
FORMERWEIGHTSNONE VERBOSEFALSE
APPLIES TRANSFORMERS TO COLUMNS OF AN ARRAY OR PANDAS DATAFRAME
THIS ESTIMATOR ALLOWS DIFFERENT COLUMNS OR COLUMN SUBSETS OF THE INPUT TO BE TRANSFORMED SEPARATELY AND THE
FEATURES GENERATED BY EACH TRANSFORMER WILL BE CONCATENATED TO FORM A SINGLE FEATURE SPACE THIS IS USEFUL FOR
HETEROGENEOUS OR COLUMNAR DATA TO COMBINE SEVERAL FEATURE EXTRACTION MECHANISMS OR TRANSFORMATIONS INTO A
SINGLE TRANSFORMER
READ MORE IN THE USER GUIDE
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NAME STRING LIKE IN PIPELINE AND FEATUREUNION THIS ALLOWS THE TRANSFORMER AND ITS PA
RAMETERS TO BE SET USING SETPARAMS AND SEARCHED IN GRID SEARCH
TRANSFORMER ESTIMATOR OR ‘PASSTHROUGH’ ‘DROP’ ESTIMATOR MUST SUPPORT FIT AND
TRANSFORM SPECIALCASED STRINGS ‘DROP’ AND ‘PASSTHROUGH’ ARE ACCEPTED AS WELL TO
INDICATE TO DROP THE COLUMNS OR TO PASS THEM THROUGH UNTRANSFORMED RESPECTIVELY
COLUMNS STRING OR INT ARRAYLIKE OF STRING OR INT SLICE BOOLEAN MASK ARRAY OR CALLABLE
INDEXES THE DATA ON ITS SECOND AXIS INTEGERS ARE INTERPRETED AS POSITIONAL COLUMNS WHILE
STRINGS CAN REFERENCE DATAFRAME COLUMNS BY NAME A SCALAR STRING OR INT SHOULD BE USED
WHERETRANSFORMER EXPECTS X TO BE A 1D ARRAYLIKE VECTOR OTHERWISE A 2D ARRAY WILL
BE PASSED TO THE TRANSFORMER A CALLABLE IS PASSED THE INPUT DATA XAND CAN RETURN ANY OF
THE ABOVE
REMAINDER ‘DROP’ ‘PASSTHROUGH’ OR ESTIMATOR DEFAULT ‘DROP’ BY DEFAULT ONLY THE
SPECIFIED COLUMNS IN TRANSFORMERS ARE TRANSFORMED AND COMBINED IN THE OUTPUT AND
THE NONSPECIFIED COLUMNS ARE DROPPED DEFAULT OF DROP BY SPECIFYING
REMAINDERPASSTHROUGH ALL REMAINING COLUMNS THAT WERE NOT SPECIFIED IN TRANS
FORMERS WILL BE AUTOMATICALLY PASSED THROUGH THIS SUBSET OF COLUMNS IS CONCATENATED WITH
THE OUTPUT OF THE TRANSFORMERS BY SETTING REMAINDER TO BE AN ESTIMATOR THE REMAINING
NONSPECIFIED COLUMNS WILL USE THE REMAINDER ESTIMATOR THE ESTIMATOR MUST SUPPORT FIT
ANDTRANSFORM NOTE THAT USING THIS FEATURE REQUIRES THAT THE DATAFRAME COLUMNS INPUT AT FIT
ANDTRANSFORM HAVE IDENTICAL ORDER

SPARSETHRESHOLD FLOAT DEFAULT 03 IF THE OUTPUT OF THE DIFFERENT TRANSFORMERS CONTAINS SPARSE
MATRICES THESE WILL BE STACKED AS A SPARSE MATRIX IF THE OVERALL DENSITY IS LOWER THAN THIS
VALUE USESPARSETHRESHOLD0 TO ALWAYS RETURN DENSE WHEN THE TRANSFORMED OUTPUT
CONSISTS OF ALL DENSE DATA THE STACKED RESULT WILL BE DENSE AND THIS KEYWORD WILL BE IGNORED
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF JOBS TO RUN IN PARALLEL NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
TRANSFORMERWEIGHTS DICT OPTIONAL MULTIPLICATIVE WEIGHTS FOR FEATURES PER TRANSFORMER THE
OUTPUT OF THE TRANSFORMER IS MULTIPLIED BY THESE WEIGHTS KEYS ARE TRANSFORMER NAMES VALUES
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TRANSFORMERS LIST THE COLLECTION OF FITTED TRANSFORMERS AS TUPLES OF NAME FITTEDTRANSFORMER
COLUMNFITTEDTRANSFORMER CAN BE AN ESTIMATOR ‘DROP’ OR ‘PASSTHROUGH’ IN
CASE THERE WERE NO COLUMNS SELECTED THIS WILL BE THE UNFITTED TRANSFORMER IF THERE
ARE REMAINING COLUMNS THE FINAL ELEMENT IS A TUPLE OF THE FORM ‘REMAINDER’ TRANS
FORMER REMAININGCOLUMNS CORRESPONDING TO THE REMAINDER PARAMETER IF THERE ARE
REMAINING COLUMNS THEN LENTRANSFORMERSLENTRANSFORMERS1 OTHER
WISELENTRANSFORMERSLENTRANSFORMERS
NAMEDTRANSFORMERS BUNCH OBJECT A DICTIONARY WITH ATTRIBUTE ACCESS ACCESS THE FITTED
TRANSFORMER BY NAME
SPARSEOUTPUT BOOLEAN BOOLEAN FLAG INDICATING WETHER THE OUTPUT OF TRANSFORM IS A SPARSE
MATRIX OR A DENSE NUMPY ARRAY WHICH DEPENDS ON THE OUTPUT OF THE INDIVIDUAL TRANSFORMERS
AND THESPARSETHRESHOLD KEYWORD
SEE ALSO
SKLEARNCOMPOSEMAKECOLUMNTRANSFORMER CONVENIENCE FUNCTION FOR COMBINING THE OUTPUTS OF
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THE ORDER OF THE COLUMNS IN THE TRANSFORMED FEATURE MATRIX FOLLOWS THE ORDER OF HOW THE COLUMNS ARE SPECIFIED
IN THE TRANSFORMERS LIST COLUMNS OF THE ORIGINAL FEATURE MATRIX THAT ARE NOT SPECIFIED ARE DROPPED FROM THE
RESULTING TRANSFORMED FEATURE MATRIX UNLESS SPECIFIED IN THE PASSTHROUGH KEYWORD THOSE COLUMNS SPECIFIED
WITHPASSTHROUGH ARE ADDED AT THE RIGHT TO THE OUTPUT OF THE TRANSFORMERS
EXAMPLES
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 IMPORT NUMPY AS NP
 FROM SKLEARNCOMPOSE IMPORT COLUMNTRANSFORMER
 FROM SKLEARNPREPROCESSING IMPORT NORMALIZER
CT  COLUMNTRANSFORMER
 NORM1 NORMALIZERNORML1 0 1
 NORM2 NORMALIZERNORML1 SLICE2 4
X  NPARRAY0 1 2 2
 1 1 0 1
 NORMALIZER SCALES EACH ROW OF X TO UNIT NORM A SEPARATE SCALING
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IS APPLIED FOR THE TWO FIRST AND TWO LAST ELEMENTS OF EACH
ROW INDEPENDENTLY
CTFITTRANSFORMX
ARRAY0 1 05 05
05 05 0 1
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FITSELF X Y FIT ALL TRANSFORMERS USING X
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FORMERWEIGHTSNONE VERBOSEFALSE
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SELF COLUMNTRANSFORMER THIS ESTIMATOR
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ACCESS THE FITTED TRANSFORMER BY NAME
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TRANSFORM X SEPARATELY BY EACH TRANSFORMER CONCATENATE RESULTS
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FUNCNONE INVERSEFUNCNONE
CHECKINVERSETRUE
METAESTIMATOR TO REGRESS ON A TRANSFORMED TARGET
USEFUL FOR APPLYING A NONLINEAR TRANSFORMATION IN REGRESSION PROBLEMS THIS TRANSFORMATION CAN BE GIVEN AS A
TRANSFORMER SUCH AS THE QUANTILETRANSFORMER OR AS A FUNCTION AND ITS INVERSE SUCH AS LOG ANDEXP
THE COMPUTATION DURING FIT IS
REGRESSORFITX FUNCY

OR
REGRESSORFITX TRANSFORMERTRANSFORMY
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OR
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TRANSFORMER OBJECT DEFAULTNONE ESTIMATOR OBJECT SUCH AS DERIVED FROM
TRANSFORMERMIXIN CANNOT BE SET AT THE SAME TIME AS FUNC ANDINVERSEFUNC IF
TRANSFORMER ISNONE AS WELL ASFUNC ANDINVERSEFUNC THE TRANSFORMER WILL BE
AN IDENTITY TRANSFORMER NOTE THAT THE TRANSFORMER WILL BE CLONED DURING FITTING ALSO THE
TRANSFORMER IS RESTRICTING YTO BE A NUMPY ARRAY
FUNC FUNCTION OPTIONAL FUNCTION TO APPLY TO YBEFORE PASSING TO FIT CANNOT BE SET AT THE
SAME TIME AS TRANSFORMER THE FUNCTION NEEDS TO RETURN A 2DIMENSIONAL ARRAY IF FUNC
ISNONE THE FUNCTION USED WILL BE THE IDENTITY FUNCTION
INVERSEFUNC FUNCTION OPTIONAL FUNCTION TO APPLY TO THE PREDICTION OF THE REGRESSOR CAN
NOT BE SET AT THE SAME TIME AS TRANSFORMER AS WELL THE FUNCTION NEEDS TO RETURN A
2DIMENSIONAL ARRAY THE INVERSE FUNCTION IS USED TO RETURN PREDICTIONS TO THE SAME SPACE OF
THE ORIGINAL TRAINING LABELS
CHECKINVERSE BOOL DEFAULTTRUE WHETHER TO CHECK THAT TRANSFORM FOLLOWED BY
INVERSETRANSFORM ORFUNC FOLLOWED BY INVERSEFUNC LEADS TO THE ORIGINAL TAR
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INTERNALLY THE TARGET YIS ALWAYS CONVERTED INTO A 2DIMENSIONAL ARRAY TO BE USED BY SCIKITLEARN TRANSFORMERS
AT THE TIME OF PREDICTION THE OUTPUT WILL BE RESHAPED TO A HAVE THE SAME NUMBER OF DIMENSIONS AS Y
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2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
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XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
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TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
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ERS
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SKLEARNCOMPOSE MAKECOLUMNTRANSFORMER TRANSFORMERS KWARGS
CONSTRUCT A COLUMNTRANSFORMER FROM THE GIVEN TRANSFORMERS

THIS IS A SHORTHAND FOR THE COLUMNTRANSFORMER CONSTRUCTOR IT DOES NOT REQUIRE AND DOES NOT PERMIT NAMING THE TRANSFORMERS INSTEAD THEY WILL BE GIVEN NAMES AUTOMATICALLY BASED ON THEIR TYPES IT ALSO DOES NOT ALLOW WEIGHTING WITH TRANSFORMERWEIGHTS

PARAMETERS

TRANSFORMERS TUPLES OF TRANSFORMERS AND COLUMN SELECTIONS

REMAINDER ‘DROP’ ‘PASSTHROUGH’ OR ESTIMATOR DEFAULT ‘DROP’ BY DEFAULT ONLY THE SPECIFIED COLUMNS IN TRANSFORMERS ARE TRANSFORMED AND COMBINED IN THE OUTPUT AND THE NONSPECIFIED COLUMNS ARE DROPPED DEFAULT OF DROP BY SPECIFYING REMAINDERPASSTHROUGH ALL REMAINING COLUMNS THAT WERE NOT SPECIFIED IN TRANS FORMERS WILL BE AUTOMATICALLY PASSED THROUGH THIS SUBSET OF COLUMNS IS CONCATENATED WITH THE OUTPUT OF THE TRANSFORMERS BY SETTING REMAINDER TO BE AN ESTIMATOR THE REMAINING NONSPECIFIED COLUMNS WILL USE THE REMAINDER ESTIMATOR THE ESTIMATOR MUST SUPPORT FIT ANDTRANSFORM

SPARSETHRESHOLD FLOAT DEFAULT 03 IF THE TRANSFORMED OUTPUT CONSISTS OF A MIX OF SPARSE AND DENSE DATA IT WILL BE STACKED AS A SPARSE MATRIX IF THE DENSITY IS LOWER THAN THIS VALUE USE SPARSETHRESHOLD0 TO ALWAYS RETURN DENSE WHEN THE TRANSFORMED OUTPUT CONSISTS OF ALL SPARSE OR ALL DENSE DATA THE STACKED RESULT WILL BE SPARSE OR DENSE RESPECTIVELY AND THIS KEYWORD WILL BE IGNORED

NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF JOBS TO RUN IN PARALLEL NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS

VERBOSE BOOLEAN OPTIONALDEFAULTFALSE IF TRUE THE TIME ELAPSED WHILE FITTING EACH TRANS FORMER WILL BE PRINTED AS IT IS COMPLETED

RETURNS

CTCOLUMNTRANSFORMER

SEE ALSO

SKLEARNCOMPOSECOLUMNTRANSFORMER CLASS THAT ALLOWS COMBINING THE OUTPUTS OF MULTIPLE TRANS FORMER OBJECTS USED ON COLUMN SUBSETS OF THE DATA INTO A SINGLE FEATURE SPACE

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```
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MAKECOLUMNTRANSFORMER
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COLUMNTRANSFORMERNJOBSNONE REMAINDERDROP SPARSETHRESHOLD03
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TRANSFORMERSSTANDARDSCALER
STANDARDSCALER
NUMERICALCOLUMN
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ONEHOTENCODER
CATEGORICALCOLUMN VERBOSEFALSE
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THESKLEARNCOVARIANCE MODULE INCLUDES METHODS AND ALGORITHMS TO ROBUSTLY ESTIMATE THE COVARIANCE OF FEA
TURES GIVEN A SET OF POINTS THE PRECISION MATRIX DEFINED AS THE INVERSE OF THE COVARIANCE IS ALSO ESTIMATED COVARIANCE
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DATASET
COVARIANCEGRAPHICALLASSO ALPHA MODE SPARSE INVERSE COVARIANCE ESTIMATION WITH AN L1PENALIZED
ESTIMATOR
COVARIANCEGRAPHICALLASSOCV ALPHAS SPARSE INVERSE COVARIANCE W CROSSVALIDATED CHOICE OF THE
L1 PENALTY
COVARIANCELEDOITWOLF STOREPRECISION LEDOITWOLF ESTIMATOR
COVARIANCEMINCOVDET STOREPRECISION MINIMUM COVARIANCE DETERMINANT MCD ROBUST ESTIMA
TOR OF COVARIANCE
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SUMECENTEREDFALSE
MAXIMUM LIKELIHOOD COVARIANCE ESTIMATOR
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ING WITH DATA WHOSE MEAN IS ALMOST BUT NOT EXACTLY ZERO IF FALSE DEFAULT DATA ARE CENTERED
BEFORE COMPUTATION
ATTRIBUTES
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COVARIANCE 2D NDARRAY SHAPE NFEATURES NFEATURES ESTIMATED COVARIANCE MATRIX
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 IMPORT NUMPY AS NP
 FROM SKLEARNCOVARIANCE IMPORT EMPIRICALCOVARIANCE
 FROM SKLEARNDATASETS IMPORT MAKEGAUSSIANQUANTILES
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 3 4
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X  RNGMULTIVARIATENORMALMEAN0 0
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NORM STR THE TYPE OF NORM USED TO COMPUTE THE ERROR AVAILABLE ERROR TYPES 'FROBENIUS'
DEFAULT SQRTTRATA 'SPECTRAL' SQRTMAXEIGENVALUESATA WHERE A IS THE ERROR
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THE SQUARED ERROR NORM IS NOT RESCALED
SQUARED BOOL WHETHER TO COMPUTE THE SQUARED ERROR NORM OR THE ERROR NORM IF TRUE
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TION THAN THE DATA USED IN FIT
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NOT EXACTLY ZERO IF FALSE THE ROBUST LOCATION AND COVARIANCE ARE DIRECTLY COMPUTED WITH THE
FASTMCD ALGORITHM WITHOUT ADDITIONAL TREATMENT
SUPPORTFRACTION FLOAT IN 0 1 OPTIONAL DEFAULTNONE THE PROPORTION OF POINTS TO BE
INCLUDED IN THE SUPPORT OF THE RAW MCD ESTIMATE IF NONE THE MINIMUM VALUE OF SUP
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2
CONTAMINATION FLOAT IN 0 05 OPTIONAL DEFAULT01 THE AMOUNT OF CONTAMINATION OF THE
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THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
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THE SQUARED ERROR NORM IS NOT RESCALED

SQUARED BOOL WHETHER TO COMPUTE THE SQUARED ERROR NORM OR THE ERROR NORM IF TRUE
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RVDRIESSEN
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SCORESAMPLES SELFX
COMPUTE THE NEGATIVE MAHALANOBIS DISTANCES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
NEGATIVEMAHALDISTANCES ARRAYLIKE SHAPE NSAMPLES OPPOSITE OF THE MAHALANOBIS
DISTANCES
66SKLEARNCOVARIANCE COVARIANCE ESTIMATORS 1539

SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNCOVARIANCEELLIPTICENVELOPE
•COMPARING ANOMALY DETECTION ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS
•OUTLIER DETECTION ON A REAL DATA SET
663SKLEARNCOVARIANCE GRAPHICALLASSO
CLASSSKLEARNCOVARIANCE GRAPHICALLASSO ALPHA001 MODE'CD' TOL00001 ENETTOL00001 MAXITER100 VERBOSEFALSE ASSUMECENTEREDFALSE
SPARSE INVERSE COVARIANCE ESTIMATION WITH AN L1PENALIZED ESTIMATOR
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA POSITIVE FLOAT DEFAULT 001 THE REGULARIZATION PARAMETER THE HIGHER ALPHA THE MORE REGULARIZATION THE SPARSER THE INVERSE COVARIANCE
MODE 'CD' 'LARS' DEFAULT 'CD' THE LASSO SOLVER TO USE COORDINATE DESCENT OR LARS USE LARS FOR VERY SPARSE UNDERLYING GRAPHS WHERE P N ELSEWHERE PREFER CD WHICH IS MORE NUMERICALLY STABLE
TOLPOSITIVE FLOAT DEFAULT 1E4 THE TOLERANCE TO DECLARE CONVERGENCE IF THE DUAL GAP GOES BELOW THIS VALUE ITERATIONS ARE STOPPED
ENETTOL POSITIVE FLOAT OPTIONAL THE TOLERANCE FOR THE ELASTIC NET SOLVER USED TO CALCULATE THE DESCENT DIRECTION THIS PARAMETER CONTROLS THE ACCURACY OF THE SEARCH DIRECTION FOR A GIVEN COLUMN UPDATE NOT OF THE OVERALL PARAMETER ESTIMATE ONLY USED FOR MODE'CD'
MAXITER INTEGER DEFAULT 100 THE MAXIMUM NUMBER OF ITERATIONS
VERBOSE BOOLEAN DEFAULT FALSE IF VERBOSE IS TRUE THE OBJECTIVE FUNCTION AND DUAL GAP ARE PLOTTED AT EACH ITERATION
ASSUMECENTERED BOOLEAN DEFAULT FALSE IF TRUE DATA ARE NOT CENTERED BEFORE COMPUTATION USEFUL WHEN WORKING WITH DATA WHOSE MEAN IS ALMOST BUT NOT EXACTLY ZERO IF FALSE DATA ARE CENTERED BEFORE COMPUTATION
ATTRIBUTES
LOCATION ARRAYLIKE SHAPE NFEATURES ESTIMATED LOCATION IE THE ESTIMATED MEAN
COVARIANCE ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED COVARIANCE MATRIX
PRECISION ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED PSEUDO INVERSE MATRIX
NITER INT NUMBER OF ITERATIONS RUN
SEE ALSO

GRAPHICALLASSO GRAPHICALLASSOCV
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNCOVARIANCE IMPORT GRAPHICALLASSO
TRUECOV  NPARRAY08 00 02 00
 00 04 00 00
 02 00 03 01
 00 00 01 07
NPRANDOMSEED0
X  NPRANDOMMULTIVARIATENORMALMEAN0 0 0 0
 COVTRUECOV
 SIZE200
COV  GRAPHICALLASSOFITX
NPAROUNDCOVCOVARIANCE DECIMALS3
ARRAY0816 0049 0218 0019
0049 0364 0017 0034
0218 0017 0322 0093
0019 0034 0093 069
NPAROUNDCOVLOCATION DECIMALS3
ARRAY0073 004  0038 0143
```
METHODS
ERRORNORM SELF COMPCOV NORM SCALING COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARI
ANCE ESTIMATORS
FITSELF X Y FITS THE GRAPHICALLASSO MODEL TO X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETPRECISION SELF GETTER FOR THE PRECISION MATRIX
MAHALANOBIS SELF X COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN
OBSERVATIONS
SCORE SELF XTEST Y COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH
SELFCOVARIANCE AS AN ESTIMATOR OF ITS COVARI
ANCE MATRIX
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHA001 MODE’CD’ TOL00001 ENETTOL00001 MAXITER100 VERBOSEFALSE
ASSUMECENTEREDFALSE
ERRORNORM SELFCOMPCOV NORM’FROBENIUS’ SCALINGTRUE SQUAREDTRUE
COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARIANCE ESTIMATORS IN THE SENSE OF THE FROBENIUS
NORM
PARAMETERS
COMPCOV ARRAYLIKE SHAPE NFEATURES NFEATURES THE COVARIANCE TO COMPARE WITH
NORM STR THE TYPE OF NORM USED TO COMPUTE THE ERROR AVAILABLE ERROR TYPES ‘FROBENIUS’
DEFAULT SQRTTRATA ‘SPECTRAL’ SQRTMAXEIGENVALUESATA WHERE A IS THE ERROR
COMPCOV SELFCOVARIANCE
SCALING BOOL IF TRUE DEFAULT THE SQUARED ERROR NORM IS DIVIDED BY NFEATURES IF FALSE
THE SQUARED ERROR NORM IS NOT RESCALED

SQUARED BOOL WHETHER TO COMPUTE THE SQUARED ERROR NORM OR THE ERROR NORM IF TRUE
DEFAULT THE SQUARED ERROR NORM IS RETURNED IF FALSE THE ERROR NORM IS RETURNED
RETURNS
THE MEAN SQUARED ERROR IN THE SENSE OF THE FROBENIUS NORM BETWEEN
SELF ANDCOMPCOV COVARIANCE ESTIMATORS
FITSELFXYNONE
FITS THE GRAPHICALLASSO MODEL TO X
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES DATA FROM WHICH TO COMPUTE THE COVARIANCE ES
TIMATE
YIGNORED
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETPRECISION SELF
GETTER FOR THE PRECISION MATRIX
RETURNS
PRECISION ARRAYLIKE THE PRECISION MATRIX ASSOCIATED TO THE CURRENT COVARIANCE OBJECT
MAHALANOBIS SELFX
COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN OBSERVATIONS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE OBSERVATIONS THE MAHALANOBIS DISTANCES
OF THE WHICH WE COMPUTE OBSERVATIONS ARE ASSUMED TO BE DRAWN FROM THE SAME DISTRIBU
TION THAN THE DATA USED IN FIT
RETURNS
DIST ARRAY SHAPE NSAMPLES SQUARED MAHALANOBIS DISTANCES OF THE OBSERVATIONS
SCORESELFXTEST YNONE
COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
COVARIANCE MATRIX
PARAMETERS
XTEST ARRAYLIKE SHAPE NSAMPLES NFEATURES TEST DATA OF WHICH WE COMPUTE THE
LIKELIHOOD WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF
FEATURES XTEST IS ASSUMED TO BE DRAWN FROM THE SAME DISTRIBUTION THAN THE DATA USED IN
FIT INCLUDING CENTERING
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS

RESFLOAT THE LIKELIHOOD OF THE DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
COVARIANCE MATRIX
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
664SKLEARNCOVARIANCE GRAPHICALLASSOCV
CLASSSKLEARNCOVARIANCE GRAPHICALLASSOCV ALPHAS4 NREFINEMENTS4 CV'WARN'
TOL00001 ENETTOL00001 MAXITER100
MODE'CD' NJOBSNONE VERBOSEFALSE AS
SUMECENTEREDFALSE
SPARSE INVERSE COVARIANCE W CROSSVALIDATED CHOICE OF THE L1 PENALTY
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHAS INTEGER OR LIST POSITIVE FLOAT OPTIONAL IF AN INTEGER IS GIVEN IT FIXES THE NUMBER OF POINTS
ON THE GRIDS OF ALPHA TO BE USED IF A LIST IS GIVEN IT GIVES THE GRID TO BE USED SEE THE NOTES
IN THE CLASS DOCSTRING FOR MORE DETAILS
NREFINEMENTS STRICTLY POSITIVE INTEGER THE NUMBER OF TIMES THE GRID IS REFINED NOT USED IF
EXPLICIT VALUES OF ALPHAS ARE PASSED
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
TOLPOSITIVE FLOAT OPTIONAL THE TOLERANCE TO DECLARE CONVERGENCE IF THE DUAL GAP GOES BELOW
THIS VALUE ITERATIONS ARE STOPPED
ENETTOL POSITIVE FLOAT OPTIONAL THE TOLERANCE FOR THE ELASTIC NET SOLVER USED TO CALCULATE THE
DESCENT DIRECTION THIS PARAMETER CONTROLS THE ACCURACY OF THE SEARCH DIRECTION FOR A GIVEN
COLUMN UPDATE NOT OF THE OVERALL PARAMETER ESTIMATE ONLY USED FOR MODE'CD'
MAXITER INTEGER OPTIONAL MAXIMUM NUMBER OF ITERATIONS

MODE ‘CD’ ‘LARS’ THE LASSO SOLVER TO USE COORDINATE DESCENT OR LARS USE LARS FOR
VERY SPARSE UNDERLYING GRAPHS WHERE NUMBER OF FEATURES IS GREATER THAN NUMBER OF SAMPLES
ELSEWHERE PREFER CD WHICH IS MORE NUMERICALLY STABLE
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF JOBS TO RUN IN PARALLEL NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
VERBOSE BOOLEAN OPTIONAL IF VERBOSE IS TRUE THE OBJECTIVE FUNCTION AND DUALITY GAP ARE PRINTED
AT EACH ITERATION
ASSUMECENTERED BOOLEAN IF TRUE DATA ARE NOT CENTERED BEFORE COMPUTATION USEFUL WHEN
WORKING WITH DATA WHOSE MEAN IS ALMOST BUT NOT EXACTLY ZERO IF FALSE DATA ARE CENTERED
BEFORE COMPUTATION
ATTRIBUTES
LOCATION ARRAYLIKE SHAPE NFEATURES ESTIMATED LOCATION IE THE ESTIMATED MEAN
COVARIANCE NUMPYNDARRAY SHAPE NFEATURES NFEATURES ESTIMATED COVARIANCE MATRIX
PRECISION NUMPYNDARRAY SHAPE NFEATURES NFEATURES ESTIMATED PRECISION MATRIX INVERSE
COVARIANCE
ALPHA FLOAT PENALIZATION PARAMETER SELECTED
CVALPHAS LIST OF FLOAT ALL PENALIZATION PARAMETERS EXPLORED
GRIDSCORES 2D NUMPYNDARRAY NALPHAS NFOLDS LOGLIKELIHOOD SCORE ON LEFTOUT DATA
ACROSS FOLDS
NITER INT NUMBER OF ITERATIONS RUN FOR THE OPTIMAL ALPHA
SEE ALSO
GRAPHICALLASSO GRAPHICALLASSO
NOTES
THE SEARCH FOR THE OPTIMAL PENALIZATION PARAMETER ALPHA IS DONE ON AN ITERATIVELY REFINED GRID FIRST THE CROSS
VALIDATED SCORES ON A GRID ARE COMPUTED THEN A NEW REFINED GRID IS CENTERED AROUND THE MAXIMUM AND SO ON
ONE OF THE CHALLENGES WHICH IS FACED HERE IS THAT THE SOLVERS CAN FAIL TO CONVERGE TO A WELLCONDITIONED ESTIMATE
THE CORRESPONDING VALUES OF ALPHA THEN COME OUT AS MISSING VALUES BUT THE OPTIMUM MAY BE CLOSE TO THESE
MISSING VALUES
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNCOVARIANCE IMPORT GRAPHICALLASSOCV
TRUECOV  NPARRAY08 00 02 00
 00 04 00 00
 02 00 03 01
 00 00 01 07
NPRANDOMSEED0
X  NPRANDOMMULTIVARIATENORMALMEAN0 0 0 0
 COVTRUECOV
 SIZE200
COV  GRAPHICALLASSOCVCV5FITX
```

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NPAROUNDCOVCOVARIANCE DECIMALS3
ARRAY0816 0051 022 0017
0051 0364 0018 0036
022 0018 0322 0094
0017 0036 0094 069
NPAROUNDCOVLOCATION DECIMALS3
ARRAY0073 004 0038 0143
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ERRORNORM SELF COMPCOV NORM SCALING COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARI
ANCE ESTIMATORS
FITSELF X Y FITS THE GRAPHICALLASSO COVARIANCE MODEL TO X
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SELFCOVARIANCE AS AN ESTIMATOR OF ITS COVARI
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SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHAS4 NREFINEMENTS4 CV'WARN' TOL00001 ENETTOL00001 MAXITER100
MODE'CD' NJOBSNONE VERBOSEFALSE ASSUMECENTEREDFALSE
ERRORNORM SELFCOMPCOV NORM'FROBENIUS' SCALINGTRUE SQUAREDTRUE
COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARIANCE ESTIMATORS IN THE SENSE OF THE FROBENIUS
NORM
PARAMETERS
COMPCOV ARRAYLIKE SHAPE NFEATURES NFEATURES THE COVARIANCE TO COMPARE WITH
NORM STR THE TYPE OF NORM USED TO COMPUTE THE ERROR AVAILABLE ERROR TYPES 'FROBENIUS'
DEFAULT SQRTTRATA 'SPECTRAL' SQRTMAXEIGENVALUESATA WHERE A IS THE ERROR
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SQUARED BOOL WHETHER TO COMPUTE THE SQUARED ERROR NORM OR THE ERROR NORM IF TRUE
DEFAULT THE SQUARED ERROR NORM IS RETURNED IF FALSE THE ERROR NORM IS RETURNED
RETURNS
THE MEAN SQUARED ERROR IN THE SENSE OF THE FROBENIUS NORM BETWEEN
SELF ANDCOMPCOV COVARIANCE ESTIMATORS
FITSELFXYNONE
FITS THE GRAPHICALLASSO COVARIANCE MODEL TO X
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES DATA FROM WHICH TO COMPUTE THE COVARIANCE ES
TIMATE
YIGNORED

GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETPRECISION SELF
GETTER FOR THE PRECISION MATRIX
RETURNS
PRECISION ARRAYLIKE THE PRECISION MATRIX ASSOCIATED TO THE CURRENT COVARIANCE OBJECT
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COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN OBSERVATIONS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE OBSERVATIONS THE MAHALANOBIS DISTANCES
OF THE WHICH WE COMPUTE OBSERVATIONS ARE ASSUMED TO BE DRAWN FROM THE SAME DISTRIBU
TION THAN THE DATA USED IN FIT
RETURNS
DIST ARRAY SHAPE NSAMPLES SQUARED MAHALANOBIS DISTANCES OF THE OBSERVATIONS
SCORESELFXTEST YNONE
COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
COVARIANCE MATRIX
PARAMETERS
XTEST ARRAYLIKE SHAPE NSAMPLES NFEATURES TEST DATA OF WHICH WE COMPUTE THE
LIKELIHOOD WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF
FEATURES XTEST IS ASSUMED TO BE DRAWN FROM THE SAME DISTRIBUTION THAN THE DATA USED IN
FIT INCLUDING CENTERING
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS
RESFLOAT THE LIKELIHOOD OF THE DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNCOVARIANCEGRAPHICALLASSOCV
•VISUALIZING THE STOCK MARKET STRUCTURE

•SPARSE INVERSE COVARIANCE ESTIMATION
665SKLEARNCOVARIANCE LEDOITWOLF
CLASSSKLEARNCOVARIANCE LEDOITWOLF STOREPRECISIONTRUE ASSUMECENTEREDFALSE
BLOCKSIZE1000
LEDOITWOLF ESTIMATOR
LEDOITWOLF IS A PARTICULAR FORM OF SHRINKAGE WHERE THE SHRINKAGE COEFFICIENT IS COMPUTED USING O LEDOIT AND
M WOLF'S FORMULA AS DESCRIBED IN "A WELLCONDITIONED ESTIMATOR FOR LARGEDIMENSIONAL COVARIANCE MATRICES"
LEDOIT AND WOLF JOURNAL OF MULTIVARIATE ANALYSIS V OLUME 88 ISSUE 2 FEBRUARY 2004 PAGES 365411
READ MORE IN THE USER GUIDE
PARAMETERS
STOREPRECISION BOOL DEFAULTTRUE SPECIFY IF THE ESTIMATED PRECISION IS STORED
ASSUMECENTERED BOOL DEFAULTFALSE IF TRUE DATA WILL NOT BE CENTERED BEFORE COMPUTATION
USEFUL WHEN WORKING WITH DATA WHOSE MEAN IS ALMOST BUT NOT EXACTLY ZERO IF FALSE DE
FAULT DATA WILL BE CENTERED BEFORE COMPUTATION
BLOCKSIZE INT DEFAULT1000 SIZE OF THE BLOCKS INTO WHICH THE COVARIANCE MATRIX WILL BE SPLIT
DURING ITS LEDOITWOLF ESTIMATION THIS IS PURELY A MEMORY OPTIMIZATION AND DOES NOT AFFECT
RESULTS
ATTRIBUTES
LOCATION ARRAYLIKE SHAPE NFEATURES ESTIMATED LOCATION IE THE ESTIMATED MEAN
COVARIANCE ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED COVARIANCE MATRIX
PRECISION ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED PSEUDO INVERSE MATRIX STORED
ONLY IF STOREPRECISION IS TRUE
SHRINKAGE FLOAT 0 SHRINKAGE 1 COEFFICIENT IN THE CONVEX COMBINATION USED FOR THE
COMPUTATION OF THE SHRUNK ESTIMATE
NOTES
THE REGULARISED COVARIANCE IS
1 SHRINKAGE COV SHRINKAGE MU NPIDENTITYNFEATURES
WHERE MU TRACECOV NFEATURES AND SHRINKAGE IS GIVEN BY THE LEDOIT AND WOLF FORMULA SEE REFERENCES
REFERENCES
"A WELLCONDITIONED ESTIMATOR FOR LARGEDIMENSIONAL COVARIANCE MATRICES" LEDOIT AND WOLF JOURNAL OF MUL
TIVARIATE ANALYSIS V OLUME 88 ISSUE 2 FEBRUARY 2004 PAGES 365411
EXAMPLES
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 IMPORT NUMPY AS NP
 FROM SKLEARNCOVARIANCE IMPORT LEDOITWOLF
REALCOV  NPARRAY4 2
 2 8
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NPRANDOMSEED0
X NPRANDOMMULTIVARIATENORMALMEAN0 0
 COVREALCOV
 SIZE50
COV LEDOITWOLFFITX
COVCOVARIANCE
ARRAY04406 01616
01616 08022
COVLOCATION
ARRAY 00595 00075
METHODS
ERRORNORM SELF COMPCOV NORM SCALING   COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARI
ANCE ESTIMATORS
FITSELF X Y FITS THE LEDOITWOLF SHRUNK COVARIANCE MODEL ACCORD
ING TO THE GIVEN TRAINING DATA AND PARAMETERS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETPRECISION SELF GETTER FOR THE PRECISION MATRIX
MAHALANOBIS SELF X COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN
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SCORE SELF XTEST Y COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH
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ANCE MATRIX
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
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ERRORNORM SELFCOMPCOV NORM'FROBENIUS' SCALINGTRUE SQUAREDTRUE
COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARIANCE ESTIMATORS IN THE SENSE OF THE FROBENIUS
NORM
PARAMETERS
COMPCOV ARRAYLIKE SHAPE NFEATURES NFEATURES THE COVARIANCE TO COMPARE WITH
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RETURNS
THE MEAN SQUARED ERROR IN THE SENSE OF THE FROBENIUS NORM BETWEEN
SELF ANDCOMPCOV COVARIANCE ESTIMATORS
FITSELFXYNONE
FITS THE LEDOITWOLF SHRUNK COVARIANCE MODEL ACCORDING TO THE GIVEN TRAINING DATA AND PARAMETERS
PARAMETERS

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XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
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PARAMETERS
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OF THE WHICH WE COMPUTE OBSERVATIONS ARE ASSUMED TO BE DRAWN FROM THE SAME DISTRIBU
TION THAN THE DATA USED IN FIT
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LIKELIHOOD WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF
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FIT INCLUDING CENTERING
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS
RESFLOAT THE LIKELIHOOD OF THE DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
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THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT

RETURNS
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EXAMPLES USING SKLEARNCOVARIANCELEDOITWOLF
•LEDOITWOLF VS OAS ESTIMATION
•SHRINKAGE COVARIANCE ESTIMATION LEDOITWOLF VS OAS AND MAXLIKELIHOOD
•MODEL SELECTION WITH PROBABILISTIC PCA AND FACTOR ANALYSIS FA
666SKLEARNCOVARIANCE MINCOVDET
CLASSSKLEARNCOVARIANCE MINCOVDET STOREPRECISIONTRUE ASSUMECENTEREDFALSE SUP
PORTFRACTIONNONE RANDOMSTATENONE
MINIMUM COVARIANCE DETERMINANT MCD ROBUST ESTIMATOR OF COVARIANCE
THE MINIMUM COVARIANCE DETERMINANT COVARIANCE ESTIMATOR IS TO BE APPLIED ON GAUSSIANDISTRIBUTED DATA BUT
COULD STILL BE RELEVANT ON DATA DRAWN FROM A UNIMODAL SYMMETRIC DISTRIBUTION IT IS NOT MEANT TO BE USED WITH
MULTIMODAL DATA THE ALGORITHM USED TO FIT A MINCOVDET OBJECT IS LIKELY TO FAIL IN SUCH A CASE ONE SHOULD
CONSIDER PROJECTION PURSUIT METHODS TO DEAL WITH MULTIMODAL DATASETS
READ MORE IN THE USER GUIDE
PARAMETERS
STOREPRECISION BOOL SPECIFY IF THE ESTIMATED PRECISION IS STORED
ASSUMECENTERED BOOL IF TRUE THE SUPPORT OF THE ROBUST LOCATION AND THE COVARIANCE ESTIMATES
IS COMPUTED AND A COVARIANCE ESTIMATE IS RECOMPUTED FROM IT WITHOUT CENTERING THE DATA
USEFUL TO WORK WITH DATA WHOSE MEAN IS SIGNIFICANTLY EQUAL TO ZERO BUT IS NOT EXACTLY ZERO IF
FALSE THE ROBUST LOCATION AND COVARIANCE ARE DIRECTLY COMPUTED WITH THE FASTMCD ALGORITHM
WITHOUT ADDITIONAL TREATMENT
SUPPORTFRACTION FLOAT 0 SUPPORTFRACTION 1 THE PROPORTION OF POINTS TO BE INCLUDED IN
THE SUPPORT OF THE RAW MCD ESTIMATE DEFAULT IS NONE WHICH IMPLIES THAT THE MINIMUM
VALUE OF SUPPORTFRACTION WILL BE USED WITHIN THE ALGORITHM NSAMPLE NFEATURES 1 2
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES
RAWLOCATION ARRAYLIKE SHAPE NFEATURES THE RAW ROBUST ESTIMATED LOCATION BEFORE COR
RECTION AND REWEIGHTING
RAWCOVARIANCE ARRAYLIKE SHAPE NFEATURES NFEATURES THE RAW ROBUST ESTIMATED COVARI
ANCE BEFORE CORRECTION AND REWEIGHTING
RAWSUPPORT ARRAYLIKE SHAPE NSAMPLES A MASK OF THE OBSERVATIONS THAT HAVE BEEN
USED TO COMPUTE THE RAW ROBUST ESTIMATES OF LOCATION AND SHAPE BEFORE CORRECTION AND RE
WEIGHTING
LOCATION ARRAYLIKE SHAPE NFEATURES ESTIMATED ROBUST LOCATION
COVARIANCE ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED ROBUST COVARIANCE MATRIX

PRECISION ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED PSEUDO INVERSE MATRIX STORED
ONLY IF STOREPRECISION IS TRUE
SUPPORT ARRAYLIKE SHAPE NSAMPLES A MASK OF THE OBSERVATIONS THAT HAVE BEEN USED TO
COMPUTE THE ROBUST ESTIMATES OF LOCATION AND SHAPE
DIST ARRAYLIKE SHAPE NSAMPLES MAHALANOBIS DISTANCES OF THE TRAINING SET ON WHICH FIT
IS CALLED OBSERVATIONS
REFERENCES
R9F63E655F7BDROUSEEUW1984 R9F63E655F7BDROUSSEEUW R9F63E655F7BDBUTLERDAVIES
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNCOVARIANCE IMPORT MINCOVDET
 FROM SKLEARNDATASETS IMPORT MAKEGAUSSIANQUANTILES
REALCOV  NPARRAY8 3
 3 4
RNG  NPRANDOMRANDOMSTATE0
X  RNGMULTIVARIATENORMALMEAN0 0
 COVREALCOV
 SIZE500
COV  MINCOVDETRANDOMSTATE0FITX
COVCOVARIANCE
ARRAY07411 02535
02535 03053
COVLOCATION
ARRAY00813  00427
```
METHODS
CORRECTCOVARIANCE SELF DATA APPLY A CORRECTION TO RAW MINIMUM COVARIANCE DETER
MINANT ESTIMATES
ERRORNORM SELF COMPCOV NORM SCALING   COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARI
ANCE ESTIMATORS
FITSELF X Y FITS A MINIMUM COVARIANCE DETERMINANT WITH THE
FASTMCD ALGORITHM
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETPRECISION SELF GETTER FOR THE PRECISION MATRIX
MAHALANOBIS SELF X COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN
OBSERVATIONS
REWEIGHTCOVARIANCE SELF DATA REWEIGHT RAW MINIMUM COVARIANCE DETERMINANT ESTI
MATES
SCORE SELF XTEST Y COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH
SELFCOVARIANCE AS AN ESTIMATOR OF ITS COVARI
ANCE MATRIX
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

INIT SELFSTOREPRECISIONTRUE ASSUMECENTEREDFALSE SUPPORTFRACTIONNONE RAN
DOMSTATENONE
CORRECTCOVARIANCE SELFDATA
APPLY A CORRECTION TO RAW MINIMUM COVARIANCE DETERMINANT ESTIMATES
CORRECTION USING THE EMPIRICAL CORRECTION FACTOR SUGGESTED BY ROUSSEEUW AND VAN DRIESSEN IN RVD
PARAMETERS
DATA ARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA MATRIX WITH P FEATURES AND N SAM
PLES THE DATA SET MUST BE THE ONE WHICH WAS USED TO COMPUTE THE RAW ESTIMATES
RETURNS
COVARIANCECORRECTED ARRAYLIKE SHAPE NFEATURES NFEATURES CORRECTED ROBUST COVARI
ANCE ESTIMATE
REFERENCES
RVD
ERRORNORM SELFCOMPCOV NORM'FROBENIUS' SCALINGTRUE SQUAREDTRUE
COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARIANCE ESTIMATORS IN THE SENSE OF THE FROBENIUS
NORM
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COMPCOV ARRAYLIKE SHAPE NFEATURES NFEATURES THE COVARIANCE TO COMPARE WITH
NORM STR THE TYPE OF NORM USED TO COMPUTE THE ERROR AVAILABLE ERROR TYPES 'FROBENIUS'
DEFAULT SQRTTRATA 'SPECTRAL' SQRTMAXEIGENVALUESATA WHERE A IS THE ERROR
COMPCOV SELFCOVARIANCE
SCALING BOOL IF TRUE DEFAULT THE SQUARED ERROR NORM IS DIVIDED BY NFEATURES IF FALSE
THE SQUARED ERROR NORM IS NOT RESCALED
SQUARED BOOL WHETHER TO COMPUTE THE SQUARED ERROR NORM OR THE ERROR NORM IF TRUE
DEFAULT THE SQUARED ERROR NORM IS RETURNED IF FALSE THE ERROR NORM IS RETURNED
RETURNS
THE MEAN SQUARED ERROR IN THE SENSE OF THE FROBENIUS NORM BETWEEN
SELF ANDCOMPCOV COVARIANCE ESTIMATORS
FITSELFXYNONE
FITS A MINIMUM COVARIANCE DETERMINANT WITH THE FASTMCD ALGORITHM
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

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DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETPRECISION SELF
GETTER FOR THE PRECISION MATRIX
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PRECISION ARRAYLIKE THE PRECISION MATRIX ASSOCIATED TO THE CURRENT COVARIANCE OBJECT
MAHALANOBIS SELFX
COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN OBSERVATIONS
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XARRAYLIKE SHAPE NSAMPLES NFEATURES THE OBSERVATIONS THE MAHALANOBIS DISTANCES
OF THE WHICH WE COMPUTE OBSERVATIONS ARE ASSUMED TO BE DRAWN FROM THE SAME DISTRIBU
TION THAN THE DATA USED IN FIT
RETURNS
DIST ARRAY SHAPE NSAMPLES SQUARED MAHALANOBIS DISTANCES OF THE OBSERVATIONS
REWEIGHTCOVARIANCE SELFDATA
REWEIGHT RAW MINIMUM COVARIANCE DETERMINANT ESTIMATES
REWEIGHT OBSERVATIONS USING ROUSSEEUW'S METHOD EQUIVALENT TO DELETING OUTLYING OBSERVATIONS FROM THE
DATA SET BEFORE COMPUTING LOCATION AND COVARIANCE ESTIMATES DESCRIBED IN RVDRIESSEN
PARAMETERS
DATA ARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA MATRIX WITH P FEATURES AND N SAM
PLES THE DATA SET MUST BE THE ONE WHICH WAS USED TO COMPUTE THE RAW ESTIMATES
RETURNS
LOCATIONREWEIGHTED ARRAYLIKE SHAPE NFEATURES REWEIGHTED ROBUST LOCATION ESTI
MATE
COVARIANCEREWEIGHTED ARRAYLIKE SHAPE NFEATURES NFEATURES REWEIGHTED ROBUST CO
VARIANCE ESTIMATE
SUPPORTREWEIGHTED ARRAYLIKE TYPE BOOLEAN SHAPE NSAMPLES A MASK OF THE OBSER
VATIONS THAT HAVE BEEN USED TO COMPUTE THE REWEIGHTED ROBUST LOCATION AND COVARIANCE
ESTIMATES
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SCORESELFXTEST YNONE
COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
COVARIANCE MATRIX
PARAMETERS
XTEST ARRAYLIKE SHAPE NSAMPLES NFEATURES TEST DATA OF WHICH WE COMPUTE THE
LIKELIHOOD WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF

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FEATURES XTEST IS ASSUMED TO BE DRAWN FROM THE SAME DISTRIBUTION THAN THE DATA USED IN
FIT INCLUDING CENTERING
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS
RESFLOAT THE LIKELIHOOD OF THE DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNCOVARIANCEMINCOVDET
•ROBUST COVARIANCE ESTIMATION AND MAHALANOBIS DISTANCES RELEVANCE
•ROBUST VS EMPIRICAL COVARIANCE ESTIMATE
667SKLEARNCOVARIANCE OAS
CLASSSKLEARNCOVARIANCE OASSTOREPRECISIONTRUE ASSUMECENTEREDFALSE
ORACLE APPROXIMATING SHRINKAGE ESTIMATOR
READ MORE IN THE USER GUIDE
OAS IS A PARTICULAR FORM OF SHRINKAGE DESCRIBED IN "SHRINKAGE ALGORITHMS FOR MMSE COVARIANCE ESTIMATION"
CHEN ET AL IEEE TRANS ON SIGN PROC V OLUME 58 ISSUE 10 OCTOBER 2010
THE FORMULA USED HERE DOES NOT CORRESPOND TO THE ONE GIVEN IN THE ARTICLE IN THE ORIGINAL ARTICLE FORMULA 23
STATES THAT 2P IS MULTIPLIED BY TRACECOVCOV IN BOTH THE NUMERATOR AND DENOMINATOR BUT THIS OPERATION IS
OMITTED BECAUSE FOR A LARGE P THE VALUE OF 2P IS SO SMALL THAT IT DOESN'T AFFECT THE VALUE OF THE ESTIMATOR
PARAMETERS
STOREPRECISION BOOL DEFAULTTRUE SPECIFY IF THE ESTIMATED PRECISION IS STORED
ASSUMECENTERED BOOL DEFAULTFALSE IF TRUE DATA WILL NOT BE CENTERED BEFORE COMPUTATION
USEFUL WHEN WORKING WITH DATA WHOSE MEAN IS ALMOST BUT NOT EXACTLY ZERO IF FALSE DE
FAULT DATA WILL BE CENTERED BEFORE COMPUTATION
ATTRIBUTES
COVARIANCE ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED COVARIANCE MATRIX
PRECISION ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED PSEUDO INVERSE MATRIX STORED
ONLY IF STOREPRECISION IS TRUE
SHRINKAGE FLOAT 0 SHRINKAGE 1 COEFFICIENT IN THE CONVEX COMBINATION USED FOR THE
COMPUTATION OF THE SHRUNK ESTIMATE

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THE REGULARISED COVARIANCE IS
1 SHRINKAGE COV SHRINKAGE MU NPIDENTITYNFEATURES
WHERE MU TRACECOV NFEATURES AND SHRINKAGE IS GIVEN BY THE OAS FORMULA SEE REFERENCES
REFERENCES
“SHRINKAGE ALGORITHMS FOR MMSE COVARIANCE ESTIMATION” CHEN ET AL IEEE TRANS ON SIGN PROC V OLUME 58
ISSUE 10 OCTOBER 2010
METHODS
ERRORNORM SELF COMPCOV NORM SCALING COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARI
ANCE ESTIMATORS
FITSELF X Y FITS THE ORACLE APPROXIMATING SHRINKAGE COVARIANCE
MODEL ACCORDING TO THE GIVEN TRAINING DATA AND PARAME
TERS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETPRECISION SELF GETTER FOR THE PRECISION MATRIX
MAHALANOBIS SELF X COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN
OBSERVATIONS
SCORE SELF XTEST Y COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH
SELFCOVARIANCE AS AN ESTIMATOR OF ITS COVARI
ANCE MATRIX
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFSTOREPRECISIONTRUE ASSUMECENTEREDFALSE
ERRORNORM SELFCOMPCOV NORM’FROBENIUS’ SCALINGTRUE SQUAREDTRUE
COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARIANCE ESTIMATORS IN THE SENSE OF THE FROBENIUS
NORM
PARAMETERS
COMPCOV ARRAYLIKE SHAPE NFEATURES NFEATURES THE COVARIANCE TO COMPARE WITH
NORM STR THE TYPE OF NORM USED TO COMPUTE THE ERROR AVAILABLE ERROR TYPES ‘FROBENIUS’
DEFAULT SQRTTRATA ‘SPECTRAL’ SQRTMAXEIGENVALUESATA WHERE A IS THE ERROR
COMPCOV SELFCOVARIANCE
SCALING BOOL IF TRUE DEFAULT THE SQUARED ERROR NORM IS DIVIDED BY NFEATURES IF FALSE
THE SQUARED ERROR NORM IS NOT RESCALED
SQUARED BOOL WHETHER TO COMPUTE THE SQUARED ERROR NORM OR THE ERROR NORM IF TRUE
DEFAULT THE SQUARED ERROR NORM IS RETURNED IF FALSE THE ERROR NORM IS RETURNED
RETURNS
THE MEAN SQUARED ERROR IN THE SENSE OF THE FROBENIUS NORM BETWEEN
SELF ANDCOMPCOV COVARIANCE ESTIMATORS

FITSELFXYNONE
FITS THE ORACLE APPROXIMATING SHRINKAGE COVARIANCE MODEL ACCORDING TO THE GIVEN TRAINING DATA AND PA
RAMETERS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETPRECISION SELF
GETTER FOR THE PRECISION MATRIX
RETURNS
PRECISION ARRAYLIKE THE PRECISION MATRIX ASSOCIATED TO THE CURRENT COVARIANCE OBJECT
MAHALANOBIS SELFX
COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN OBSERVATIONS
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XARRAYLIKE SHAPE NSAMPLES NFEATURES THE OBSERVATIONS THE MAHALANOBIS DISTANCES
OF THE WHICH WE COMPUTE OBSERVATIONS ARE ASSUMED TO BE DRAWN FROM THE SAME DISTRIBU
TION THAN THE DATA USED IN FIT
RETURNS
DIST ARRAY SHAPE NSAMPLES SQUARED MAHALANOBIS DISTANCES OF THE OBSERVATIONS
SCORESELFXTEST YNONE
COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
COVARIANCE MATRIX
PARAMETERS
XTEST ARRAYLIKE SHAPE NSAMPLES NFEATURES TEST DATA OF WHICH WE COMPUTE THE
LIKELIHOOD WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF
FEATURES XTEST IS ASSUMED TO BE DRAWN FROM THE SAME DISTRIBUTION THAN THE DATA USED IN
FIT INCLUDING CENTERING
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS
RESFLOAT THE LIKELIHOOD OF THE DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
COVARIANCE MATRIX

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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNCOVARIANCEOAS
•LEDOITWOLF VS OAS ESTIMATION
•SHRINKAGE COVARIANCE ESTIMATION LEDOITWOLF VS OAS AND MAXLIKELIHOOD
668SKLEARNCOVARIANCE SHRUNKCOVARIANCE
CLASSSKLEARNCOVARIANCE SHRUNKCOVARIANCE STOREPRECISIONTRUE ASSUMECENTEREDFALSE
SHRINKAGE01
COVARIANCE ESTIMATOR WITH SHRINKAGE
READ MORE IN THE USER GUIDE
PARAMETERS
STOREPRECISION BOOLEAN DEFAULT TRUE SPECIFY IF THE ESTIMATED PRECISION IS STORED
ASSUMECENTERED BOOLEAN DEFAULT FALSE IF TRUE DATA WILL NOT BE CENTERED BEFORE COMPUTA
TION USEFUL WHEN WORKING WITH DATA WHOSE MEAN IS ALMOST BUT NOT EXACTLY ZERO IF FALSE
DATA WILL BE CENTERED BEFORE COMPUTATION
SHRINKAGE FLOAT 0 SHRINKAGE 1 DEFAULT 01 COEFFICIENT IN THE CONVEX COMBINATION USED
FOR THE COMPUTATION OF THE SHRUNK ESTIMATE
ATTRIBUTES
LOCATION ARRAYLIKE SHAPE NFEATURES ESTIMATED LOCATION IE THE ESTIMATED MEAN
COVARIANCE ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED COVARIANCE MATRIX
PRECISION ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED PSEUDO INVERSE MATRIX STORED
ONLY IF STOREPRECISION IS TRUE
SHRINKAGE FLOAT 0 SHRINKAGE 1 COEFFICIENT IN THE CONVEX COMBINATION USED FOR THE
COMPUTATION OF THE SHRUNK ESTIMATE
NOTES
THE REGULARIZED COVARIANCE IS GIVEN BY
1 SHRINKAGE COV SHRINKAGE MU NPIDENTITYNFEATURES
WHERE MU TRACECOV NFEATURES

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EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNCOVARIANCE IMPORT SHRUNKCOVARIANCE
 FROM SKLEARNDATASETS IMPORT MAKEGAUSSIANQUANTILES
REALCOV  NPARRAY8 3
 3 4
RNG  NPRANDOMRANDOMSTATE0
X  RNGMULTIVARIATENORMALMEAN0 0
 COVREALCOV
 SIZE500
COV  SHRUNKCOVARIANCEFITX
COVCOVARIANCE
ARRAY07387 02536
02536 04110
COVLOCATION
ARRAY00622 00193
```
METHODS
ERRORNORM SELF COMPCOV NORM SCALING COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARI
ANCE ESTIMATORS
FITSELF X Y FITS THE SHRUNK COVARIANCE MODEL ACCORDING TO THE GIVEN
TRAINING DATA AND PARAMETERS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETPRECISION SELF GETTER FOR THE PRECISION MATRIX
MAHALANOBIS SELF X COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN
OBSERVATIONS
SCORE SELF XTEST Y COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH
SELFCOVARIANCE AS AN ESTIMATOR OF ITS COVARI
ANCE MATRIX
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFSTOREPRECISIONTRUE ASSUMECENTEREDFALSE SHRINKAGE01
ERRORNORM SELFCOMPCOV NORM'FROBENIUS' SCALINGTRUE SQUAREDTRUE
COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARIANCE ESTIMATORS IN THE SENSE OF THE FROBENIUS
NORM
PARAMETERS
COMPCOV ARRAYLIKE SHAPE NFEATURES NFEATURES THE COVARIANCE TO COMPARE WITH
NORM STR THE TYPE OF NORM USED TO COMPUTE THE ERROR AVAILABLE ERROR TYPES 'FROBENIUS'
DEFAULT SQRTTRATA 'SPECTRAL' SQRTMAXEIGENVALUESATA WHERE A IS THE ERROR
COMPCOV SELFCOVARIANCE
SCALING BOOL IF TRUE DEFAULT THE SQUARED ERROR NORM IS DIVIDED BY NFEATURES IF FALSE
THE SQUARED ERROR NORM IS NOT RESCALED
SQUARED BOOL WHETHER TO COMPUTE THE SQUARED ERROR NORM OR THE ERROR NORM IF TRUE
DEFAULT THE SQUARED ERROR NORM IS RETURNED IF FALSE THE ERROR NORM IS RETURNED
RETURNS
THE MEAN SQUARED ERROR IN THE SENSE OF THE FROBENIUS NORM BETWEEN

SELF ANDCOMPCOV COVARIANCE ESTIMATORS
FITSELFXYNONE
FITS THE SHRUNK COVARIANCE MODEL ACCORDING TO THE GIVEN TRAINING DATA AND PARAMETERS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
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PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
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XARRAYLIKE SHAPE NSAMPLES NFEATURES THE OBSERVATIONS THE MAHALANOBIS DISTANCES
OF THE WHICH WE COMPUTE OBSERVATIONS ARE ASSUMED TO BE DRAWN FROM THE SAME DISTRIBU
TION THAN THE DATA USED IN FIT
RETURNS
DIST ARRAY SHAPE NSAMPLES SQUARED MAHALANOBIS DISTANCES OF THE OBSERVATIONS
SCORESELFXTEST YNONE
COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
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PARAMETERS
XTEST ARRAYLIKE SHAPE NSAMPLES NFEATURES TEST DATA OF WHICH WE COMPUTE THE
LIKELIHOOD WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF
FEATURES XTEST IS ASSUMED TO BE DRAWN FROM THE SAME DISTRIBUTION THAN THE DATA USED IN
FIT INCLUDING CENTERING
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
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•SHRINKAGE COVARIANCE ESTIMATION LEDOITWOLF VS OAS AND MAXLIKELIHOOD
•MODEL SELECTION WITH PROBABILISTIC PCA AND FACTOR ANALYSIS FA
COVARIANCEEMPIRICALCOVARIANCE X COMPUTES THE MAXIMUM LIKELIHOOD COVARIANCE ESTIMATOR
COVARIANCEGRAPHICALLASSO EMPCOV ALPHA
L1PENALIZED COVARIANCE ESTIMATOR
COVARIANCELEDOITWOLF X ASSUMECENTERED
ESTIMATES THE SHRUNK LEDOITWOLF COVARIANCE MATRIX
COVARIANCEOAS X ASSUMECENTERED ESTIMATE COVARIANCE WITH THE ORACLE APPROXIMATING
SHRINKAGE ALGORITHM
COVARIANCESHRUNKCOVARIANCE EMPCOV CALCULATES A COVARIANCE MATRIX SHRUNK ON THE DIAGONAL
669SKLEARNCOVARIANCE EMPIRICALCOVARIANCE
SKLEARNCOVARIANCE EMPIRICALCOVARIANCE XASSUMECENTEREDFALSE
COMPUTES THE MAXIMUM LIKELIHOOD COVARIANCE ESTIMATOR
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES DATA FROM WHICH TO COMPUTE THE COVARIANCE ESTIMATE
ASSUMECENTERED BOOLEAN IF TRUE DATA WILL NOT BE CENTERED BEFORE COMPUTATION USEFUL WHEN
WORKING WITH DATA WHOSE MEAN IS ALMOST BUT NOT EXACTLY ZERO IF FALSE DATA WILL BE CENTERED
BEFORE COMPUTATION
RETURNS
COVARIANCE 2D NDARRAY SHAPE NFEATURES NFEATURES EMPIRICAL COVARIANCE MAXIMUM LIKE
LIHOOD ESTIMATOR
EXAMPLES USING SKLEARNCOVARIANCEEMPIRICALCOVARIANCE
•SHRINKAGE COVARIANCE ESTIMATION LEDOITWOLF VS OAS AND MAXLIKELIHOOD
6610SKLEARNCOVARIANCE GRAPHICALLASSO
SKLEARNCOVARIANCE GRAPHICALLASSO EMPCOV ALPHA COVINITNONE MODE'CD' TOL00001
ENETTOL00001 MAXITER100 VERBOSEFALSE RE
TURNCOSTSFALSE EPS2220446049250313E16 RE
TURNNITERFALSE
L1PENALIZED COVARIANCE ESTIMATOR

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READ MORE IN THE USER GUIDE
PARAMETERS
EMPCOV 2D NDARRAY SHAPE NFEATURES NFEATURES EMPIRICAL COVARIANCE FROM WHICH TO
COMPUTE THE COVARIANCE ESTIMATE
ALPHA POSITIVE FLOAT THE REGULARIZATION PARAMETER THE HIGHER ALPHA THE MORE REGULARIZATION
THE SPARSER THE INVERSE COVARIANCE
COVINIT 2D ARRAY NFEATURES NFEATURES OPTIONAL THE INITIAL GUESS FOR THE COVARIANCE
MODE ‘CD’ ‘LARS’ THE LASSO SOLVER TO USE COORDINATE DESCENT OR LARS USE LARS FOR
VERY SPARSE UNDERLYING GRAPHS WHERE P N ELSEWHERE PREFER CD WHICH IS MORE NUMERICALLY
STABLE
TOLPOSITIVE FLOAT OPTIONAL THE TOLERANCE TO DECLARE CONVERGENCE IF THE DUAL GAP GOES BELOW
THIS VALUE ITERATIONS ARE STOPPED
ENETTOL POSITIVE FLOAT OPTIONAL THE TOLERANCE FOR THE ELASTIC NET SOLVER USED TO CALCULATE THE
DESCENT DIRECTION THIS PARAMETER CONTROLS THE ACCURACY OF THE SEARCH DIRECTION FOR A GIVEN
COLUMN UPDATE NOT OF THE OVERALL PARAMETER ESTIMATE ONLY USED FOR MODE’CD’
MAXITER INTEGER OPTIONAL THE MAXIMUM NUMBER OF ITERATIONS
VERBOSE BOOLEAN OPTIONAL IF VERBOSE IS TRUE THE OBJECTIVE FUNCTION AND DUAL GAP ARE PRINTED
AT EACH ITERATION
RETURNCOSTS BOOLEAN OPTIONAL IF RETURNCOSTS IS TRUE THE OBJECTIVE FUNCTION AND DUAL GAP AT
EACH ITERATION ARE RETURNED
EPS FLOAT OPTIONAL THE MACHINEPRECISION REGULARIZATION IN THE COMPUTATION OF THE CHOLESKY
DIAGONAL FACTORS INCREASE THIS FOR VERY ILLCONDITIONED SYSTEMS
RETURNNITER BOOL OPTIONAL WHETHER OR NOT TO RETURN THE NUMBER OF ITERATIONS
RETURNS
COVARIANCE 2D NDARRAY SHAPE NFEATURES NFEATURES THE ESTIMATED COVARIANCE MATRIX
PRECISION 2D NDARRAY SHAPE NFEATURES NFEATURES THE ESTIMATED SPARSE PRECISION MATRIX
COSTS LIST OF OBJECTIVE DUALGAP PAIRS THE LIST OF VALUES OF THE OBJECTIVE FUNCTION AND THE DUAL
GAP AT EACH ITERATION RETURNED ONLY IF RETURNCOSTS IS TRUE
NITER INT NUMBER OF ITERATIONS RETURNED ONLY IF RETURNNITER IS SET TO TRUE
SEE ALSO
GRAPHICALLASSO GRAPHICALLASSOCV
NOTES
THE ALGORITHM EMPLOYED TO SOLVE THIS PROBLEM IS THE GLASSO ALGORITHM FROM THE FRIEDMAN 2008 BIOSTATISTICS
PAPER IT IS THE SAME ALGORITHM AS IN THE R GLASSO PACKAGE
ONE POSSIBLE DIFFERENCE WITH THE GLASSO R PACKAGE IS THAT THE DIAGONAL COEFFICIENTS ARE NOT PENALIZED

6611SKLEARNCOVARIANCE LEDOITWOLF
SKLEARNCOVARIANCE LEDOITWOLF XASSUMECENTEREDFALSE BLOCKSIZE1000
ESTIMATES THE SHRUNK LEDOITWOLF COVARIANCE MATRIX
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES DATA FROM WHICH TO COMPUTE THE COVARIANCE ESTI
MATE
ASSUMECENTERED BOOLEAN DEFAULTFALSE IF TRUE DATA WILL NOT BE CENTERED BEFORE COMPUTA
TION USEFUL TO WORK WITH DATA WHOSE MEAN IS SIGNIFICANTLY EQUAL TO ZERO BUT IS NOT EXACTLY
ZERO IF FALSE DATA WILL BE CENTERED BEFORE COMPUTATION
BLOCKSIZE INT DEFAULT1000 SIZE OF THE BLOCKS INTO WHICH THE COVARIANCE MATRIX WILL BE SPLIT
THIS IS PURELY A MEMORY OPTIMIZATION AND DOES NOT AFFECT RESULTS
RETURNS
SHRUNKCOV ARRAYLIKE SHAPE NFEATURES NFEATURES SHRUNK COVARIANCE
SHRINKAGE FLOAT COEFFICIENT IN THE CONVEX COMBINATION USED FOR THE COMPUTATION OF THE SHRUNK
ESTIMATE
NOTES
THE REGULARIZED SHRUNK COVARIANCE IS
1 SHRINKAGE COV SHRINKAGE MU NPIDENTITYNFEATURES
WHERE MU TRACECOV NFEATURES
EXAMPLES USING SKLEARNCOVARIANCELEDOITWOLF
•SPARSE INVERSE COVARIANCE ESTIMATION
6612SKLEARNCOVARIANCE OAS
SKLEARNCOVARIANCE OASXASSUMECENTEREDFALSE
ESTIMATE COVARIANCE WITH THE ORACLE APPROXIMATING SHRINKAGE ALGORITHM
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES DATA FROM WHICH TO COMPUTE THE COVARIANCE ESTI
MATE
ASSUMECENTERED BOOLEAN IF TRUE DATA WILL NOT BE CENTERED BEFORE COMPUTATION USEFUL TO
WORK WITH DATA WHOSE MEAN IS SIGNIFICANTLY EQUAL TO ZERO BUT IS NOT EXACTLY ZERO IF FALSE
DATA WILL BE CENTERED BEFORE COMPUTATION
RETURNS
SHRUNKCOV ARRAYLIKE SHAPE NFEATURES NFEATURES SHRUNK COVARIANCE
SHRINKAGE FLOAT COEFFICIENT IN THE CONVEX COMBINATION USED FOR THE COMPUTATION OF THE SHRUNK
ESTIMATE

NOTES
THE REGULARISED SHRUNK COVARIANCE IS
1 SHRINKAGE COV SHRINKAGE MU NPIDENTITYNFEATURES
WHERE MU TRACECOV NFEATURES
THE FORMULA WE USED TO IMPLEMENT THE OAS IS SLIGHTLY MODIFIED COMPARED TO THE ONE GIVEN IN THE ARTICLE SEE
OAS FOR MORE DETAILS
6613SKLEARNCOVARIANCE SHRUNKCOVARIANCE
SKLEARNCOVARIANCE SHRUNKCOVARIANCE EMPCOV SHRINKAGE01
CALCULATES A COVARIANCE MATRIX SHRUNK ON THE DIAGONAL
READ MORE IN THE USER GUIDE
PARAMETERS
EMPCOV ARRAYLIKE SHAPE NFEATURES NFEATURES COVARIANCE MATRIX TO BE SHRUNK
SHRINKAGE FLOAT 0 SHRINKAGE 1 COEFFICIENT IN THE CONVEX COMBINATION USED FOR THE
COMPUTATION OF THE SHRUNK ESTIMATE
RETURNS
SHRUNKCOV ARRAYLIKE SHRUNK COVARIANCE
NOTES
THE REGULARIZED SHRUNK COVARIANCE IS GIVEN BY
1 SHRINKAGE COV SHRINKAGE MU NPIDENTITYNFEATURES
WHERE MU TRACECOV NFEATURES
67SKLEARNCROSSDECOMPOSITION CROSS DECOMPOSITION
USER GUIDE SEE THE CROSS DECOMPOSITION SECTION FOR FURTHER DETAILS
CROSSDECOMPOSITIONCCA NCOMPONENTS   CCA CANONICAL CORRELATION ANALYSIS
CROSSDECOMPOSITIONPLSCANONICAL   PLSCANONICAL IMPLEMENTS THE 2 BLOCKS CANONICAL PLS OF
THE ORIGINAL WOLD ALGORITHM TENENHAUS 1998 P204 RE
FERRED AS PLSC2A IN WEGELIN 2000
CROSSDECOMPOSITIONPLSREGRESSION   PLS REGRESSION
CROSSDECOMPOSITIONPLSSVD NCOMPONENTS
   PARTIAL LEAST SQUARE SVD
671SKLEARNCROSSDECOMPOSITION CCA
CLASSSKLEARNCROSSDECOMPOSITION CCANCOMPONENTS2 SCALETRUE MAXITER500 TOL1E06
COPYTRUE
CCA CANONICAL CORRELATION ANALYSIS

CCA INHERITS FROM PLS WITH MODE”B” AND DEFLATIONMODE”CANONICAL”
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT DEFAULT 2 NUMBER OF COMPONENTS TO KEEP
SCALE BOOLEAN DEFAULT TRUE WHETHER TO SCALE THE DATA
MAXITER AN INTEGER DEFAULT 500 THE MAXIMUM NUMBER OF ITERATIONS OF THE NIPALS INNER
LOOP
TOLNONNEGATIVE REAL DEFAULT 1E06 THE TOLERANCE USED IN THE ITERATIVE ALGORITHM
COPY BOOLEAN WHETHER THE DEFLATION BE DONE ON A COPY LET THE DEFAULT VALUE TO TRUE UNLESS
YOU DON’T CARE ABOUT SIDE EFFECTS
ATTRIBUTES
XWEIGHTS ARRAY P NCOMPONENTS X BLOCK WEIGHTS VECTORS
YWEIGHTS ARRAY Q NCOMPONENTS Y BLOCK WEIGHTS VECTORS
XLOADINGS ARRAY P NCOMPONENTS X BLOCK LOADINGS VECTORS
YLOADINGS ARRAY Q NCOMPONENTS Y BLOCK LOADINGS VECTORS
XSCORES ARRAY NSAMPLES NCOMPONENTS X SCORES
YSCORES ARRAY NSAMPLES NCOMPONENTS Y SCORES
XROTATIONS ARRAY P NCOMPONENTS X BLOCK TO LATENTS ROTATIONS
YROTATIONS ARRAY Q NCOMPONENTS Y BLOCK TO LATENTS ROTATIONS
NITER ARRAYLIKE NUMBER OF ITERATIONS OF THE NIPALS INNER LOOP FOR EACH COMPONENT
SEE ALSO
PLSCANONICAL
PLSSVD
NOTES
FOR EACH COMPONENT K FIND THE WEIGHTS U V THAT MAXIMIZES MAX CORRXK U YK V SUCH THAT U V
1
NOTE THAT IT MAXIMIZES ONLY THE CORRELATIONS BETWEEN THE SCORES
THE RESIDUAL MATRIX OF X XK1 BLOCK IS OBTAINED BY THE DEFLATION ON THE CURRENT X SCORE XSCORE
THE RESIDUAL MATRIX OF Y YK1 BLOCK IS OBTAINED BY DEFLATION ON THE CURRENT Y SCORE
REFERENCES
JACOB A WEGELIN A SURVEY OF PARTIAL LEAST SQUARES PLS METHODS WITH EMPHASIS ON THE TWOBLOCK CASE
TECHNICAL REPORT 371 DEPARTMENT OF STATISTICS UNIVERSITY OF WASHINGTON SEATTLE 2000
IN FRENCH BUT STILL A REFERENCE TENENHAUS M 1998 LA REGRESSION PLS THEORIE ET PRATIQUE PARIS EDITIONS
TECHNIC

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EXAMPLES
FROM SKLEARNCROSSDECOMPOSITION IMPORT CCA
X 0 0 1 100 222 354
Y 01 02 09 11 62 59 119 123
CCA CCANCOMPONENTS1
CCAFITX Y

CCACOPYTRUE MAXITER500 NCOMPONENTS1 SCALETRUE TOL1E06
XC YC CCATRANSFORMX Y
METHODS
FITSELF X Y FIT MODEL TO DATA
FITTRANSFORM SELF X Y LEARN AND APPLY THE DIMENSION REDUCTION ON THE TRAIN
DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X COPY APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X Y COPY APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
INIT SELFNCOMPONENTS2 SCALETRUE MAXITER500 TOL1E06 COPYTRUE
FITSELFXY
FIT MODEL TO DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES
FITTRANSFORM SELFXYNONE
LEARN AND APPLY THE DIMENSION REDUCTION ON THE TRAIN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES
RETURNS
XSCORES IF Y IS NOT GIVEN XSCORES YSCORES OTHERWISE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS

RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXCOPYTRUE
APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
COPY BOOLEAN DEFAULT TRUE WHETHER TO COPY X AND Y OR PERFORM INPLACE NORMALIZATION
NOTES
THIS CALL REQUIRES THE ESTIMATION OF A P X Q MATRIX WHICH MAY BE AN ISSUE IN HIGH DIMENSIONAL SPACE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF

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TRANSFORM SELFXYNONE COPYTRUE
APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES
COPY BOOLEAN DEFAULT TRUE WHETHER TO COPY X AND Y OR PERFORM INPLACE NORMALIZATION
RETURNS
XSCORES IF Y IS NOT GIVEN XSCORES YSCORES OTHERWISE
EXAMPLES USING SKLEARNCROSSDECOMPOSITIONCCA
•MULTILABEL CLASSIFICATION
•COMPARE CROSS DECOMPOSITION METHODS
672SKLEARNCROSSDECOMPOSITION PLSCANONICAL
CLASSSKLEARNCROSSDECOMPOSITION PLSCANONICAL NCOMPONENTS2 SCALETRUE ALGO
RITHM’NIPALS’ MAXITER500 TOL1E06
COPYTRUE
PLSCANONICAL IMPLEMENTS THE 2 BLOCKS CANONICAL PLS OF THE ORIGINAL WOLD ALGORITHM TENENHAUS 1998 P204
REFERRED AS PLSC2A IN WEGELIN 2000
THIS CLASS INHERITS FROM PLS WITH MODE”A” AND DEFLATIONMODE”CANONICAL” NORMYWEIGHTSTRUE AND AL
GORITHM”NIPALS” BUT SVD SHOULD PROVIDE SIMILAR RESULTS UP TO NUMERICAL ERRORS
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT DEFAULT 2 NUMBER OF COMPONENTS TO KEEP
SCALE BOOLEAN DEFAULT TRUE OPTION TO SCALE DATA
ALGORITHM STRING “NIPALS” OR “SVD” THE ALGORITHM USED TO ESTIMATE THE WEIGHTS IT WILL BE
CALLED NCOMPONENTS TIMES IE ONCE FOR EACH ITERATION OF THE OUTER LOOP
MAXITER AN INTEGER DEFAULT 500 THE MAXIMUM NUMBER OF ITERATIONS OF THE NIPALS INNER
LOOP USED ONLY IF ALGORITHM”NIPALS”
TOLNONNEGATIVE REAL DEFAULT 1E06 THE TOLERANCE USED IN THE ITERATIVE ALGORITHM
COPY BOOLEAN DEFAULT TRUE WHETHER THE DEFLATION SHOULD BE DONE ON A COPY LET THE DEFAULT
VALUE TO TRUE UNLESS YOU DON’T CARE ABOUT SIDE EFFECT
ATTRIBUTES
XWEIGHTS ARRAY SHAPE P NCOMPONENTS X BLOCK WEIGHTS VECTORS
YWEIGHTS ARRAY SHAPE Q NCOMPONENTS Y BLOCK WEIGHTS VECTORS
XLOADINGS ARRAY SHAPE P NCOMPONENTS X BLOCK LOADINGS VECTORS
YLOADINGS ARRAY SHAPE Q NCOMPONENTS Y BLOCK LOADINGS VECTORS
XSCORES ARRAY SHAPE NSAMPLES NCOMPONENTS X SCORES
67SKLEARNCROSSDECOMPOSITION CROSS DECOMPOSITION 1567

YSCORES ARRAY SHAPE NSAMPLES NCOMPONENTS Y SCORES
XROTATIONS ARRAY SHAPE P NCOMPONENTS X BLOCK TO LATENTS ROTATIONS
YROTATIONS ARRAY SHAPE Q NCOMPONENTS Y BLOCK TO LATENTS ROTATIONS
NITER ARRAYLIKE NUMBER OF ITERATIONS OF THE NIPALS INNER LOOP FOR EACH COMPONENT NOT
USEFUL IF THE ALGORITHM PROVIDED IS “SVD”
SEE ALSO
CCA
PLSSVD
NOTES
MATRICES
T XSCORES
U YSCORES
W XWEIGHTS
C YWEIGHTS
P XLOADINGS
Q YLOADINGS
ARE COMPUTED SUCH THAT
X T PT ERR ANDY U QT ERR
T K XK W K FORKINRANGENCOMPONENTS
U K YK C K FORKINRANGENCOMPONENTS
XROTATIONS W PT W1
YROTATIONS C QT C1
WHERE XK AND YK ARE RESIDUAL MATRICES AT ITERATION K
SLIDES EXPLAINING PLS
FOR EACH COMPONENT K FIND WEIGHTS U V THAT OPTIMIZE
MAX CORRXK U YK V STDXK U STDYK U SUCH THAT U V 1
NOTE THAT IT MAXIMIZES BOTH THE CORRELATIONS BETWEEN THE SCORES AND THE INTRABLOCK VARIANCES
THE RESIDUAL MATRIX OF X XK1 BLOCK IS OBTAINED BY THE DEFLATION ON THE CURRENT X SCORE XSCORE
THE RESIDUAL MATRIX OF Y YK1 BLOCK IS OBTAINED BY DEFLATION ON THE CURRENT Y SCORE THIS PERFORMS A CANONICAL
SYMMETRIC VERSION OF THE PLS REGRESSION BUT SLIGHTLY DIFFERENT THAN THE CCA THIS IS MOSTLY USED FOR MODELING
THIS IMPLEMENTATION PROVIDES THE SAME RESULTS THAT THE “PLSPM” PACKAGE PROVIDED IN THE R LANGUAGE R
PROJECT USING THE FUNCTION PLSCAX Y RESULTS ARE EQUAL OR COLLINEAR WITH THE FUNCTION PLS MODE
 CANONICAL OF THE “MIXOMICS” PACKAGE THE DIFFERENCE RELIES IN THE FACT THAT MIXOMICS IMPLEMENTA
TION DOES NOT EXACTLY IMPLEMENT THE WOLD ALGORITHM SINCE IT DOES NOT NORMALIZE YWEIGHTS TO ONE
REFERENCES
JACOB A WEGELIN A SURVEY OF PARTIAL LEAST SQUARES PLS METHODS WITH EMPHASIS ON THE TWOBLOCK CASE
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TENENHAUS M 1998 LA REGRESSION PLS THEORIE ET PRATIQUE PARIS EDITIONS TECHNIC
EXAMPLES
FROM SKLEARNCROSSDECOMPOSITION IMPORT PLSCANONICAL
X 0 0 1 100 222 254
Y 01 02 09 11 62 59 119 123
PLSCA PLSCANONICALNCOMPONENTS2
PLSCAFITX Y

PLSCANONICALALGORITHMNIPALS COPYTRUE MAXITER500 NCOMPONENTS2
SCALETRUE TOL1E06
XC YC PLSCATRANSFORMX Y
METHODS
FITSELF X Y FIT MODEL TO DATA
FITTRANSFORM SELF X Y LEARN AND APPLY THE DIMENSION REDUCTION ON THE TRAIN
DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X COPY APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X Y COPY APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
INIT SELFNCOMPONENTS2 SCALETRUE ALGORITHM'NIPALS' MAXITER500 TOL1E06
COPYTRUE
FITSELFXY
FIT MODEL TO DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES
FITTRANSFORM SELFXYNONE
LEARN AND APPLY THE DIMENSION REDUCTION ON THE TRAIN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES
RETURNS
XSCORES IF Y IS NOT GIVEN XSCORES YSCORES OTHERWISE

GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXCOPYTRUE
APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
COPY BOOLEAN DEFAULT TRUE WHETHER TO COPY X AND Y OR PERFORM INPLACE NORMALIZATION
NOTES
THIS CALL REQUIRES THE ESTIMATION OF A P X Q MATRIX WHICH MAY BE AN ISSUE IN HIGH DIMENSIONAL SPACE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR

THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFXYNONE COPYTRUE
APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES
COPY BOOLEAN DEFAULT TRUE WHETHER TO COPY X AND Y OR PERFORM INPLACE NORMALIZATION
RETURNS
XSCORES IF Y IS NOT GIVEN XSCORES YSCORES OTHERWISE
EXAMPLES USING SKLEARNCROSSDECOMPOSITIONPLSCANONICAL
•COMPARE CROSS DECOMPOSITION METHODS
673SKLEARNCROSSDECOMPOSITION PLSREGRESSION
CLASSSKLEARNCROSSDECOMPOSITION PLSREGRESSION NCOMPONENTS2 SCALETRUE
MAXITER500 TOL1E06 COPYTRUE
PLS REGRESSION
PLSREGRESSION IMPLEMENTS THE PLS 2 BLOCKS REGRESSION KNOWN AS PLS2 OR PLS1 IN CASE OF ONE DIMENSIONAL
RESPONSE THIS CLASS INHERITS FROM PLS WITH MODE"A" DEFLATIONMODE"REGRESSION" NORMYWEIGHTSFALSE
AND ALGORITHM"NIPALS"
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT DEFAULT 2 NUMBER OF COMPONENTS TO KEEP
SCALE BOOLEAN DEFAULT TRUE WHETHER TO SCALE THE DATA
MAXITER AN INTEGER DEFAULT 500 THE MAXIMUM NUMBER OF ITERATIONS OF THE NIPALS INNER
LOOP USED ONLY IF ALGORITHM"NIPALS"
TOLNONNEGATIVE REAL TOLERANCE USED IN THE ITERATIVE ALGORITHM DEFAULT 1E06
COPY BOOLEAN DEFAULT TRUE WHETHER THE DEFLATION SHOULD BE DONE ON A COPY LET THE DEFAULT
VALUE TO TRUE UNLESS YOU DON'T CARE ABOUT SIDE EFFECT
ATTRIBUTES
XWEIGHTS ARRAY P NCOMPONENTS X BLOCK WEIGHTS VECTORS
YWEIGHTS ARRAY Q NCOMPONENTS Y BLOCK WEIGHTS VECTORS
XLOADINGS ARRAY P NCOMPONENTS X BLOCK LOADINGS VECTORS
YLOADINGS ARRAY Q NCOMPONENTS Y BLOCK LOADINGS VECTORS

XSCORES ARRAY NSAMPLES NCOMPONENTS X SCORES
YSCORES ARRAY NSAMPLES NCOMPONENTS Y SCORES
XROTATIONS ARRAY P NCOMPONENTS X BLOCK TO LATENTS ROTATIONS
YROTATIONS ARRAY Q NCOMPONENTS Y BLOCK TO LATENTS ROTATIONS
COEF ARRAY P Q THE COEFFICIENTS OF THE LINEAR MODEL Y X COEF ERR
NITER ARRAYLIKE NUMBER OF ITERATIONS OF THE NIPALS INNER LOOP FOR EACH COMPONENT
NOTES
MATRICES
T XSCORES
U YSCORES
W XWEIGHTS
C YWEIGHTS
P XLOADINGS
Q YLOADINGS
ARE COMPUTED SUCH THAT
X T PT ERR ANDY U QT ERR
T K XK W K FORKINRANGENCOMPONENTS
U K YK C K FORKINRANGENCOMPONENTS
XROTATIONS W PT W1
YROTATIONS C QT C1
WHERE XK AND YK ARE RESIDUAL MATRICES AT ITERATION K
SLIDES EXPLAINING PLS
FOR EACH COMPONENT K FIND WEIGHTS U V THAT OPTIMIZES MAX CORRXK U YK V STDXK U
STDYK U SUCH THATU 1
NOTE THAT IT MAXIMIZES BOTH THE CORRELATIONS BETWEEN THE SCORES AND THE INTRABLOCK VARIANCES
THE RESIDUAL MATRIX OF X XK1 BLOCK IS OBTAINED BY THE DEFLATION ON THE CURRENT X SCORE XSCORE
THE RESIDUAL MATRIX OF Y YK1 BLOCK IS OBTAINED BY DEFLATION ON THE CURRENT X SCORE THIS PERFORMS THE PLS
REGRESSION KNOWN AS PLS2 THIS MODE IS PREDICTION ORIENTED
THIS IMPLEMENTATION PROVIDES THE SAME RESULTS THAT 3 PLS PACKAGES PROVIDED IN THE R LANGUAGE RPROJECT
• “MIXOMICS” WITH FUNCTION PLSX Y MODE “REGRESSION”
• “PLSPM ” WITH FUNCTION PLSREG2X Y
• “PLS” WITH FUNCTION OSCORESPLSFITX Y
REFERENCES
JACOB A WEGELIN A SURVEY OF PARTIAL LEAST SQUARES PLS METHODS WITH EMPHASIS ON THE TWOBLOCK CASE
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IN FRENCH BUT STILL A REFERENCE TENENHAUS M 1998 LA REGRESSION PLS THEORIE ET PRATIQUE PARIS EDITIONS
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EXAMPLES
FROM SKLEARNCROSSDECOMPOSITION IMPORT PLSREGRESSION
X 0 0 1 100 222 254
Y 01 02 09 11 62 59 119 123
PLS2 PLSREGRESSIONNCOMPONENTS2
PLS2FITX Y

PLSREGRESSIONCOPYTRUE MAXITER500 NCOMPONENTS2 SCALETRUE
TOL1E06
YPRED PLS2PREDICTX
METHODS
FITSELF X Y FIT MODEL TO DATA
FITTRANSFORM SELF X Y LEARN AND APPLY THE DIMENSION REDUCTION ON THE TRAIN
DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X COPY APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X Y COPY APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
INIT SELFNCOMPONENTS2 SCALETRUE MAXITER500 TOL1E06 COPYTRUE
FITSELFXY
FIT MODEL TO DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES
FITTRANSFORM SELFXYNONE
LEARN AND APPLY THE DIMENSION REDUCTION ON THE TRAIN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES
RETURNS
XSCORES IF Y IS NOT GIVEN XSCORES YSCORES OTHERWISE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXCOPYTRUE
APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
COPY BOOLEAN DEFAULT TRUE WHETHER TO COPY X AND Y OR PERFORM INPLACE NORMALIZATION
NOTES
THIS CALL REQUIRES THE ESTIMATION OF A P X Q MATRIX WHICH MAY BE AN ISSUE IN HIGH DIMENSIONAL SPACE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS

SELF
TRANSFORM SELFXYNONE COPYTRUE
APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES
COPY BOOLEAN DEFAULT TRUE WHETHER TO COPY X AND Y OR PERFORM INPLACE NORMALIZATION
RETURNS
XSCORES IF Y IS NOT GIVEN XSCORES YSCORES OTHERWISE
EXAMPLES USING SKLEARNCROSSDECOMPOSITIONPLSREGRESSION
•COMPARE CROSS DECOMPOSITION METHODS
674SKLEARNCROSSDECOMPOSITION PLSSVD
CLASSSKLEARNCROSSDECOMPOSITION PLSSVDNCOMPONENTS2 SCALETRUE COPYTRUE
PARTIAL LEAST SQUARE SVD
SIMPLY PERFORM A SVD ON THE CROSSCOVARIANCE MATRIX X’Y THERE ARE NO ITERATIVE DEFLATION HERE
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT DEFAULT 2 NUMBER OF COMPONENTS TO KEEP
SCALE BOOLEAN DEFAULT TRUE WHETHER TO SCALE X AND Y
COPY BOOLEAN DEFAULT TRUE WHETHER TO COPY X AND Y OR PERFORM INPLACE COMPUTATIONS
ATTRIBUTES
XWEIGHTS ARRAY P NCOMPONENTS X BLOCK WEIGHTS VECTORS
YWEIGHTS ARRAY Q NCOMPONENTS Y BLOCK WEIGHTS VECTORS
XSCORES ARRAY NSAMPLES NCOMPONENTS X SCORES
YSCORES ARRAY NSAMPLES NCOMPONENTS Y SCORES
SEE ALSO
PLSCANONICAL
CCA
EXAMPLES

```
 IMPORT NUMPY AS NP
 FROM SKLEARNCROSSDECOMPOSITION IMPORT PLSSVD
X  NPARRAY0 0 1
 100
 222
 254
Y  NPARRAY01 02
 09 11
 62 59
 119 123
PLSCA  PLSSVDNCOMPONENTS2
PLSCAFITX Y
PLSSVDCOPYTRUE NCOMPONENTS2 SCALETRUE
XC YC  PLSCATRANSFORMX Y
XCSHAPE YCSHAPE
4 2 4 2
```
METHODS

FITSELF X Y FIT MODEL TO DATA

FITTRANSFORM SELF X Y LEARN AND APPLY THE DIMENSION REDUCTION ON THE TRAIN DATA

GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR

SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

TRANSFORM SELF X Y APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA

INIT SELFNCOMPONENTS2 SCALETRUE COPYTRUE

FITSELFXY

FIT MODEL TO DATA

PARAMETERS

XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS

YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES

FITTRANSFORM SELFXYNONE

LEARN AND APPLY THE DIMENSION REDUCTION ON THE TRAIN DATA

PARAMETERS

XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS

YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES

RETURNS

XSCORES IF Y IS NOT GIVEN XSCORES YSCORES OTHERWISE

GETPARAMS SELFDEEPTRUE

GET PARAMETERS FOR THIS ESTIMATOR

PARAMETERS

DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFXYNONE
APPLY THE DIMENSION REDUCTION LEARNED ON THE TRAIN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF PREDICTORS
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VECTORS WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NTARGETS IS THE NUMBER OF RESPONSE VARIABLES
68SKLEARNDATASETS DATASETS
THESKLEARNDATASETS MODULE INCLUDES UTILITIES TO LOAD DATASETS INCLUDING METHODS TO LOAD AND FETCH POPULAR
REFERENCE DATASETS IT ALSO FEATURES SOME ARTIFICIAL DATA GENERATORS
USER GUIDE SEE THE DATASET LOADING UTILITIES SECTION FOR FURTHER DETAILS
681 LOADERS
DATASETSCLEARDATAHOME DATAHOME DELETE ALL THE CONTENT OF THE DATA HOME CACHE
DATASETSDUMPSVMLIGHTFILE X Y F DUMP THE DATASET IN SVMLIGHT LIBSVM FILE FORMAT
DATASETSFETCH20NEWSGROUPS DATAHOME
  LOAD THE FILENAMES AND DATA FROM THE 20 NEWSGROUPS
DATASET CLASSIFICATION
DATASETSFETCH20NEWSGROUPSVECTORIZED LOAD THE 20 NEWSGROUPS DATASET AND VECTORIZE IT INTO TOKEN
COUNTS CLASSIFICATION
DATASETSFETCHCALIFORNIAHOUSING LOAD THE CALIFORNIA HOUSING DATASET REGRESSION
DATASETSFETCHCOVTYPE DATAHOME LOAD THE COVERTYPE DATASET CLASSIFICATION
DATASETSFETCHKDDCUP99 SUBSET DATAHOME
  LOAD THE KDDCUP99 DATASET CLASSIFICATION
DATASETSFETCHLFWPAIRS SUBSET LOAD THE LABELED FACES IN THE WILD LFW PAIRS DATASET
CLASSIFICATION
DATASETSFETCHLFWPEOPLE DATAHOME LOAD THE LABELED FACES IN THE WILD LFW PEOPLE DATASET
CLASSIFICATION
DATASETSFETCHOLIVETTIFACES DATAHOME
  LOAD THE OLIVETTI FACES DATASET FROM ATT CLASSIFICATION
DATASETSFETCHOPENML NAME VERSION FETCH DATASET FROM OPENML BY NAME OR DATASET ID
CONTINUED ON NEXT PAGE

TABLE 647 – CONTINUED FROM PREVIOUS PAGE
DATASETSFETCHRCV1 DATAHOME SUBSET LOAD THE RCV1 MULTILABEL DATASET CLASSIFICATION
DATASETSFETCHSPECIESDISTRIBUTIONS LOADER FOR SPECIES DISTRIBUTION DATASET FROM PHILLIPS ET
DATASETSGETDATAHOME DATAHOME RETURN THE PATH OF THE SCIKITLEARN DATA DIR
DATASETSLOADBOSTON RETURNXY LOAD AND RETURN THE BOSTON HOUSEPRICES DATASET REGRES
SION
DATASETSLOADBREASTCANCER RETURNXY LOAD AND RETURN THE BREAST CANCER WISCONSIN DATASET CLAS
SIFICATION
DATASETSLOADDIABETES RETURNXY LOAD AND RETURN THE DIABETES DATASET REGRESSION
DATASETSLOADDIGITS NCLASS RETURNXY LOAD AND RETURN THE DIGITS DATASET CLASSIFICATION
DATASETSLOADFILES CONTAINERPATH LOAD TEXT FILES WITH CATEGORIES AS SUBFOLDER NAMES
DATASETSLOADIRIS RETURNXY LOAD AND RETURN THE IRIS DATASET CLASSIFICATION
DATASETSLOADLINNERUD RETURNXY LOAD AND RETURN THE LINNERUD DATASET MULTIVARIATE REGRES
SION
DATASETSLOADSAMPLEIMAGE IMAGENAME LOAD THE NUMPY ARRAY OF A SINGLE SAMPLE IMAGE
DATASETSLOADSAMPLEIMAGES LOAD SAMPLE IMAGES FOR IMAGE MANIPULATION
DATASETSLOADSVMLIGHTFILE F NFEATURES
LOAD DATASETS IN THE SVMLIGHT LIBSVM FORMAT INTO SPARSE
CSR MATRIX
DATASETSLOADSVMLIGHTFILES FILES LOAD DATASET FROM MULTIPLE FILES IN SVMLIGHT FORMAT
DATASETSLOADWINE RETURNXY LOAD AND RETURN THE WINE DATASET CLASSIFICATION
SKLEARNDATASETS CLEARDATAHOME
SKLEARNDATASETS CLEARDATAHOME DATAHOMENONE
DELETE ALL THE CONTENT OF THE DATA HOME CACHE
PARAMETERS
DATAHOME STR NONE THE PATH TO SCIKITLEARN DATA DIR
SKLEARNDATASETS DUMPSVMLIGHTFILE
SKLEARNDATASETS DUMPSVMLIGHTFILE XY F ZEROBASEDTRUE COMMENTNONE
QUERYIDNONE MULTILABELFALSE
DUMP THE DATASET IN SVMLIGHT LIBSVM FILE FORMAT
THIS FORMAT IS A TEXTBASED FORMAT WITH ONE SAMPLE PER LINE IT DOES NOT STORE ZERO VALUED FEATURES HENCE IS
SUITABLE FOR SPARSE DATASET
THE FIRST ELEMENT OF EACH LINE CAN BE USED TO STORE A TARGET VARIABLE TO PREDICT
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NLABELS TARGET VALUES CLASS LABELS
MUST BE AN INTEGER OR FLOAT OR ARRAYLIKE OBJECTS OF INTEGER OR FLOAT FOR MULTILABEL CLASSIFICA
TIONS
FSTRING OR FILELIKE IN BINARY MODE IF STRING SPECIFIES THE PATH THAT WILL CONTAIN THE DATA IF
FILELIKE DATA WILL BE WRITTEN TO F F SHOULD BE OPENED IN BINARY MODE
ZEROBASED BOOLEAN OPTIONAL WHETHER COLUMN INDICES SHOULD BE WRITTEN ZEROBASED TRUE OR
ONEBASED FALSE
COMMENT STRING OPTIONAL COMMENT TO INSERT AT THE TOP OF THE FILE THIS SHOULD BE EITHER A
UNICODE STRING WHICH WILL BE ENCODED AS UTF8 OR AN ASCII BYTE STRING IF A COMMENT

SCIKITLEARN USER GUIDE RELEASE 0213
IS GIVEN THEN IT WILL BE PRECEDED BY ONE THAT IDENTIFIES THE FILE AS HAVING BEEN DUMPED BY
SCIKITLEARN NOTE THAT NOT ALL TOOLS GROK COMMENTS IN SVMLIGHT FILES
QUERYID ARRAYLIKE SHAPE NSAMPLES ARRAY CONTAINING PAIRWISE PREFERENCE CONSTRAINTS
QID IN SVMLIGHT FORMAT
MULTILABEL BOOLEAN OPTIONAL SAMPLES MAY HAVE SEVERAL LABELS EACH SEE HTTPSWWWCSIENTU
EDUTWCJLINLIBSVMTOOLSDATASETSMULTILABELHTML
NEW IN VERSION 017 PARAMETER MULTILABEL TO SUPPORT MULTILABEL DATASETS
EXAMPLES USING SKLEARNDATASETSDUMPSVMLIGHTFILE
•LIBSVM GUI
SKLEARNDATASETS FETCH20NEWSGROUPS
SKLEARNDATASETS FETCH20NEWSGROUPS DATAHOMENONE SUBSET'TRAIN' CATEGORIESNONE
SHUFFLETRUE RANDOMSTATE42 REMOVE DOWN
LOADIFMISSINGTRUE
LOAD THE FILENAMES AND DATA FROM THE 20 NEWSGROUPS DATASET CLASSIFICATION
DOWNLOAD IT IF NECESSARY
CLASSES 20
SAMPLES TOTAL 18846
DIMENSIONALITY 1
FEATURES TEXT
READ MORE IN THE USER GUIDE
PARAMETERS
DATAHOME OPTIONAL DEFAULT NONE SPECIFY A DOWNLOAD AND CACHE FOLDER FOR THE DATASETS IF
NONE ALL SCIKITLEARN DATA IS STORED IN 'SCIKITLEARNDATA' SUBFOLDERS
SUBSET 'TRAIN' OR 'TEST' 'ALL' OPTIONAL SELECT THE DATASET TO LOAD 'TRAIN' FOR THE TRAINING SET
'TEST' FOR THE TEST SET 'ALL' FOR BOTH WITH SHUFFLED ORDERING
CATEGORIES NONE OR COLLECTION OF STRING OR UNICODE IF NONE DEFAULT LOAD ALL THE CATEGORIES IF
NOT NONE LIST OF CATEGORY NAMES TO LOAD OTHER CATEGORIES IGNORED
SHUFFLE BOOL OPTIONAL WHETHER OR NOT TO SHUFFLE THE DATA MIGHT BE IMPORTANT FOR MODELS THAT
MAKE THE ASSUMPTION THAT THE SAMPLES ARE INDEPENDENT AND IDENTICALLY DISTRIBUTED IID
SUCH AS STOCHASTIC GRADIENT DESCENT
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET SHUFFLING PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
REMOVE TUPLE MAY CONTAIN ANY SUBSET OF 'HEADERS' 'FOOTERS' 'QUOTES' EACH OF THESE ARE
KINDS OF TEXT THAT WILL BE DETECTED AND REMOVED FROM THE NEWSGROUP POSTS PREVENTING CLAS
SIFIERS FROM OVERFITTING ON METADATA
'HEADERS' REMOVES NEWSGROUP HEADERS 'FOOTERS' REMOVES BLOCKS AT THE ENDS OF POSTS THAT
LOOK LIKE SIGNATURES AND 'QUOTES' REMOVES LINES THAT APPEAR TO BE QUOTING ANOTHER POST
'HEADERS' FOLLOWS AN EXACT STANDARD THE OTHER FILTERS ARE NOT ALWAYS CORRECT
68SKLEARNDATASETS DATASETS 1579

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DOWNLOADIFMISSING OPTIONAL TRUE BY DEFAULT IF FALSE RAISE AN IOERROR IF THE DATA IS NOT
LOCALLY AVAILABLE INSTEAD OF TRYING TO DOWNLOAD THE DATA FROM THE SOURCE SITE
RETURNS
BUNCH BUNCH OBJECT WITH THE FOLLOWING ATTRIBUTE
• BUNCHDATA LIST LENGTH NSAMPLES
• BUNCHTARGET ARRAY SHAPE NSAMPLES
• BUNCHFILENAMES LIST LENGTH NSAMPLES
• BUNCHDESCR A DESCRIPTION OF THE DATASET
• BUNCHTARGETNAMES A LIST OF CATEGORIES OF THE RETURNED DATA LENGTH NCLASSES THIS
DEPENDS ON THE CATEGORIES PARAMETER
EXAMPLES USING SKLEARNDATASETSFETCH20NEWSGROUPS
•TOPIC EXTRACTION WITH NONNEGATIVE MATRIX FACTORIZATION AND LATENT DIRICHLET ALLOCATION
•BICLUSTERING DOCUMENTS WITH THE SPECTRAL COCLUSTERING ALGORITHM
•COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
•SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
•FEATUREHASHER AND DICTVECTORIZER COMPARISON
•CLUSTERING TEXT DOCUMENTS USING KMEANS
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
SKLEARNDATASETS FETCH20NEWSGROUPSVECTORIZED
SKLEARNDATASETS FETCH20NEWSGROUPSVECTORIZED SUBSET’TRAIN’ REMOVE
DATAHOMENONE DOWN
LOADIFMISSINGTRUE RE
TURNXYFALSE
LOAD THE 20 NEWSGROUPS DATASET AND VECTORIZE IT INTO TOKEN COUNTS CLASSIFICATION
DOWNLOAD IT IF NECESSARY
THIS IS A CONVENIENCE FUNCTION THE TRANSFORMATION IS DONE USING THE DEFAULT SETTINGS FOR SKLEARN
FEATUREEXTRACTIONTEXTCOUNTVECTORIZER FOR MORE ADVANCED USAGE STOPWORD
FILTERING NGRAM EXTRACTION ETC COMBINE FETCH20NEWSGROUPS WITH A CUSTOM SKLEARN
FEATUREEXTRACTIONTEXTCOUNTVECTORIZER SKLEARNFEATUREEXTRACTIONTEXT
HASHINGVECTORIZER SKLEARNFEATUREEXTRACTIONTEXTTFIDFTRANSFORMER OR
SKLEARNFEATUREEXTRACTIONTEXTTFIDFVECTORIZER
CLASSES 20
SAMPLES TOTAL 18846
DIMENSIONALITY 130107
FEATURES REAL
READ MORE IN THE USER GUIDE
PARAMETERS

SCIKITLEARN USER GUIDE RELEASE 0213
SUBSET ‘TRAIN’ OR ‘TEST’ ‘ALL’ OPTIONAL SELECT THE DATASET TO LOAD ‘TRAIN’ FOR THE TRAINING SET
‘TEST’ FOR THE TEST SET ‘ALL’ FOR BOTH WITH SHUFFLED ORDERING
REMOVE TUPLE MAY CONTAIN ANY SUBSET OF ‘HEADERS’ ‘FOOTERS’ ‘QUOTES’ EACH OF THESE ARE
KINDS OF TEXT THAT WILL BE DETECTED AND REMOVED FROM THE NEWSGROUP POSTS PREVENTING CLAS
SIFIERS FROM OVERFITTING ON METADATA
‘HEADERS’ REMOVES NEWSGROUP HEADERS ‘FOOTERS’ REMOVES BLOCKS AT THE ENDS OF POSTS THAT
LOOK LIKE SIGNATURES AND ‘QUOTES’ REMOVES LINES THAT APPEAR TO BE QUOTING ANOTHER POST
DATAHOME OPTIONAL DEFAULT NONE SPECIFY AN DOWNLOAD AND CACHE FOLDER FOR THE DATASETS IF
NONE ALL SCIKITLEARN DATA IS STORED IN ‘SCIKITLEARNDATA’ SUBFOLDERS
DOWNLOADIFMISSING OPTIONAL TRUE BY DEFAULT IF FALSE RAISE AN IOERROR IF THE DATA IS NOT
LOCALLY AVAILABLE INSTEAD OF TRYING TO DOWNLOAD THE DATA FROM THE SOURCE SITE
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATADATA DATATARGET IN
STEAD OF A BUNCH OBJECT
NEW IN VERSION 020
RETURNS
BUNCH BUNCH OBJECT WITH THE FOLLOWING ATTRIBUTE
• BUNCHDATA SPARSE MATRIX SHAPE NSAMPLES NFEATURES
• BUNCHTARGET ARRAY SHAPE NSAMPLES
• BUNCHTARGETNAMES A LIST OF CATEGORIES OF THE RETURNED DATA LENGTH NCLASSES
• BUNCHDESCR A DESCRIPTION OF THE DATASET
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 020
EXAMPLES USING SKLEARNDATASETSFETCH20NEWSGROUPSVECTORIZED
•THE JOHNSONLINDENSTRAUSS BOUND FOR EMBEDDING WITH RANDOM PROJECTIONS
•MODEL COMPLEXITY INFLUENCE
•MULTICLASS SPARSE LOGISITIC REGRESSION ON NEWGROUPS20
SKLEARNDATASETS FETCHCALIFORNIAHOUSING
SKLEARNDATASETS FETCHCALIFORNIAHOUSING DATAHOMENONE DOWNLOADIFMISSINGTRUE
RETURNXYFALSE
LOAD THE CALIFORNIA HOUSING DATASET REGRESSION
SAMPLES TOTAL 20640
DIMENSIONALITY 8
FEATURES REAL
TARGET REAL 015 5
READ MORE IN THE USER GUIDE
PARAMETERS
DATAHOME OPTIONAL DEFAULT NONE SPECIFY ANOTHER DOWNLOAD AND CACHE FOLDER FOR THE
DATASETS BY DEFAULT ALL SCIKITLEARN DATA IS STORED IN ‘SCIKITLEARNDATA’ SUBFOLDERS
68SKLEARNDATASETS DATASETS 1581

DOWNLOADIFMISSING OPTIONAL DEFAULTTRUE IF FALSE RAISE A IOERROR IF THE DATA IS NOT LOCALLY AVAILABLE INSTEAD OF TRYING TO DOWNLOAD THE DATA FROM THE SOURCE SITE
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATADATA DATATARGET IN STEAD OF A BUNCH OBJECT
NEW IN VERSION 020
RETURNS
DATASET DICTLIKE OBJECT WITH THE FOLLOWING ATTRIBUTES
DATASETDATA NDARRAY SHAPE 20640 8 EACH ROW CORRESPONDING TO THE 8 FEATURE VALUES IN ORDER
DATASETTARGET NUMPY ARRAY OF SHAPE 20640 EACH VALUE CORRESPONDS TO THE AVERAGE HOUSE VALUE IN UNITS OF 100000
DATASETFEATURENAMES ARRAY OF LENGTH 8 ARRAY OF ORDERED FEATURE NAMES USED IN THE DATASET
DATASETDESCR STRING DESCRIPTION OF THE CALIFORNIA HOUSING DATASET
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 020
NOTES
THIS DATASET CONSISTS OF 20640 SAMPLES AND 9 FEATURES
EXAMPLES USING SKLEARNDATASETSFETCHCALIFORNIAHOUSING
•IMPUTING MISSING VALUES WITH VARIANTS OF ITERATIVEIMPUTER
•PARTIAL DEPENDENCE PLOTS
•COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS
SKLEARNDATASETS FETCHCOVTYPE
SKLEARNDATASETS FETCHCOVTYPE DATAHOMENONE DOWNLOADIFMISSINGTRUE RAN DOMSTATENONE SHUFFLEFALSE RETURNXYFALSE
LOAD THE COVERTYPE DATASET CLASSIFICATION
DOWNLOAD IT IF NECESSARY
CLASSES 7
SAMPLES TOTAL 581012
DIMENSIONALITY 54
FEATURES INT
READ MORE IN THE USER GUIDE
PARAMETERS
DATAHOME STRING OPTIONAL SPECIFY ANOTHER DOWNLOAD AND CACHE FOLDER FOR THE DATASETS BY DEFAULT ALL SCIKITLEARN DATA IS STORED IN ‘SCIKITLEARNDATA’ SUBFOLDERS
DOWNLOADIFMISSING BOOLEAN DEFAULTTRUE IF FALSE RAISE A IOERROR IF THE DATA IS NOT LOCALLY AVAILABLE INSTEAD OF TRYING TO DOWNLOAD THE DATA FROM THE SOURCE SITE

SCIKITLEARN USER GUIDE RELEASE 0213
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET SHUFFLING PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
SHUFFLE BOOL DEFAULTFALSE WHETHER TO SHUFFLE DATASET
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATADATA DATATARGET IN
STEAD OF A BUNCH OBJECT
NEW IN VERSION 020
RETURNS
DATASET DICTLIKE OBJECT WITH THE FOLLOWING ATTRIBUTES
DATASETDATA NUMPY ARRAY OF SHAPE 581012 54 EACH ROW CORRESPONDS TO THE 54 FEATURES IN
THE DATASET
DATASETTARGET NUMPY ARRAY OF SHAPE 581012 EACH VALUE CORRESPONDS TO ONE OF THE 7 FOREST
COVERTYPES WITH VALUES RANGING BETWEEN 1 TO 7
DATASETDESCR STRING DESCRIPTION OF THE FOREST COVERTYPE DATASET
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 020
SKLEARNDATASETS FETCHKDDCUP99
SKLEARNDATASETS FETCHKDDCUP99 SUBSETNONE DATAHOMENONE SHUFFLEFALSE
RANDOMSTATENONE PERCENT10TRUE DOWN
LOADIFMISSINGTRUE RETURNXYFALSE
LOAD THE KDDCUP99 DATASET CLASSIFICATION
DOWNLOAD IT IF NECESSARY
CLASSES 23
SAMPLES TOTAL 4898431
DIMENSIONALITY 41
FEATURES DISCRETE INT OR CONTINUOUS FLOAT
READ MORE IN THE USER GUIDE
NEW IN VERSION 018
PARAMETERS
SUBSET NONE ‘SA’ ‘SF’ ‘HTTP’ ‘SMTP’ TO RETURN THE CORRESPONDING CLASSICAL SUBSETS OF KDDCUP
99 IF NONE RETURN THE ENTIRE KDDCUP 99 DATASET
DATAHOME STRING OPTIONAL SPECIFY ANOTHER DOWNLOAD AND CACHE FOLDER FOR THE DATASETS BY
DEFAULT ALL SCIKITLEARN DATA IS STORED IN ‘SCIKITLEARNDATA’ SUBFOLDERS VERSIONADDED
019
SHUFFLE BOOL DEFAULTFALSE WHETHER TO SHUFFLE DATASET
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET SHUFFLING AND FOR SELECTION OF ABNORMAL SAMPLES IF SUBSETSA PASS
AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION CALLS SEE GLOSSARY
PERCENT10 BOOL DEFAULTTRUE WHETHER TO LOAD ONLY 10 PERCENT OF THE DATA
DOWNLOADIFMISSING BOOL DEFAULTTRUE IF FALSE RAISE A IOERROR IF THE DATA IS NOT LOCALLY
AVAILABLE INSTEAD OF TRYING TO DOWNLOAD THE DATA FROM THE SOURCE SITE
68SKLEARNDATASETS DATASETS 1583

RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATA TARGET INSTEAD OF A BUNCH
OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATA ANDTARGET OBJECT
NEW IN VERSION 020
RETURNS
DATA BUNCH
DICTIONARYLIKE OBJECT THE INTERESTING ATTRIBUTES ARE
• 'DATA' THE DATA TO LEARN
• 'TARGET' THE REGRESSION TARGET FOR EACH SAMPLE
• 'DESCR' A DESCRIPTION OF THE DATASET
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 020
SKLEARNDATASETS FETCHLFWPAIRS
SKLEARNDATASETS FETCHLFWPAIRS SUBSET'TRAIN' DATAHOMENONE FUNNELEDTRUE RE
SIZE05 COLORFALSE SLICESLICE70 195NONE SLICE78
172NONE DOWNLOADIFMISSINGTRUE
LOAD THE LABELED FACES IN THE WILD LFW PAIRS DATASET CLASSIFICATION
DOWNLOAD IT IF NECESSARY
CLASSES 5749
SAMPLES TOTAL 13233
DIMENSIONALITY 5828
FEATURES REAL BETWEEN 0 AND 255
IN THE OFFICIAL READMETXT THIS TASK IS DESCRIBED AS THE "RESTRICTED" TASK AS I AM NOT SURE AS TO IMPLEMENT THE
"UNRESTRICTED" VARIANT CORRECTLY I LEFT IT AS UNSUPPORTED FOR NOW
THE ORIGINAL IMAGES ARE 250 X 250 PIXELS BUT THE DEFAULT SLICE AND RESIZE ARGUMENTS REDUCE THEM TO 62 X 47
READ MORE IN THE USER GUIDE
PARAMETERS
SUBSET OPTIONAL DEFAULT 'TRAIN' SELECT THE DATASET TO LOAD 'TRAIN' FOR THE DEVELOPMENT TRAINING
SET 'TEST' FOR THE DEVELOPMENT TEST SET AND '10FOLDS' FOR THE OFFICIAL EVALUATION SET THAT IS
MEANT TO BE USED WITH A 10FOLDS CROSS VALIDATION
DATAHOME OPTIONAL DEFAULT NONE SPECIFY ANOTHER DOWNLOAD AND CACHE FOLDER FOR THE
DATASETS BY DEFAULT ALL SCIKITLEARN DATA IS STORED IN 'SCIKITLEARNDATA' SUBFOLDERS
FUNNELED BOOLEAN OPTIONAL DEFAULT TRUE DOWNLOAD AND USE THE FUNNELED VARIANT OF THE
DATASET
RESIZE FLOAT OPTIONAL DEFAULT 05 RATIO USED TO RESIZE THE EACH FACE PICTURE
COLOR BOOLEAN OPTIONAL DEFAULT FALSE KEEP THE 3 RGB CHANNELS INSTEAD OF AVERAGING THEM TO
A SINGLE GRAY LEVEL CHANNEL IF COLOR IS TRUE THE SHAPE OF THE DATA HAS ONE MORE DIMENSION
THAN THE SHAPE WITH COLOR FALSE
SLICE OPTIONAL PROVIDE A CUSTOM 2D SLICE HEIGHT WIDTH TO EXTRACT THE 'INTERESTING' PART OF
THE JPEG FILES AND AVOID USE STATISTICAL CORRELATION FROM THE BACKGROUND

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DOWNLOADIFMISSING OPTIONAL TRUE BY DEFAULT IF FALSE RAISE A IOERROR IF THE DATA IS NOT
LOCALLY AVAILABLE INSTEAD OF TRYING TO DOWNLOAD THE DATA FROM THE SOURCE SITE
RETURNS
THE DATA IS RETURNED AS A BUNCH OBJECT WITH THE FOLLOWING ATTRIBUTES
DATA NUMPY ARRAY OF SHAPE 2200 5828 SHAPE DEPENDS ON SUBSET EACH ROW CORRESPONDS
TO 2 RAVEL'D FACE IMAGES OF ORIGINAL SIZE 62 X 47 PIXELS CHANGING THE SLICE RESIZE OR
SUBSET PARAMETERS WILL CHANGE THE SHAPE OF THE OUTPUT
PAIRS NUMPY ARRAY OF SHAPE 2200 2 62 47 SHAPE DEPENDS ON SUBSET EACH ROW HAS 2
FACE IMAGES CORRESPONDING TO SAME OR DIFFERENT PERSON FROM THE DATASET CONTAINING 5749
PEOPLE CHANGING THE SLICE RESIZE ORSUBSET PARAMETERS WILL CHANGE THE SHAPE OF
THE OUTPUT
TARGET NUMPY ARRAY OF SHAPE 2200 SHAPE DEPENDS ON SUBSET LABELS ASSOCIATED TO EACH
PAIR OF IMAGES THE TWO LABEL VALUES BEING DIFFERENT PERSONS OR THE SAME PERSON
DESCR STRING DESCRIPTION OF THE LABELED FACES IN THE WILD LFW DATASET
SKLEARNDATASETS FETCHLFWPEOPLE
SKLEARNDATASETS FETCHLFWPEOPLE DATAHOMENONE FUNNELEDTRUE RESIZE05
MINFACESPERPERSON0 COLORFALSE SLICESLICE70
195 NONE SLICE78 172 NONE DOWN
LOADIFMISSINGTRUE RETURNXYFALSE
LOAD THE LABELED FACES IN THE WILD LFW PEOPLE DATASET CLASSIFICATION
DOWNLOAD IT IF NECESSARY
CLASSES 5749
SAMPLES TOTAL 13233
DIMENSIONALITY 5828
FEATURES REAL BETWEEN 0 AND 255
READ MORE IN THE USER GUIDE
PARAMETERS
DATAHOME OPTIONAL DEFAULT NONE SPECIFY ANOTHER DOWNLOAD AND CACHE FOLDER FOR THE
DATASETS BY DEFAULT ALL SCIKITLEARN DATA IS STORED IN 'SCIKITLEARNDATA' SUBFOLDERS
FUNNELED BOOLEAN OPTIONAL DEFAULT TRUE DOWNLOAD AND USE THE FUNNELED VARIANT OF THE
DATASET
RESIZE FLOAT OPTIONAL DEFAULT 05 RATIO USED TO RESIZE THE EACH FACE PICTURE
MINFACESPERPERSON INT OPTIONAL DEFAULT NONE THE EXTRACTED DATASET WILL ONLY RETAIN PIC
TURES OF PEOPLE THAT HAVE AT LEAST MINFACESPERPERSON DIFFERENT PICTURES
COLOR BOOLEAN OPTIONAL DEFAULT FALSE KEEP THE 3 RGB CHANNELS INSTEAD OF AVERAGING THEM TO
A SINGLE GRAY LEVEL CHANNEL IF COLOR IS TRUE THE SHAPE OF THE DATA HAS ONE MORE DIMENSION
THAN THE SHAPE WITH COLOR FALSE
SLICE OPTIONAL PROVIDE A CUSTOM 2D SLICE HEIGHT WIDTH TO EXTRACT THE 'INTERESTING' PART OF
THE JPEG FILES AND AVOID USE STATISTICAL CORRELATION FROM THE BACKGROUND
DOWNLOADIFMISSING OPTIONAL TRUE BY DEFAULT IF FALSE RAISE A IOERROR IF THE DATA IS NOT
LOCALLY AVAILABLE INSTEAD OF TRYING TO DOWNLOAD THE DATA FROM THE SOURCE SITE
68SKLEARNDATASETS DATASETS 1585

RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATASETDATA DATASET
TARGET INSTEAD OF A BUNCH OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATASET
DATA ANDDATASETTARGET OBJECT
NEW IN VERSION 020
RETURNS
DATASET DICTLIKE OBJECT WITH THE FOLLOWING ATTRIBUTES
DATASETDATA NUMPY ARRAY OF SHAPE 13233 2914 EACH ROW CORRESPONDS TO A RAVELLED FACE
IMAGE OF ORIGINAL SIZE 62 X 47 PIXELS CHANGING THE SLICE OR RESIZE PARAMETERS WILL
CHANGE THE SHAPE OF THE OUTPUT
DATASETIMAGES NUMPY ARRAY OF SHAPE 13233 62 47 EACH ROW IS A FACE IMAGE CORRESPONDING
TO ONE OF THE 5749 PEOPLE IN THE DATASET CHANGING THE SLICE OR RESIZE PARAMETERS WILL
CHANGE THE SHAPE OF THE OUTPUT
DATASETTARGET NUMPY ARRAY OF SHAPE 13233 LABELS ASSOCIATED TO EACH FACE IMAGE THOSE
LABELS RANGE FROM 05748 AND CORRESPOND TO THE PERSON IDS
DATASETDESCR STRING DESCRIPTION OF THE LABELED FACES IN THE WILD LFW DATASET
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 020
EXAMPLES USING SKLEARNDATASETSFETCHLFWPEOPLE
•FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
SKLEARNDATASETS FETCHOLIVETTIFACES
SKLEARNDATASETS FETCHOLIVETTIFACES DATAHOMENONE SHUFFLEFALSE RANDOMSTATE0
DOWNLOADIFMISSINGTRUE
LOAD THE OLIVETTI FACES DATASET FROM ATT CLASSIFICATION
DOWNLOAD IT IF NECESSARY
CLASSES 40
SAMPLES TOTAL 400
DIMENSIONALITY 4096
FEATURES REAL BETWEEN 0 AND 1
READ MORE IN THE USER GUIDE
PARAMETERS
DATAHOME OPTIONAL DEFAULT NONE SPECIFY ANOTHER DOWNLOAD AND CACHE FOLDER FOR THE
DATASETS BY DEFAULT ALL SCIKITLEARN DATA IS STORED IN ‘SCIKITLEARNDATA’ SUBFOLDERS
SHUFFLE BOOLEAN OPTIONAL IF TRUE THE ORDER OF THE DATASET IS SHUFFLED TO AVOID HAVING IMAGES OF
THE SAME PERSON GROUPED
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT0 DETERMINES RANDOM NUMBER
GENERATION FOR DATASET SHUFFLING PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
DOWNLOADIFMISSING OPTIONAL TRUE BY DEFAULT IF FALSE RAISE A IOERROR IF THE DATA IS NOT
LOCALLY AVAILABLE INSTEAD OF TRYING TO DOWNLOAD THE DATA FROM THE SOURCE SITE

RETURNS
AN OBJECT WITH THE FOLLOWING ATTRIBUTES
DATA NUMPY ARRAY OF SHAPE 400 4096 EACH ROW CORRESPONDS TO A RAVELLED FACE IMAGE OF
ORIGINAL SIZE 64 X 64 PIXELS
IMAGES NUMPY ARRAY OF SHAPE 400 64 64 EACH ROW IS A FACE IMAGE CORRESPONDING TO ONE OF
THE 40 SUBJECTS OF THE DATASET
TARGET NUMPY ARRAY OF SHAPE 400 LABELS ASSOCIATED TO EACH FACE IMAGE THOSE LABELS ARE
RANGING FROM 039 AND CORRESPOND TO THE SUBJECT IDS
DESCR STRING DESCRIPTION OF THE MODIFIED OLIVETTI FACES DATASET
EXAMPLES USING SKLEARNDATASETSFETCHOLIVETTIFACES
•FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS
•ONLINE LEARNING OF A DICTIONARY OF PARTS OF FACES
•FACES DATASET DECOMPOSITIONS
•PIXEL IMPORTANCES WITH A PARALLEL FOREST OF TREES
SKLEARNDATASETS FETCHOPENML
SKLEARNDATASETS FETCHOPENML NAMENONE VERSION‘ACTIVE’ DATAIDNONE DATAHOMENONE
TARGETCOLUMN‘DEFAULTTARGET’ CACHETRUE RETURNXYFALSE
FETCH DATASET FROM OPENML BY NAME OR DATASET ID
DATASETS ARE UNIQUELY IDENTIFIED BY EITHER AN INTEGER ID OR BY A COMBINATION OF NAME AND VERSION IE THERE
MIGHT BE MULTIPLE VERSIONS OF THE ‘IRIS’ DATASET PLEASE GIVE EITHER NAME OR DATAID NOT BOTH IN CASE A NAME IS
GIVEN A VERSION CAN ALSO BE PROVIDED
READ MORE IN THE USER GUIDE
NOTE EXPERIMENTAL
THE API IS EXPERIMENTAL PARTICULARLY THE RETURN VALUE STRUCTURE AND MIGHT HAVE SMALL BACKWARDINCOMPATIBLE
CHANGES IN FUTURE RELEASES
PARAMETERS
NAME STR OR NONE STRING IDENTIFIER OF THE DATASET NOTE THAT OPENML CAN HAVE MULTIPLE
DATASETS WITH THE SAME NAME
VERSION INTEGER OR ‘ACTIVE’ DEFAULT‘ACTIVE’ VERSION OF THE DATASET CAN ONLY BE PROVIDED IF
ALSONAME IS GIVEN IF ‘ACTIVE’ THE OLDEST VERSION THAT’S STILL ACTIVE IS USED SINCE THERE
MAY BE MORE THAN ONE ACTIVE VERSION OF A DATASET AND THOSE VERSIONS MAY FUNDAMENTALLY BE
DIFFERENT FROM ONE ANOTHER SETTING AN EXACT VERSION IS HIGHLY RECOMMENDED
DATAID INT OR NONE OPENML ID OF THE DATASET THE MOST SPECIFIC WAY OF RETRIEVING A DATASET
IF DATAID IS NOT GIVEN NAME AND POTENTIAL VERSION ARE USED TO OBTAIN A DATASET
DATAHOME STRING OR NONE DEFAULT NONE SPECIFY ANOTHER DOWNLOAD AND CACHE FOLDER FOR THE
DATA SETS BY DEFAULT ALL SCIKITLEARN DATA IS STORED IN ‘SCIKITLEARNDATA’ SUBFOLDERS

TARGETCOLUMN STRING LIST OR NONE DEFAULT ‘DEFAULTTARGET’ SPECIFY THE COLUMN NAME IN THE
DATA TO USE AS TARGET IF ‘DEFAULTTARGET’ THE STANDARD TARGET COLUMN A STORED ON THE SERVER IS
USED IFNONE ALL COLUMNS ARE RETURNED AS DATA AND THE TARGET IS NONE IF LIST OF STRINGS ALL
COLUMNS WITH THESE NAMES ARE RETURNED AS MULTITARGET NOTE NOT ALL SCIKITLEARN CLASSIFIERS
CAN HANDLE ALL TYPES OF MULTIOUTPUT COMBINATIONS
CACHE BOOLEAN DEFAULTTRUE WHETHER TO CACHE DOWNLOADED DATASETS USING JOBLIB
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATA TARGET INSTEAD OF A BUNCH
OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATA ANDTARGET OBJECTS
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT WITH ATTRIBUTES
DATA NPARRAY OR SCIPYSPARSECSRMATRIX OF FLOATS THE FEATURE MATRIX CATEGORICAL FEATURES
ARE ENCODED AS ORDINALS
TARGET NPARRAY THE REGRESSION TARGET OR CLASSIFICATION LABELS IF APPLICABLE DTYPE IS FLOAT
IF NUMERIC AND OBJECT IF CATEGORICAL
DESCR STR THE FULL DESCRIPTION OF THE DATASET
FEATURENAMES LIST THE NAMES OF THE DATASET COLUMNS
CATEGORIES DICT MAPS EACH CATEGORICAL FEATURE NAME TO A LIST OF VALUES SUCH THAT THE VALUE
ENCODED AS I IS ITH IN THE LIST
DETAILS DICT MORE METADATA FROM OPENML
DATA TARGET TUPLE IFRETURNXY IS TRUE
NOTE EXPERIMENTAL
THIS INTERFACE IS EXPERIMENTAL AND SUBSEQUENT RELEASES MAY CHANGE ATTRIBUTES WITHOUT NOTICE
ALTHOUGH THERE SHOULD ONLY BE MINOR CHANGES TO DATA ANDTARGET
MISSING VALUES IN THE ‘DATA’ ARE REPRESENTED AS NAN’S MISSING VALUES IN ‘TARGET’ ARE REPRE
SENTED AS NAN’S NUMERICAL TARGET OR NONE CATEGORICAL TARGET
EXAMPLES USING SKLEARNDATASETSFETCHOPENML
•GAUSSIAN PROCESS REGRESSION GPR ON MAUNA LOA CO2 DATA
•MNIST CLASSFIFICATION USING MULTINOMIAL LOGISTIC L1
•EARLY STOPPING OF STOCHASTIC GRADIENT DESCENT
•CLASSIFIER CHAIN
•VISUALIZATION OF MLP WEIGHTS ON MNIST
SKLEARNDATASETS FETCHRCV1
SKLEARNDATASETS FETCHRCV1 DATAHOMENONE SUBSET’ALL’ DOWNLOADIFMISSINGTRUE RAN
DOMSTATENONE SHUFFLEFALSE RETURNXYFALSE
LOAD THE RCV1 MULTILABEL DATASET CLASSIFICATION
DOWNLOAD IT IF NECESSARY

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VERSION RCV1V2 VECTORS FULL SETS TOPICS MULTILABELS
CLASSES 103
SAMPLES TOTAL 804414
DIMENSIONALITY 47236
FEATURES REAL BETWEEN 0 AND 1
READ MORE IN THE USER GUIDE
NEW IN VERSION 017
PARAMETERS
DATAHOME STRING OPTIONAL SPECIFY ANOTHER DOWNLOAD AND CACHE FOLDER FOR THE DATASETS BY DEFAULT ALL SCIKITLEARN DATA IS STORED IN ‘SCIKITLEARNDATA’ SUBFOLDERS
SUBSET STRING ‘TRAIN’ ‘TEST’ OR ‘ALL’ DEFAULT’ALL’ SELECT THE DATASET TO LOAD ‘TRAIN’ FOR THE TRAINING SET 23149 SAMPLES ‘TEST’ FOR THE TEST SET 781265 SAMPLES ‘ALL’ FOR BOTH WITH THE TRAINING SAMPLES FIRST IF SHUFFLE IS FALSE THIS FOLLOWS THE OFFICIAL LYRL2004 CHRONOLOGICAL SPLIT
DOWNLOADIFMISSING BOOLEAN DEFAULTTRUE IF FALSE RAISE A IOERROR IF THE DATA IS NOT LOCALLY AVAILABLE INSTEAD OF TRYING TO DOWNLOAD THE DATA FROM THE SOURCE SITE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN ERATION FOR DATASET SHUFFLING PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION CALLS SEE GLOSSARY
SHUFFLE BOOL DEFAULTFALSE WHETHER TO SHUFFLE DATASET
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATASETDATA DATASET
TARGET INSTEAD OF A BUNCH OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATASET DATA ANDDATASETTARGET OBJECT
NEW IN VERSION 020
RETURNS
DATASET DICTLIKE OBJECT WITH THE FOLLOWING ATTRIBUTES
DATASETDATA SCIPY CSR ARRAY DTYPE NPFLOAT64 SHAPE 804414 47236 THE ARRAY HAS 016 OF NON ZERO VALUES
DATASETTARGET SCIPY CSR ARRAY DTYPE NPUINT8 SHAPE 804414 103 EACH SAMPLE HAS A VALUE OF 1 IN ITS CATEGORIES AND 0 IN OTHERS THE ARRAY HAS 315 OF NON ZERO VALUES
DATASETSAMPLEID NUMPY ARRAY DTYPE NPUINT32 SHAPE 804414 IDENTIFICATION NUMBER OF EACH SAMPLE AS ORDERED IN DATASETDATA
DATASETTARGETNAMES NUMPY ARRAY DTYPE OBJECT LENGTH 103 NAMES OF EACH TARGET RCV1 TOPICS AS ORDERED IN DATASETTARGET
DATASETDESCR STRING DESCRIPTION OF THE RCV1 DATASET
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 020
SKLEARNDATASETS FETCHSPECIESDISTRIBUTIONS
SKLEARNDATASETS FETCHSPECIESDISTRIBUTIONS DATAHOMENONE DOWN LOADIFMISSINGTRUE
LOADER FOR SPECIES DISTRIBUTION DATASET FROM PHILLIPS ET AL 2006
68SKLEARNDATASETS DATASETS 1589

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READ MORE IN THE USER GUIDE
PARAMETERS
DATAHOME OPTIONAL DEFAULT NONE SPECIFY ANOTHER DOWNLOAD AND CACHE FOLDER FOR THE
DATASETS BY DEFAULT ALL SCIKITLEARN DATA IS STORED IN ‘SCIKITLEARNDATA’ SUBFOLDERS
DOWNLOADIFMISSING OPTIONAL TRUE BY DEFAULT IF FALSE RAISE A IOERROR IF THE DATA IS NOT
LOCALLY AVAILABLE INSTEAD OF TRYING TO DOWNLOAD THE DATA FROM THE SOURCE SITE
RETURNS
THE DATA IS RETURNED AS A BUNCH OBJECT WITH THE FOLLOWING ATTRIBUTES
COVERAGES ARRAY SHAPE 14 1592 1212 THESE REPRESENT THE 14 FEATURES MEASURED AT EACH
POINT OF THE MAP GRID THE LATITUDELONGITUDE VALUES FOR THE GRID ARE DISCUSSED BELOW MISS
ING DATA IS REPRESENTED BY THE VALUE 9999
TRAIN RECORD ARRAY SHAPE 1624 THE TRAINING POINTS FOR THE DATA EACH POINT HAS THREE FIELDS
• TRAIN‘SPECIES’ IS THE SPECIES NAME
• TRAIN‘DD LONG’ IS THE LONGITUDE IN DEGREES
• TRAIN‘DD LAT’ IS THE LATITUDE IN DEGREES
TEST RECORD ARRAY SHAPE 620 THE TEST POINTS FOR THE DATA SAME FORMAT AS THE TRAINING DATA
NX NY INTEGERS THE NUMBER OF LONGITUDES X AND LATITUDES Y IN THE GRID
XLEFTLOWERCORNER YLEFTLOWERCORNER FLOATS THE XY POSITION OF THE LOWERLEFT CORNER
IN DEGREES
GRIDSIZE FLOAT THE SPACING BETWEEN POINTS OF THE GRID IN DEGREES
NOTES
THIS DATASET REPRESENTS THE GEOGRAPHIC DISTRIBUTION OF SPECIES THE DATASET IS PROVIDED BY PHILLIPS ET AL 2006
THE TWO SPECIES ARE
• “BRADYPUS VARIEGATUS” THE BROWNTHROATED SLOTH
• “MICRORYZOMYS MINUTUS” ALSO KNOWN AS THE FOREST SMALL RICE RAT A RODENT THAT LIVES IN PERU COLOMBIA
ECUADOR PERU AND VENEZUELA
• FOR AN EXAMPLE OF USING THIS DATASET WITH SCIKITLEARN SEE EXAM
PLESAPPLICATIONSPLOTSPECIESDISTRIBUTIONMODELINGPY
REFERENCES
• “MAXIMUM ENTROPY MODELING OF SPECIES GEOGRAPHIC DISTRIBUTIONS” S J PHILLIPS R P ANDERSON R E
SCHAPIRE ECOLOGICAL MODELLING 190231259 2006
EXAMPLES USING SKLEARNDATASETSFETCHSPECIESDISTRIBUTIONS
•SPECIES DISTRIBUTION MODELING
•KERNEL DENSITY ESTIMATE OF SPECIES DISTRIBUTIONS

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SKLEARNDATASETS GETDATAHOME
SKLEARNDATASETS GETDATAHOME DATAHOMENONE
RETURN THE PATH OF THE SCIKITLEARN DATA DIR
THIS FOLDER IS USED BY SOME LARGE DATASET LOADERS TO AVOID DOWNLOADING THE DATA SEVERAL TIMES
BY DEFAULT THE DATA DIR IS SET TO A FOLDER NAMED ‘SCIKITLEARNDATA’ IN THE USER HOME FOLDER
ALTERNATIVELY IT CAN BE SET BY THE ‘SCIKITLEARNDATA’ ENVIRONMENT VARIABLE OR PROGRAMMATICALLY BY GIVING
AN EXPLICIT FOLDER PATH THE ‘’ SYMBOL IS EXPANDED TO THE USER HOME FOLDER
IF THE FOLDER DOES NOT ALREADY EXIST IT IS AUTOMATICALLY CREATED
PARAMETERS
DATAHOME STR NONE THE PATH TO SCIKITLEARN DATA DIR
EXAMPLES USING SKLEARNDATASETSGETDATAHOME
•OUTOFCORE CLASSIFICATION OF TEXT DOCUMENTS
SKLEARNDATASETS LOADBOSTON
SKLEARNDATASETS LOADBOSTON RETURNXYFALSE
LOAD AND RETURN THE BOSTON HOUSEPRICES DATASET REGRESSION
SAMPLES TOTAL 506
DIMENSIONALITY 13
FEATURES REAL POSITIVE
TARGETS REAL 5 50
READ MORE IN THE USER GUIDE
PARAMETERS
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATA TARGET INSTEAD OF A BUNCH
OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATA ANDTARGET OBJECT
NEW IN VERSION 018
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT THE INTERESTING ATTRIBUTES ARE ‘DATA’ THE DATA TO LEARN
‘TARGET’ THE REGRESSION TARGETS ‘DESCR’ THE FULL DESCRIPTION OF THE DATASET AND ‘FILENAME’
THE PHYSICAL LOCATION OF BOSTON CSV DATASET ADDED IN VERSION 020
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 018
NOTES
CHANGED IN VERSION 020 FIXED A WRONG DATA POINT AT 445 0

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EXAMPLES
FROM SKLEARNDATASETS IMPORT LOADBOSTON
BOSTON LOADBOSTON
PRINTBOSTONDATASHAPE
506 13
EXAMPLES USING SKLEARNDATASETSLOADBOSTON
•OUTLIER DETECTION ON A REAL DATA SET
•MODEL COMPLEXITY INFLUENCE
•EFFECT OF TRANSFORMING THE TARGETS IN REGRESSION MODEL
•PLOT INDIVIDUAL AND VOTING REGRESSION PREDICTIONS
•GRADIENT BOOSTING REGRESSION
•FEATURE SELECTION USING SELECTFROMMODEL AND LASSOCV
•IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR
•PLOTTING CROSSVALIDATED PREDICTIONS
SKLEARNDATASETS LOADBREASTCANCER
SKLEARNDATASETS LOADBREASTCANCER RETURNXYFALSE
LOAD AND RETURN THE BREAST CANCER WISCONSIN DATASET CLASSIFICATION
THE BREAST CANCER DATASET IS A CLASSIC AND VERY EASY BINARY CLASSIFICATION DATASET
CLASSES 2
SAMPLES PER CLASS 212M357B
SAMPLES TOTAL 569
DIMENSIONALITY 30
FEATURES REAL POSITIVE
READ MORE IN THE USER GUIDE
PARAMETERS
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATA TARGET INSTEAD OF A BUNCH
OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATA ANDTARGET OBJECT
NEW IN VERSION 018
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT THE INTERESTING ATTRIBUTES ARE ‘DATA’ THE DATA TO LEARN
‘TARGET’ THE CLASSIFICATION LABELS ‘TARGETNAMES’ THE MEANING OF THE LABELS ‘FEATURENAMES’
THE MEANING OF THE FEATURES AND ‘DESCR’ THE FULL DESCRIPTION OF THE DATASET ‘FILENAME’ THE
PHYSICAL LOCATION OF BREAST CANCER CSV DATASET ADDED IN VERSION 020
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 018
THE COPY OF UCI ML BREAST CANCER WISCONSIN DIAGNOSTIC DATASET IS
DOWNLOADED FROM

SCIKITLEARN USER GUIDE RELEASE 0213
HTTPSGOOGLU2UWZ2
EXAMPLES
LET’S SAY YOU ARE INTERESTED IN THE SAMPLES 10 50 AND 85 AND WANT TO KNOW THEIR CLASS NAME
FROM SKLEARNDATASETS IMPORT LOADBREASTCANCER
DATA LOADBREASTCANCER
DATATARGET10 50 85
ARRAY0 1 0
LISTDATATARGETNAMES
MALIGNANT BENIGN
SKLEARNDATASETS LOADDIABETES
SKLEARNDATASETS LOADDIABETES RETURNXYFALSE
LOAD AND RETURN THE DIABETES DATASET REGRESSION
SAMPLES TOTAL 442
DIMENSIONALITY 10
FEATURES REAL 2 X 2
TARGETS INTEGER 25 346
READ MORE IN THE USER GUIDE
PARAMETERS
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATA TARGET INSTEAD OF A BUNCH
OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATA ANDTARGET OBJECT
NEW IN VERSION 018
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT THE INTERESTING ATTRIBUTES ARE ‘DATA’ THE DATA TO LEARN ‘TAR
GET’ THE REGRESSION TARGET FOR EACH SAMPLE ‘DATAFILENAME’ THE PHYSICAL LOCATION OF DIABETES
DATA CSV DATASET AND ‘TARGETFILENAME’ THE PHYSICAL LOCATION OF DIABETES TARGETS CSV DATATASET
ADDED IN VERSION 020
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 018
EXAMPLES USING SKLEARNDATASETSLOADDIABETES
•CROSSVALIDATION ON DIABETES DATASET EXERCISE
•IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR
•LASSO PATH USING LARS
•LINEAR REGRESSION EXAMPLE
•SPARSITY EXAMPLE FITTING ONLY FEATURES 1 AND 2
•LASSO AND ELASTIC NET
•LASSO MODEL SELECTION CROSSVALIDATION AIC BIC
68SKLEARNDATASETS DATASETS 1593

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SKLEARNDATASETS LOADDIGITS
SKLEARNDATASETS LOADDIGITS NCLASS10 RETURNXYFALSE
LOAD AND RETURN THE DIGITS DATASET CLASSIFICATION
EACH DATAPOINT IS A 8X8 IMAGE OF A DIGIT
CLASSES 10
SAMPLES PER CLASS 180
SAMPLES TOTAL 1797
DIMENSIONALITY 64
FEATURES INTEGERS 016
READ MORE IN THE USER GUIDE
PARAMETERS
NCLASS INTEGER BETWEEN 0 AND 10 OPTIONAL DEFAULT10 THE NUMBER OF CLASSES TO RETURN
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATA TARGET INSTEAD OF A BUNCH
OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATA ANDTARGET OBJECT
NEW IN VERSION 018
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT THE INTERESTING ATTRIBUTES ARE ‘DATA’ THE DATA TO LEARN
‘IMAGES’ THE IMAGES CORRESPONDING TO EACH SAMPLE ‘TARGET’ THE CLASSIFICATION LABELS FOR
EACH SAMPLE ‘TARGETNAMES’ THE MEANING OF THE LABELS AND ‘DESCR’ THE FULL DESCRIPTION
OF THE DATASET
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 018
THIS IS A COPY OF THE TEST SET OF THE UCI ML HANDWRITTEN DIGITS DATASETS
HTTPSARCHIVEICSUCIEDUMLDATASETSOPTICALRECOGNITIONOFHANDWRITTENDIGITS
EXAMPLES
TO LOAD THE DATA AND VISUALIZE THE IMAGES
 FROM SKLEARNDATASETS IMPORT LOADDIGITS
DIGITS LOADDIGITS
PRINTDIGITSDATASHAPE
1797 64
 IMPORT MATPLOTLIBPYPLOT AS PLT
PLTGRAY
PLTMATSHOWDIGITSIMAGES0
PLTSHOW
EXAMPLES USING SKLEARNDATASETSLOADDIGITS
•THE JOHNSONLINDENSTRAUSS BOUND FOR EMBEDDING WITH RANDOM PROJECTIONS
•EXPLICIT FEATURE MAP APPROXIMATION FOR RBF KERNELS
•RECOGNIZING HANDWRITTEN DIGITS
1594 CHAPTER 6 API REFERENCE

•FEATURE AGGLOMERATION
•VARIOUS AGGLOMERATIVE CLUSTERING ON A 2D EMBEDDING OF DIGITS
•A DEMO OF KMEANS CLUSTERING ON THE HANDWRITTEN DIGITS DATA
•PIPELINING CHAINING A PCA AND A LOGISTIC REGRESSION
•SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV
•THE DIGIT DATASET
•EARLY STOPPING OF GRADIENT BOOSTING
•DIGITS CLASSIFICATION EXERCISE
•CROSSVALIDATION ON DIGITS DATASET EXERCISE
•RECURSIVE FEATURE ELIMINATION
•COMPARING VARIOUS ONLINE SOLVERS
•L1 PENALTY AND SPARSITY IN LOGISTIC REGRESSION
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
•PLOTTING VALIDATION CURVES
•PARAMETER ESTIMATION USING GRID SEARCH WITH CROSSVALIDATION
•COMPARING RANDOMIZED SEARCH AND GRID SEARCH FOR HYPERPARAMETER ESTIMATION
•BALANCE MODEL COMPLEXITY AND CROSSVALIDATED SCORE
•PLOTTING LEARNING CURVES
•KERNEL DENSITY ESTIMATION
•DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
•RESTRICTED BOLTZMANN MACHINE FEATURES FOR DIGIT CLASSIFICATION
•COMPARE STOCHASTIC LEARNING STRATEGIES FOR MLPCLASSIFIER
•LABEL PROPAGATION DIGITS DEMONSTRATING PERFORMANCE
•LABEL PROPAGATION DIGITS ACTIVE LEARNING
SKLEARNDATASETS LOADFILES
SKLEARNDATASETS LOADFILES CONTAINERPATH DESCRIPTIONNONE CATEGORIESNONE
LOADCONTENTTRUE SHUFFLETRUE ENCODINGNONE DE
CODEERROR'STRICT' RANDOMSTATE0
LOAD TEXT FILES WITH CATEGORIES AS SUBFOLDER NAMES
INDIVIDUAL SAMPLES ARE ASSUMED TO BE FILES STORED A TWO LEVELS FOLDER STRUCTURE SUCH AS THE FOLLOWING
CONTAINERFOLDER
CATEGORY1FOLDER FILE1TXT FILE2TXT FILE42TXT
CATEGORY2FOLDER FILE43TXT FILE44TXT
THE FOLDER NAMES ARE USED AS SUPERVISED SIGNAL LABEL NAMES THE INDIVIDUAL FILE NAMES ARE NOT IMPORTANT
THIS FUNCTION DOES NOT TRY TO EXTRACT FEATURES INTO A NUMPY ARRAY OR SCIPY SPARSE MATRIX IN ADDITION IF
LOADCONTENT IS FALSE IT DOES NOT TRY TO LOAD THE FILES IN MEMORY

TO USE TEXT FILES IN A SCIKITLEARN CLASSIFICATION OR CLUSTERING ALGORITHM YOU WILL NEED TO USE THE SKLEARN FEATUREEXTRACTIONTEXT MODULE TO BUILD A FEATURE EXTRACTION TRANSFORMER THAT SUITS YOUR PROBLEM
IF YOU SET LOADCONTENTTRUE YOU SHOULD ALSO SPECIFY THE ENCODING OF THE TEXT USING THE 'ENCODING' PARAMETER FOR MANY MODERN TEXT FILES 'UTF8' WILL BE THE CORRECT ENCODING IF YOU LEAVE ENCODING EQUAL TO NONE THEN THE CONTENT WILL BE MADE OF BYTES INSTEAD OF UNICODE AND YOU WILL NOT BE ABLE TO USE MOST FUNCTIONS IN SKLEARN FEATUREEXTRACTIONTEXT
SIMILAR FEATURE EXTRACTORS SHOULD BE BUILT FOR OTHER KIND OF UNSTRUCTURED DATA INPUT SUCH AS IMAGES AUDIO VIDEO

READ MORE IN THE USER GUIDE
PARAMETERS
CONTAINERPATH STRING OR UNICODE PATH TO THE MAIN FOLDER HOLDING ONE SUBFOLDER PER CATEGORY
DESCRIPTION STRING OR UNICODE OPTIONAL DEFAULTNONE A PARAGRAPH DESCRIBING THE CHARACTER ISTIC OF THE DATASET ITS SOURCE REFERENCE ETC
CATEGORIES A COLLECTION OF STRINGS OR NONE OPTIONAL DEFAULTNONE IF NONE DEFAULT LOAD ALL THE CATEGORIES IF NOT NONE LIST OF CATEGORY NAMES TO LOAD OTHER CATEGORIES IGNORED
LOADCONTENT BOOLEAN OPTIONAL DEFAULTTRUE WHETHER TO LOAD OR NOT THE CONTENT OF THE DIF FERENT FILES IF TRUE A 'DATA' ATTRIBUTE CONTAINING THE TEXT INFORMATION IS PRESENT IN THE DATA STRUCTURE RETURNED IF NOT A FILENAMES ATTRIBUTE GIVES THE PATH TO THE FILES
SHUFFLE BOOL OPTIONAL DEFAULTTRUE WHETHER OR NOT TO SHUFFLE THE DATA MIGHT BE IMPORTANT FOR MODELS THAT MAKE THE ASSUMPTION THAT THE SAMPLES ARE INDEPENDENT AND IDENTICALLY DIS TRIBUTED IID SUCH AS STOCHASTIC GRADIENT DESCENT
ENCODING STRING OR NONE DEFAULT IS NONE IF NONE DO NOT TRY TO DECODE THE CONTENT OF THE FILES EG FOR IMAGES OR OTHER NONTEXT CONTENT IF NOT NONE ENCODING TO USE TO DECODE TEXT FILES TO UNICODE IF LOADCONTENT IS TRUE
DECODEERROR 'STRICT' 'IGNORE' 'REPLACE' OPTIONAL INSTRUCTION ON WHAT TO DO IF A BYTE SE QUENCE IS GIVEN TO ANALYZE THAT CONTAINS CHARACTERS NOT OF THE GIVEN ENCODING PASSED AS KEYWORD ARGUMENT 'ERRORS' TO BYTESDECODE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT0 DETERMINES RANDOM NUMBER GENERATION FOR DATASET SHUFFLING PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION CALLS SEE GLOSSARY
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT THE INTERESTING ATTRIBUTES ARE EITHER DATA THE RAW TEXT DATA TO LEARN OR 'FILENAMES' THE FILES HOLDING IT 'TARGET' THE CLASSIFICATION LABELS INTEGER INDEX 'TARGETNAMES' THE MEANING OF THE LABELS AND 'DESCR' THE FULL DESCRIPTION OF THE DATASET
SKLEARNDATASETS LOADIRIS
SKLEARNDATASETS LOADIRIS RETURNXYFALSE
LOAD AND RETURN THE IRIS DATASET CLASSIFICATION
THE IRIS DATASET IS A CLASSIC AND VERY EASY MULTICLASS CLASSIFICATION DATASET

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CLASSES 3
SAMPLES PER CLASS 50
SAMPLES TOTAL 150
DIMENSIONALITY 4
FEATURES REAL POSITIVE
READ MORE IN THE USER GUIDE
PARAMETERS
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATA TARGET INSTEAD OF A BUNCH
OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATA ANDTARGET OBJECT
NEW IN VERSION 018
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT THE INTERESTING ATTRIBUTES ARE ‘DATA’ THE DATA TO LEARN
‘TARGET’ THE CLASSIFICATION LABELS ‘TARGETNAMES’ THE MEANING OF THE LABELS ‘FEATURENAMES’
THE MEANING OF THE FEATURES ‘DESCR’ THE FULL DESCRIPTION OF THE DATASET ‘FILENAME’ THE
PHYSICAL LOCATION OF IRIS CSV DATASET ADDED IN VERSION 020
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 018
NOTES
CHANGED IN VERSION 020 FIXED TWO WRONG DATA POINTS ACCORDING TO FISHER’S PAPER THE NEW VERSION IS THE SAME
AS IN R BUT NOT AS IN THE UCI MACHINE LEARNING REPOSITORY
EXAMPLES
LET’S SAY YOU ARE INTERESTED IN THE SAMPLES 10 25 AND 50 AND WANT TO KNOW THEIR CLASS NAME
 FROM SKLEARNDATASETS IMPORT LOADIRIS
DATA LOADIRIS
DATATARGET10 25 50
ARRAY0 0 1
LISTDATATARGETNAMES
SETOSA VERSICOLOR VIRGINICA
EXAMPLES USING SKLEARNDATASETSLOADIRIS
•PLOT CLASSIFICATION PROBABILITY
•KMEANS CLUSTERING
•CONCATENATING MULTIPLE FEATURE EXTRACTION METHODS
•THE IRIS DATASET
•PCA EXAMPLE WITH IRIS DATASET
•INCREMENTAL PCA
•COMPARISON OF LDA AND PCA 2D PROJECTION OF IRIS DATASET
•PLOT THE DECISION BOUNDARIES OF A VOTINGCLASSIFIER
68SKLEARNDATASETS DATASETS 1597

•EARLY STOPPING OF GRADIENT BOOSTING
•PLOT THE DECISION SURFACES OF ENSEMBLES OF TREES ON THE IRIS DATASET
•SVM EXERCISE
•TEST WITH PERMUTATIONS THE SIGNIFICANCE OF A CLASSIFICATION SCORE
•UNIVARIATE FEATURE SELECTION
•GAUSSIAN PROCESS CLASSIFICATION GPC ON IRIS DATASET
•REGULARIZATION PATH OF L1 LOGISTIC REGRESSION
•LOGISTIC REGRESSION 3CLASS CLASSIFIER
•PLOT MULTICLASS SGD ON THE IRIS DATASET
•GMM COVARIANCES
•RECEIVER OPERATING CHARACTERISTIC ROC WITH CROSS VALIDATION
•NESTED VERSUS NONNESTED CROSSVALIDATION
•CONFUSION MATRIX
•RECEIVER OPERATING CHARACTERISTIC ROC
•PRECISIONRECALL
•NEAREST NEIGHBORS CLASSIFICATION
•NEAREST CENTROID CLASSIFICATION
•COMPARING NEAREST NEIGHBORS WITH AND WITHOUT NEIGHBORHOOD COMPONENTS ANALYSIS
•COMPARE STOCHASTIC LEARNING STRATEGIES FOR MLPCLASSIFIER
•DECISION BOUNDARY OF LABEL PROPAGATION VERSUS SVM ON THE IRIS DATASET
•SVM WITH CUSTOM KERNEL
•SVMANOVA SVM WITH UNIVARIATE FEATURE SELECTION
•PLOT DIFFERENT SVM CLASSIFIERS IN THE IRIS DATASET
•RBF SVM PARAMETERS
•PLOT THE DECISION SURFACE OF A DECISION TREE ON THE IRIS DATASET
•UNDERSTANDING THE DECISION TREE STRUCTURE
SKLEARNDATASETS LOADLINNERUD
SKLEARNDATASETS LOADLINNERUD RETURNXYFALSE
LOAD AND RETURN THE LINNERUD DATASET MULTIVARIATE REGRESSION
SAMPLES TOTAL 20
DIMENSIONALITY 3 FOR BOTH DATA AND TARGET
FEATURES INTEGER
TARGETS INTEGER
READ MORE IN THE USER GUIDE
PARAMETERS

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RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATA TARGET INSTEAD OF A BUNCH
OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATA ANDTARGET OBJECT
NEW IN VERSION 018
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT THE INTERESTING ATTRIBUTES ARE ‘DATA’ AND ‘TARGET’ THE TWO
MULTIVARIATE DATASETS WITH ‘DATA’ CORRESPONDING TO THE EXERCISE AND ‘TARGET’ CORRESPONDING
TO THE PHYSIOLOGICAL MEASUREMENTS AS WELL AS ‘FEATURENAMES’ AND ‘TARGETNAMES’ IN ADDI
TION YOU WILL ALSO HAVE ACCESS TO ‘DATAFILENAME’ THE PHYSICAL LOCATION OF LINNERUD DATA CSV
DATASET AND ‘TARGETFILENAME’ THE PHYSICAL LOCATION OF LINNERUD TARGETS CSV DATATASET ADDED
IN VERSION020
DATA TARGET TUPLE IFRETURNXY IS TRUE NEW IN VERSION 018
SKLEARNDATASETS LOADSAMPLEIMAGE
SKLEARNDATASETS LOADSAMPLEIMAGE IMAGENAME
LOAD THE NUMPY ARRAY OF A SINGLE SAMPLE IMAGE
READ MORE IN THE USER GUIDE
PARAMETERS
IMAGENAME CHINAJPG FLOWERJPG THE NAME OF THE SAMPLE IMAGE LOADED
RETURNS
IMG 3D ARRAY THE IMAGE AS A NUMPY ARRAY HEIGHT X WIDTH X COLOR
EXAMPLES
 FROM SKLEARNDATASETS IMPORT LOADSAMPLEIMAGE
CHINA LOADSAMPLEIMAGECHINAJPG
CHINADTYPE
DTYPEUINT8
CHINASHAPE
427 640 3
FLOWER LOADSAMPLEIMAGEFLOWERJPG
FLOWERDTYPE
DTYPEUINT8
FLOWERSHAPE
427 640 3
EXAMPLES USING SKLEARNDATASETSLOADSAMPLEIMAGE
•COLOR QUANTIZATION USING KMEANS
SKLEARNDATASETS LOADSAMPLEIMAGES
SKLEARNDATASETS LOADSAMPLEIMAGES
LOAD SAMPLE IMAGES FOR IMAGE MANIPULATION
LOADS BOTH CHINA ANDFLOWER

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READ MORE IN THE USER GUIDE
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT WITH THE FOLLOWING ATTRIBUTES ‘IMAGES’ THE TWO SAMPLE IMAGES ‘FILENAMES’ THE FILE NAMES FOR THE IMAGES AND ‘DESCR’ THE FULL DESCRIPTION OF THE DATASET
EXAMPLES
TO LOAD THE DATA AND VISUALIZE THE IMAGES
FROM SKLEARNDATASETS IMPORT LOADSAMPLEIMAGES
DATASET LOADSAMPLEIMAGES
LENDATASETIMAGES
2
FIRSTIMGDATA DATASETIMAGES0
FIRSTIMGDATASHAPE
427 640 3
FIRSTIMGDATADTYPE
DTYPEUINT8
SKLEARNDATASETS LOADSVMLIGHTFILE
SKLEARNDATASETS LOADSVMLIGHTFILE FNFEATURESNONE DTYPECLASS ‘NUMPYFLOAT64’ MULTILABELFALSE ZEROBASED’AUTO’ QUERYIDFALSE OFFSET0 LENGTH1
LOAD DATASETS IN THE SVMLIGHT LIBSVM FORMAT INTO SPARSE CSR MATRIX
THIS FORMAT IS A TEXTBASED FORMAT WITH ONE SAMPLE PER LINE IT DOES NOT STORE ZERO VALUED FEATURES HENCE IS SUITABLE FOR SPARSE DATASET
THE FIRST ELEMENT OF EACH LINE CAN BE USED TO STORE A TARGET VARIABLE TO PREDICT
THIS FORMAT IS USED AS THE DEFAULT FORMAT FOR BOTH SVMLIGHT AND THE LIBSVM COMMAND LINE PROGRAMS
PARSING A TEXT BASED SOURCE CAN BE EXPENSIVE WHEN WORKING ON REPEATEDLY ON THE SAME DATASET IT IS RECOM MENDED TO WRAP THIS LOADER WITH JOBLIBMEMORYCACHE TO STORE A MEMMAPPED BACKUP OF THE CSR RESULTS OF THE FIRST CALL AND BENEFIT FROM THE NEAR INSTANTANEOUS LOADING OF MEMMAPPED STRUCTURES FOR THE SUBSEQUENT CALLS
IN CASE THE FILE CONTAINS A PAIRWISE PREFERENCE CONSTRAINT KNOWN AS “QID” IN THE SVMLIGHT FORMAT THESE ARE IGNORED UNLESS THE QUERYID PARAMETER IS SET TO TRUE THESE PAIRWISE PREFERENCE CONSTRAINTS CAN BE USED TO CONSTRAINT THE COMBINATION OF SAMPLES WHEN USING PAIRWISE LOSS FUNCTIONS AS IS THE CASE IN SOME LEARNING TO RANK PROBLEMS SO THAT ONLY PAIRS WITH THE SAME QUERYID VALUE ARE CONSIDERED
THIS IMPLEMENTATION IS WRITTEN IN CYTHON AND IS REASONABLY FAST HOWEVER A FASTER APICOMPATIBLE LOADER IS ALSO AVAILABLE AT
HTTPSGITHUBCOMMBLONDELSVMLIGHTLOADER
PARAMETERS
FSTR FILELIKE INT PATH TO A FILE TO LOAD IF A PATH ENDS IN “GZ” OR “BZ2” IT WILL BE UNCOM PRESSED ON THE FLY IF AN INTEGER IS PASSED IT IS ASSUMED TO BE A FILE DESCRIPTOR A FILELIKE OR FILE DESCRIPTOR WILL NOT BE CLOSED BY THIS FUNCTION A FILELIKE OBJECT MUST BE OPENED IN BINARY MODE

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NFEATURES INT OR NONE THE NUMBER OF FEATURES TO USE IF NONE IT WILL BE INFERRED THIS
ARGUMENT IS USEFUL TO LOAD SEVERAL FILES THAT ARE SUBSETS OF A BIGGER SLICED DATASET EACH
SUBSET MIGHT NOT HAVE EXAMPLES OF EVERY FEATURE HENCE THE INFERRED SHAPE MIGHT VARY FROM
ONE SLICE TO ANOTHER NFEATURES IS ONLY REQUIRED IF OFFSET ORLENGTH ARE PASSED A NON
DEFAULT VALUE
DTYPE NUMPY DATA TYPE DEFAULT NPFLOAT64 DATA TYPE OF DATASET TO BE LOADED THIS WILL BE THE
DATA TYPE OF THE OUTPUT NUMPY ARRAYS XANDY
MULTILABEL BOOLEAN OPTIONAL DEFAULT FALSE SAMPLES MAY HAVE SEVERAL LABELS EACH SEE HTTPS
WWWCSIENTUEDUTWCJLINLIBSVMTOOLSDATASETSMULTILABELHTML
ZEROBASED BOOLEAN OR “AUTO” OPTIONAL DEFAULT “AUTO” WHETHER COLUMN INDICES IN F ARE ZERO
BASED TRUE OR ONEBASED FALSE IF COLUMN INDICES ARE ONEBASED THEY ARE TRANSFORMED
TO ZEROBASED TO MATCH PYTHONNUMPY CONVENTIONS IF SET TO “AUTO” A HEURISTIC CHECK IS
APPLIED TO DETERMINE THIS FROM THE FILE CONTENTS BOTH KINDS OF FILES OCCUR “IN THE WILD” BUT
THEY ARE UNFORTUNATELY NOT SELFIDENTIFYING USING “AUTO” OR TRUE SHOULD ALWAYS BE SAFE WHEN
NOOFFSET ORLENGTH IS PASSED IF OFFSET ORLENGTH ARE PASSED THE “AUTO” MODE FALLS
BACK TOZEROBASEDTRUE TO AVOID HAVING THE HEURISTIC CHECK YIELD INCONSISTENT RESULTS
ON DIFFERENT SEGMENTS OF THE FILE
QUERYID BOOLEAN DEFAULT FALSE IF TRUE WILL RETURN THE QUERYID ARRAY FOR EACH FILE
OFFSET INTEGER OPTIONAL DEFAULT 0 IGNORE THE OFFSET FIRST BYTES BY SEEKING FORWARD THEN DIS
CARDING THE FOLLOWING BYTES UP UNTIL THE NEXT NEW LINE CHARACTER
LENGTH INTEGER OPTIONAL DEFAULT 1 IF STRICTLY POSITIVE STOP READING ANY NEW LINE OF DATA ONCE
THE POSITION IN THE FILE HAS REACHED THE OFFSET LENGTH BYTES THRESHOLD
RETURNS
XSCIPYSPARSE MATRIX OF SHAPE NSAMPLES NFEATURES
YNDARRAY OF SHAPE NSAMPLES OR IN THE MULTILABEL A LIST OF TUPLES OF LENGTH NSAMPLES
QUERYID ARRAY OF SHAPE NSAMPLES QUERYID FOR EACH SAMPLE ONLY RETURNED WHEN QUERYID
IS SET TO TRUE
SEE ALSO
LOADSVMLIGHTFILES SIMILAR FUNCTION FOR LOADING MULTIPLE FILES IN THIS FORMAT ENFORCING THE SAME NUM
BER OF FEATURESCOLUMNS ON ALL OF THEM
EXAMPLES
TO USE JOBLIBMEMORY TO CACHE THE SVMLIGHT FILE
FROM JOBLIB IMPORT MEMORY
FROM DATASETS IMPORT LOADSVMLIGHTFILE
MEM MEMORYMYCACHE
MEMCACHE
DEFGETDATA
DATA LOADSVMLIGHTFILEMYSVMLIGHTFILE
RETURNDATA0 DATA1
X Y GETDATA
68SKLEARNDATASETS DATASETS 1601

SKLEARNDATASETS LOADSVMLIGHTFILES
SKLEARNDATASETS LOADSVMLIGHTFILES FILES NFEATURESNONE DTYPECLASS
'NUMPYFLOAT64' MULTILABELFALSE
ZEROBASED'AUTO' QUERYIDFALSE OFFSET0 LENGTH
1
LOAD DATASET FROM MULTIPLE FILES IN SVMLIGHT FORMAT
THIS FUNCTION IS EQUIVALENT TO MAPPING LOADSVMLIGHTFILE OVER A LIST OF FILES EXCEPT THAT THE RESULTS ARE CONCATE
NATED INTO A SINGLE FLAT LIST AND THE SAMPLES VECTORS ARE CONSTRAINED TO ALL HAVE THE SAME NUMBER OF FEATURES
IN CASE THE FILE CONTAINS A PAIRWISE PREFERENCE CONSTRAINT KNOWN AS "QID" IN THE SVMLIGHT FORMAT THESE ARE
IGNORED UNLESS THE QUERYID PARAMETER IS SET TO TRUE THESE PAIRWISE PREFERENCE CONSTRAINTS CAN BE USED TO
CONSTRAINT THE COMBINATION OF SAMPLES WHEN USING PAIRWISE LOSS FUNCTIONS AS IS THE CASE IN SOME LEARNING TO
RANK PROBLEMS SO THAT ONLY PAIRS WITH THE SAME QUERYID VALUE ARE CONSIDERED
PARAMETERS
FILES ITERABLE OVER STR FILELIKE INT PATHS OF FILES TO LOAD IF A PATH ENDS IN "GZ" OR "BZ2" IT
WILL BE UNCOMPRESSED ON THE FLY IF AN INTEGER IS PASSED IT IS ASSUMED TO BE A FILE DESCRIPTOR
FILELIKES AND FILE DESCRIPTORS WILL NOT BE CLOSED BY THIS FUNCTION FILELIKE OBJECTS MUST BE
OPENED IN BINARY MODE
NFEATURES INT OR NONE THE NUMBER OF FEATURES TO USE IF NONE IT WILL BE INFERRED FROM THE
MAXIMUM COLUMN INDEX OCCURRING IN ANY OF THE FILES
THIS CAN BE SET TO A HIGHER VALUE THAN THE ACTUAL NUMBER OF FEATURES IN ANY OF THE INPUT FILES
BUT SETTING IT TO A LOWER VALUE WILL CAUSE AN EXCEPTION TO BE RAISED
DTYPE NUMPY DATA TYPE DEFAULT NPFLOAT64 DATA TYPE OF DATASET TO BE LOADED THIS WILL BE THE
DATA TYPE OF THE OUTPUT NUMPY ARRAYS XANDY
MULTILABEL BOOLEAN OPTIONAL SAMPLES MAY HAVE SEVERAL LABELS EACH SEE HTTPSWWWCSIENTU
EDUTWCJLINLIBSVMTOOLSDATASETSMULTILABELHTML
ZEROBASED BOOLEAN OR "AUTO" OPTIONAL WHETHER COLUMN INDICES IN F ARE ZEROBASED TRUE OR
ONEBASED FALSE IF COLUMN INDICES ARE ONEBASED THEY ARE TRANSFORMED TO ZEROBASED TO
MATCH PYTHONNUMPY CONVENTIONS IF SET TO "AUTO" A HEURISTIC CHECK IS APPLIED TO DETERMINE
THIS FROM THE FILE CONTENTS BOTH KINDS OF FILES OCCUR "IN THE WILD" BUT THEY ARE UNFORTUNATELY
NOT SELFIDENTIFYING USING "AUTO" OR TRUE SHOULD ALWAYS BE SAFE WHEN NO OFFSET OR LENGTH
IS PASSED IF OFFSET OR LENGTH ARE PASSED THE "AUTO" MODE FALLS BACK TO ZEROBASEDTRUE TO
AVOID HAVING THE HEURISTIC CHECK YIELD INCONSISTENT RESULTS ON DIFFERENT SEGMENTS OF THE FILE
QUERYID BOOLEAN DEFAULTS TO FALSE IF TRUE WILL RETURN THE QUERYID ARRAY FOR EACH FILE
OFFSET INTEGER OPTIONAL DEFAULT 0 IGNORE THE OFFSET FIRST BYTES BY SEEKING FORWARD THEN DIS
CARDING THE FOLLOWING BYTES UP UNTIL THE NEXT NEW LINE CHARACTER
LENGTH INTEGER OPTIONAL DEFAULT 1 IF STRICTLY POSITIVE STOP READING ANY NEW LINE OF DATA ONCE
THE POSITION IN THE FILE HAS REACHED THE OFFSET LENGTH BYTES THRESHOLD
RETURNS
X1 Y1 XN YN
WHERE EACH XI YI PAIR IS THE RESULT FROM LOADSVMLIGHTFILEFILESI
IF QUERYID IS SET TO TRUE THIS WILL RETURN INSTEAD X1 Y1 Q1
  XN YN QN WHERE XI YI QI IS THE RESULT FROM
LOADSVMLIGHTFILEFILESI
SEE ALSO

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LOADSVMLIGHTFILE
NOTES
WHEN FITTING A MODEL TO A MATRIX XTRAIN AND EVALUATING IT AGAINST A MATRIX XTEST IT IS ESSENTIAL THAT XTRAIN AND XTEST HAVE THE SAME NUMBER OF FEATURES XTRAINSHAPE1 XTESTSHAPE1 THIS MAY NOT BE THE CASE IF YOU LOAD THE FILES INDIVIDUALLY WITH LOADSVMLIGHTFILE
SKLEARNDATASETS LOADWINE
SKLEARNDATASETS LOADWINE RETURNXYFALSE
LOAD AND RETURN THE WINE DATASET CLASSIFICATION
NEW IN VERSION 018
THE WINE DATASET IS A CLASSIC AND VERY EASY MULTICLASS CLASSIFICATION DATASET
CLASSES 3
SAMPLES PER CLASS 597148
SAMPLES TOTAL 178
DIMENSIONALITY 13
FEATURES REAL POSITIVE
READ MORE IN THE USER GUIDE
PARAMETERS
RETURNXY BOOLEAN DEFAULTFALSE IF TRUE RETURNS DATA TARGET INSTEAD OF A BUNCH OBJECT SEE BELOW FOR MORE INFORMATION ABOUT THE DATA ANDTARGET OBJECT
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT THE INTERESTING ATTRIBUTES ARE ‘DATA’ THE DATA TO LEARN ‘TARGET’ THE CLASSIFICATION LABELS ‘TARGETNAMES’ THE MEANING OF THE LABELS ‘FEATURENAMES’ THE MEANING OF THE FEATURES AND ‘DESCR’ THE FULL DESCRIPTION OF THE DATASET
DATA TARGET TUPLE IFRETURNXY IS TRUE
THE COPY OF UCI ML WINE DATA SET DATASET IS DOWNLOADED AND MODIFIED TO FIT STANDARD FORMAT FROM HTTPSARCHIVEICSUCIEDUMLMACHINELEARNINGDATABASESWINEWINEDATA
EXAMPLES
LET’S SAY YOU ARE INTERESTED IN THE SAMPLES 10 80 AND 140 AND WANT TO KNOW THEIR CLASS NAME
 FROM SKLEARNDATASETS IMPORT LOADWINE
DATA LOADWINE
DATATARGET10 80 140
ARRAY0 1 2
LISTDATATARGETNAMES
CLASS0 CLASS1 CLASS2

EXAMPLES USING SKLEARNDATASETSLOADWINE
•IMPORTANCE OF FEATURE SCALING
682 SAMPLES GENERATOR
DATASETSMAKEBICLUSTERS SHAPE NCLUSTERS GENERATE AN ARRAY WITH CONSTANT BLOCK DIAGONAL STRUCTURE FOR BICLUSTERING
DATASETSMAKEBLOBS NSAMPLES NFEATURES GENERATE ISOTROPIC GAUSSIAN BLOBS FOR CLUSTERING
DATASETSMAKECHECKERBOARD SHAPE NCLUSTERS GENERATE AN ARRAY WITH BLOCK CHECKERBOARD STRUCTURE FOR BI CLUSTERING
DATASETSMAKECIRCLES NSAMPLES SHUFFLE MAKE A LARGE CIRCLE CONTAINING A SMALLER CIRCLE IN 2D
DATASETSMAKECLASSIFICATION NSAMPLES
GENERATE A RANDOM NCLASS CLASSIFICATION PROBLEM
DATASETSMAKEFRIEDMAN1 NSAMPLES GENERATE THE “FRIEDMAN 1” REGRESSION PROBLEM
DATASETSMAKEFRIEDMAN2 NSAMPLES NOISE
GENERATE THE “FRIEDMAN 2” REGRESSION PROBLEM
DATASETSMAKEFRIEDMAN3 NSAMPLES NOISE
GENERATE THE “FRIEDMAN 3” REGRESSION PROBLEM
DATASETSMAKEGAUSSIANQUANTILES MEAN
GENERATE ISOTROPIC GAUSSIAN AND LABEL SAMPLES BY QUANTILE
DATASETSMAKEHASTIE102 NSAMPLES GENERATES DATA FOR BINARY CLASSIFICATION USED IN HASTIE ET AL
DATASETSMAKELOWRANKMATRIX NSAMPLES
GENERATE A MOSTLY LOW RANK MATRIX WITH BELLSHAPED SINGU
LAR VALUES
DATASETSMAKEMOONS NSAMPLES SHUFFLE MAKE TWO INTERLEAVING HALF CIRCLES
DATASETSMAKEMULTILABELCLASSIFICATION GENERATE A RANDOM MULTILABEL CLASSIFICATION PROBLEM
DATASETSMAKEREGRESSION NSAMPLES GENERATE A RANDOM REGRESSION PROBLEM
DATASETSMAKESCURVE NSAMPLES NOISE GENERATE AN S CURVE DATASET
DATASETSMAKESPARSECODEDSIGNAL NSAMPLES
GENERATE A SIGNAL AS A SPARSE COMBINATION OF DICTIONARY EL
EMENTS
DATASETSMAKESPARSESPDMATRIX DIM GENERATE A SPARSE SYMMETRIC DEFINITE POSITIVE MATRIX
DATASETSMAKESPARSEUNCORRELATED GENERATE A RANDOM REGRESSION PROBLEM WITH SPARSE UNCOR RELATED DESIGN
DATASETSMAKESPDMATRIX NDIM RAN
DOMSTATEGENERATE A RANDOM SYMMETRIC POSITIVEDEFINITE MATRIX
DATASETSMAKESWISSROLL NSAMPLES NOISE
GENERATE A SWISS ROLL DATASET
SKLEARNDATASETS MAKEBICLUSTERS
SKLEARNDATASETS MAKEBICLUSTERS SHAPE NCLUSTERS NOISE00 MINVAL10 MAXVAL100 SHUF FLETRUE RANDOMSTATENONE
GENERATE AN ARRAY WITH CONSTANT BLOCK DIAGONAL STRUCTURE FOR BICLUSTERING
READ MORE IN THE USER GUIDE
PARAMETERS
SHAPE ITERABLE NROWS NCOLS THE SHAPE OF THE RESULT
NCLUSTERS INTEGER THE NUMBER OF BICLUSTERS
NOISE FLOAT OPTIONAL DEFAULT00 THE STANDARD DEVIATION OF THE GAUSSIAN NOISE

MINVAL INT OPTIONAL DEFAULT10 MINIMUM VALUE OF A BICLUSTER
MAXVAL INT OPTIONAL DEFAULT100 MAXIMUM VALUE OF A BICLUSTER
SHUFFLE BOOLEAN OPTIONAL DEFAULTTRUE SHUFFLE THE SAMPLES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE SHAPE THE GENERATED ARRAY
ROWS ARRAY OF SHAPE NCLUSTERS XSHAPE0 THE INDICATORS FOR CLUSTER MEMBERSHIP OF EACH
ROW
COLS ARRAY OF SHAPE NCLUSTERS XSHAPE1 THE INDICATORS FOR CLUSTER MEMBERSHIP OF EACH
COLUMN
SEE ALSO
MAKECHECKERBOARD
REFERENCES
1
EXAMPLES USING SKLEARNDATASETSMAKEBICLUSTERS
•A DEMO OF THE SPECTRAL COCLUSTERING ALGORITHM
SKLEARNDATASETS MAKEBLOBS
SKLEARNDATASETS MAKEBLOBS NSAMPLES100 NFEATURES2 CENTERSNONE CLUSTERSTD10
CENTERBOX100 100 SHUFFLETRUE RANDOMSTATENONE
GENERATE ISOTROPIC GAUSSIAN BLOBS FOR CLUSTERING
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OR ARRAYLIKE OPTIONAL DEFAULT100 IF INT IT IS THE TOTAL NUMBER OF POINTS
EQUALLY DIVIDED AMONG CLUSTERS IF ARRAYLIKE EACH ELEMENT OF THE SEQUENCE INDICATES THE
NUMBER OF SAMPLES PER CLUSTER
NFEATURES INT OPTIONAL DEFAULT2 THE NUMBER OF FEATURES FOR EACH SAMPLE
CENTERS INT OR ARRAY OF SHAPE NCENTERS NFEATURES OPTIONAL DEFAULTNONE THE NUMBER OF
CENTERS TO GENERATE OR THE FIXED CENTER LOCATIONS IF NSAMPLES IS AN INT AND CENTERS IS NONE
3 CENTERS ARE GENERATED IF NSAMPLES IS ARRAYLIKE CENTERS MUST BE EITHER NONE OR AN ARRAY
OF LENGTH EQUAL TO THE LENGTH OF NSAMPLES
CLUSTERSTD FLOAT OR SEQUENCE OF FLOATS OPTIONAL DEFAULT10 THE STANDARD DEVIATION OF THE
CLUSTERS
CENTERBOX PAIR OF FLOATS MIN MAX OPTIONAL DEFAULT100 100 THE BOUNDING BOX FOR
EACH CLUSTER CENTER WHEN CENTERS ARE GENERATED AT RANDOM

SHUFFLE BOOLEAN OPTIONAL DEFAULTTRUE SHUFFLE THE SAMPLES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES NFEATURES THE GENERATED SAMPLES
YARRAY OF SHAPE NSAMPLES THE INTEGER LABELS FOR CLUSTER MEMBERSHIP OF EACH SAMPLE
SEE ALSO
MAKECLASSIFICATION A MORE INTRICATE VARIANT
EXAMPLES
```
 FROM SKLEARNDATASETSSAMPLESGENERATOR IMPORT MAKEBLOBS
X Y  MAKEBLOBSNSAMPLES10 CENTERS3 NFEATURES2
 RANDOMSTATE0
PRINTXSHAPE
10 2
Y
ARRAY0 0 1 0 2 2 2 1 1 0
X Y  MAKEBLOBSNSAMPLES3 3 4 CENTERS NONE NFEATURES2
 RANDOMSTATE0
PRINTXSHAPE
10 2
Y
ARRAY0 1 2 0 2 2 2 1 1 0
```
EXAMPLES USING SKLEARNDATASETSMAKEBLOBS
•COMPARING ANOMALY DETECTION ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS
•PROBABILITY CALIBRATION OF CLASSIFIERS
•PROBABILITY CALIBRATION FOR 3CLASS CLASSIFICATION
•NORMAL AND SHRINKAGE LINEAR DISCRIMINANT ANALYSIS FOR CLASSIFICATION
•A DEMO OF THE MEANSHIFT CLUSTERING ALGORITHM
•DEMONSTRATION OF KMEANS ASSUMPTIONS
•DEMO OF AFFINITY PROPAGATION CLUSTERING ALGORITHM
•DEMO OF DBSCAN CLUSTERING ALGORITHM
•INDUCTIVE CLUSTERING
•COMPARE BIRCH AND MINIBATCHKMEANS
•COMPARISON OF THE KMEANS AND MINIBATCHKMEANS CLUSTERING ALGORITHMS
•COMPARING DIFFERENT HIERARCHICAL LINKAGE METHODS ON TOY DATASETS
•SELECTING THE NUMBER OF CLUSTERS WITH SILHOUETTE ANALYSIS ON KMEANS CLUSTERING
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS

•PLOT RANDOMLY GENERATED CLASSIFICATION DATASET
•SGD MAXIMUM MARGIN SEPARATING HYPERPLANE
•PLOT MULTINOMIAL AND ONEVSREST LOGISTIC REGRESSION
•DEMONSTRATING THE DIFFERENT STRATEGIES OF KBINSDISCRETIZER
•SVM MAXIMUM MARGIN SEPARATING HYPERPLANE
•SVM SEPARATING HYPERPLANE FOR UNBALANCED CLASSES
SKLEARNDATASETS MAKECHECKERBOARD
SKLEARNDATASETS MAKECHECKERBOARD SHAPE NCLUSTERS NOISE00 MINVAL10 MAXVAL100
SHUFFLETRUE RANDOMSTATENONE
GENERATE AN ARRAY WITH BLOCK CHECKERBOARD STRUCTURE FOR BICLUSTERING
READ MORE IN THE USER GUIDE
PARAMETERS
SHAPE ITERABLE NROWS NCOLS THE SHAPE OF THE RESULT
NCLUSTERS INTEGER OR ITERABLE NROWCLUSTERS NCOLUMNCLUSTERS THE NUMBER OF ROW AND
COLUMN CLUSTERS
NOISE FLOAT OPTIONAL DEFAULT00 THE STANDARD DEVIATION OF THE GAUSSIAN NOISE
MINVAL INT OPTIONAL DEFAULT10 MINIMUM VALUE OF A BICLUSTER
MAXVAL INT OPTIONAL DEFAULT100 MAXIMUM VALUE OF A BICLUSTER
SHUFFLE BOOLEAN OPTIONAL DEFAULTTRUE SHUFFLE THE SAMPLES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE SHAPE THE GENERATED ARRAY
ROWS ARRAY OF SHAPE NCLUSTERS XSHAPE0 THE INDICATORS FOR CLUSTER MEMBERSHIP OF EACH
ROW
COLS ARRAY OF SHAPE NCLUSTERS XSHAPE1 THE INDICATORS FOR CLUSTER MEMBERSHIP OF EACH
COLUMN
SEE ALSO
MAKEBICLUSTERS
REFERENCES
1
EXAMPLES USING SKLEARNDATASETSMAKECHECKERBOARD
•A DEMO OF THE SPECTRAL BICLUSTERING ALGORITHM

SCIKITLEARN USER GUIDE RELEASE 0213
SKLEARNDATASETS MAKECIRCLES
SKLEARNDATASETS MAKECIRCLES NSAMPLES100 SHUFFLETRUE NOISENONE RANDOMSTATENONE
FACTOR08
MAKE A LARGE CIRCLE CONTAINING A SMALLER CIRCLE IN 2D
A SIMPLE TOY DATASET TO VISUALIZE CLUSTERING AND CLASSIFICATION ALGORITHMS
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE TOTAL NUMBER OF POINTS GENERATED IF ODD THE INNER
CIRCLE WILL HAVE ONE POINT MORE THAN THE OUTER CIRCLE
SHUFFLE BOOL OPTIONAL DEFAULTTRUE WHETHER TO SHUFFLE THE SAMPLES
NOISE DOUBLE OR NONE DEFAULTNONE STANDARD DEVIATION OF GAUSSIAN NOISE ADDED TO THE DATA
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET SHUFFLING AND NOISE PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE
FUNCTION CALLS SEE GLOSSARY
FACTOR 0 DOUBLE 1 DEFAULT8 SCALE FACTOR BETWEEN INNER AND OUTER CIRCLE
RETURNS
XARRAY OF SHAPE NSAMPLES 2 THE GENERATED SAMPLES
YARRAY OF SHAPE NSAMPLES THE INTEGER LABELS 0 OR 1 FOR CLASS MEMBERSHIP OF EACH SAMPLE
EXAMPLES USING SKLEARNDATASETSMAKECIRCLES
•CLASSIFIER COMPARISON
•COMPARING DIFFERENT HIERARCHICAL LINKAGE METHODS ON TOY DATASETS
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
•KERNEL PCA
•HASHING FEATURE TRANSFORMATION USING TOTALLY RANDOM TREES
•TSNE THE EFFECT OF VARIOUS PERPLEXITY VALUES ON THE SHAPE
•VARYING REGULARIZATION IN MULTILAYER PERCEPTRON
•COMPARE STOCHASTIC LEARNING STRATEGIES FOR MLPCLASSIFIER
•FEATURE DISCRETIZATION
•LABEL PROPAGATION LEARNING A COMPLEX STRUCTURE
SKLEARNDATASETS MAKECLASSIFICATION
SKLEARNDATASETS MAKECLASSIFICATION NSAMPLES100 NFEATURES20 NINFORMATIVE2
NREDUNDANT2 NREPEATED0 NCLASSES2
NCLUSTERSPERCLASS2 WEIGHTSNONE FLIPY001
CLASSSEP10 HYPERCUBETRUE SHIFT00 SCALE10
SHUFFLETRUE RANDOMSTATENONE
GENERATE A RANDOM NCLASS CLASSIFICATION PROBLEM

THIS INITIALLY CREATES CLUSTERS OF POINTS NORMALLY DISTRIBUTED STD1 ABOUT VERTICES OF AN NINFORMATIVE
DIMENSIONAL HYPERCUBE WITH SIDES OF LENGTH 2CLASSSEP AND ASSIGNS AN EQUAL NUMBER OF CLUSTERS TO EACH
CLASS IT INTRODUCES INTERDEPENDENCE BETWEEN THESE FEATURES AND ADDS VARIOUS TYPES OF FURTHER NOISE TO THE DATA
WITHOUT SHUFFLING XHORIZONTALLY STACKS FEATURES IN THE FOLLOWING ORDER THE PRIMARY NINFORMATIVE FEA
TURES FOLLOWED BY NREDUNDANT LINEAR COMBINATIONS OF THE INFORMATIVE FEATURES FOLLOWED BY NREPEATED
DUPLICATES DRAWN RANDOMLY WITH REPLACEMENT FROM THE INFORMATIVE AND REDUNDANT FEATURES THE REMAINING FEA
TURES ARE FILLED WITH RANDOM NOISE THUS WITHOUT SHUFFLING ALL USEFUL FEATURES ARE CONTAINED IN THE COLUMNS
X NINFORMATIVE NREDUNDANT NREPEATED
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE NUMBER OF SAMPLES
NFEATURES INT OPTIONAL DEFAULT20 THE TOTAL NUMBER OF FEA
TURES THESE COMPRISE NINFORMATIVE INFORMATIVE FEATURES
NREDUNDANT REDUNDANT FEATURES NREPEATED DUPLICATED FEATURES AND
NFEATURESNINFORMATIVENREDUNDANTNREPEATED USELESS FEATURES
DRAWN AT RANDOM
NINFORMATIVE INT OPTIONAL DEFAULT2 THE NUMBER OF INFORMATIVE FEATURES EACH CLASS IS
COMPOSED OF A NUMBER OF GAUSSIAN CLUSTERS EACH LOCATED AROUND THE VERTICES OF A HYPERCUBE
IN A SUBSPACE OF DIMENSION NINFORMATIVE FOR EACH CLUSTER INFORMATIVE FEATURES ARE
DRAWN INDEPENDENTLY FROM N0 1 AND THEN RANDOMLY LINEARLY COMBINED WITHIN EACH CLUSTER
IN ORDER TO ADD COVARIANCE THE CLUSTERS ARE THEN PLACED ON THE VERTICES OF THE HYPERCUBE
NREDUNDANT INT OPTIONAL DEFAULT2 THE NUMBER OF REDUNDANT FEATURES THESE FEATURES ARE
GENERATED AS RANDOM LINEAR COMBINATIONS OF THE INFORMATIVE FEATURES
NREPEATED INT OPTIONAL DEFAULT0 THE NUMBER OF DUPLICATED FEATURES DRAWN RANDOMLY
FROM THE INFORMATIVE AND THE REDUNDANT FEATURES
NCLASSES INT OPTIONAL DEFAULT2 THE NUMBER OF CLASSES OR LABELS OF THE CLASSIFICATION PROB
LEM
NCLUSTERSPERCLASS INT OPTIONAL DEFAULT2 THE NUMBER OF CLUSTERS PER CLASS
WEIGHTS LIST OF FLOATS OR NONE DEFAULTNONE THE PROPORTIONS OF SAMPLES ASSIGNED TO EACH
CLASS IF NONE THEN CLASSES ARE BALANCED NOTE THAT IF LENWEIGHTS NCLASSES
 1 THEN THE LAST CLASS WEIGHT IS AUTOMATICALLY INFERRED MORE THAN NSAMPLES SAMPLES
MAY BE RETURNED IF THE SUM OF WEIGHTS EXCEEDS 1
FLIPY FLOAT OPTIONAL DEFAULT001 THE FRACTION OF SAMPLES WHOSE CLASS ARE RANDOMLY EX
CHANGED LARGER VALUES INTRODUCE NOISE IN THE LABELS AND MAKE THE CLASSIFICATION TASK HARDER
CLASSSEP FLOAT OPTIONAL DEFAULT10 THE FACTOR MULTIPLYING THE HYPERCUBE SIZE LARGER VAL
UES SPREAD OUT THE CLUSTERSCLASSES AND MAKE THE CLASSIFICATION TASK EASIER
HYPERCUBE BOOLEAN OPTIONAL DEFAULTTRUE IF TRUE THE CLUSTERS ARE PUT ON THE VERTICES OF A
HYPERCUBE IF FALSE THE CLUSTERS ARE PUT ON THE VERTICES OF A RANDOM POLYTOPE
SHIFT FLOAT ARRAY OF SHAPE NFEATURES OR NONE OPTIONAL DEFAULT00 SHIFT FEATURES BY THE
SPECIFIED VALUE IF NONE THEN FEATURES ARE SHIFTED BY A RANDOM VALUE DRAWN IN CLASSSEP
CLASSSEP
SCALE FLOAT ARRAY OF SHAPE NFEATURES OR NONE OPTIONAL DEFAULT10 MULTIPLY FEATURES BY
THE SPECIFIED VALUE IF NONE THEN FEATURES ARE SCALED BY A RANDOM VALUE DRAWN IN 1 100
NOTE THAT SCALING HAPPENS AFTER SHIFTING
SHUFFLE BOOLEAN OPTIONAL DEFAULTTRUE SHUFFLE THE SAMPLES AND THE FEATURES

RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES NFEATURES THE GENERATED SAMPLES
YARRAY OF SHAPE NSAMPLES THE INTEGER LABELS FOR CLASS MEMBERSHIP OF EACH SAMPLE
SEE ALSO
MAKEBLOBS SIMPLIFIED VARIANT
MAKEMULTILABELCLASSIFICATION UNRELATED GENERATOR FOR MULTILABEL TASKS
NOTES
THE ALGORITHM IS ADAPTED FROM GUYON 1 AND WAS DESIGNED TO GENERATE THE “MADELON” DATASET
REFERENCES
1
EXAMPLES USING SKLEARNDATASETSMAKECLASSIFICATION
•COMPARISON OF CALIBRATION OF CLASSIFIERS
•PROBABILITY CALIBRATION CURVES
•CLASSIFIER COMPARISON
•PLOT RANDOMLY GENERATED CLASSIFICATION DATASET
•FEATURE IMPORTANCES WITH FORESTS OF TREES
•OOB ERRORS FOR RANDOM FORESTS
•FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES
•PIPELINE ANOVA SVM
•RECURSIVE FEATURE ELIMINATION WITH CROSSVALIDATION
•NEIGHBORHOOD COMPONENTS ANALYSIS ILLUSTRATION
•VARYING REGULARIZATION IN MULTILAYER PERCEPTRON
•FEATURE DISCRETIZATION
•SCALING THE REGULARIZATION PARAMETER FOR SVCS
SKLEARNDATASETS MAKEFRIEDMAN1
SKLEARNDATASETS MAKEFRIEDMAN1 NSAMPLES100 NFEATURES10 NOISE00 RAN
DOMSTATENONE
GENERATE THE “FRIEDMAN 1” REGRESSION PROBLEM
THIS DATASET IS DESCRIBED IN FRIEDMAN 1 AND BREIMAN 2

INPUTSXARE INDEPENDENT FEATURES UNIFORMLY DISTRIBUTED ON THE INTERVAL 0 1 THE OUTPUT YIS CREATED ACCORDING TO THE FORMULA
YX 10 SINPIX 0 X 1 20 X 2 05 2 10X
‹→3 5X 4 NOISE N0 1
OUT OF THE NFEATURES FEATURES ONLY 5 ARE ACTUALLY USED TO COMPUTE Y THE REMAINING FEATURES ARE INDEPENDENT OFY
THE NUMBER OF FEATURES HAS TO BE 5
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE NUMBER OF SAMPLES
NFEATURES INT OPTIONAL DEFAULT10 THE NUMBER OF FEATURES SHOULD BE AT LEAST 5
NOISE FLOAT OPTIONAL DEFAULT00 THE STANDARD DEVIATION OF THE GAUSSIAN NOISE APPLIED TO THE OUTPUT
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN ERATION FOR DATASET NOISE PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION CALLS SEEGLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
YARRAY OF SHAPE NSAMPLES THE OUTPUT VALUES
REFERENCES
12
SKLEARNDATASETS MAKEFRIEDMAN2
SKLEARNDATASETS MAKEFRIEDMAN2 NSAMPLES100 NOISE00 RANDOMSTATENONE
GENERATE THE “FRIEDMAN 2” REGRESSION PROBLEM
THIS DATASET IS DESCRIBED IN FRIEDMAN 1 AND BREIMAN 2
INPUTSXARE 4 INDEPENDENT FEATURES UNIFORMLY DISTRIBUTED ON THE INTERVALS
0 X 0 100
40PI X 1 560 PI
0 X 2 1
1 X 3 11
THE OUTPUT YIS CREATED ACCORDING TO THE FORMULA
YX X 0 2 X 1 X 2 1 X 1 X 3 20
‹→5 NOISE N0 1
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE NUMBER OF SAMPLES

NOISE FLOAT OPTIONAL DEFAULT00 THE STANDARD DEVIATION OF THE GAUSSIAN NOISE APPLIED TO THE OUTPUT
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN ERATION FOR DATASET NOISE PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION CALLS SEEGLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES 4 THE INPUT SAMPLES
YARRAY OF SHAPE NSAMPLES THE OUTPUT VALUES
REFERENCES
12
SKLEARNDATASETS MAKEFRIEDMAN3
SKLEARNDATASETS MAKEFRIEDMAN3 NSAMPLES100 NOISE00 RANDOMSTATENONE
GENERATE THE “FRIEDMAN 3” REGRESSION PROBLEM
THIS DATASET IS DESCRIBED IN FRIEDMAN 1 AND BREIMAN 2
INPUTSXARE 4 INDEPENDENT FEATURES UNIFORMLY DISTRIBUTED ON THE INTERVALS
0 X 0 100
40PI X 1 560 PI
0 X 2 1
1 X 3 11
THE OUTPUT YIS CREATED ACCORDING TO THE FORMULA
YX ARCTANX 1 X 2 1 X 1 X 3 X 0 NOISE
‘→N0 1
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE NUMBER OF SAMPLES
NOISE FLOAT OPTIONAL DEFAULT00 THE STANDARD DEVIATION OF THE GAUSSIAN NOISE APPLIED TO THE OUTPUT
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN ERATION FOR DATASET NOISE PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION CALLS SEEGLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES 4 THE INPUT SAMPLES
YARRAY OF SHAPE NSAMPLES THE OUTPUT VALUES
REFERENCES
12

SKLEARNDATASETS MAKEGAUSSIANQUANTILES
SKLEARNDATASETS MAKEGAUSSIANQUANTILES MEANNONE COV10 NSAMPLES100
NFEATURES2 NCLASSES3 SHUFFLETRUE
RANDOMSTATENONE
GENERATE ISOTROPIC GAUSSIAN AND LABEL SAMPLES BY QUANTILE
THIS CLASSIFICATION DATASET IS CONSTRUCTED BY TAKING A MULTIDIMENSIONAL STANDARD NORMAL DISTRIBUTION AND DEFINING
CLASSES SEPARATED BY NESTED CONCENTRIC MULTIDIMENSIONAL SPHERES SUCH THAT ROUGHLY EQUAL NUMBERS OF SAMPLES
ARE IN EACH CLASS QUANTILES OF THE □2DISTRIBUTION
READ MORE IN THE USER GUIDE
PARAMETERS
MEAN ARRAY OF SHAPE NFEATURES OPTIONAL DEFAULTNONE THE MEAN OF THE MULTI
DIMENSIONAL NORMAL DISTRIBUTION IF NONE THEN USE THE ORIGIN 0 0
COV FLOAT OPTIONAL DEFAULT1 THE COVARIANCE MATRIX WILL BE THIS VALUE TIMES THE UNIT MATRIX
THIS DATASET ONLY PRODUCES SYMMETRIC NORMAL DISTRIBUTIONS
NSAMPLES INT OPTIONAL DEFAULT100 THE TOTAL NUMBER OF POINTS EQUALLY DIVIDED AMONG
CLASSES
NFEATURES INT OPTIONAL DEFAULT2 THE NUMBER OF FEATURES FOR EACH SAMPLE
NCLASSES INT OPTIONAL DEFAULT3 THE NUMBER OF CLASSES
SHUFFLE BOOLEAN OPTIONAL DEFAULTTRUE SHUFFLE THE SAMPLES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES NFEATURES THE GENERATED SAMPLES
YARRAY OF SHAPE NSAMPLES THE INTEGER LABELS FOR QUANTILE MEMBERSHIP OF EACH SAMPLE
NOTES
THE DATASET IS FROM ZHU ET AL 1
REFERENCES
1
EXAMPLES USING SKLEARNDATASETSMAKEGAUSSIANQUANTILES
•PLOT RANDOMLY GENERATED CLASSIFICATION DATASET
•TWOCLASS ADABOOST
•MULTICLASS ADABOOSTED DECISION TREES

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SKLEARNDATASETS MAKEHASTIE102
SKLEARNDATASETS MAKEHASTIE102 NSAMPLES12000 RANDOMSTATENONE
GENERATES DATA FOR BINARY CLASSIFICATION USED IN HASTIE ET AL 2009 EXAMPLE 102
THE TEN FEATURES ARE STANDARD INDEPENDENT GAUSSIAN AND THE TARGET YIS DEFINED BY
YI 1 IFNPSUMXI 2 934 ELSE1
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT12000 THE NUMBER OF SAMPLES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES 10 THE INPUT SAMPLES
YARRAY OF SHAPE NSAMPLES THE OUTPUT VALUES
SEE ALSO
MAKEGAUSSIANQUANTILES A GENERALIZATION OF THIS DATASET APPROACH
REFERENCES
1
EXAMPLES USING SKLEARNDATASETSMAKEHASTIE102
•GRADIENT BOOSTING REGULARIZATION
•DISCRETE VERSUS REAL ADABOOST
•EARLY STOPPING OF GRADIENT BOOSTING
•DEMONSTRATION OF MULTIMETRIC EVALUATION ON CROSSVALSCORE AND GRIDSEARCHCV
SKLEARNDATASETS MAKELOWRANKMATRIX
SKLEARNDATASETS MAKELOWRANKMATRIX NSAMPLES100 NFEATURES100 EFFECTIVERANK10
TAILSTRENGTH05 RANDOMSTATENONE
GENERATE A MOSTLY LOW RANK MATRIX WITH BELLSHAPED SINGULAR VALUES
MOST OF THE VARIANCE CAN BE EXPLAINED BY A BELLSHAPED CURVE OF WIDTH EFFECTIVERANK THE LOW RANK PART OF THE
SINGULAR VALUES PROFILE IS
1 TAILSTRENGTH EXP10 I EFFECTIVERANK 2
THE REMAINING SINGULAR VALUES' TAIL IS FAT DECREASING AS
TAILSTRENGTH EXP01 I EFFECTIVERANK

THE LOW RANK PART OF THE PROFILE CAN BE CONSIDERED THE STRUCTURED SIGNAL PART OF THE DATA WHILE THE TAIL CAN BE CONSIDERED THE NOISY PART OF THE DATA THAT CANNOT BE SUMMARIZED BY A LOW NUMBER OF LINEAR COMPONENTS SINGULAR VECTORS
THIS KIND OF SINGULAR PROFILES IS OFTEN SEEN IN PRACTICE FOR INSTANCE
• GRAY LEVEL PICTURES OF FACES
• TFIDF VECTORS OF TEXT DOCUMENTS CRAWLED FROM THE WEB
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE NUMBER OF SAMPLES
NFEATURES INT OPTIONAL DEFAULT100 THE NUMBER OF FEATURES
EFFECTIVERANK INT OPTIONAL DEFAULT10 THE APPROXIMATE NUMBER OF SINGULAR VECTORS RE QUIRED TO EXPLAIN MOST OF THE DATA BY LINEAR COMBINATIONS
TAILSTRENGTH FLOAT BETWEEN 00 AND 10 OPTIONAL DEFAULT05 THE RELATIVE IMPORTANCE OF THE FAT NOISY TAIL OF THE SINGULAR VALUES PROFILE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES NFEATURES THE MATRIX
SKLEARNDATASETS MAKEMOONS
SKLEARNDATASETS MAKEMOONS NSAMPLES100 SHUFFLETRUE NOISENONE RANDOMSTATENONE
MAKE TWO INTERLEAVING HALF CIRCLES
A SIMPLE TOY DATASET TO VISUALIZE CLUSTERING AND CLASSIFICATION ALGORITHMS READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE TOTAL NUMBER OF POINTS GENERATED
SHUFFLE BOOL OPTIONAL DEFAULTTRUE WHETHER TO SHUFFLE THE SAMPLES
NOISE DOUBLE OR NONE DEFAULTNONE STANDARD DEVIATION OF GAUSSIAN NOISE ADDED TO THE DATA
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN ERATION FOR DATASET SHUFFLING AND NOISE PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES 2 THE GENERATED SAMPLES
YARRAY OF SHAPE NSAMPLES THE INTEGER LABELS 0 OR 1 FOR CLASS MEMBERSHIP OF EACH SAMPLE
EXAMPLES USING SKLEARNDATASETSMAKEMOONS
•COMPARING ANOMALY DETECTION ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS
•CLASSIFIER COMPARISON
•COMPARING DIFFERENT HIERARCHICAL LINKAGE METHODS ON TOY DATASETS

•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
•VARYING REGULARIZATION IN MULTILAYER PERCEPTRON
•COMPARE STOCHASTIC LEARNING STRATEGIES FOR MLPCLASSIFIER
•FEATURE DISCRETIZATION
SKLEARNDATASETS MAKEMULTILABELCLASSIFICATION
SKLEARNDATASETS MAKEMULTILABELCLASSIFICATION NSAMPLES100 NFEATURES20
NCLASSES5 NLABELS2 LENGTH50
ALLOWUNLABELEDTRUE SPARSEFALSE
RETURNINDICATOR'DENSE' RE
TURNDISTRIBUTIONSFALSE RAN
DOMSTATENONE
GENERATE A RANDOM MULTILABEL CLASSIFICATION PROBLEM
FOR EACH SAMPLE THE GENERATIVE PROCESS IS
• PICK THE NUMBER OF LABELS N POISSONNLABELS
• N TIMES CHOOSE A CLASS C C MULTINOMIALTHETA
• PICK THE DOCUMENT LENGTH K POISSONLENGTH
• K TIMES CHOOSE A WORD W MULTINOMIALTHETAC
IN THE ABOVE PROCESS REJECTION SAMPLING IS USED TO MAKE SURE THAT N IS NEVER ZERO OR MORE THAN NCLASSES
AND THAT THE DOCUMENT LENGTH IS NEVER ZERO LIKEWISE WE REJECT CLASSES WHICH HAVE ALREADY BEEN CHOSEN
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE NUMBER OF SAMPLES
NFEATURES INT OPTIONAL DEFAULT20 THE TOTAL NUMBER OF FEATURES
NCLASSES INT OPTIONAL DEFAULT5 THE NUMBER OF CLASSES OF THE CLASSIFICATION PROBLEM
NLABELS INT OPTIONAL DEFAULT2 THE AVERAGE NUMBER OF LABELS PER INSTANCE MORE PRECISELY
THE NUMBER OF LABELS PER SAMPLE IS DRAWN FROM A POISSON DISTRIBUTION WITH NLABELS AS ITS
EXPECTED VALUE BUT SAMPLES ARE BOUNDED USING REJECTION SAMPLING BY NCLASSES AND
MUST BE NONZERO IF ALLOWUNLABELED IS FALSE
LENGTH INT OPTIONAL DEFAULT50 THE SUM OF THE FEATURES NUMBER OF WORDS IF DOCUMENTS IS
DRAWN FROM A POISSON DISTRIBUTION WITH THIS EXPECTED VALUE
ALLOWUNLABELED BOOL OPTIONAL DEFAULTTRUE IF TRUE SOME INSTANCES MIGHT NOT BELONG TO
ANY CLASS
SPARSE BOOL OPTIONAL DEFAULTFALSE IF TRUE RETURN A SPARSE FEATURE MATRIX
NEW IN VERSION 017 PARAMETER TO ALLOW SPARSE OUTPUT
RETURNINDICATOR 'DENSE' DEFAULT 'SPARSE' FALSE IF DENSE RETURNYIN THE DENSE BINARY
INDICATOR FORMAT IF SPARSE RETURNYIN THE SPARSE BINARY INDICATOR FORMAT FALSE
RETURNS A LIST OF LISTS OF LABELS
RETURNDISTRIBUTIONS BOOL OPTIONAL DEFAULTFALSE IF TRUE RETURN THE PRIOR CLASS PROBABILITY
AND CONDITIONAL PROBABILITIES OF FEATURES GIVEN CLASSES FROM WHICH THE DATA WAS DRAWN

RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES NFEATURES THE GENERATED SAMPLES
YARRAY OR SPARSE CSR MATRIX OF SHAPE NSAMPLES NCLASSES THE LABEL SETS
PC ARRAY SHAPE NCLASSES THE PROBABILITY OF EACH CLASS BEING DRAWN ONLY RETURNED IF
RETURNDISTRIBUTIONSTRUE
PWC ARRAY SHAPE NFEATURES NCLASSES THE PROBABILITY OF EACH FEATURE BEING DRAWN GIVEN
EACH CLASS ONLY RETURNED IF RETURNDISTRIBUTIONSTRUE
EXAMPLES USING SKLEARNDATASETSMAKEMULTILABELCLASSIFICATION
•MULTILABEL CLASSIFICATION
•PLOT RANDOMLY GENERATED MULTILABEL DATASET
SKLEARNDATASETS MAKEREGRESSION
SKLEARNDATASETS MAKEREGRESSION NSAMPLES100 NFEATURES100 NINFORMATIVE10
NTARGETS1 BIAS00 EFFECTIVERANKNONE
TAILSTRENGTH05 NOISE00 SHUFFLETRUE COEFFALSE
RANDOMSTATENONE
GENERATE A RANDOM REGRESSION PROBLEM
THE INPUT SET CAN EITHER BE WELL CONDITIONED BY DEFAULT OR HAVE A LOW RANKFAT TAIL SINGULAR PROFILE SEE
MAKELOWRANKMATRIX FOR MORE DETAILS
THE OUTPUT IS GENERATED BY APPLYING A POTENTIALLY BIASED RANDOM LINEAR REGRESSION MODEL WITH
NINFORMATIVE NONZERO REGRESSORS TO THE PREVIOUSLY GENERATED INPUT AND SOME GAUSSIAN CENTERED NOISE WITH
SOME ADJUSTABLE SCALE
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE NUMBER OF SAMPLES
NFEATURES INT OPTIONAL DEFAULT100 THE NUMBER OF FEATURES
NINFORMATIVE INT OPTIONAL DEFAULT10 THE NUMBER OF INFORMATIVE FEATURES IE THE NUMBER
OF FEATURES USED TO BUILD THE LINEAR MODEL USED TO GENERATE THE OUTPUT
NTARGETS INT OPTIONAL DEFAULT1 THE NUMBER OF REGRESSION TARGETS IE THE DIMENSION OF THE
Y OUTPUT VECTOR ASSOCIATED WITH A SAMPLE BY DEFAULT THE OUTPUT IS A SCALAR
BIAS FLOAT OPTIONAL DEFAULT00 THE BIAS TERM IN THE UNDERLYING LINEAR MODEL
EFFECTIVERANK INT OR NONE OPTIONAL DEFAULTNONE
IF NOT NONE THE APPROXIMATE NUMBER OF SINGULAR VECTORS REQUIRED TO EXPLAIN MOST OF THE
INPUT DATA BY LINEAR COMBINATIONS USING THIS KIND OF SINGULAR SPECTRUM IN THE INPUT ALLOWS
THE GENERATOR TO REPRODUCE THE CORRELATIONS OFTEN OBSERVED IN PRACTICE
IF NONE THE INPUT SET IS WELL CONDITIONED CENTERED AND GAUSSIAN WITH UNIT VARIANCE

TAILSTRENGTH FLOAT BETWEEN 00 AND 10 OPTIONAL DEFAULT05 THE RELATIVE IMPORTANCE OF THE FAT NOISY TAIL OF THE SINGULAR VALUES PROFILE IF EFFECTIVERANK IS NOT NONE
NOISE FLOAT OPTIONAL DEFAULT00 THE STANDARD DEVIATION OF THE GAUSSIAN NOISE APPLIED TO THE OUTPUT
SHUFFLE BOOLEAN OPTIONAL DEFAULTTRUE SHUFFLE THE SAMPLES AND THE FEATURES
COEF BOOLEAN OPTIONAL DEFAULTFALSE IF TRUE THE COEFFICIENTS OF THE UNDERLYING LINEAR MODEL ARE RETURNED
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
YARRAY OF SHAPE NSAMPLES OR NSAMPLES NTARGETS THE OUTPUT VALUES
COEF ARRAY OF SHAPE NFEATURES OR NFEATURES NTARGETS OPTIONAL THE COEFFICIENT OF THE UNDERLYING LINEAR MODEL IT IS RETURNED ONLY IF COEF IS TRUE
EXAMPLES USING SKLEARNDATASETSMAKEREGRESSION
•PREDICTION LATENCY
•EFFECT OF TRANSFORMING THE TARGETS IN REGRESSION MODEL
•PLOT RIDGE COEFFICIENTS AS A FUNCTION OF THE L2 REGULARIZATION
•ROBUST LINEAR MODEL ESTIMATION USING RANSAC
•LASSO ON DENSE AND SPARSE DATA
•HUBERREGRESSOR VS RIDGE ON DATASET WITH STRONG OUTLIERS
SKLEARNDATASETS MAKESCURVE
SKLEARNDATASETS MAKESCURVE NSAMPLES100 NOISE00 RANDOMSTATENONE
GENERATE AN S CURVE DATASET
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE NUMBER OF SAMPLE POINTS ON THE S CURVE
NOISE FLOAT OPTIONAL DEFAULT00 THE STANDARD DEVIATION OF THE GAUSSIAN NOISE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES 3 THE POINTS
TARRAY OF SHAPE NSAMPLES THE UNIVARIATE POSITION OF THE SAMPLE ACCORDING TO THE MAIN DIMENSION OF THE POINTS IN THE MANIFOLD

EXAMPLES USING SKLEARNDATASETSMAKESCURVE
•TSNE THE EFFECT OF VARIOUS PERPLEXITY VALUES ON THE SHAPE
•COMPARISON OF MANIFOLD LEARNING METHODS
SKLEARNDATASETS MAKESPARSECODEDSIGNAL
SKLEARNDATASETS MAKESPARSECODEDSIGNAL NSAMPLES NCOMPONENTS NFEATURES
NNONZEROCOEFS RANDOMSTATENONE
GENERATE A SIGNAL AS A SPARSE COMBINATION OF DICTIONARY ELEMENTS
RETURNS A MATRIX Y DX SUCH AS D IS NFEATURES NCOMPONENTS X IS NCOMPONENTS NSAMPLES AND EACH
COLUMN OF X HAS EXACTLY NNONZEROCOEFS NONZERO ELEMENTS
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT NUMBER OF SAMPLES TO GENERATE
NCOMPONENTS INT NUMBER OF COMPONENTS IN THE DICTIONARY
NFEATURES INT NUMBER OF FEATURES OF THE DATASET TO GENERATE
NNONZEROCOEFS INT NUMBER OF ACTIVE NONZERO COEFFICIENTS IN EACH SAMPLE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
DATA ARRAY OF SHAPE NFEATURES NSAMPLES THE ENCODED SIGNAL Y
DICTIONARY ARRAY OF SHAPE NFEATURES NCOMPONENTS THE DICTIONARY WITH NORMALIZED COM
PONENTS D
CODE ARRAY OF SHAPE NCOMPONENTS NSAMPLES THE SPARSE CODE SUCH THAT EACH COLUMN OF
THIS MATRIX HAS EXACTLY NNONZEROCOEFS NONZERO ITEMS X
EXAMPLES USING SKLEARNDATASETSMAKESPARSECODEDSIGNAL
•ORTHOGONAL MATCHING PURSUIT
SKLEARNDATASETS MAKESPARSESPDMATRIX
SKLEARNDATASETS MAKESPARSESPDMATRIX DIM1 ALPHA095 NORMDIAGFALSE
SMALLESTCOEF01 LARGESTCOEF09 RAN
DOMSTATENONE
GENERATE A SPARSE SYMMETRIC DEFINITE POSITIVE MATRIX
READ MORE IN THE USER GUIDE
PARAMETERS
DIM INTEGER OPTIONAL DEFAULT1 THE SIZE OF THE RANDOM MATRIX TO GENERATE
ALPHA FLOAT BETWEEN 0 AND 1 OPTIONAL DEFAULT095 THE PROBABILITY THAT A COEFFICIENT IS ZERO
SEE NOTES LARGER VALUES ENFORCE MORE SPARSITY

NORMDIAG BOOLEAN OPTIONAL DEFAULTFALSE WHETHER TO NORMALIZE THE OUTPUT MATRIX TO MAKE
THE LEADING DIAGONAL ELEMENTS ALL 1
SMALLESTCOEF FLOAT BETWEEN 0 AND 1 OPTIONAL DEFAULT01 THE VALUE OF THE SMALLEST COEFFI
CIENT
LARGESTCOEF FLOAT BETWEEN 0 AND 1 OPTIONAL DEFAULT09 THE VALUE OF THE LARGEST COEFFICIENT
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
PREC SPARSE MATRIX OF SHAPE DIM DIM THE GENERATED MATRIX
SEE ALSO
MAKESPDMATRIX
NOTES
THE SPARSITY IS ACTUALLY IMPOSED ON THE CHOLESKY FACTOR OF THE MATRIX THUS ALPHA DOES NOT TRANSLATE DIRECTLY INTO
THE FILLING FRACTION OF THE MATRIX ITSELF
EXAMPLES USING SKLEARNDATASETSMAKESPARSESPDMATRIX
•SPARSE INVERSE COVARIANCE ESTIMATION
SKLEARNDATASETS MAKESPARSEUNCORRELATED
SKLEARNDATASETS MAKESPARSEUNCORRELATED NSAMPLES100 NFEATURES10 RAN
DOMSTATENONE
GENERATE A RANDOM REGRESSION PROBLEM WITH SPARSE UNCORRELATED DESIGN
THIS DATASET IS DESCRIBED IN CELEUX ET AL 1 AS
X N0 1
YX X 0 2 X 1 2 X 2 15 X 3
ONLY THE FIRST 4 FEATURES ARE INFORMATIVE THE REMAINING FEATURES ARE USELESS
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE NUMBER OF SAMPLES
NFEATURES INT OPTIONAL DEFAULT10 THE NUMBER OF FEATURES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
YARRAY OF SHAPE NSAMPLES THE OUTPUT VALUES

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1
SKLEARNDATASETS MAKESPDMATRIX
SKLEARNDATASETS MAKESPDMATRIX NDIM RANDOMSTATENONE
GENERATE A RANDOM SYMMETRIC POSITIVEDEFINITE MATRIX
READ MORE IN THE USER GUIDE
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NDIM INT THE MATRIX DIMENSION
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
RETURNS
XARRAY OF SHAPE NDIM NDIM THE RANDOM SYMMETRIC POSITIVEDEFINITE MATRIX
SEE ALSO
MAKESPARSESPDMATRIX
SKLEARNDATASETS MAKESWISSROLL
SKLEARNDATASETS MAKESWISSROLL NSAMPLES100 NOISE00 RANDOMSTATENONE
GENERATE A SWISS ROLL DATASET
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OPTIONAL DEFAULT100 THE NUMBER OF SAMPLE POINTS ON THE S CURVE
NOISE FLOAT OPTIONAL DEFAULT00 THE STANDARD DEVIATION OF THE GAUSSIAN NOISE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT DETERMINES RANDOM NUMBER GEN
ERATION FOR DATASET CREATION PASS AN INT FOR REPRODUCIBLE OUTPUT ACROSS MULTIPLE FUNCTION
CALLS SEE GLOSSARY
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XARRAY OF SHAPE NSAMPLES 3 THE POINTS
TARRAY OF SHAPE NSAMPLES THE UNIVARIATE POSITION OF THE SAMPLE ACCORDING TO THE MAIN
DIMENSION OF THE POINTS IN THE MANIFOLD
NOTES
THE ALGORITHM IS FROM MARSLAND 1
REFERENCES
1

EXAMPLES USING SKLEARNDATASETSMAKESWISSROLL
•HIERARCHICAL CLUSTERING STRUCTURED VS UNSTRUCTURED WARD
•SWISS ROLL REDUCTION WITH LLE
69SKLEARNDECOMPOSITION MATRIX DECOMPOSITION
THESKLEARNDECOMPOSITION MODULE INCLUDES MATRIX DECOMPOSITION ALGORITHMS INCLUDING AMONG OTHERS PCA
NMF OR ICA MOST OF THE ALGORITHMS OF THIS MODULE CAN BE REGARDED AS DIMENSIONALITY REDUCTION TECHNIQUES
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DECOMPOSITIONFACTORANALYSIS NCOMPONENTS
FACTOR ANALYSIS FA
DECOMPOSITIONFASTICA NCOMPONENTS FASTICA A FAST ALGORITHM FOR INDEPENDENT COMPONENT
ANALYSIS
DECOMPOSITIONINCREMENTALPCA NCOMPONENTS
INCREMENTAL PRINCIPAL COMPONENTS ANALYSIS IPCA
DECOMPOSITIONKERNELPCA NCOMPONENTS KERNEL PRINCIPAL COMPONENT ANALYSIS KPCA
DECOMPOSITIONLATENTDIRICHLETALLOCATION LATENT DIRICHLET ALLOCATION WITH ONLINE VARIATIONAL BAYES
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DECOMPOSITIONMINIBATCHDICTIONARYLEARNING MINIBATCH DICTIONARY LEARNING
DECOMPOSITIONMINIBATCHSPARSEPCA MINIBATCH SPARSE PRINCIPAL COMPONENTS ANALYSIS
DECOMPOSITIONNMF NCOMPONENTS INIT NONNEGATIVE MATRIX FACTORIZATION NMF
DECOMPOSITIONPCA NCOMPONENTS COPY PRINCIPAL COMPONENT ANALYSIS PCA
DECOMPOSITIONSPARSEPCA NCOMPONENTS SPARSE PRINCIPAL COMPONENTS ANALYSIS SPARSEPCA
DECOMPOSITIONSPARSECODER DICTIONARY SPARSE CODING
DECOMPOSITIONTRUNCATEDSVD NCOMPONENTS
DIMENSIONALITY REDUCTION USING TRUNCATED SVD AKA LSA
691SKLEARNDECOMPOSITION DICTIONARYLEARNING
CLASSSKLEARNDECOMPOSITION DICTIONARYLEARNING NCOMPONENTSNONE ALPHA1
MAXITER1000 TOL1E08
FITALGORITHM'LARS' TRANS
FORMALGORITHM'OMP' TRANS
FORMNNONZEROCOEFSNONE TRANS
FORMALPHANONE NJOBSNONE
CODEINITNONE DICTINITNONE VER
BOSEFALSE SPLITSIGNFALSE RAN
DOMSTATENONE POSITIVECODEFALSE
POSITIVEDICTFALSE
DICTIONARY LEARNING
FINDS A DICTIONARY A SET OF ATOMS THAT CAN BEST BE USED TO REPRESENT DATA USING A SPARSE CODE
SOLVES THE OPTIMIZATION PROBLEM
UV ARGMIN 05 Y U V 22 ALPHA U 1
UV
WITH VK 2 1 FORALL 0 K NCOMPONENTS

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READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT NUMBER OF DICTIONARY ELEMENTS TO EXTRACT
ALPHA FLOAT SPARSITY CONTROLLING PARAMETER
MAXITER INT MAXIMUM NUMBER OF ITERATIONS TO PERFORM
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FITALGORITHM ‘LARS’ ‘CD’ LARS USES THE LEAST ANGLE REGRESSION METHOD TO SOLVE THE LASSO
PROBLEM LINEARMODELLARSPATH CD USES THE COORDINATE DESCENT METHOD TO COMPUTE THE
LASSO SOLUTION LINEARMODELLASSO LARS WILL BE FASTER IF THE ESTIMATED COMPONENTS ARE
SPARSE
NEW IN VERSION 017 CDCOORDINATE DESCENT METHOD TO IMPROVE SPEED
TRANSFORMALGORITHM ‘LASSOLARS’ ‘LASSOCD’ ‘LARS’ ‘OMP’ ‘THRESHOLD’ ALGORITHM USED
TO TRANSFORM THE DATA LARS USES THE LEAST ANGLE REGRESSION METHOD LINEARMODELLARSPATH
LASSOLARS USES LARS TO COMPUTE THE LASSO SOLUTION LASSOCD USES THE COORDINATE DESCENT
METHOD TO COMPUTE THE LASSO SOLUTION LINEARMODELLASSO LASSOLARS WILL BE FASTER IF
THE ESTIMATED COMPONENTS ARE SPARSE OMP USES ORTHOGONAL MATCHING PURSUIT TO ESTIMATE
THE SPARSE SOLUTION THRESHOLD SQUASHES TO ZERO ALL COEFFICIENTS LESS THAN ALPHA FROM THE
PROJECTIONDICTIONARY X
NEW IN VERSION 017 LASSOCD COORDINATE DESCENT METHOD TO IMPROVE SPEED
TRANSFORMNNONZEROCOEFS INT01NFEATURES BY DEFAULT NUMBER OF NONZERO
COEFFICIENTS TO TARGET IN EACH COLUMN OF THE SOLUTION THIS IS ONLY USED BY
ALGORITHMLARS ANDALGORITHMOMP AND IS OVERRIDDEN BY ALPHA IN THE OR
THOGONAL MATCHING PURSUIT OMP CASE
TRANSFORMALPHA FLOAT 1 BY DEFAULT IF ALGORITHMLASSOLARS OR
ALGORITHMLASSOCD ALPHA IS THE PENALTY APPLIED TO THE L1 NORM IF
ALGORITHMTHRESHOLD ALPHA IS THE ABSOLUTE VALUE OF THE THRESHOLD BELOW
WHICH COEFFICIENTS WILL BE SQUASHED TO ZERO IF ALGORITHMOMP ALPHA IS THE
TOLERANCE PARAMETER THE VALUE OF THE RECONSTRUCTION ERROR TARGETED IN THIS CASE IT OVERRIDES
NNONZEROCOEFS
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
CODEINIT ARRAY OF SHAPE NSAMPLES NCOMPONENTS INITIAL VALUE FOR THE CODE FOR WARM
RESTART
DICTINIT ARRAY OF SHAPE NCOMPONENTS NFEATURES INITIAL VALUES FOR THE DICTIONARY FOR WARM
RESTART
VERBOSE BOOL OPTIONAL DEFAULT FALSE TO CONTROL THE VERBOSITY OF THE PROCEDURE
SPLITSIGN BOOL FALSE BY DEFAULT WHETHER TO SPLIT THE SPARSE FEATURE VECTOR INTO THE CONCATE
NATION OF ITS NEGATIVE PART AND ITS POSITIVE PART THIS CAN IMPROVE THE PERFORMANCE OF DOWN
STREAM CLASSIFIERS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM

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POSITIVECODE BOOL WHETHER TO ENFORCE POSITIVITY WHEN FINDING THE CODE
NEW IN VERSION 020
POSITIVEDICT BOOL WHETHER TO ENFORCE POSITIVITY WHEN FINDING THE DICTIONARY
NEW IN VERSION 020
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COMPONENTS ARRAY NCOMPONENTS NFEATURES DICTIONARY ATOMS EXTRACTED FROM THE DATA
ERROR ARRAY VECTOR OF ERRORS AT EACH ITERATION
NITER INT NUMBER OF ITERATIONS RUN
SEE ALSO
SPARSECODER
MINIBATCHDICTIONARYLEARNING
SPARSEPCA
MINIBATCHSPARSEPCA
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J MAIRAL F BACH J PONCE G SAPIRO 2009 ONLINE DICTIONARY LEARNING FOR SPARSE CODING HTTPSWWWDIENS
FRSIERRAPDFSICML09PDF
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FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X ENCODE THE DATA AS A SPARSE COMBINATION OF THE DICTIO
NARY ATOMS
INIT SELFNCOMPONENTSNONE ALPHA1 MAXITER1000 TOL1E08 FITALGORITHM'LARS'
TRANSFORMALGORITHM'OMP' TRANSFORMNNONZEROCOEFSNONE TRANSFORMALPHANONE
NJOBSNONE CODEINITNONE DICTINITNONE VERBOSEFALSE SPLITSIGNFALSE RAN
DOMSTATENONE POSITIVECODEFALSE POSITIVEDICTFALSE
FITSELFXYNONE
FIT THE MODEL FROM DATA IN X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IN THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
RETURNS
SELF OBJECT RETURNS THE OBJECT ITSELF

FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
ENCODE THE DATA AS A SPARSE COMBINATION OF THE DICTIONARY ATOMS
CODING METHOD IS DETERMINED BY THE OBJECT PARAMETER TRANSFORMALGORITHM
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES TEST DATA TO BE TRANSFORMED MUST HAVE THE SAME
NUMBER OF FEATURES AS THE DATA USED TO TRAIN THE MODEL
RETURNS
XNEW ARRAY SHAPE NSAMPLES NCOMPONENTS TRANSFORMED DATA
692SKLEARNDECOMPOSITION FACTORANALYSIS
CLASSSKLEARNDECOMPOSITION FACTORANALYSIS NCOMPONENTSNONE TOL001 COPYTRUE
MAXITER1000 NOISEVARIANCEINITNONE
SVDMETHOD’RANDOMIZED’ ITERATEDPOWER3
RANDOMSTATE0
FACTOR ANALYSIS FA
A SIMPLE LINEAR GENERATIVE MODEL WITH GAUSSIAN LATENT VARIABLES
THE OBSERVATIONS ARE ASSUMED TO BE CAUSED BY A LINEAR TRANSFORMATION OF LOWER DIMENSIONAL LATENT FACTORS AND
ADDED GAUSSIAN NOISE WITHOUT LOSS OF GENERALITY THE FACTORS ARE DISTRIBUTED ACCORDING TO A GAUSSIAN WITH ZERO
MEAN AND UNIT COVARIANCE THE NOISE IS ALSO ZERO MEAN AND HAS AN ARBITRARY DIAGONAL COVARIANCE MATRIX

IF WE WOULD RESTRICT THE MODEL FURTHER BY ASSUMING THAT THE GAUSSIAN NOISE IS EVEN ISOTROPIC ALL DIAGONAL ENTRIES ARE THE SAME WE WOULD OBTAIN PPCA
FACTORANALYSIS PERFORMS A MAXIMUM LIKELIHOOD ESTIMATE OF THE SOCALLED LOADING MATRIX THE TRANSFORMATION OF THE LATENT VARIABLES TO THE OBSERVED ONES USING EXPECTATIONMAXIMIZATION EM
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT NONE DIMENSIONALITY OF LATENT SPACE THE NUMBER OF COMPONENTS OF XTHAT ARE OBTAINED AFTER TRANSFORM IF NONE NCOMPONENTS IS SET TO THE NUMBER OF FEATURES
TOLFLOAT STOPPING TOLERANCE FOR EM ALGORITHM
COPY BOOL WHETHER TO MAKE A COPY OF X IF FALSE THE INPUT X GETS OVERWRITTEN DURING FITTING
MAXITER INT MAXIMUM NUMBER OF ITERATIONS
NOISEVARIANCEINIT NONE ARRAY SHAPENFEATURES THE INITIAL GUESS OF THE NOISE VARIANCE FOR EACH FEATURE IF NONE IT DEFAULTS TO NPONESNFEATURES
SVDMETHOD ‘LAPACK’ ‘RANDOMIZED’ WHICH SVD METHOD TO USE IF ‘LAPACK’ USE STANDARD SVD FROM SCIPYLINALG IF ‘RANDOMIZED’ USE FAST RANDOMIZEDSVD FUNCTION DEFAULTS TO ‘RANDOMIZED’ FOR MOST APPLICATIONS ‘RANDOMIZED’ WILL BE SUFFICIENTLY PRECISE WHILE PRO VIDING SIGNIFICANT SPEED GAINS ACCURACY CAN ALSO BE IMPROVED BY SETTING HIGHER VALUES FOR ITERATEDPOWER IF THIS IS NOT SUFFICIENT FOR MAXIMUM PRECISION YOU SHOULD CHOOSE ‘LAPACK’
ITERATEDPOWER INT OPTIONAL NUMBER OF ITERATIONS FOR THE POWER METHOD 3 BY DEFAULT ONLY USED IFSVDMETHOD EQUALS ‘RANDOMIZED’
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT0 IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM ONLY USED WHEN SVDMETHOD EQUALS ‘RANDOMIZED’
ATTRIBUTES
COMPONENTS ARRAY NCOMPONENTS NFEATURES COMPONENTS WITH MAXIMUM VARIANCE
LOGLIKE LIST NITERATIONS THE LOG LIKELIHOOD AT EACH ITERATION
NOISEVARIANCE ARRAY SHAPENFEATURES THE ESTIMATED NOISE VARIANCE FOR EACH FEATURE
NITER INT NUMBER OF ITERATIONS RUN
SEE ALSO
PCA PRINCIPAL COMPONENT ANALYSIS IS ALSO A LATENT LINEAR VARIABLE MODEL WHICH HOWEVER ASSUMES EQUAL NOISE VARIANCE FOR EACH FEATURE THIS EXTRA ASSUMPTION MAKES PROBABILISTIC PCA FASTER AS IT CAN BE COMPUTED IN CLOSED FORM
FASTICA INDEPENDENT COMPONENT ANALYSIS A LATENT VARIABLE MODEL WITH NONGAUSSIAN LATENT VARIABLES
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FROM SKLEARNDECOMPOSITION IMPORT FACTORANALYSIS
X LOADDIGITSRETURNXY TRUE
TRANSFORMER FACTORANALYSISNCOMPONENTS7 RANDOMSTATE0
XTRANSFORMED TRANSFORMERFITTRANSFORMX
XTRANSFORMEDSHAPE
1797 7
METHODS
FITSELF X Y FIT THE FACTORANALYSIS MODEL TO X USING EM
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETCOVARIANCE SELF COMPUTE DATA COVARIANCE WITH THE FACTORANALYSIS
MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETPRECISION SELF COMPUTE DATA PRECISION MATRIX WITH THE FACTORANALYSIS
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SCORE SELF X Y COMPUTE THE AVERAGE LOGLIKELIHOOD OF THE SAMPLES
SCORESAMPLES SELF X COMPUTE THE LOGLIKELIHOOD OF EACH SAMPLE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X APPLY DIMENSIONALITY REDUCTION TO X USING THE MODEL
INIT SELF NCOMPONENTSNONE TOL001 COPYTRUE MAXITER1000
NOISEVARIANCEINITNONE SVDMETHOD’RANDOMIZED’ ITERATEDPOWER3 RAN
DOMSTATE0
FITSELFXYNONE
FIT THE FACTORANALYSIS MODEL TO X USING EM
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XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YIGNORED
RETURNS
SELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
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COMPUTE DATA COVARIANCE WITH THE FACTORANALYSIS MODEL
COV COMPONENTST COMPONENTS DIAGNOISEVARIANCE
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GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
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SCORESELFXYNONE
COMPUTE THE AVERAGE LOGLIKELIHOOD OF THE SAMPLES
PARAMETERS
XARRAY SHAPE NSAMPLES NFEATURES THE DATA
YIGNORED
RETURNS
LLFLOAT AVERAGE LOGLIKELIHOOD OF THE SAMPLES UNDER THE CURRENT MODEL
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COMPUTE THE LOGLIKELIHOOD OF EACH SAMPLE
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XARRAY SHAPE NSAMPLES NFEATURES THE DATA
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LLARRAY SHAPE NSAMPLES LOGLIKELIHOOD OF EACH SAMPLE UNDER THE CURRENT MODEL
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
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•FACES DATASET DECOMPOSITIONS
693SKLEARNDECOMPOSITION FASTICA
CLASSSKLEARNDECOMPOSITION FASTICANCOMPONENTSNONE ALGORITHM'PARALLEL' WHITENTRUE
FUN'LOGCOSH' FUNARGSNONE MAXITER200 TOL00001
WINITNONE RANDOMSTATENONE
FASTICA A FAST ALGORITHM FOR INDEPENDENT COMPONENT ANALYSIS
READ MORE IN THE USER GUIDE
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NCOMPONENTS INT OPTIONAL NUMBER OF COMPONENTS TO USE IF NONE IS PASSED ALL ARE USED
ALGORITHM 'PARALLEL' 'DEFLATION' APPLY PARALLEL OR DEFLATIONAL ALGORITHM FOR FASTICA
WHITEN BOOLEAN OPTIONAL IF WHITEN IS FALSE THE DATA IS ALREADY CONSIDERED TO BE WHITENED AND
NO WHITENING IS PERFORMED
FUN STRING OR FUNCTION OPTIONAL DEFAULT 'LOGCOSH' THE FUNCTIONAL FORM OF THE G FUNCTION USED
IN THE APPROXIMATION TO NEGENTROPY COULD BE EITHER 'LOGCOSH' 'EXP' OR 'CUBE' YOU CAN
ALSO PROVIDE YOUR OWN FUNCTION IT SHOULD RETURN A TUPLE CONTAINING THE VALUE OF THE FUNCTION
AND OF ITS DERIVATIVE IN THE POINT EXAMPLE
DEF MYGX RETURN X 3 3 X 2MEANAXIS1
FUNARGS DICTIONARY OPTIONAL ARGUMENTS TO SEND TO THE FUNCTIONAL FORM IF EMPTY AND IF
FUN'LOGCOSH' FUNARGS WILL TAKE VALUE 'ALPHA' 10
MAXITER INT OPTIONAL MAXIMUM NUMBER OF ITERATIONS DURING FIT
TOLFLOAT OPTIONAL TOLERANCE ON UPDATE AT EACH ITERATION
WINIT NONE OF AN NCOMPONENTS NCOMPONENTS NDARRAY THE MIXING MATRIX TO BE USED TO
INITIALIZE THE ALGORITHM
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES
COMPONENTS 2D ARRAY SHAPE NCOMPONENTS NFEATURES THE UNMIXING MATRIX
MIXING ARRAY SHAPE NFEATURES NCOMPONENTS THE MIXING MATRIX
NITER INT IF THE ALGORITHM IS "DEFLATION" NITER IS THE MAXIMUM NUMBER OF ITERATIONS RUN
ACROSS ALL COMPONENTS ELSE THEY ARE JUST THE NUMBER OF ITERATIONS TAKEN TO CONVERGE

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IMPLEMENTATION BASED ON A HYVARINEN AND E OJA INDEPENDENT COMPONENT ANALYSIS ALGORITHMS AND APPLI
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```
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 FROM SKLEARNDECOMPOSITION IMPORT FASTICA
X   LOADDIGITSRETURNXY TRUE
TRANSFORMER  FASTICANCOMPONENTS7
 RANDOMSTATE0
XTRANSFORMED  TRANSFORMERFITTRANSFORMX
XTRANSFORMEDSHAPE
1797 7
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FITSELF X Y FIT THE MODEL TO X
FITTRANSFORM SELF X Y FIT THE MODEL AND RECOVER THE SOURCES FROM X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X COPY TRANSFORM THE SOURCES BACK TO THE MIXED DATA APPLY
MIXING MATRIX
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X COPY RECOVER THE SOURCES FROM X APPLY THE UNMIXING MA
TRIX
INIT SELFNCOMPONENTSNONE ALGORITHM’PARALLEL’ WHITENTRUE FUN’LOGCOSH’
FUNARGSNONE MAXITER200 TOL00001 WINITNONE RANDOMSTATENONE
FITSELFXYNONE
FIT THE MODEL TO X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
RETURNS
SELF
FITTRANSFORM SELFXYNONE
FIT THE MODEL AND RECOVER THE SOURCES FROM X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
RETURNS

XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFXCOPYTRUE
TRANSFORM THE SOURCES BACK TO THE MIXED DATA APPLY MIXING MATRIX
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NCOMPONENTS SOURCES WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NCOMPONENTS IS THE NUMBER OF COMPONENTS
COPY BOOL OPTIONAL IF FALSE DATA PASSED TO FIT ARE OVERWRITTEN DEFAULTS TO TRUE
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NFEATURES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFXCOPYTRUE
RECOVER THE SOURCES FROM X APPLY THE UNMIXING MATRIX
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES DATA TO TRANSFORM WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
COPY BOOL OPTIONAL IF FALSE DATA PASSED TO FIT ARE OVERWRITTEN DEFAULTS TO TRUE
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
EXAMPLES USING SKLEARNDECOMPOSITIONFASTICA
•BLIND SOURCE SEPARATION USING FASTICA
•FASTICA ON 2D POINT CLOUDS
•FACES DATASET DECOMPOSITIONS

694SKLEARNDECOMPOSITION INCREMENTALPCA
CLASSSKLEARNDECOMPOSITION INCREMENTALPCA NCOMPONENTSNONE WHITENFALSE COPYTRUE
BATCHSIZENONE
INCREMENTAL PRINCIPAL COMPONENTS ANALYSIS IPCA
LINEAR DIMENSIONALITY REDUCTION USING SINGULAR VALUE DECOMPOSITION OF THE DATA KEEPING ONLY THE MOST SIGNIF
ICANT SINGULAR VECTORS TO PROJECT THE DATA TO A LOWER DIMENSIONAL SPACE THE INPUT DATA IS CENTERED BUT NOT SCALED
FOR EACH FEATURE BEFORE APPLYING THE SVD
DEPENDING ON THE SIZE OF THE INPUT DATA THIS ALGORITHM CAN BE MUCH MORE MEMORY EFFICIENT THAN A PCA
THIS ALGORITHM HAS CONSTANT MEMORY COMPLEXITY ON THE ORDER OF BATCHSIZE ENABLING USE OF NPMEMMAP
FILES WITHOUT LOADING THE ENTIRE FILE INTO MEMORY
THE COMPUTATIONAL OVERHEAD OF EACH SVD IS OBATCHSIZE NFEATURES 2 BUT ONLY 2
BATCHSIZE SAMPLES REMAIN IN MEMORY AT A TIME THERE WILL BE NSAMPLES BATCHSIZE SVD COMPU
TATIONS TO GET THE PRINCIPAL COMPONENTS VERSUS 1 LARGE SVD OF COMPLEXITY ONSAMPLES NFEATURES
2FOR PCA
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT OR NONE DEFAULTNONE NUMBER OF COMPONENTS TO KEEP IF
NCOMPONENTS IS NONE THENNCOMPONENTS IS SET TOMINNSAMPLES
NFEATURES
WHITEN BOOL OPTIONAL WHEN TRUE FALSE BY DEFAULT THE COMPONENTS VECTORS ARE DI
VIDED BYNSAMPLES TIMESCOMPONENTS TO ENSURE UNCORRELATED OUTPUTS WITH UNIT
COMPONENTWISE VARIANCES
WHITENING WILL REMOVE SOME INFORMATION FROM THE TRANSFORMED SIGNAL THE RELATIVE VARIANCE
SCALES OF THE COMPONENTS BUT CAN SOMETIMES IMPROVE THE PREDICTIVE ACCURACY OF THE DOWN
STREAM ESTIMATORS BY MAKING DATA RESPECT SOME HARDWIRED ASSUMPTIONS
COPY BOOL DEFAULTTRUE IF FALSE X WILL BE OVERWRITTEN COPYFALSE CAN BE USED TO SAVE
MEMORY BUT IS UNSAFE FOR GENERAL USE
BATCHSIZE INT OR NONE DEFAULTNONE THE NUMBER OF SAMPLES TO USE FOR EACH BATCH ONLY
USED WHEN CALLING FIT IFBATCHSIZE ISNONE THENBATCHSIZE IS INFERRED FROM THE
DATA AND SET TO 5NFEATURES TO PROVIDE A BALANCE BETWEEN APPROXIMATION ACCURACY
AND MEMORY CONSUMPTION
ATTRIBUTES
COMPONENTS ARRAY SHAPE NCOMPONENTS NFEATURES COMPONENTS WITH MAXIMUM VARIANCE
EXPLAINEDVARIANCE ARRAY SHAPE NCOMPONENTS VARIANCE EXPLAINED BY EACH OF THE SE
LECTED COMPONENTS
EXPLAINEDVARIANCERATIO ARRAY SHAPE NCOMPONENTS PERCENTAGE OF VARIANCE EXPLAINED
BY EACH OF THE SELECTED COMPONENTS IF ALL COMPONENTS ARE STORED THE SUM OF EXPLAINED
VARIANCES IS EQUAL TO 10
SINGULARVALUES ARRAY SHAPE NCOMPONENTS THE SINGULAR VALUES CORRESPONDING TO EACH
OF THE SELECTED COMPONENTS THE SINGULAR VALUES ARE EQUAL TO THE 2NORMS OF THE
NCOMPONENTS VARIABLES IN THE LOWERDIMENSIONAL SPACE
MEAN ARRAY SHAPE NFEATURES PERFEATURE EMPIRICAL MEAN AGGREGATE OVER CALLS TO
PARTIALFIT

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VAR ARRAY SHAPE NFEATURES PERFEATURE EMPIRICAL VARIANCE AGGREGATE OVER CALLS TO
PARTIALFIT
NOISEVARIANCE FLOAT THE ESTIMATED NOISE COVARIANCE FOLLOWING THE PROBABILISTIC PCA MODEL
FROM TIPPING AND BISHOP 1999 SEE “PATTERN RECOGNITION AND MACHINE LEARNING” BY C
BISHOP 1221 P 574 OR HTTPWWWMIKETIPPINGCOMPAPERSMETMPPCAPDF
NCOMPONENTS INT THE ESTIMATED NUMBER OF COMPONENTS RELEVANT WHEN
NCOMPONENTSNONE
NSAMPLESSEEN INT THE NUMBER OF SAMPLES PROCESSED BY THE ESTIMATOR WILL BE RESET ON
NEW CALLS TO FIT BUT INCREMENTS ACROSS PARTIALFIT CALLS
SEE ALSO
PCA
KERNELPCA
SPARSEPCA
TRUNCATEDSVD
NOTES
IMPLEMENTS THE INCREMENTAL PCA MODEL FROM D ROSS J LIM R LIN M YANG INCREMENTAL LEARNING FOR
ROBUST VISUAL TRACKING INTERNATIONAL JOURNAL OF COMPUTER VISION VOLUME 77 ISSUE 13 PP 125141 MAY
2008 SEE HTTPSWWWCSTORONTOEDUDROSSIVTROSSLIMLINYANGIJCVPDF
THIS MODEL IS AN EXTENSION OF THE SEQUENTIAL KARHUNENLOEVE TRANSFORM FROM A LEVY AND M LINDENBAUM SE
QUENTIAL KARHUNENLOEVE BASIS EXTRACTION AND ITS APPLICATION TO IMAGES IEEE TRANSACTIONS ON IMAGE PROCESS
ING VOLUME 9 NUMBER 8 PP 13711374 AUGUST 2000 SEE HTTPSWWWCSTECHNIONACILMICDOCSKLIPPDF
WE HAVE SPECIFICALLY ABSTAINED FROM AN OPTIMIZATION USED BY AUTHORS OF BOTH PAPERS A QR DECOMPOSITION USED
IN SPECIFIC SITUATIONS TO REDUCE THE ALGORITHMIC COMPLEXITY OF THE SVD THE SOURCE FOR THIS TECHNIQUE IS MATRIX
COMPUTATIONS THIRD EDITION G HOLUB AND C VAN LOAN CHAPTER 5 SECTION 544 PP 252253 THIS TECHNIQUE
HAS BEEN OMITTED BECAUSE IT IS ADVANTAGEOUS ONLY WHEN DECOMPOSING A MATRIX WITH NSAMPLES ROWS
53 NFEATURES COLUMNS AND HURTS THE READABILITY OF THE IMPLEMENTED ALGORITHM THIS WOULD BE A GOOD
OPPORTUNITY FOR FUTURE OPTIMIZATION IF IT IS DEEMED NECESSARY
REFERENCES
D ROSS J LIM R LIN M YANG INCREMENTAL LEARNING FOR ROBUST VISUAL TRACKING INTERNATIONAL JOURNAL OF
COMPUTER VISION V OLUME 77 ISSUE 13 PP 125141 MAY 2008
G GOLUB AND C VAN LOAN MATRIX COMPUTATIONS THIRD EDITION CHAPTER 5 SECTION 544 PP 252253
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADDIGITS
 FROM SKLEARNDECOMPOSITION IMPORT INCREMENTALPCA
X   LOADDIGITSRETURNXY TRUE
TRANSFORMER  INCREMENTALPCANCOMPONENTS7 BATCHSIZE200
 EITHER PARTIALLY FIT ON SMALLER BATCHES OF DATA
TRANSFORMERPARTIALFITX100
INCREMENTALPCABATCHSIZE200 COPYTRUE NCOMPONENTS7 WHITENFALSE
```

OR LET THE FIT FUNCTION ITSELF DIVIDE THE DATA INTO BATCHES
XTRANSFORMED TRANSFORMERFITTRANSFORMX
XTRANSFORMEDSHAPE
1797 7
METHODS
FITSELF X Y FIT THE MODEL WITH X USING MINIBATCHES OF SIZE
BATCHSIZE
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETCOVARIANCE SELF COMPUTE DATA COVARIANCE WITH THE GENERATIVE MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETPRECISION SELF COMPUTE DATA PRECISION MATRIX WITH THE GENERATIVE
MODEL
INVERSETRANSFORM SELF X TRANSFORM DATA BACK TO ITS ORIGINAL SPACE
PARTIALFIT SELF X Y CHECKINPUT INCREMENTAL FIT WITH X
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X APPLY DIMENSIONALITY REDUCTION TO X
INIT SELFNCOMPONENTSNONE WHITENFALSE COPYTRUE BATCHSIZENONE
FITSELFXYNONE
FIT THE MODEL WITH X USING MINIBATCHES OF SIZE BATCHSIZE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
RETURNS
SELF OBJECT RETURNS THE INSTANCE ITSELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETCOVARIANCE SELF
COMPUTE DATA COVARIANCE WITH THE GENERATIVE MODEL
COV COMPONENTST S2COMPONENTS SIGMA2 EYENFEATURES
WHERE S2 CONTAINS THE EXPLAINED VARIANCES AND SIGMA2 CONTAINS THE NOISE VARIANCES
RETURNS
COV ARRAY SHAPENFEATURES NFEATURES ESTIMATED COVARIANCE OF DATA

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GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETPRECISION SELF
COMPUTE DATA PRECISION MATRIX WITH THE GENERATIVE MODEL
EQUALS THE INVERSE OF THE COVARIANCE BUT COMPUTED WITH THE MATRIX INVERSION LEMMA FOR EFFICIENCY
RETURNS
PRECISION ARRAY SHAPENFEATURES NFEATURES ESTIMATED PRECISION OF DATA
INVERSETRANSFORM SELFX
TRANSFORM DATA BACK TO ITS ORIGINAL SPACE
IN OTHER WORDS RETURN AN INPUT XORIGINAL WHOSE TRANSFORM WOULD BE X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NCOMPONENTS NEW DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NCOMPONENTS IS THE NUMBER OF COMPONENTS
RETURNS
XORIGINAL ARRAYLIKE SHAPE NSAMPLES NFEATURES
NOTES
IF WHITENING IS ENABLED INVERSETRANSFORM WILL COMPUTE THE EXACT INVERSE OPERATION WHICH INCLUDES RE
VERSING WHITENING
PARTIALFIT SELFXYNONE CHECKINPUTTRUE
INCREMENTAL FIT WITH X ALL OF X IS PROCESSED AS A SINGLE BATCH
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
CHECKINPUT BOOL RUN CHECKARRAY ON X
YIGNORED
RETURNS
SELF OBJECT RETURNS THE INSTANCE ITSELF
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS

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SELF
TRANSFORM SELFX
APPLY DIMENSIONALITY REDUCTION TO X
X IS PROJECTED ON THE FIRST PRINCIPAL COMPONENTS PREVIOUSLY EXTRACTED FROM A TRAINING SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES NEW DATA WHERE NSAMPLES IS THE NUMBER OF
SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
EXAMPLES
IMPORT NUMPY AS NP
FROM SKLEARNDECOMPOSITION IMPORT INCREMENTALPCA
X NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
IPCA INCREMENTALPCANCOMPONENTS2 BATCHSIZE3
IPCAFITX
INCREMENTALPCABATCHSIZE3 COPYTRUE NCOMPONENTS2 WHITENFALSE
IPCATRANSFORMX
EXAMPLES USING SKLEARNDECOMPOSITIONINCREMENTALPCA
•INCREMENTAL PCA
695SKLEARNDECOMPOSITION KERNELPCA
CLASSSKLEARNDECOMPOSITION KERNELPCA NCOMPONENTSNONE KERNEL'LINEAR' GAMMANONE
DEGREE3 COEF01 KERNELPARAMSNONE ALPHA10
FITINVERSETRANSFORMFALSE EIGENSOLVER'AUTO'
TOL0 MAXITERNONE REMOVEZEROEIGFALSE RAN
DOMSTATENONE COPYXTRUE NJOBSNONE
KERNEL PRINCIPAL COMPONENT ANALYSIS KPCA
NONLINEAR DIMENSIONALITY REDUCTION THROUGH THE USE OF KERNELS SEE PAIRWISE METRICS AFFINITIES AND KERNELS
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT DEFAULTNONE NUMBER OF COMPONENTS IF NONE ALL NONZERO COMPONENTS
ARE KEPT
KERNEL "LINEAR" "POLY" "RBF" "SIGMOID" "COSINE" "PRECOMPUTED" KERNEL DE
FAULT"LINEAR"
GAMMA FLOAT DEFAULT1NFEATURES KERNEL COEFFICIENT FOR RBF POLY AND SIGMOID KERNELS IG
NORED BY OTHER KERNELS
DEGREE INT DEFAULT3 DEGREE FOR POLY KERNELS IGNORED BY OTHER KERNELS
COEF0 FLOAT DEFAULT1 INDEPENDENT TERM IN POLY AND SIGMOID KERNELS IGNORED BY OTHER KERNELS

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KERNELPARAMS MAPPING OF STRING TO ANY DEFAULTNONE PARAMETERS KEYWORD ARGUMENTS AND
VALUES FOR KERNEL PASSED AS CALLABLE OBJECT IGNORED BY OTHER KERNELS
ALPHA INT DEFAULT10 HYPERPARAMETER OF THE RIDGE REGRESSION THAT LEARNS THE INVERSE TRANSFORM
WHEN FITINVERSETRANSFORMTRUE
FITINVERSETRANSFORM BOOL DEFAULTFALSE LEARN THE INVERSE TRANSFORM FOR NONPRECOMPUTED
KERNELS IE LEARN TO FIND THE PREIMAGE OF A POINT
EIGENSOLVER STRING 'AUTO''DENSE''ARPACK' DEFAULT'AUTO' SELECT EIGENSOLVER TO USE IF
NCOMPONENTS IS MUCH LESS THAN THE NUMBER OF TRAINING SAMPLES ARPACK MAY BE MORE EFFI
CIENT THAN THE DENSE EIGENSOLVER
TOLFLOAT DEFAULT0 CONVERGENCE TOLERANCE FOR ARPACK IF 0 OPTIMAL VALUE WILL BE CHOSEN BY
ARPACK
MAXITER INT DEFAULTNONE MAXIMUM NUMBER OF ITERATIONS FOR ARPACK IF NONE OPTIMAL VALUE
WILL BE CHOSEN BY ARPACK
REMOVEZEROEIG BOOLEAN DEFAULTFALSE IF TRUE THEN ALL COMPONENTS WITH ZERO EIGENVALUES
ARE REMOVED SO THAT THE NUMBER OF COMPONENTS IN THE OUTPUT MAY BE NCOMPONENTS
AND SOMETIMES EVEN ZERO DUE TO NUMERICAL INSTABILITY WHEN NCOMPONENTS IS NONE THIS
PARAMETER IS IGNORED AND COMPONENTS WITH ZERO EIGENVALUES ARE REMOVED REGARDLESS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RAN
DOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE
RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN EIGENSOLVER 'ARPACK'
NEW IN VERSION 018
COPYX BOOLEAN DEFAULTTRUE IF TRUE INPUT X IS COPIED AND STORED BY THE MODEL IN THE
XFIT ATTRIBUTE IF NO FURTHER CHANGES WILL BE DONE TO X SETTING COPYXFALSE SAVES
MEMORY BY STORING A REFERENCE
NEW IN VERSION 018
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS
1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
NEW IN VERSION 018
ATTRIBUTES
LAMBDAS ARRAY NCOMPONENTS EIGENVALUES OF THE CENTERED KERNEL MATRIX IN DECREASING
ORDER IF NCOMPONENTS ANDREMOVEZEROEIG ARE NOT SET THEN ALL VALUES ARE STORED
ALPHAS ARRAY NSAMPLES NCOMPONENTS EIGENVECTORS OF THE CENTERED KERNEL MATRIX IF
NCOMPONENTS ANDREMOVEZEROEIG ARE NOT SET THEN ALL COMPONENTS ARE STORED
DUALCOEF ARRAY NSAMPLES NFEATURES INVERSE TRANSFORM MATRIX ONLY AVAILABLE WHEN
FITINVERSETRANSFORM IS TRUE
XTRANSFORMEDFIT ARRAY NSAMPLES NCOMPONENTS PROJECTION OF THE FITTED DATA ON THE
KERNEL PRINCIPAL COMPONENTS ONLY AVAILABLE WHEN FITINVERSETRANSFORM IS TRUE
XFIT NSAMPLES NFEATURES THE DATA USED TO FIT THE MODEL IF COPYXFALSE THEN
XFIT IS A REFERENCE THIS ATTRIBUTE IS USED FOR THE CALLS TO TRANSFORM
69SKLEARNDECOMPOSITION MATRIX DECOMPOSITION 1637

REFERENCES
KERNEL PCA WAS INTRODUCED IN BERNHARD SCHOELKOPF ALEXANDER J SMOLA AND KLAUSROBERT MUELLER 1999
KERNEL PRINCIPAL COMPONENT ANALYSIS IN ADVANCES IN KERNEL METHODS MIT PRESS CAMBRIDGE MA USA
327352
EXAMPLES
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 FROM SKLEARNDATASETS IMPORT LOADDIGITS
 FROM SKLEARNDECOMPOSITION IMPORT KERNELPCA
X   LOADDIGITSRETURNXY TRUE
TRANSFORMER  KERNELPCANCOMPONENTS7 KERNELLINEAR
XTRANSFORMED  TRANSFORMERFITTRANSFORMX
XTRANSFORMEDSHAPE
1797 7
```
METHODS
FITSELF X Y FIT THE MODEL FROM DATA IN X
FITTRANSFORM SELF X Y FIT THE MODEL FROM DATA IN X AND TRANSFORM X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X TRANSFORM X BACK TO ORIGINAL SPACE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM X
INIT SELFNCOMPONENTSNONE KERNEL’LINEAR’ GAMMANONE DEGREE3 COEF01 KER
NELPARAMSNONE ALPHA10 FITINVERSETRANSFORMFALSE EIGENSOLVER’AUTO’
TOL0 MAXITERNONE REMOVEZEROEIGFALSE RANDOMSTATENONE COPYXTRUE
NJOBSNONE
FITSELFXYNONE
FIT THE MODEL FROM DATA IN X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IN THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
RETURNS
SELF OBJECT RETURNS THE INSTANCE ITSELF
FITTRANSFORM SELFXYNONE PARAMS
FIT THE MODEL FROM DATA IN X AND TRANSFORM X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IN THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR

PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFX
TRANSFORM X BACK TO ORIGINAL SPACE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NFEATURES
REFERENCES
“LEARNING TO FIND PREIMAGES” G BAKIR ET AL 2004
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
EXAMPLES USING SKLEARNDECOMPOSITIONKERNELPCA
•KERNEL PCA

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696SKLEARNDECOMPOSITION LATENTDIRICHLETALLOCATION
CLASSSKLEARNDECOMPOSITION LATENTDIRICHLETALLOCATION NCOMPONENTS10
DOCTOPICPRIORNONE
TOPICWORDPRIORNONE
LEARNINGMETHOD'BATCH'
LEARNINGDECAY07
LEARNINGOFFSET100
MAXITER10 BATCHSIZE128
EVALUATEEVERY1 TO
TALSAMPLES10000000
PERPTOL01
MEANCHANGETOL0001
MAXDOCUPDATEITER100
NJOBSNONE VERBOSE0 RAN
DOMSTATENONE
LATENT DIRICHLET ALLOCATION WITH ONLINE VARIATIONAL BAYES ALGORITHM
NEW IN VERSION 017
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT OPTIONAL DEFAULT10 NUMBER OF TOPICS
DOCTOPICPRIOR FLOAT OPTIONAL DEFAULTNONE PRIOR OF DOCUMENT TOPIC DISTRIBUTION THETA
IF THE VALUE IS NONE DEFAULTS TO 1 NCOMPONENTS IN1 THIS IS CALLED ALPHA
TOPICWORDPRIOR FLOAT OPTIONAL DEFAULTNONE PRIOR OF TOPIC WORD DISTRIBUTION BETA IF
THE VALUE IS NONE DEFAULTS TO 1 NCOMPONENTS IN1 THIS IS CALLED ETA
LEARNINGMETHOD 'BATCH' 'ONLINE' DEFAULT'BATCH' METHOD USED TO UPDATE COMPONENT
ONLY USED IN FIT METHOD IN GENERAL IF THE DATA SIZE IS LARGE THE ONLINE UPDATE WILL BE
MUCH FASTER THAN THE BATCH UPDATE
VALID OPTIONS
BATCH BATCH VARIATIONAL BAYES METHOD USE ALL TRAINING DATA IN
EACH EM UPDATE
OLD COMPONENTS WILL BE OVERWRITTEN IN EACH ITERATION
ONLINE ONLINE VARIATIONAL BAYES METHOD IN EACH EM UPDATE USE
MINIBATCH OF TRAINING DATA TO UPDATE THE COMPONENTS
VARIABLE INCREMENTALLY THE LEARNING RATE IS CONTROLLED BY THE
LEARNINGDECAY AND THE LEARNINGOFFSET PARAMETERS
CHANGED IN VERSION 020 THE DEFAULT LEARNING METHOD IS NOW BATCH
LEARNINGDECAY FLOAT OPTIONAL DEFAULT07 IT IS A PARAMETER THAT CONTROL LEARNING RATE IN THE
ONLINE LEARNING METHOD THE VALUE SHOULD BE SET BETWEEN 05 10 TO GUARANTEE ASYMPTOTIC
CONVERGENCE WHEN THE VALUE IS 00 AND BATCHSIZE IS NSAMPLES THE UPDATE METHOD IS
SAME AS BATCH LEARNING IN THE LITERATURE THIS IS CALLED KAPPA
LEARNINGOFFSET FLOAT OPTIONAL DEFAULT10 A POSITIVE PARAMETER THAT DOWNWEIGHTS EARLY
ITERATIONS IN ONLINE LEARNING IT SHOULD BE GREATER THAN 10 IN THE LITERATURE THIS IS CALLED
TAU0
MAXITER INTEGER OPTIONAL DEFAULT10 THE MAXIMUM NUMBER OF ITERATIONS
BATCHSIZE INT OPTIONAL DEFAULT128 NUMBER OF DOCUMENTS TO USE IN EACH EM ITERATION
ONLY USED IN ONLINE LEARNING

EVALUATEEVERY INT OPTIONAL DEFAULT0 HOW OFTEN TO EVALUATE PERPLEXITY ONLY USED IN FIT METHOD SET IT TO 0 OR NEGATIVE NUMBER TO NOT EVALUTE PERPLEXITY IN TRAINING AT ALL EVALUATING PERPLEXITY CAN HELP YOU CHECK CONVERGENCE IN TRAINING PROCESS BUT IT WILL ALSO INCREASE TOTAL TRAINING TIME EVALUATING PERPLEXITY IN EVERY ITERATION MIGHT INCREASE TRAINING TIME UP TO TWOFOLD
TOTALSAMPLES INT OPTIONAL DEFAULT1E6 TOTAL NUMBER OF DOCUMENTS ONLY USED IN THE PARTIALFIT METHOD
PERPTOL FLOAT OPTIONAL DEFAULT1E1 PERPLEXITY TOLERANCE IN BATCH LEARNING ONLY USED WHEN EVALUATEEVERY IS GREATER THAN 0
MEANCHANGETOL FLOAT OPTIONAL DEFAULT1E3 STOPPING TOLERANCE FOR UPDATING DOCUMENT TOPIC DISTRIBUTION IN ESTEP
MAXDOCUPDATEITER INT DEFAULT100 MAX NUMBER OF ITERATIONS FOR UPDATING DOCUMENT TOPIC DISTRIBUTION IN THE ESTEP
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE IN THE ESTEP NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCES SORS SEE GLOSSARY FOR MORE DETAILS
VERBOSE INT OPTIONAL DEFAULT0 VERBOSITY LEVEL
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES
COMPONENTS ARRAY NCOMPONENTS NFEATURES VARIATIONAL PARAMETERS FOR TOPIC WORD DIS TRIBUTION SINCE THE COMPLETE CONDITIONAL FOR TOPIC WORD DISTRIBUTION IS A DIRICHLET COMPONENTSI J CAN BE VIEWED AS PSEUDOCOUNT THAT REPRESENTS THE NUMBER OF TIMES WORDJWAS ASSIGNED TO TOPIC I IT CAN ALSO BE VIEWED AS DISTRIBUTION OVER THE WORDS FOR EACH TOPIC AFTER NORMALIZATION MODELCOMPONENTS MODELCOMPONENTS SUMAXIS1 NPNEWAXIS
NBATCHITER INT NUMBER OF ITERATIONS OF THE EM STEP
NITER INT NUMBER OF PASSES OVER THE DATASET
REFERENCES
1 “ONLINE LEARNING FOR LATENT DIRICHLET ALLOCATION” MATTHEW D HOFFMAN DAVID M BLEI FRANCIS BACH 2010
2 “STOCHASTIC VARIATIONAL INFERENCE” MATTHEW D HOFFMAN DAVID M BLEI CHONG WANG JOHN PAISLEY 2013
3 MATTHEW D HOFFMAN’S ONLINELDAVB CODE LINK HTTPSGITHUBCOMBLEILABONLINELDAVB
EXAMPLES
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 FROM SKLEARNDECOMPOSITION IMPORT LATENTDIRICHLETALLOCATION
 FROM SKLEARNDATASETS IMPORT MAKEMULTILABELCLASSIFICATION
 THIS PRODUCES A FEATURE MATRIX OF TOKEN COUNTS SIMILAR TO WHAT
 COUNTVECTORIZER WOULD PRODUCE ON TEXT
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X MAKEMULTILABELCLASSIFICATIONRANDOMSTATE0
LDA LATENTDIRICHLETALLOCATIONNCOMPONENTS5
RANDOMSTATE0
LDAFITX
LATENTDIRICHLETALLOCATION
GET TOPICS FOR SOME GIVEN SAMPLES
LDATRANSFORMX2
ARRAY000360392 025499205 00036211 064236448 009541846
015297572 000362644 044412786 039568399 0003586
METHODS
FITSELF X Y LEARN MODEL FOR THE DATA X WITH VARIATIONAL BAYES
METHOD
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y ONLINE VB WITH MINIBATCH UPDATE
PERPLEXITY SELF X SUBSAMPLING CALCULATE APPROXIMATE PERPLEXITY FOR DATA X
SCORE SELF X Y CALCULATE APPROXIMATE LOGLIKELIHOOD AS SCORE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM DATA X ACCORDING TO THE FITTED MODEL
INIT SELFNCOMPONENTS10 DOCTOPICPRIORNONE TOPICWORDPRIORNONE LEARN
INGMETHOD'BATCH' LEARNINGDECAY07 LEARNINGOFFSET100 MAXITER10
BATCHSIZE128 EVALUATEEVERY1 TOTALSAMPLES10000000 PERPTOL01
MEANCHANGETOL0001 MAXDOCUPDATEITER100 NJOBSNONE VERBOSE0 RAN
DOMSTATENONE
FITSELFXYNONE
LEARN MODEL FOR THE DATA X WITH VARIATIONAL BAYES METHOD
WHENLEARNINGMETHOD IS 'ONLINE' USE MINIBATCH UPDATE OTHERWISE USE BATCH UPDATE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPENSAMPLES NFEATURES DOCUMENT WORD MATRIX
YIGNORED
RETURNS
SELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY

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GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYNONE
ONLINE VB WITH MINIBATCH UPDATE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPENSAMPLES NFEATURES DOCUMENT WORD MATRIX
YIGNORED
RETURNS
SELF
PERPLEXITY SELFXSUBSAMPLINGFALSE
CALCULATE APPROXIMATE PERPLEXITY FOR DATA X
PERPLEXITY IS DEFINED AS EXP1 LOGLIKELIHOOD PER WORD
CHANGED IN VERSION 019 DOCTOPICDISTR ARGUMENT HAS BEEN DEPRECATED AND IS IGNORED BECAUSE USER NO
LONGER HAS ACCESS TO UNNORMALIZED DISTRIBUTION
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX NSAMPLES NFEATURES DOCUMENT WORD MATRIX
SUBSAMPLING BOOL DO SUBSAMPLING OR NOT
RETURNS
SCORE FLOAT PERPLEXITY SCORE
SCORESELFXYNONE
CALCULATE APPROXIMATE LOGLIKELIHOOD AS SCORE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPENSAMPLES NFEATURES DOCUMENT WORD MATRIX
YIGNORED
RETURNS
SCORE FLOAT USE APPROXIMATE BOUND AS SCORE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
69SKLEARNDECOMPOSITION MATRIX DECOMPOSITION 1643

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TRANSFORM SELFX
TRANSFORM DATA X ACCORDING TO THE FITTED MODEL
CHANGED IN VERSION 018 DOCTOPICDISTR IS NOW NORMALIZED
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPENSAMPLES NFEATURES DOCUMENT WORD MATRIX
RETURNS
DOCTOPICDISTR SHAPENSAMPLES NCOMPONENTS DOCUMENT TOPIC DISTRIBUTION FOR X
EXAMPLES USING SKLEARNDECOMPOSITIONLATENTDIRICHLETALLOCATION
•TOPIC EXTRACTION WITH NONNEGATIVE MATRIX FACTORIZATION AND LATENT DIRICHLET ALLOCATION
697SKLEARNDECOMPOSITION MINIBATCHDICTIONARYLEARNING
CLASSSKLEARNDECOMPOSITION MINIBATCHDICTIONARYLEARNING NCOMPONENTSNONE AL
PHA1 NITER1000
FITALGORITHM'LARS'
NJOBSNONE
BATCHSIZE3 SHUFFLETRUE
DICTINITNONE TRANS
FORMALGORITHM'OMP' TRANS
FORMNNONZEROCOEFSNONE
TRANSFORMALPHANONE VER
BOSEFALSE SPLITSIGNFALSE
RANDOMSTATENONE POS
ITIVECODEFALSE POSI
TIVEDICTFALSE
MINIBATCH DICTIONARY LEARNING
FINDS A DICTIONARY A SET OF ATOMS THAT CAN BEST BE USED TO REPRESENT DATA USING A SPARSE CODE
SOLVES THE OPTIMIZATION PROBLEM
UV ARGMIN 05 Y U V 22 ALPHA U 1
UV
WITH VK 2 1 FORALL 0 K NCOMPONENTS
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT NUMBER OF DICTIONARY ELEMENTS TO EXTRACT
ALPHA FLOAT SPARSITY CONTROLLING PARAMETER
NITER INT TOTAL NUMBER OF ITERATIONS TO PERFORM
FITALGORITHM 'LARS' 'CD' LARS USES THE LEAST ANGLE REGRESSION METHOD TO SOLVE THE LASSO
PROBLEM LINEARMODELLARSPATH CD USES THE COORDINATE DESCENT METHOD TO COMPUTE THE
LASSO SOLUTION LINEARMODELLASSO LARS WILL BE FASTER IF THE ESTIMATED COMPONENTS ARE
SPARSE

NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
BATCHSIZE INT NUMBER OF SAMPLES IN EACH MINIBATCH
SHUFFLE BOOL WHETHER TO SHUFFLE THE SAMPLES BEFORE FORMING BATCHES
DICTINIT ARRAY OF SHAPE NCOMPONENTS NFEATURES INITIAL VALUE OF THE DICTIONARY FOR WARM
RESTART SCENARIOS
TRANSFORMALGORITHM 'LASSOLARS' 'LASSOCD' 'LARS' 'OMP' 'THRESHOLD' ALGORITHM USED TO
TRANSFORM THE DATA LARS USES THE LEAST ANGLE REGRESSION METHOD LINEARMODELLARSPATH
LASSOLARS USES LARS TO COMPUTE THE LASSO SOLUTION LASSOCD USES THE COORDINATE DESCENT
METHOD TO COMPUTE THE LASSO SOLUTION LINEARMODELLASSO LASSOLARS WILL BE FASTER IF
THE ESTIMATED COMPONENTS ARE SPARSE OMP USES ORTHOGONAL MATCHING PURSUIT TO ESTIMATE
THE SPARSE SOLUTION THRESHOLD SQUASHES TO ZERO ALL COEFFICIENTS LESS THAN ALPHA FROM THE
PROJECTION DICTIONARY X'
TRANSFORMNNONZEROCOEFS INT01NFEATURES BY DEFAULT NUMBER OF NONZERO
COEFFICIENTS TO TARGET IN EACH COLUMN OF THE SOLUTION THIS IS ONLY USED BY
ALGORITHMLARS ANDALGORITHMOMP AND IS OVERRIDDEN BY ALPHA IN THE OR
THOGONAL MATCHING PURSUIT OMP CASE
TRANSFORMALPHA FLOAT 1 BY DEFAULT IF ALGORITHMLASSOLARS OR
ALGORITHMLASSOCD ALPHA IS THE PENALTY APPLIED TO THE L1 NORM IF
ALGORITHMTHRESHOLD ALPHA IS THE ABSOLUTE VALUE OF THE THRESHOLD BELOW
WHICH COEFFICIENTS WILL BE SQUASHED TO ZERO IF ALGORITHMOMP ALPHA IS THE
TOLERANCE PARAMETER THE VALUE OF THE RECONSTRUCTION ERROR TARGETED IN THIS CASE IT OVERRIDES
NNONZEROCOEFS
VERBOSE BOOL OPTIONAL DEFAULT FALSE TO CONTROL THE VERBOSITY OF THE PROCEDURE
SPLITSIGN BOOL FALSE BY DEFAULT WHETHER TO SPLIT THE SPARSE FEATURE VECTOR INTO THE CONCATE
NATION OF ITS NEGATIVE PART AND ITS POSITIVE PART THIS CAN IMPROVE THE PERFORMANCE OF DOWN
STREAM CLASSIFIERS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
POSITIVECODE BOOL WHETHER TO ENFORCE POSITIVITY WHEN FINDING THE CODE
NEW IN VERSION 020
POSITIVEDICT BOOL WHETHER TO ENFORCE POSITIVITY WHEN FINDING THE DICTIONARY
NEW IN VERSION 020
ATTRIBUTES
COMPONENTS ARRAY NCOMPONENTS NFEATURES COMPONENTS EXTRACTED FROM THE DATA
INNERSTATS TUPLE OF A B NDARRAYS INTERNAL SUFFICIENT STATISTICS THAT ARE KEPT BY THE ALGO
RITHM KEEPING THEM IS USEFUL IN ONLINE SETTINGS TO AVOID LOOSING THE HISTORY OF THE EVOLU
TION BUT THEY SHOULDN'T HAVE ANY USE FOR THE END USER A NCOMPONENTS NCOMPONENTS IS
THE DICTIONARY COVARIANCE MATRIX B NFEATURES NCOMPONENTS IS THE DATA APPROXIMATION
MATRIX
NITER INT NUMBER OF ITERATIONS RUN
SEE ALSO
69SKLEARNDECOMPOSITION MATRIX DECOMPOSITION 1645

SPARSECODER
DICTIONARYLEARNING
SPARSEPCA
MINIBATCHSPARSEPCA
NOTES
REFERENCES
J MAIRAL F BACH J PONCE G SAPIRO 2009 ONLINE DICTIONARY LEARNING FOR SPARSE CODING HTTPSWWWDIENS
FRSIERRAPDFSICML09PDF
METHODS
FITSELF X Y FIT THE MODEL FROM DATA IN X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y ITEROFFSET UPDATES THE MODEL USING THE DATA IN X AS A MINIBATCH
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X ENCODE THE DATA AS A SPARSE COMBINATION OF THE DICTIO
NARY ATOMS
INIT SELFNCOMPONENTSNONE ALPHA1 NITER1000 FITALGORITHM'LARS' NJOBSNONE
BATCHSIZE3 SHUFFLETRUE DICTINITNONE TRANSFORMALGORITHM'OMP' TRANS
FORMNNONZEROCOEFSNONE TRANSFORMALPHANONE VERBOSEFALSE SPLITSIGNFALSE
RANDOMSTATENONE POSITIVECODEFALSE POSITIVEDICTFALSE
FITSELFXYNONE
FIT THE MODEL FROM DATA IN X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IN THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
RETURNS
SELF OBJECT RETURNS THE INSTANCE ITSELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY

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GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYNONE ITEROFFSETNONE
UPDATES THE MODEL USING THE DATA IN X AS A MINIBATCH
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IN THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
ITEROFFSET INTEGER OPTIONAL THE NUMBER OF ITERATION ON DATA BATCHES THAT HAS BEEN PER
FORMED BEFORE THIS CALL TO PARTIALFIT THIS IS OPTIONAL IF NO NUMBER IS PASSED THE MEMORY
OF THE OBJECT IS USED
RETURNS
SELF OBJECT RETURNS THE INSTANCE ITSELF
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
ENCODE THE DATA AS A SPARSE COMBINATION OF THE DICTIONARY ATOMS
CODING METHOD IS DETERMINED BY THE OBJECT PARAMETER TRANSFORMALGORITHM
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES TEST DATA TO BE TRANSFORMED MUST HAVE THE SAME
NUMBER OF FEATURES AS THE DATA USED TO TRAIN THE MODEL
RETURNS
XNEW ARRAY SHAPE NSAMPLES NCOMPONENTS TRANSFORMED DATA
EXAMPLES USING SKLEARNDECOMPOSITIONMINIBATCHDICTIONARYLEARNING
•IMAGE DENOISING USING DICTIONARY LEARNING
•FACES DATASET DECOMPOSITIONS

698SKLEARNDECOMPOSITION MINIBATCHSPARSEPCA
CLASSSKLEARNDECOMPOSITION MINIBATCHSPARSEPCA NCOMPONENTSNONE ALPHA1
RIDGEALPHA001 NITER100 CALL
BACKNONE BATCHSIZE3 VER
BOSEFALSE SHUFFLETRUE NJOBSNONE
METHOD'LARS' RANDOMSTATENONE
NORMALIZECOMPONENTSFALSE
MINIBATCH SPARSE PRINCIPAL COMPONENTS ANALYSIS
FINDS THE SET OF SPARSE COMPONENTS THAT CAN OPTIMALLY RECONSTRUCT THE DATA THE AMOUNT OF SPARSENESS IS CONTROL
LABLE BY THE COEFFICIENT OF THE L1 PENALTY GIVEN BY THE PARAMETER ALPHA
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT NUMBER OF SPARSE ATOMS TO EXTRACT
ALPHA INT SPARSITY CONTROLLING PARAMETER HIGHER VALUES LEAD TO SPARSER COMPONENTS
RIDGEALPHA FLOAT AMOUNT OF RIDGE SHRINKAGE TO APPLY IN ORDER TO IMPROVE CONDITIONING WHEN
CALLING THE TRANSFORM METHOD
NITER INT NUMBER OF ITERATIONS TO PERFORM FOR EACH MINI BATCH
CALLBACK CALLABLE OR NONE OPTIONAL DEFAULT NONE CALLABLE THAT GETS INVOKED EVERY FIVE ITER
ATIONS
BATCHSIZE INT THE NUMBER OF FEATURES TO TAKE IN EACH MINI BATCH
VERBOSE INT CONTROLS THE VERBOSITY THE HIGHER THE MORE MESSAGES DEFAULTS TO 0
SHUFFLE BOOLEAN WHETHER TO SHUFFLE THE DATA BEFORE SPLITTING IT IN BATCHES
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
METHOD 'LARS' 'CD' LARS USES THE LEAST ANGLE REGRESSION METHOD TO SOLVE THE LASSO PROB
LEM LINEARMODELLARSPATH CD USES THE COORDINATE DESCENT METHOD TO COMPUTE THE LASSO
SOLUTION LINEARMODELLASSO LARS WILL BE FASTER IF THE ESTIMATED COMPONENTS ARE SPARSE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
NORMALIZECOMPONENTS BOOLEAN OPTIONAL DEFAULTFALSE
• IF FALSE USE A VERSION OF SPARSE PCA WITHOUT COMPONENTS NORMALIZATION AND WITHOUT DATA
CENTERING THIS IS LIKELY A BUG AND EVEN THOUGH IT'S THE DEFAULT FOR BACKWARD COMPATIBILITY
THIS SHOULD NOT BE USED
• IF TRUE USE A VERSION OF SPARSE PCA WITH COMPONENTS NORMALIZATION AND DATA CENTERING
NEW IN VERSION 020
DEPRECATED SINCE VERSION 022 NORMALIZECOMPONENTS WAS ADDED AND SET TO FALSE
FOR BACKWARD COMPATIBILITY IT WOULD BE SET TO TRUE FROM 022 ONWARDS
ATTRIBUTES
COMPONENTS ARRAY NCOMPONENTS NFEATURES SPARSE COMPONENTS EXTRACTED FROM THE DATA

NITER INT NUMBER OF ITERATIONS RUN
MEAN ARRAY SHAPE NFEATURES PERFEATURE EMPIRICAL MEAN ESTIMATED FROM THE TRAINING SET
EQUAL TOXMEANAXIS0
SEE ALSO
PCA
SPARSEPCA
DICTIONARYLEARNING
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNDATASETS IMPORT MAKEFRIEDMAN1
 FROM SKLEARNDECOMPOSITION IMPORT MINIBATCHSPARSEPCA
X   MAKEFRIEDMAN1NSAMPLES200 NFEATURES30 RANDOMSTATE0
TRANSFORMER  MINIBATCHSPARSEPCANCOMPONENTS5
 BATCHSIZE50
 NORMALIZECOMPONENTS TRUE
 RANDOMSTATE0
TRANSFORMERFITX
MINIBATCHSPARSEPCA
XTRANSFORMED  TRANSFORMERTRANSFORMX
XTRANSFORMEDSHAPE
200 5
 MOST VALUES IN THE COMPONENTS ARE ZERO SPARSITY
NPMEANTRANSFORMERCOMPONENTS  0
094
```
METHODS
FITSELF X Y FIT THE MODEL FROM DATA IN X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X LEAST SQUARES PROJECTION OF THE DATA ONTO THE SPARSE
COMPONENTS
INIT SELFNCOMPONENTSNONE ALPHA1 RIDGEALPHA001 NITER100 CALLBACKNONE
BATCHSIZE3 VERBOSEFALSE SHUFFLETRUE NJOBSNONE METHOD’LARS’ RAN
DOMSTATENONE NORMALIZECOMPONENTSFALSE
FITSELFXYNONE
FIT THE MODEL FROM DATA IN X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IN THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
RETURNS

SELF OBJECT RETURNS THE INSTANCE ITSELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
LEAST SQUARES PROJECTION OF THE DATA ONTO THE SPARSE COMPONENTS
TO AVOID INSTABILITY ISSUES IN CASE THE SYSTEM IS UNDERDETERMINED REGULARIZATION CAN BE APPLIED RIDGE
REGRESSION VIA THE RIDGEALPHA PARAMETER
NOTE THAT SPARSE PCA COMPONENTS ORTHOGONALITY IS NOT ENFORCED AS IN PCA HENCE ONE CANNOT USE A SIMPLE
LINEAR PROJECTION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES TEST DATA TO BE TRANSFORMED MUST HAVE THE SAME
NUMBER OF FEATURES AS THE DATA USED TO TRAIN THE MODEL
RETURNS
XNEW ARRAY SHAPE NSAMPLES NCOMPONENTS TRANSFORMED DATA
EXAMPLES USING SKLEARNDECOMPOSITIONMINIBATCHSPARSEPCA
•FACES DATASET DECOMPOSITIONS

699SKLEARNDECOMPOSITION NMF
CLASSSKLEARNDECOMPOSITION NMFNCOMPONENTSNONE INITNONE SOLVER'CD'
BETALOSS'FROBENIUS' TOL00001 MAXITER200 RAN
DOMSTATENONE ALPHA00 L1RATIO00 VERBOSE0 SHUF
FLEFALSE
NONNEGATIVE MATRIX FACTORIZATION NMF
FIND TWO NONNEGATIVE MATRICES W H WHOSE PRODUCT APPROXIMATES THE NON NEGATIVE MATRIX X THIS FACTORIZA
TION CAN BE USED FOR EXAMPLE FOR DIMENSIONALITY REDUCTION SOURCE SEPARATION OR TOPIC EXTRACTION
THE OBJECTIVE FUNCTION IS
05X WHFRO2
 ALPHA L1RATIO VECW1
 ALPHA L1RATIO VECH1
 05ALPHA1 L1RATIO WFRO2
 05ALPHA1 L1RATIO HFRO2
WHERE
AFRO2 SUMIJ AIJ2 FROBENIUS NORM
VECA1 SUMIJ ABSAIJ ELEMENTWISE L1 NORM
FOR MULTIPLICATIVEUPDATE 'MU' SOLVER THE FROBENIUS NORM 05 X WHFRO2 CAN BE CHANGED INTO
ANOTHER BETADIVERGENCE LOSS BY CHANGING THE BETALOSS PARAMETER
THE OBJECTIVE FUNCTION IS MINIMIZED WITH AN ALTERNATING MINIMIZATION OF W AND H
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT OR NONE NUMBER OF COMPONENTS IF NCOMPONENTS IS NOT SET ALL FEATURES
ARE KEPT
INIT NONE 'RANDOM' 'NNDSVD' 'NNDSVDA' 'NNDSVDAR' 'CUSTOM' METHOD USED TO INITIALIZE
THE PROCEDURE DEFAULT NONE VALID OPTIONS
•NONE 'NNDSVD' IF NCOMPONENTS MINNSAMPLES NFEATURES OTHERWISE RANDOM
•'RANDOM' NONNEGATIVE RANDOM MATRICES SCALED WITH SQRTXMEAN
NCOMPONENTS
•'NNDSVD' NONNEGATIVE DOUBLE SINGULAR VALUE DECOMPOSITION NNDSVD
INITIALIZATION BETTER FOR SPARSENESS
•'NNDSVDA' NNDSVD WITH ZEROS FILLED WITH THE AVERAGE OF X BETTER WHEN SPARSITY IS
NOT DESIRED
•'NNDSVDAR' NNDSVD WITH ZEROS FILLED WITH SMALL RANDOM VALUES GENERALLY FASTER
LESS ACCURATE ALTERNATIVE TO NNDSVDA FOR WHEN SPARSITY IS NOT DESIRED
• 'CUSTOM' USE CUSTOM MATRICES W AND H
SOLVER 'CD' 'MU' NUMERICAL SOLVER TO USE 'CD' IS A COORDINATE DESCENT SOLVER 'MU' IS A
MULTIPLICATIVE UPDATE SOLVER
NEW IN VERSION 017 COORDINATE DESCENT SOLVER
NEW IN VERSION 019 MULTIPLICATIVE UPDATE SOLVER

BETALOSS FLOAT OR STRING DEFAULT ‘FROBENIUS’ STRING MUST BE IN ‘FROBENIUS’ ‘KULLBACKLEIBLER’
‘ITAKURASAITO’ BETA DIVERGENCE TO BE MINIMIZED MEASURING THE DISTANCE BETWEEN X AND
THE DOT PRODUCT WH NOTE THAT VALUES DIFFERENT FROM ‘FROBENIUS’ OR 2 AND ‘KULLBACKLEIBLER’
OR 1 LEAD TO SIGNIFICANTLY SLOWER FITS NOTE THAT FOR BETALOSS 0 OR ‘ITAKURASAITO’ THE
INPUT MATRIX X CANNOT CONTAIN ZEROS USED ONLY IN ‘MU’ SOLVER
NEW IN VERSION 019
TOLFLOAT DEFAULT 1E4 TOLERANCE OF THE STOPPING CONDITION
MAXITER INTEGER DEFAULT 200 MAXIMUM NUMBER OF ITERATIONS BEFORE TIMING OUT
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ALPHA DOUBLE DEFAULT 0 CONSTANT THAT MULTIPLIES THE REGULARIZATION TERMS SET IT TO ZERO TO
HAVE NO REGULARIZATION
NEW IN VERSION 017 ALPHA USED IN THE COORDINATE DESCENT SOLVER
L1RATIO DOUBLE DEFAULT 0 THE REGULARIZATION MIXING PARAMETER WITH 0 L1RATIO 1 FOR
L1RATIO 0 THE PENALTY IS AN ELEMENTWISE L2 PENALTY AKA FROBENIUS NORM FOR L1RATIO
1 IT IS AN ELEMENTWISE L1 PENALTY FOR 0 L1RATIO 1 THE PENALTY IS A COMBINATION OF L1
AND L2
NEW IN VERSION 017 REGULARIZATION PARAMETER L1RATIO USED IN THE COORDINATE DESCENT
SOLVER
VERBOSE BOOL DEFAULTFALSE WHETHER TO BE VERBOSE
SHUFFLE BOOLEAN DEFAULT FALSE IF TRUE RANDOMIZE THE ORDER OF COORDINATES IN THE CD SOLVER
NEW IN VERSION 017 SHUFFLE PARAMETER USED IN THE COORDINATE DESCENT SOLVER
ATTRIBUTES
COMPONENTS ARRAY NCOMPONENTS NFEATURES FACTORIZATION MATRIX SOMETIMES CALLED ‘DIC
TIONARY’
RECONSTRUCTIONERR NUMBER FROBENIUS NORM OF THE MATRIX DIFFERENCE OR BETADIVERGENCE
BETWEEN THE TRAINING DATA XAND THE RECONSTRUCTED DATA WHFROM THE FITTED MODEL
NITER INT ACTUAL NUMBER OF ITERATIONS
REFERENCES
CICHOCKI ANDRZEJ AND P H A N ANHHUY “FAST LOCAL ALGORITHMS FOR LARGE SCALE NONNEGATIVE MATRIX AND TEN
SOR FACTORIZATIONS” IEICE TRANSACTIONS ON FUNDAMENTALS OF ELECTRONICS COMMUNICATIONS AND COMPUTER SCIENCES
923 708721 2009
FEVOTTE C IDIER J 2011 ALGORITHMS FOR NONNEGATIVE MATRIX FACTORIZATION WITH THE BETADIVERGENCE NEURAL
COMPUTATION 239
EXAMPLES

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IMPORT NUMPY AS NP
X NPARRAY1 1 2 1 3 12 4 1 5 08 6 1
FROM SKLEARNDECOMPOSITION IMPORT NMF
MODEL NMFNCOMPONENTS2 INITRANDOM RANDOMSTATE0
W MODELFITTRANSFORMX
H MODELCOMPONENTS
METHODS
FITSELF X Y LEARN A NMF MODEL FOR THE DATA X
FITTRANSFORM SELF X Y W H LEARN A NMF MODEL FOR THE DATA X AND RETURNS THE TRANS
FORMED DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF W TRANSFORM DATA BACK TO ITS ORIGINAL SPACE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM THE DATA X ACCORDING TO THE FITTED NMF MODEL
INIT SELFNCOMPONENTSNONE INITNONE SOLVER'CD' BETALOSS'FROBENIUS' TOL00001
MAXITER200 RANDOMSTATENONE ALPHA00 L1RATIO00 VERBOSE0 SHUFFLEFALSE
FITSELFXYNONE PARAMS
LEARN A NMF MODEL FOR THE DATA X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES DATA MATRIX TO BE DECOM
POSED
YIGNORED
RETURNS
SELF
FITTRANSFORM SELFXYNONE WNONE HNONE
LEARN A NMF MODEL FOR THE DATA X AND RETURNS THE TRANSFORMED DATA
THIS IS MORE EFFICIENT THAN CALLING FIT FOLLOWED BY TRANSFORM
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES DATA MATRIX TO BE DECOM
POSED
YIGNORED
WARRAYLIKE SHAPE NSAMPLES NCOMPONENTS IF INIT'CUSTOM' IT IS USED AS INITIAL GUESS
FOR THE SOLUTION
HARRAYLIKE SHAPE NCOMPONENTS NFEATURES IF INIT'CUSTOM' IT IS USED AS INITIAL GUESS
FOR THE SOLUTION
RETURNS
WARRAY SHAPE NSAMPLES NCOMPONENTS TRANSFORMED DATA
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFW
TRANSFORM DATA BACK TO ITS ORIGINAL SPACE
PARAMETERS
WARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NCOMPONENTS TRANSFORMED DATA MATRIX
RETURNS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES DATA MATRIX OF ORIGINAL SHAPE
NEW IN VERSION 018
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM THE DATA X ACCORDING TO THE FITTED NMF MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES DATA MATRIX TO BE TRANS
FORMED BY THE MODEL
RETURNS
WARRAY SHAPE NSAMPLES NCOMPONENTS TRANSFORMED DATA
EXAMPLES USING SKLEARNDECOMPOSITIONNMF
•TOPIC EXTRACTION WITH NONNEGATIVE MATRIX FACTORIZATION AND LATENT DIRICHLET ALLOCATION
•SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV
•FACES DATASET DECOMPOSITIONS
6910SKLEARNDECOMPOSITION PCA
CLASSSKLEARNDECOMPOSITION PCANCOMPONENTSNONE COPYTRUE WHITENFALSE
SVDSOLVER'AUTO' TOL00 ITERATEDPOWER'AUTO' RAN
DOMSTATENONE
PRINCIPAL COMPONENT ANALYSIS PCA
LINEAR DIMENSIONALITY REDUCTION USING SINGULAR VALUE DECOMPOSITION OF THE DATA TO PROJECT IT TO A LOWER DIMEN
SIONAL SPACE THE INPUT DATA IS CENTERED BUT NOT SCALED FOR EACH FEATURE BEFORE APPLYING THE SVD
IT USES THE LAPACK IMPLEMENTATION OF THE FULL SVD OR A RANDOMIZED TRUNCATED SVD BY THE METHOD OF HALKO
ET AL 2009 DEPENDING ON THE SHAPE OF THE INPUT DATA AND THE NUMBER OF COMPONENTS TO EXTRACT

IT CAN ALSO USE THE SCIPYSPARSELINALG ARPACK IMPLEMENTATION OF THE TRUNCATED SVD
NOTICE THAT THIS CLASS DOES NOT SUPPORT SPARSE INPUT SEE TRUNCATEDSVD FOR AN ALTERNATIVE WITH SPARSE DATA
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT FLOAT NONE OR STRING NUMBER OF COMPONENTS TO KEEP IF NCOMPONENTS IS
NOT SET ALL COMPONENTS ARE KEPT
NCOMPONENTS MINNSAMPLES NFEATURES
IFNCOMPONENTS MLE ANDSVDSOLVER FULL MINKA'S MLE IS USED
TO GUESS THE DIMENSION USE OF NCOMPONENTS MLE WILL INTERPRET SVDSOLVER
 AUTO ASSVDSOLVER FULL
IF0 NCOMPONENTS 1 ANDSVDSOLVER FULL SELECT THE NUMBER OF
COMPONENTS SUCH THAT THE AMOUNT OF VARIANCE THAT NEEDS TO BE EXPLAINED IS GREATER THAN THE
PERCENTAGE SPECIFIED BY NCOMPONENTS
IFSVDSOLVER ARPACK THE NUMBER OF COMPONENTS MUST BE STRICTLY LESS THAN THE
MINIMUM OF NFEATURES AND NSAMPLES
HENCE THE NONE CASE RESULTS IN
NCOMPONENTS MINNSAMPLES NFEATURES 1
COPY BOOL DEFAULT TRUE IF FALSE DATA PASSED TO FIT ARE OVERWRITTEN AND RUNNING
FITXTRANSFORMX WILL NOT YIELD THE EXPECTED RESULTS USE FITTRANSFORMX INSTEAD
WHITEN BOOL OPTIONAL DEFAULT FALSE WHEN TRUE FALSE BY DEFAULT THE COMPONENTS VECTORS
ARE MULTIPLIED BY THE SQUARE ROOT OF NSAMPLES AND THEN DIVIDED BY THE SINGULAR VALUES TO
ENSURE UNCORRELATED OUTPUTS WITH UNIT COMPONENTWISE VARIANCES
WHITENING WILL REMOVE SOME INFORMATION FROM THE TRANSFORMED SIGNAL THE RELATIVE VARIANCE
SCALES OF THE COMPONENTS BUT CAN SOMETIME IMPROVE THE PREDICTIVE ACCURACY OF THE DOWN
STREAM ESTIMATORS BY MAKING THEIR DATA RESPECT SOME HARDWIRED ASSUMPTIONS
SVDSOLVER STRING 'AUTO' 'FULL' 'ARPACK' 'RANDOMIZED'
AUTO THE SOLVER IS SELECTED BY A DEFAULT POLICY BASED ON XSHAPE ANDNCOMPONENTS IF
THE INPUT DATA IS LARGER THAN 500X500 AND THE NUMBER OF COMPONENTS TO EXTRACT IS LOWER
THAN 80 OF THE SMALLEST DIMENSION OF THE DATA THEN THE MORE EFFICIENT 'RANDOMIZED'
METHOD IS ENABLED OTHERWISE THE EXACT FULL SVD IS COMPUTED AND OPTIONALLY TRUNCATED
AFTERWARDS
FULL RUN EXACT FULL SVD CALLING THE STANDARD LAPACK SOLVER VIA SCIPYLINALGSVD
AND SELECT THE COMPONENTS BY POSTPROCESSING
ARPACK RUN SVD TRUNCATED TO NCOMPONENTS CALLING ARPACK SOLVER VIA SCIPY
SPARSELINALGSVDS IT REQUIRES STRICTLY 0 NCOMPONENTS MINXSHAPE
RANDOMIZED RUN RANDOMIZED SVD BY THE METHOD OF HALKO ET AL
NEW IN VERSION 0180
TOLFLOAT 0 OPTIONAL DEFAULT 0 TOLERANCE FOR SINGULAR VALUES COMPUTED BY SVDSOLVER
'ARPACK'
NEW IN VERSION 0180

ITERATEDPOWER INT 0 OR ‘AUTO’ DEFAULT ‘AUTO’ NUMBER OF ITERATIONS FOR THE POWER METHOD
COMPUTED BY SVDSOLVER ‘RANDOMIZED’
NEW IN VERSION 0180
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SVDSOLVER ‘ARPACK’ OR
‘RANDOMIZED’
NEW IN VERSION 0180
ATTRIBUTES
COMPONENTS ARRAY SHAPE NCOMPONENTS NFEATURES PRINCIPAL AXES IN FEATURE SPACE REP
RESENTING THE DIRECTIONS OF MAXIMUM VARIANCE IN THE DATA THE COMPONENTS ARE SORTED BY
EXPLAINEDVARIANCE
EXPLAINEDVARIANCE ARRAY SHAPE NCOMPONENTS THE AMOUNT OF VARIANCE EXPLAINED BY
EACH OF THE SELECTED COMPONENTS
EQUAL TO NCOMPONENTS LARGEST EIGENVALUES OF THE COVARIANCE MATRIX OF X
NEW IN VERSION 018
EXPLAINEDVARIANCERATIO ARRAY SHAPE NCOMPONENTS PERCENTAGE OF VARIANCE EXPLAINED
BY EACH OF THE SELECTED COMPONENTS
IFNCOMPONENTS IS NOT SET THEN ALL COMPONENTS ARE STORED AND THE SUM OF THE RATIOS IS
EQUAL TO 10
SINGULARVALUES ARRAY SHAPE NCOMPONENTS THE SINGULAR VALUES CORRESPONDING TO EACH
OF THE SELECTED COMPONENTS THE SINGULAR VALUES ARE EQUAL TO THE 2NORMS OF THE
NCOMPONENTS VARIABLES IN THE LOWERDIMENSIONAL SPACE
NEW IN VERSION 019
MEAN ARRAY SHAPE NFEATURES PERFEATURE EMPIRICAL MEAN ESTIMATED FROM THE TRAINING SET
EQUAL TOXMEANAXIS0
NCOMPONENTS INT THE ESTIMATED NUMBER OF COMPONENTS WHEN NCOMPONENTS IS SET TO
‘MLE’ OR A NUMBER BETWEEN 0 AND 1 WITH SVDSOLVER ‘FULL’ THIS NUMBER IS ESTIMATED
FROM INPUT DATA OTHERWISE IT EQUALS THE PARAMETER NCOMPONENTS OR THE LESSER VALUE OF
NFEATURES AND NSAMPLES IF NCOMPONENTS IS NONE
NOISEVARIANCE FLOAT THE ESTIMATED NOISE COVARIANCE FOLLOWING THE PROBABILISTIC PCA MODEL
FROM TIPPING AND BISHOP 1999 SEE “PATTERN RECOGNITION AND MACHINE LEARNING” BY C
BISHOP 1221 P 574 OR HTTPWWWMIKETIPPINGCOMPAPERSMETMPPCAPDF IT IS REQUIRED
TO COMPUTE THE ESTIMATED DATA COVARIANCE AND SCORE SAMPLES
EQUAL TO THE AVERAGE OF MINNFEATURES NSAMPLES NCOMPONENTS SMALLEST EIGENVALUES
OF THE COVARIANCE MATRIX OF X
SEE ALSO
KERNELPCA
SPARSEPCA
TRUNCATEDSVD
INCREMENTALPCA

REFERENCES
FOR NCOMPONENTS ‘MLE’ THIS CLASS USES THE METHOD OF MINKA T P “AUTOMATIC CHOICE OF DIMENSIONALITY FOR PCA” IN NIPS PP 598604
IMPLEMENTS THE PROBABILISTIC PCA MODEL FROM TIPPING M E AND BISHOP C M 1999 “PROBABILISTIC PRINCIPAL COMPONENT ANALYSIS” JOURNAL OF THE ROYAL STATISTICAL SOCIETY SERIES B STATISTICAL METHODOLOGY 613 611622 VIA THE SCORE AND SCORESAMPLES METHODS SEE HTTPWWWMIKETIPPINGCOMPAPERSMETMPPCA PDF
FOR SVDSOLVER ‘ARPACK’ REFER TO SCIPYSPARSELINALGSVDS
FOR SVDSOLVER ‘RANDOMIZED’ SEE HALKO N MARTINSSON P G AND TROPP J A 2011 “FINDING STRUCTURE WITH RANDOMNESS PROBABILISTIC ALGORITHMS FOR CONSTRUCTING APPROXIMATE MATRIX DECOMPOSITIONS” SIAM REVIEW 532 217288 AND ALSO MARTINSSON P G ROKHLIN V AND TYGERT M 2011 “A RANDOMIZED ALGORITHM FOR THE DECOMPOSITION OF MATRICES” APPLIED AND COMPUTATIONAL HARMONIC ANALYSIS 301 4768
EXAMPLES
```
IMPORT NUMPY AS NP
FROM SKLEARNDECOMPOSITION IMPORT PCA
X NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
PCA PCANCOMPONENTS2
PCAFITX
PCACOPYTRUE ITERATEDPOWERAUTO NCOMPONENTS2 RANDOMSTATENONE
SVDSOLVERAUTO TOL00 WHITENFALSE
PRINTPCAEXPLAINEDVARIANCERATIO
09924 00075
PRINTPCASINGULARVALUES
630061 054980
PCA PCANCOMPONENTS2 SVDSOLVERFULL
PCAFITX
PCACOPYTRUE ITERATEDPOWERAUTO NCOMPONENTS2 RANDOMSTATENONE
SVDSOLVERFULL TOL00 WHITENFALSE
PRINTPCAEXPLAINEDVARIANCERATIO
09924 000755
PRINTPCASINGULARVALUES
630061 054980
PCA PCANCOMPONENTS1 SVDSOLVERARPACK
PCAFITX
PCACOPYTRUE ITERATEDPOWERAUTO NCOMPONENTS1 RANDOMSTATENONE
SVDSOLVERARPACK TOL00 WHITENFALSE
PRINTPCAEXPLAINEDVARIANCERATIO
099244
PRINTPCASINGULARVALUES
630061
```
METHODS
FITSELF X Y FIT THE MODEL WITH X
CONTINUED ON NEXT PAGE

TABLE 659 – CONTINUED FROM PREVIOUS PAGE
FITTRANSFORM SELF X Y FIT THE MODEL WITH X AND APPLY THE DIMENSIONALITY RE
DUCTION ON X
GETCOVARIANCE SELF COMPUTE DATA COVARIANCE WITH THE GENERATIVE MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETPRECISION SELF COMPUTE DATA PRECISION MATRIX WITH THE GENERATIVE
MODEL
INVERSETRANSFORM SELF X TRANSFORM DATA BACK TO ITS ORIGINAL SPACE
SCORE SELF X Y RETURN THE AVERAGE LOGLIKELIHOOD OF ALL SAMPLES
SCORESAMPLES SELF X RETURN THE LOGLIKELIHOOD OF EACH SAMPLE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X APPLY DIMENSIONALITY REDUCTION TO X
INIT SELFNCOMPONENTSNONE COPYTRUE WHITENFALSE SVDSOLVER'AUTO' TOL00 ITER
ATEDPOWER'AUTO' RANDOMSTATENONE
FITSELFXYNONE
FIT THE MODEL WITH X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
RETURNS
SELF OBJECT RETURNS THE INSTANCE ITSELF
FITTRANSFORM SELFXYNONE
FIT THE MODEL WITH X AND APPLY THE DIMENSIONALITY REDUCTION ON X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
GETCOVARIANCE SELF
COMPUTE DATA COVARIANCE WITH THE GENERATIVE MODEL
COV COMPONENTST S2COMPONENTS SIGMA2 EYENFEATURES
WHERE S2 CONTAINS THE EXPLAINED VARIANCES AND SIGMA2 CONTAINS THE NOISE VARIANCES
RETURNS
COV ARRAY SHAPENFEATURES NFEATURES ESTIMATED COVARIANCE OF DATA
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS

PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETPRECISION SELF
COMPUTE DATA PRECISION MATRIX WITH THE GENERATIVE MODEL
EQUALS THE INVERSE OF THE COVARIANCE BUT COMPUTED WITH THE MATRIX INVERSION LEMMA FOR EFFICIENCY
RETURNS
PRECISION ARRAY SHAPENFEATURES NFEATURES ESTIMATED PRECISION OF DATA
INVERSETRANSFORM SELFX
TRANSFORM DATA BACK TO ITS ORIGINAL SPACE
IN OTHER WORDS RETURN AN INPUT XORIGINAL WHOSE TRANSFORM WOULD BE X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NCOMPONENTS NEW DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NCOMPONENTS IS THE NUMBER OF COMPONENTS
RETURNS
XORIGINAL ARRAYLIKE SHAPE NSAMPLES NFEATURES
NOTES
IF WHITENING IS ENABLED INVERSETRANSFORM WILL COMPUTE THE EXACT INVERSE OPERATION WHICH INCLUDES RE
VERSING WHITENING
SCORESELFXYNONE
RETURN THE AVERAGE LOGLIKELIHOOD OF ALL SAMPLES
SEE “PATTERN RECOGNITION AND MACHINE LEARNING” BY C BISHOP 1221 P 574 OR HTTPWWWMIKETIPPING
COMPAPERSMETMPPCAPDF
PARAMETERS
XARRAY SHAPENSAMPLES NFEATURES THE DATA
YIGNORED
RETURNS
LLFLOAT AVERAGE LOGLIKELIHOOD OF THE SAMPLES UNDER THE CURRENT MODEL
SCORESAMPLES SELFX
RETURN THE LOGLIKELIHOOD OF EACH SAMPLE
SEE “PATTERN RECOGNITION AND MACHINE LEARNING” BY C BISHOP 1221 P 574 OR HTTPWWWMIKETIPPING
COMPAPERSMETMPPCAPDF
PARAMETERS
XARRAY SHAPENSAMPLES NFEATURES THE DATA
RETURNS
LLARRAY SHAPE NSAMPLES LOGLIKELIHOOD OF EACH SAMPLE UNDER THE CURRENT MODEL
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR

THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT

RETURNS

SELF

TRANSFORM SELFX

APPLY DIMENSIONALITY REDUCTION TO X

X IS PROJECTED ON THE FIRST PRINCIPAL COMPONENTS PREVIOUSLY EXTRACTED FROM A TRAINING SET

PARAMETERS

XARRAYLIKE SHAPE NSAMPLES NFEATURES NEW DATA WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES

RETURNS

XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS

EXAMPLES

```
 IMPORT NUMPY AS NP
 FROM SKLEARNDECOMPOSITION IMPORT INCREMENTALPCA
X  NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
IPCA  INCREMENTALPCANCOMPONENTS2 BATCHSIZE3
IPCAFITX
INCREMENTALPCABATCHSIZE3 COPYTRUE NCOMPONENTS2 WHITENFALSE
IPCATRANSFORMX
```

EXAMPLES USING SKLEARNDECOMPOSITIONPCA

- MULTILABEL CLASSIFICATION
- EXPLICIT FEATURE MAP APPROXIMATION FOR RBF KERNELS
- FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
- A DEMO OF KMEANS CLUSTERING ON THE HANDWRITTEN DIGITS DATA
- CONCATENATING MULTIPLE FEATURE EXTRACTION METHODS
- PIPELINING CHAINING A PCA AND A LOGISTIC REGRESSION
- SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV
- THE IRIS DATASET
- PCA EXAMPLE WITH IRIS DATASET
- INCREMENTAL PCA
- COMPARISON OF LDA AND PCA 2D PROJECTION OF IRIS DATASET
- BLIND SOURCE SEPARATION USING FASTICA
- PRINCIPAL COMPONENTS ANALYSIS PCA
- FASTICA ON 2D POINT CLOUDS
- KERNEL PCA

•MODEL SELECTION WITH PROBABILISTIC PCA AND FACTOR ANALYSIS FA
•FACES DATASET DECOMPOSITIONS
•MULTIDIMENSIONAL SCALING
•BALANCE MODEL COMPLEXITY AND CROSSVALIDATED SCORE
•KERNEL DENSITY ESTIMATION
•DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
•USING FUNCTIONTRANSFORMER TO SELECT COLUMNS
•IMPORTANCE OF FEATURE SCALING
6911SKLEARNDECOMPOSITION SPARSEPCA
CLASSSKLEARNDECOMPOSITION SPARSEPCA NCOMPONENTSNONE ALPHA1 RIDGEALPHA001
MAXITER1000 TOL1E08 METHOD'LARS'
NJOBSNONE UINITNONE VINITNONE
VERBOSEFALSE RANDOMSTATENONE NORMAL
IZECOMPONENTSFALSE
SPARSE PRINCIPAL COMPONENTS ANALYSIS SPARSEPCA
FINDS THE SET OF SPARSE COMPONENTS THAT CAN OPTIMALLY RECONSTRUCT THE DATA THE AMOUNT OF SPARSENESS IS CONTROL
LABLE BY THE COEFFICIENT OF THE L1 PENALTY GIVEN BY THE PARAMETER ALPHA
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT NUMBER OF SPARSE ATOMS TO EXTRACT
ALPHA FLOAT SPARSITY CONTROLLING PARAMETER HIGHER VALUES LEAD TO SPARSER COMPONENTS
RIDGEALPHA FLOAT AMOUNT OF RIDGE SHRINKAGE TO APPLY IN ORDER TO IMPROVE CONDITIONING WHEN
CALLING THE TRANSFORM METHOD
MAXITER INT MAXIMUM NUMBER OF ITERATIONS TO PERFORM
TOLFLOAT TOLERANCE FOR THE STOPPING CONDITION
METHOD 'LARS' 'CD' LARS USES THE LEAST ANGLE REGRESSION METHOD TO SOLVE THE LASSO PROB
LEM LINEARMODELLARSPATH CD USES THE COORDINATE DESCENT METHOD TO COMPUTE THE LASSO
SOLUTION LINEARMODELLASSO LARS WILL BE FASTER IF THE ESTIMATED COMPONENTS ARE SPARSE
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
UINIT ARRAY OF SHAPE NSAMPLES NCOMPONENTS INITIAL VALUES FOR THE LOADINGS FOR WARM
RESTART SCENARIOS
VINIT ARRAY OF SHAPE NCOMPONENTS NFEATURES INITIAL VALUES FOR THE COMPONENTS FOR WARM
RESTART SCENARIOS
VERBOSE INT CONTROLS THE VERBOSITY THE HIGHER THE MORE MESSAGES DEFAULTS TO 0
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM

NORMALIZECOMPONENTS BOOLEAN OPTIONAL DEFAULTFALSE
• IF FALSE USE A VERSION OF SPARSE PCA WITHOUT COMPONENTS NORMALIZATION AND WITHOUT DATA CENTERING THIS IS LIKELY A BUG AND EVEN THOUGH IT'S THE DEFAULT FOR BACKWARD COMPATIBILITY THIS SHOULD NOT BE USED
• IF TRUE USE A VERSION OF SPARSE PCA WITH COMPONENTS NORMALIZATION AND DATA CENTERING
NEW IN VERSION 020
DEPRECATED SINCE VERSION 022 NORMALIZECOMPONENTS WAS ADDED AND SET TO FALSE
FOR BACKWARD COMPATIBILITY IT WOULD BE SET TO TRUE FROM 022 ONWARDS
ATTRIBUTES
COMPONENTS ARRAY NCOMPONENTS NFEATURES SPARSE COMPONENTS EXTRACTED FROM THE DATA
ERROR ARRAY VECTOR OF ERRORS AT EACH ITERATION
NITER INT NUMBER OF ITERATIONS RUN
MEAN ARRAY SHAPE NFEATURES PERFEATURE EMPIRICAL MEAN ESTIMATED FROM THE TRAINING SET
EQUAL TOXMEANAXIS0
SEE ALSO
PCA
MINIBATCHSPARSEPCA
DICTIONARYLEARNING
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNDATASETS IMPORT MAKEFRIEDMAN1
 FROM SKLEARNDECOMPOSITION IMPORT SPARSEPCA
X   MAKEFRIEDMAN1NSAMPLES200 NFEATURES30 RANDOMSTATE0
TRANSFORMER  SPARSEPCANCOMPONENTS5
 NORMALIZECOMPONENTS TRUE
 RANDOMSTATE0
TRANSFORMERFITX
SPARSEPCA
XTRANSFORMED  TRANSFORMERTRANSFORMX
XTRANSFORMEDSHAPE
200 5
 MOST VALUES IN THE COMPONENTS ARE ZERO SPARSITY
NPMEANTRANSFORMERCOMPONENTS  0
09666
```
METHODS
FITSELF X Y FIT THE MODEL FROM DATA IN X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
CONTINUED ON NEXT PAGE

TABLE 660 – CONTINUED FROM PREVIOUS PAGE
TRANSFORM SELF X LEAST SQUARES PROJECTION OF THE DATA ONTO THE SPARSE
COMPONENTS
INIT SELFNCOMPONENTSNONE ALPHA1 RIDGEALPHA001 MAXITER1000 TOL1E
08METHOD'LARS' NJOBSNONE UINITNONE VINITNONE VERBOSEFALSE RAN
DOMSTATENONE NORMALIZECOMPONENTSFALSE
FITSELFXYNONE
FIT THE MODEL FROM DATA IN X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IN THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
RETURNS
SELF OBJECT RETURNS THE INSTANCE ITSELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
LEAST SQUARES PROJECTION OF THE DATA ONTO THE SPARSE COMPONENTS
TO AVOID INSTABILITY ISSUES IN CASE THE SYSTEM IS UNDERDETERMINED REGULARIZATION CAN BE APPLIED RIDGE
REGRESSION VIA THE RIDGEALPHA PARAMETER

NOTE THAT SPARSE PCA COMPONENTS ORTHOGONALITY IS NOT ENFORCED AS IN PCA HENCE ONE CANNOT USE A SIMPLE LINEAR PROJECTION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES TEST DATA TO BE TRANSFORMED MUST HAVE THE SAME NUMBER OF FEATURES AS THE DATA USED TO TRAIN THE MODEL
RETURNS
XNEW ARRAY SHAPE NSAMPLES NCOMPONENTS TRANSFORMED DATA
6912SKLEARNDECOMPOSITION SPARSECODER
CLASSSKLEARNDECOMPOSITION SPARSECODER DICTIONARY TRANSFORMALGORITHM'OMP' TRANSFORMNNONZEROCOEFSNONE TRANS FORMALPHANONE SPLITSIGNFALSE NJOBSNONE POSITIVECODEFALSE
SPARSE CODING
FINDS A SPARSE REPRESENTATION OF DATA AGAINST A FIXED PRECOMPUTED DICTIONARY
EACH ROW OF THE RESULT IS THE SOLUTION TO A SPARSE CODING PROBLEM THE GOAL IS TO FIND A SPARSE ARRAY CODE SUCH THAT
X CODE DICTIONARY
READ MORE IN THE USER GUIDE
PARAMETERS
DICTIONARY ARRAY NCOMPONENTS NFEATURES THE DICTIONARY ATOMS USED FOR SPARSE CODING LINES ARE ASSUMED TO BE NORMALIZED TO UNIT NORM
TRANSFORMALGORITHM 'LASSOLARS' 'LASSOCD' 'LARS' 'OMP' 'THRESHOLD' ALGORITHM USED TO TRANSFORM THE DATA LARS USES THE LEAST ANGLE REGRESSION METHOD LINEARMODELLARSPATH LASSOLARS USES LARS TO COMPUTE THE LASSO SOLUTION LASSOCD USES THE COORDINATE DESCENT METHOD TO COMPUTE THE LASSO SOLUTION LINEARMODELLASSO LASSOLARS WILL BE FASTER IF THE ESTIMATED COMPONENTS ARE SPARSE OMP USES ORTHOGONAL MATCHING PURSUIT TO ESTIMATE THE SPARSE SOLUTION THRESHOLD SQUASHES TO ZERO ALL COEFFICIENTS LESS THAN ALPHA FROM THE PROJECTIONDICTIONARY X
TRANSFORMNNONZEROCOEFS INT01NFEATURES BY DEFAULT NUMBER OF NONZERO COEFFICIENTS TO TARGET IN EACH COLUMN OF THE SOLUTION THIS IS ONLY USED BY ALGORITHMLARS ANDALGORITHMOMP AND IS OVERRIDDEN BY ALPHA IN THE OR THOGONAL MATCHING PURSUIT OMP CASE
TRANSFORMALPHA FLOAT 1 BY DEFAULT IF ALGORITHMLASSOLARS OR ALGORITHMLASSOCD ALPHA IS THE PENALTY APPLIED TO THE L1 NORM IF ALGORITHMTHRESHOLD ALPHA IS THE ABSOLUTE VALUE OF THE THRESHOLD BELOW WHICH COEFFICIENTS WILL BE SQUASHED TO ZERO IF ALGORITHMOMP ALPHA IS THE TOLERANCE PARAMETER THE VALUE OF THE RECONSTRUCTION ERROR TARGETED IN THIS CASE IT OVERRIDES NNONZEROCOEFS
SPLITSIGN BOOL FALSE BY DEFAULT WHETHER TO SPLIT THE SPARSE FEATURE VECTOR INTO THE CONCATE NATION OF ITS NEGATIVE PART AND ITS POSITIVE PART THIS CAN IMPROVE THE PERFORMANCE OF DOWN STREAM CLASSIFIERS

SCIKITLEARN USER GUIDE RELEASE 0213
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
POSITIVECODE BOOL WHETHER TO ENFORCE POSITIVITY WHEN FINDING THE CODE
NEW IN VERSION 020
ATTRIBUTES
COMPONENTS ARRAY NCOMPONENTS NFEATURES THE UNCHANGED DICTIONARY ATOMS
SEE ALSO
DICTIONARYLEARNING
MINIBATCHDICTIONARYLEARNING
SPARSEPCA
MINIBATCHSPARSEPCA
SPARSEENCODE
METHODS
FITSELF X Y DO NOTHING AND RETURN THE ESTIMATOR UNCHANGED
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X ENCODE THE DATA AS A SPARSE COMBINATION OF THE DICTIO
NARY ATOMS
INIT SELFDICTIONARY TRANSFORMALGORITHM'OMP' TRANSFORMNNONZEROCOEFSNONE TRANS
FORMALPHANONE SPLITSIGNFALSE NJOBSNONE POSITIVECODEFALSE
FITSELFXYNONE
DO NOTHING AND RETURN THE ESTIMATOR UNCHANGED
THIS METHOD IS JUST THERE TO IMPLEMENT THE USUAL API AND HENCE WORK IN PIPELINES
PARAMETERS
XIGNORED
YIGNORED
RETURNS
SELF OBJECT RETURNS THE OBJECT ITSELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS

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XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
ENCODE THE DATA AS A SPARSE COMBINATION OF THE DICTIONARY ATOMS
CODING METHOD IS DETERMINED BY THE OBJECT PARAMETER TRANSFORMALGORITHM
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES TEST DATA TO BE TRANSFORMED MUST HAVE THE SAME
NUMBER OF FEATURES AS THE DATA USED TO TRAIN THE MODEL
RETURNS
XNEW ARRAY SHAPE NSAMPLES NCOMPONENTS TRANSFORMED DATA
EXAMPLES USING SKLEARNDECOMPOSITIONSPARSECODER
•SPARSE CODING WITH A PRECOMPUTED DICTIONARY
6913SKLEARNDECOMPOSITION TRUNCATEDSVD
CLASSSKLEARNDECOMPOSITION TRUNCATEDSVD NCOMPONENTS2 ALGORITHM'RANDOMIZED'
NITER5 RANDOMSTATENONE TOL00
DIMENSIONALITY REDUCTION USING TRUNCATED SVD AKA LSA
THIS TRANSFORMER PERFORMS LINEAR DIMENSIONALITY REDUCTION BY MEANS OF TRUNCATED SINGULAR VALUE DECOMPOSITION
SVD CONTRARY TO PCA THIS ESTIMATOR DOES NOT CENTER THE DATA BEFORE COMPUTING THE SINGULAR VALUE DECOMPO
SITION THIS MEANS IT CAN WORK WITH SCIPYSPARSE MATRICES EFFICIENTLY
IN PARTICULAR TRUNCATED SVD WORKS ON TERM COUNTTFIDF MATRICES AS RETURNED BY THE VECTORIZERS IN
SKLEARNFEATUREEXTRACTIONTEXT IN THAT CONTEXT IT IS KNOWN AS LATENT SEMANTIC ANALYSIS LSA
THIS ESTIMATOR SUPPORTS TWO ALGORITHMS A FAST RANDOMIZED SVD SOLVER AND A "NAIVE" ALGORITHM THAT USES
ARPACK AS AN EIGENSOLVER ON X XT OR XT X WHICHEVER IS MORE EFFICIENT
READ MORE IN THE USER GUIDE
PARAMETERS

NCOMPONENTS INT DEFAULT 2 DESIRED DIMENSIONALITY OF OUTPUT DATA MUST BE STRICTLY LESS
THAN THE NUMBER OF FEATURES THE DEFAULT VALUE IS USEFUL FOR VISUALISATION FOR LSA A VALUE
OF 100 IS RECOMMENDED
ALGORITHM STRING DEFAULT “RANDOMIZED” SVD SOLVER TO USE EITHER “ARPACK” FOR THE
ARPACK WRAPPER IN SCIPY SCIPYSPARSELINALGSVDS OR “RANDOMIZED” FOR THE RANDOMIZED
ALGORITHM DUE TO HALKO 2009
NITER INT OPTIONAL DEFAULT 5 NUMBER OF ITERATIONS FOR RANDOMIZED SVD SOLVER NOT USED
BY ARPACK THE DEFAULT IS LARGER THAN THE DEFAULT IN RANDOMIZEDSVD TO HANDLE SPARSE
MATRICES THAT MAY HAVE LARGE SLOWLY DECAYING SPECTRUM
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
TOLFLOAT OPTIONAL TOLERANCE FOR ARPACK 0 MEANS MACHINE PRECISION IGNORED BY RANDOM
IZED SVD SOLVER
ATTRIBUTES
COMPONENTS ARRAY SHAPE NCOMPONENTS NFEATURES
EXPLAINEDVARIANCE ARRAY SHAPE NCOMPONENTS THE VARIANCE OF THE TRAINING SAMPLES
TRANSFORMED BY A PROJECTION TO EACH COMPONENT
EXPLAINEDVARIANCERATIO ARRAY SHAPE NCOMPONENTS PERCENTAGE OF VARIANCE EXPLAINED
BY EACH OF THE SELECTED COMPONENTS
SINGULARVALUES ARRAY SHAPE NCOMPONENTS THE SINGULAR VALUES CORRESPONDING TO EACH
OF THE SELECTED COMPONENTS THE SINGULAR VALUES ARE EQUAL TO THE 2NORMS OF THE
NCOMPONENTS VARIABLES IN THE LOWERDIMENSIONAL SPACE
SEE ALSO
PCA
NOTES
SVD SUFFERS FROM A PROBLEM CALLED “SIGN INDETERMINACY” WHICH MEANS THE SIGN OF THE COMPONENTS AND THE
OUTPUT FROM TRANSFORM DEPEND ON THE ALGORITHM AND RANDOM STATE TO WORK AROUND THIS FIT INSTANCES OF THIS CLASS
TO DATA ONCE THEN KEEP THE INSTANCE AROUND TO DO TRANSFORMATIONS
REFERENCES
FINDING STRUCTURE WITH RANDOMNESS STOCHASTIC ALGORITHMS FOR CONSTRUCTING APPROXIMATE MATRIX DECOMPOSITIONS
HALKO ET AL 2009 ARXIV909 HTTPSARXIVORGPDF09094061PDF
EXAMPLES
```
 FROM SKLEARNDECOMPOSITION IMPORT TRUNCATEDSVD
 FROM SKLEARNRANDOMPROJECTION IMPORT SPARSERANDOMMATRIX
X  SPARSERANDOMMATRIX100 100 DENSITY001 RANDOMSTATE42
SVD  TRUNCATEDSVDNCOMPONENTS5 NITER7 RANDOMSTATE42
SVDFITX
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TRUNCATEDSVDALGORITHMRANDOMIZED NCOMPONENTS5 NITER7
RANDOMSTATE42 TOL00
PRINTSVDEXPLAINEDVARIANCERATIO
00606 00584 00497 00434 00372
PRINTSVDEXPLAINEDVARIANCERATIOSUM
0249
PRINTSVDSINGULARVALUES
25841 25245 23201 21753 20443
METHODS
FITSELF X Y FIT LSI MODEL ON TRAINING DATA X
FITTRANSFORM SELF X Y FIT LSI MODEL TO X AND PERFORM DIMENSIONALITY REDUC
TION ON X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X TRANSFORM X BACK TO ITS ORIGINAL SPACE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X PERFORM DIMENSIONALITY REDUCTION ON X
INIT SELFNCOMPONENTS2 ALGORITHM'RANDOMIZED' NITER5 RANDOMSTATENONE TOL00
FITSELFXYNONE
FIT LSI MODEL ON TRAINING DATA X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA
YIGNORED
RETURNS
SELF OBJECT RETURNS THE TRANSFORMER OBJECT
FITTRANSFORM SELFXYNONE
FIT LSI MODEL TO X AND PERFORM DIMENSIONALITY REDUCTION ON X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA
YIGNORED
RETURNS
XNEW ARRAY SHAPE NSAMPLES NCOMPONENTS REDUCED VERSION OF X THIS WILL ALWAYS
BE A DENSE ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES

INVERSETRANSFORM SELFX
TRANSFORM X BACK TO ITS ORIGINAL SPACE
RETURNS AN ARRAY XORIGINAL WHOSE TRANSFORM WOULD BE X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NCOMPONENTS NEW DATA
RETURNS
XORIGINAL ARRAY SHAPE NSAMPLES NFEATURES NOTE THAT THIS IS ALWAYS A DENSE ARRAY
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
PERFORM DIMENSIONALITY REDUCTION ON X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA
RETURNS
XNEW ARRAY SHAPE NSAMPLES NCOMPONENTS REDUCED VERSION OF X THIS WILL ALWAYS
BE A DENSE ARRAY
EXAMPLES USING SKLEARNDECOMPOSITIONTRUNCATEDSVD
•COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
•HASHING FEATURE TRANSFORMATION USING TOTALLY RANDOM TREES
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
•CLUSTERING TEXT DOCUMENTS USING KMEANS
DECOMPOSITIONDICTLEARNING X
NCOMPONENTS SOLVES A DICTIONARY LEARNING MATRIX FACTORIZATION PROBLEM
DECOMPOSITIONDICTLEARNINGONLINE X
  SOLVES A DICTIONARY LEARNING MATRIX FACTORIZATION PROBLEM
ONLINE
DECOMPOSITIONFASTICA X NCOMPONENTS PERFORM FAST INDEPENDENT COMPONENT ANALYSIS
DECOMPOSITIONNONNEGATIVEFACTORIZATION X COMPUTE NONNEGATIVE MATRIX FACTORIZATION NMF
DECOMPOSITIONSPARSEENCODE X DICTIONARY
  SPARSE CODING

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6914SKLEARNDECOMPOSITION DICTLEARNING
SKLEARNDECOMPOSITION DICTLEARNING XNCOMPONENTS ALPHA MAXITER100 TOL1E
08METHOD'LARS' NJOBSNONE DICTINITNONE
CODEINITNONE CALLBACKNONE VERBOSEFALSE
RANDOMSTATENONE RETURNNITERFALSE POSI
TIVEDICTFALSE POSITIVECODEFALSE
SOLVES A DICTIONARY LEARNING MATRIX FACTORIZATION PROBLEM
FINDS THE BEST DICTIONARY AND THE CORRESPONDING SPARSE CODE FOR APPROXIMATING THE DATA MATRIX X BY SOLVING
U V ARGMIN 05 X U V 22 ALPHA U 1
UV
WITH VK 2 1 FORALL 0 K NCOMPONENTS
WHERE V IS THE DICTIONARY AND U IS THE SPARSE CODE
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES DATA MATRIX
NCOMPONENTS INT NUMBER OF DICTIONARY ATOMS TO EXTRACT
ALPHA INT SPARSITY CONTROLLING PARAMETER
MAXITER INT MAXIMUM NUMBER OF ITERATIONS TO PERFORM
TOLFLOAT TOLERANCE FOR THE STOPPING CONDITION
METHOD 'LARS' 'CD' LARS USES THE LEAST ANGLE REGRESSION METHOD TO SOLVE THE LASSO PROB
LEM LINEARMODELLARSPATH CD USES THE COORDINATE DESCENT METHOD TO COMPUTE THE LASSO
SOLUTION LINEARMODELLASSO LARS WILL BE FASTER IF THE ESTIMATED COMPONENTS ARE SPARSE
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
DICTINIT ARRAY OF SHAPE NCOMPONENTS NFEATURES INITIAL VALUE FOR THE DICTIONARY FOR WARM
RESTART SCENARIOS
CODEINIT ARRAY OF SHAPE NSAMPLES NCOMPONENTS INITIAL VALUE FOR THE SPARSE CODE FOR
WARM RESTART SCENARIOS
CALLBACK CALLABLE OR NONE OPTIONAL DEFAULT NONE CALLABLE THAT GETS INVOKED EVERY FIVE ITER
ATIONS
VERBOSE BOOL OPTIONAL DEFAULT FALSE TO CONTROL THE VERBOSITY OF THE PROCEDURE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
RETURNNITER BOOL WHETHER OR NOT TO RETURN THE NUMBER OF ITERATIONS
POSITIVEDICT BOOL WHETHER TO ENFORCE POSITIVITY WHEN FINDING THE DICTIONARY
NEW IN VERSION 020
POSITIVECODE BOOL WHETHER TO ENFORCE POSITIVITY WHEN FINDING THE CODE
NEW IN VERSION 020

RETURNS
CODE ARRAY OF SHAPE NSAMPLES NCOMPONENTS THE SPARSE CODE FACTOR IN THE MATRIX FACTOR
IZATION
DICTIONARY ARRAY OF SHAPE NCOMPONENTS NFEATURES THE DICTIONARY FACTOR IN THE MATRIX
FACTORIZATION
ERRORS ARRAY VECTOR OF ERRORS AT EACH ITERATION
NITER INT NUMBER OF ITERATIONS RUN RETURNED ONLY IF RETURNNITER IS SET TO TRUE
SEE ALSO
DICTLEARNINGONLINE
DICTIONARYLEARNING
MINIBATCHDICTIONARYLEARNING
SPARSEPCA
MINIBATCHSPARSEPCA
6915SKLEARNDECOMPOSITION DICTLEARNINGONLINE
SKLEARNDECOMPOSITION DICTLEARNINGONLINE XNCOMPONENTS2 ALPHA1 NITER100
RETURNCODETRUE DICTINITNONE CALL
BACKNONE BATCHSIZE3 VERBOSEFALSE
SHUFFLETRUE NJOBSNONE METHOD'LARS'
ITEROFFSET0 RANDOMSTATENONE RE
TURNINNERSTATSFALSE INNERSTATSNONE
RETURNNITERFALSE POSITIVEDICTFALSE
POSITIVECODEFALSE
SOLVES A DICTIONARY LEARNING MATRIX FACTORIZATION PROBLEM ONLINE
FINDS THE BEST DICTIONARY AND THE CORRESPONDING SPARSE CODE FOR APPROXIMATING THE DATA MATRIX X BY SOLVING
U V ARGMIN 05 X U V 22 ALPHA U 1
UV
WITH VK 2 1 FORALL 0 K NCOMPONENTS
WHERE V IS THE DICTIONARY AND U IS THE SPARSE CODE THIS IS ACCOMPLISHED BY REPEATEDLY ITERATING OVER MINI
BATCHES BY SLICING THE INPUT DATA
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES DATA MATRIX
NCOMPONENTS INT NUMBER OF DICTIONARY ATOMS TO EXTRACT
ALPHA FLOAT SPARSITY CONTROLLING PARAMETER
NITER INT NUMBER OF ITERATIONS TO PERFORM
RETURNCODE BOOLEAN WHETHER TO ALSO RETURN THE CODE U OR JUST THE DICTIONARY V
DICTINIT ARRAY OF SHAPE NCOMPONENTS NFEATURES INITIAL VALUE FOR THE DICTIONARY FOR WARM
RESTART SCENARIOS

CALLBACK CALLABLE OR NONE OPTIONAL DEFAULT NONE CALLABLE THAT GETS INVOKED EVERY FIVE ITER
ATIONS
BATCHSIZE INT THE NUMBER OF SAMPLES TO TAKE IN EACH BATCH
VERBOSE BOOL OPTIONAL DEFAULT FALSE TO CONTROL THE VERBOSITY OF THE PROCEDURE
SHUFFLE BOOLEAN WHETHER TO SHUFFLE THE DATA BEFORE SPLITTING IT IN BATCHES
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
METHOD ‘LARS’ ‘CD’ LARS USES THE LEAST ANGLE REGRESSION METHOD TO SOLVE THE LASSO PROB
LEM LINEARMODELLARSPATH CD USES THE COORDINATE DESCENT METHOD TO COMPUTE THE LASSO
SOLUTION LINEARMODELLASSO LARS WILL BE FASTER IF THE ESTIMATED COMPONENTS ARE SPARSE
ITEROFFSET INT DEFAULT 0 NUMBER OF PREVIOUS ITERATIONS COMPLETED ON THE DICTIONARY USED FOR
INITIALIZATION
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
RETURNINNERSTATS BOOLEAN OPTIONAL RETURN THE INNER STATISTICS A DICTIONARY COVARIANCE
AND B DATA APPROXIMATION USEFUL TO RESTART THE ALGORITHM IN AN ONLINE SETTING IF RE
TURNINNERSTATS IS TRUE RETURNCODE IS IGNORED
INNERSTATS TUPLE OF A B NDARRAYS INNER SUFFICIENT STATISTICS THAT ARE KEPT BY THE ALGORITHM
PASSING THEM AT INITIALIZATION IS USEFUL IN ONLINE SETTINGS TO AVOID LOOSING THE HISTORY OF
THE EVOLUTION A NCOMPONENTS NCOMPONENTS IS THE DICTIONARY COVARIANCE MATRIX B
NFEATURES NCOMPONENTS IS THE DATA APPROXIMATION MATRIX
RETURNNITER BOOL WHETHER OR NOT TO RETURN THE NUMBER OF ITERATIONS
POSITIVEDICT BOOL WHETHER TO ENFORCE POSITIVITY WHEN FINDING THE DICTIONARY
NEW IN VERSION 020
POSITIVECODE BOOL WHETHER TO ENFORCE POSITIVITY WHEN FINDING THE CODE
NEW IN VERSION 020
RETURNS
CODE ARRAY OF SHAPE NSAMPLES NCOMPONENTS THE SPARSE CODE ONLY RETURNED IF
RETURNCODETRUE
DICTIONARY ARRAY OF SHAPE NCOMPONENTS NFEATURES THE SOLUTIONS TO THE DICTIONARY LEARNING
PROBLEM
NITER INT NUMBER OF ITERATIONS RUN RETURNED ONLY IF RETURNNITER IS SET TOTRUE
SEE ALSO
DICTLEARNING
DICTIONARYLEARNING
MINIBATCHDICTIONARYLEARNING
SPARSEPCA
MINIBATCHSPARSEPCA

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6916SKLEARNDECOMPOSITION FASTICA
SKLEARNDECOMPOSITION FASTICAXNCOMPONENTSNONE ALGORITHM’PARALLEL’ WHITENTRUE
FUN’LOGCOSH’ FUNARGSNONE MAXITER200 TOL00001
WINITNONE RANDOMSTATENONE RETURNXMEANFALSE
COMPUTESOURCESTRUE RETURNNITERFALSE
PERFORM FAST INDEPENDENT COMPONENT ANALYSIS
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
NCOMPONENTS INT OPTIONAL NUMBER OF COMPONENTS TO EXTRACT IF NONE NO DIMENSION REDUC
TION IS PERFORMED
ALGORITHM ‘PARALLEL’ ‘DEFLATION’ OPTIONAL APPLY A PARALLEL OR DEFLATIONAL FASTICA ALGO
RITHM
WHITEN BOOLEAN OPTIONAL IF TRUE PERFORM AN INITIAL WHITENING OF THE DATA IF FALSE THE DATA
IS ASSUMED TO HAVE ALREADY BEEN PREPROCESSED IT SHOULD BE CENTERED NORMED AND WHITE
OTHERWISE YOU WILL GET INCORRECT RESULTS IN THIS CASE THE PARAMETER NCOMPONENTS WILL BE
IGNORED
FUN STRING OR FUNCTION OPTIONAL DEFAULT ‘LOGCOSH’ THE FUNCTIONAL FORM OF THE G FUNCTION
USED IN THE APPROXIMATION TO NEGENTROPY COULD BE EITHER ‘LOGCOSH’ ‘EXP’ OR ‘CUBE’ YOU
CAN ALSO PROVIDE YOUR OWN FUNCTION IT SHOULD RETURN A TUPLE CONTAINING THE VALUE OF THE
FUNCTION AND OF ITS DERIVATIVE IN THE POINT THE DERIVATIVE SHOULD BE AVERAGED ALONG ITS LAST
DIMENSION EXAMPLE
DEF MYGX RETURN X 3 NPMEAN3 X 2 AXIS1
FUNARGS DICTIONARY OPTIONAL ARGUMENTS TO SEND TO THE FUNCTIONAL FORM IF EMPTY OR NONE
AND IF FUN’LOGCOSH’ FUNARGS WILL TAKE VALUE ‘ALPHA’ 10
MAXITER INT OPTIONAL MAXIMUM NUMBER OF ITERATIONS TO PERFORM
TOLFLOAT OPTIONAL A POSITIVE SCALAR GIVING THE TOLERANCE AT WHICH THE UNMIXING MATRIX IS
CONSIDERED TO HAVE CONVERGED
WINIT NCOMPONENTS NCOMPONENTS ARRAY OPTIONAL INITIAL UNMIXING ARRAY OF DIMENSION
NCOMPNCOMP IF NONE DEFAULT THEN AN ARRAY OF NORMAL RV’S IS USED
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
RETURNXMEAN BOOL OPTIONAL IF TRUE XMEAN IS RETURNED TOO
COMPUTESOURCES BOOL OPTIONAL IF FALSE SOURCES ARE NOT COMPUTED BUT ONLY THE ROTATION
MATRIX THIS CAN SAVE MEMORY WHEN WORKING WITH BIG DATA DEFAULTS TO TRUE
RETURNNITER BOOL OPTIONAL WHETHER OR NOT TO RETURN THE NUMBER OF ITERATIONS
RETURNS
KARRAY SHAPE NCOMPONENTS NFEATURES NONE IF WHITEN IS ‘TRUE’ K IS THE PREWHITENING
MATRIX THAT PROJECTS DATA ONTO THE FIRST NCOMPONENTS PRINCIPAL COMPONENTS IF WHITEN IS
‘FALSE’ K IS ‘NONE’
69SKLEARNDECOMPOSITION MATRIX DECOMPOSITION 1673

WARRAY SHAPE NCOMPONENTS NCOMPONENTS ESTIMATED UNMIXING MATRIX THE MIXING
MATRIX CAN BE OBTAINED BY
W NPDOTW KT
A WT WWTI
SARRAY SHAPE NSAMPLES NCOMPONENTS NONE ESTIMATED SOURCE MATRIX
XMEAN ARRAY SHAPE NFEATURES THE MEAN OVER FEATURES RETURNED ONLY IF RETURNXMEAN
IS TRUE
NITER INT IF THE ALGORITHM IS “DEFLATION” NITER IS THE MAXIMUM NUMBER OF ITERATIONS RUN
ACROSS ALL COMPONENTS ELSE THEY ARE JUST THE NUMBER OF ITERATIONS TAKEN TO CONVERGE THIS IS
RETURNED ONLY WHEN RETURNNITER IS SET TO TRUE
NOTES
THE DATA MATRIX X IS CONSIDERED TO BE A LINEAR COMBINATION OF NONGAUSSIAN INDEPENDENT COMPONENTS IE X
 AS WHERE COLUMNS OF S CONTAIN THE INDEPENDENT COMPONENTS AND A IS A LINEAR MIXING MATRIX IN SHORT ICA
ATTEMPTS TO UNMIX THE DATA BY ESTIMATING AN UNMIXING MATRIX W WHERE S W
K X
THIS IMPLEMENTATION WAS ORIGINALLY MADE FOR DATA OF SHAPE NFEATURES NSAMPLES NOW THE INPUT IS TRANSPOSED
BEFORE THE ALGORITHM IS APPLIED THIS MAKES IT SLIGHTLY FASTER FOR FORTRANORDERED INPUT
IMPLEMENTED USING FASTICA A HYVARINEN AND E OJA INDEPENDENT COMPONENT ANALYSIS ALGORITHMS AND
APPLICATIONS NEURAL NETWORKS 1345 2000 PP 411430
6917SKLEARNDECOMPOSITION NONNEGATIVEFACTORIZATION
SKLEARNDECOMPOSITION NONNEGATIVEFACTORIZATION X WNONE HNONE
NCOMPONENTSNONE INIT’WARN’
UPDATEHTRUE SOLVER’CD’
BETALOSS’FROBENIUS’ TOL00001
MAXITER200 ALPHA00
L1RATIO00 REGULARIZATIONNONE
RANDOMSTATENONE VERBOSE0
SHUFFLEFALSE
COMPUTE NONNEGATIVE MATRIX FACTORIZATION NMF
FIND TWO NONNEGATIVE MATRICES W H WHOSE PRODUCT APPROXIMATES THE NON NEGATIVE MATRIX X THIS FACTORIZA
TION CAN BE USED FOR EXAMPLE FOR DIMENSIONALITY REDUCTION SOURCE SEPARATION OR TOPIC EXTRACTION
THE OBJECTIVE FUNCTION IS
05X WHFRO2
 ALPHA L1RATIO VECW1
 ALPHA L1RATIO VECH1
 05ALPHA1 L1RATIO WFRO2
 05ALPHA1 L1RATIO HFRO2
WHERE
AFRO2 SUMIJ AIJ2 FROBENIUS NORM
VECA1 SUMIJ ABSAIJ ELEMENTWISE L1 NORM

FOR MULTIPLICATIVEUPDATE ‘MU’ SOLVER THE FROBENIUS NORM 05 X WHFRO2 CAN BE CHANGED INTO
ANOTHER BETADIVERGENCE LOSS BY CHANGING THE BETALOSS PARAMETER
THE OBJECTIVE FUNCTION IS MINIMIZED WITH AN ALTERNATING MINIMIZATION OF W AND H IF H IS GIVEN AND UP
DATEHFALSE IT SOLVES FOR W ONLY
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES CONSTANT MATRIX
WARRAYLIKE SHAPE NSAMPLES NCOMPONENTS IF INIT’CUSTOM’ IT IS USED AS INITIAL GUESS FOR
THE SOLUTION
HARRAYLIKE SHAPE NCOMPONENTS NFEATURES IF INIT’CUSTOM’ IT IS USED AS INITIAL GUESS FOR
THE SOLUTION IF UPDATEHFALSE IT IS USED AS A CONSTANT TO SOLVE FOR W ONLY
NCOMPONENTS INTEGER NUMBER OF COMPONENTS IF NCOMPONENTS IS NOT SET ALL FEATURES ARE
KEPT
INIT NONE ‘RANDOM’ ‘NNDSVD’ ‘NNDSVDA’ ‘NNDSVDAR’ ‘CUSTOM’ METHOD USED TO INITIALIZE
THE PROCEDURE DEFAULT ‘RANDOM’
THE DEFAULT VALUE WILL CHANGE FROM ‘RANDOM’ TO NONE IN VERSION 023 TO MAKE IT CONSISTENT
WITH DECOMPOSITIONNMF
VALID OPTIONS
• NONE ‘NNDSVD’ IF NCOMPONENTS NFEATURES OTHERWISE ‘RANDOM’
•‘RANDOM’ NONNEGATIVE RANDOM MATRICES SCALED WITH SQRTXMEAN
NCOMPONENTS
•‘NNDSVD’ NONNEGATIVE DOUBLE SINGULAR VALUE DECOMPOSITION NNDSVD
INITIALIZATION BETTER FOR SPARSENESS
•‘NNDSVDA’ NNDSVD WITH ZEROS FILLED WITH THE AVERAGE OF X BETTER WHEN SPARSITY IS
NOT DESIRED
•‘NNDSVDAR’ NNDSVD WITH ZEROS FILLED WITH SMALL RANDOM VALUES GENERALLY FASTER
LESS ACCURATE ALTERNATIVE TO NNDSVDA FOR WHEN SPARSITY IS NOT DESIRED
• ‘CUSTOM’ USE CUSTOM MATRICES W AND H
UPDATEH BOOLEAN DEFAULT TRUE SET TO TRUE BOTH W AND H WILL BE ESTIMATED FROM INITIAL
GUESSES SET TO FALSE ONLY W WILL BE ESTIMATED
SOLVER ‘CD’ ‘MU’ NUMERICAL SOLVER TO USE ‘CD’ IS A COORDINATE DESCENT SOLVER THAT USES FAST
HIERARCHICAL
ALTERNATING LEAST SQUARES FAST HALS
‘MU’ IS A MULTIPLICATIVE UPDATE SOLVER
NEW IN VERSION 017 COORDINATE DESCENT SOLVER
NEW IN VERSION 019 MULTIPLICATIVE UPDATE SOLVER
BETALOSS FLOAT OR STRING DEFAULT ‘FROBENIUS’ STRING MUST BE IN ‘FROBENIUS’ ‘KULLBACKLEIBLER’
‘ITAKURASAITO’ BETA DIVERGENCE TO BE MINIMIZED MEASURING THE DISTANCE BETWEEN X AND
THE DOT PRODUCT WH NOTE THAT VALUES DIFFERENT FROM ‘FROBENIUS’ OR 2 AND ‘KULLBACKLEIBLER’
OR 1 LEAD TO SIGNIFICANTLY SLOWER FITS NOTE THAT FOR BETALOSS 0 OR ‘ITAKURASAITO’ THE
INPUT MATRIX X CANNOT CONTAIN ZEROS USED ONLY IN ‘MU’ SOLVER
NEW IN VERSION 019
TOLFLOAT DEFAULT 1E4 TOLERANCE OF THE STOPPING CONDITION

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MAXITER INTEGER DEFAULT 200 MAXIMUM NUMBER OF ITERATIONS BEFORE TIMING OUT
ALPHA DOUBLE DEFAULT 0 CONSTANT THAT MULTIPLIES THE REGULARIZATION TERMS
L1RATIO DOUBLE DEFAULT 0 THE REGULARIZATION MIXING PARAMETER WITH 0 L1RATIO 1 FOR
L1RATIO 0 THE PENALTY IS AN ELEMENTWISE L2 PENALTY AKA FROBENIUS NORM FOR L1RATIO
1 IT IS AN ELEMENTWISE L1 PENALTY FOR 0 L1RATIO 1 THE PENALTY IS A COMBINATION OF L1
AND L2
REGULARIZATION 'BOTH' 'COMPONENTS' 'TRANSFORMATION' NONE SELECT WHETHER THE REGULARIZA
TION AFFECTS THE COMPONENTS H THE TRANSFORMATION W BOTH OR NONE OF THEM
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
VERBOSE INTEGER DEFAULT 0 THE VERBOSITY LEVEL
SHUFFLE BOOLEAN DEFAULT FALSE IF TRUE RANDOMIZE THE ORDER OF COORDINATES IN THE CD SOLVER
RETURNS
WARRAYLIKE SHAPE NSAMPLES NCOMPONENTS SOLUTION TO THE NONNEGATIVE LEAST SQUARES
PROBLEM
HARRAYLIKE SHAPE NCOMPONENTS NFEATURES SOLUTION TO THE NONNEGATIVE LEAST SQUARES
PROBLEM
NITER INT ACTUAL NUMBER OF ITERATIONS
REFERENCES
CICHOCKI ANDRZEJ AND P H A N ANHHUY "FAST LOCAL ALGORITHMS FOR LARGE SCALE NONNEGATIVE MATRIX AND TEN
SOR FACTORIZATIONS" IEICE TRANSACTIONS ON FUNDAMENTALS OF ELECTRONICS COMMUNICATIONS AND COMPUTER SCIENCES
923 708721 2009
FEVOTTE C IDIER J 2011 ALGORITHMS FOR NONNEGATIVE MATRIX FACTORIZATION WITH THE BETADIVERGENCE NEURAL
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W H NITER NONNEGATIVEFACTORIZATIONX NCOMPONENTS2
INITRANDOM RANDOMSTATE0
6918SKLEARNDECOMPOSITION SPARSEENCODE
SKLEARNDECOMPOSITION SPARSEENCODE XDICTIONARY GRAMNONE COVNONE ALGO
RITHM'LASSOLARS' NNONZEROCOEFSNONE AL
PHANONE COPYCOVTRUE INITNONE MAXITER1000
NJOBSNONE CHECKINPUTTRUE VERBOSE0 POSI
TIVEFALSE
SPARSE CODING

EACH ROW OF THE RESULT IS THE SOLUTION TO A SPARSE CODING PROBLEM THE GOAL IS TO FIND A SPARSE ARRAY CODE SUCH THAT
X CODE DICTIONARY
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XARRAY OF SHAPE NSAMPLES NFEATURES DATA MATRIX
DICTIONARY ARRAY OF SHAPE NCOMPONENTS NFEATURES THE DICTIONARY MATRIX AGAINST WHICH TO SOLVE THE SPARSE CODING OF THE DATA SOME OF THE ALGORITHMS ASSUME NORMALIZED ROWS FOR MEANINGFUL OUTPUT
GRAM ARRAY SHAPENCOMPONENTS NCOMPONENTS PRECOMPUTED GRAM MATRIX DICTIONARY DICTIONARY'
COV ARRAY SHAPENCOMPONENTS NSAMPLES PRECOMPUTED COVARIANCE DICTIONARY' X
ALGORITHM 'LASSOLARS' 'LASSOCD' 'LARS' 'OMP' 'THRESHOLD' LARS USES THE LEAST ANGLE RE GRESSION METHOD LINEARMODELLARSPATH LASSOLARS USES LARS TO COMPUTE THE LASSO SO LUTION LASSOCD USES THE COORDINATE DESCENT METHOD TO COMPUTE THE LASSO SOLUTION LIN EARMODELLASSO LASSOLARS WILL BE FASTER IF THE ESTIMATED COMPONENTS ARE SPARSE OMP USES ORTHOGONAL MATCHING PURSUIT TO ESTIMATE THE SPARSE SOLUTION THRESHOLD SQUASHES TO ZERO ALL COEFFICIENTS LESS THAN ALPHA FROM THE PROJECTION DICTIONARY X'
NNONZEROCOEFS INT 01 NFEATURES BY DEFAULT NUMBER OF NONZERO COEFFICIENTS TO TAR GET IN EACH COLUMN OF THE SOLUTION THIS IS ONLY USED BY ALGORITHMLARS AND ALGORITHMOMP AND IS OVERRIDDEN BY ALPHA IN THE ORTHOGONAL MATCHING PURSUIT OMP CASE
ALPHA FLOAT 1 BY DEFAULT IF ALGORITHMLASSOLARS OR ALGORITHMLASSOCD ALPHA IS THE PENALTY APPLIED TO THE L1 NORM IF ALGORITHMTHRESHOLD ALPHA IS THE ABSOLUTE VALUE OF THE THRESHOLD BELOW WHICH COEFFICIENTS WILL BE SQUASHED TO ZERO IF ALGORITHMOMP ALPHA IS THE TOLERANCE PARAMETER THE VALUE OF THE RECONSTRUCTION ERROR TARGETED IN THIS CASE IT OVERRIDES NNONZEROCOEFS
COPYCOV BOOLEAN OPTIONAL WHETHER TO COPY THE PRECOMPUTED COVARIANCE MATRIX IF FALSE IT MAY BE OVERWRITTEN
INIT ARRAY OF SHAPE NSAMPLES NCOMPONENTS INITIALIZATION VALUE OF THE SPARSE CODES ONLY USED IFALGORITHMLASSOCD
MAXITER INT 1000 BY DEFAULT MAXIMUM NUMBER OF ITERATIONS TO PERFORM IF ALGORITHMLASSOCD
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
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VERBOSE INT OPTIONAL CONTROLS THE VERBOSITY THE HIGHER THE MORE MESSAGES DEFAULTS TO 0
POSITIVE BOOLEAN OPTIONAL WHETHER TO ENFORCE POSITIVITY WHEN FINDING THE ENCODING NEW IN VERSION 020
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6101SKLEARNDISCRIMINANTANALYSIS LINEARDISCRIMINANTANALYSIS
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SHRINKAGENONE
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LINEAR DISCRIMINANT ANALYSIS
A CLASSIFIER WITH A LINEAR DECISION BOUNDARY GENERATED BY FITTING CLASS CONDITIONAL DENSITIES TO THE DATA AND USING BAYES' RULE
THE MODEL FITS A GAUSSIAN DENSITY TO EACH CLASS ASSUMING THAT ALL CLASSES SHARE THE SAME COVARIANCE MATRIX
THE FITTED MODEL CAN ALSO BE USED TO REDUCE THE DIMENSIONALITY OF THE INPUT BY PROJECTING IT TO THE MOST DISCRIM INATIVE DIRECTIONS
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SOLVER STRING OPTIONAL
SOLVER TO USE POSSIBLE VALUES
• 'SVD' SINGULAR VALUE DECOMPOSITION DEFAULT DOES NOT COMPUTE THE COVARIANCE MA TRIX THEREFORE THIS SOLVER IS RECOMMENDED FOR DATA WITH A LARGE NUMBER OF FEATURES
• 'LSQR' LEAST SQUARES SOLUTION CAN BE COMBINED WITH SHRINKAGE
• 'EIGEN' EIGENVALUE DECOMPOSITION CAN BE COMBINED WITH SHRINKAGE
SHRINKAGE STRING OR FLOAT OPTIONAL
SHRINKAGE PARAMETER POSSIBLE VALUES

• NONE NO SHRINKAGE DEFAULT
• ‘AUTO’ AUTOMATIC SHRINKAGE USING THE LEDOITWOLF LEMMA
• FLOAT BETWEEN 0 AND 1 FIXED SHRINKAGE PARAMETER
NOTE THAT SHRINKAGE WORKS ONLY WITH ‘LSQR’ AND ‘EIGEN’ SOLVERS
PRIORS ARRAY OPTIONAL SHAPE NCLASSES CLASS PRIORS
NCOMPONENTS INT OPTIONAL DEFAULTNONE NUMBER OF COMPONENTS MINNCLASSES
1 NFEATURES FOR DIMENSIONALITY REDUCTION IF NONE WILL BE SET TO MINNCLASSES 1
NFEATURES
STORECOVARIANCE BOOL OPTIONAL ADDITIONALLY COMPUTE CLASS COVARIANCE MATRIX DEFAULT
FALSE USED ONLY IN ‘SVD’ SOLVER
NEW IN VERSION 017
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INTERCEPT ARRAY SHAPE NFEATURES INTERCEPT TERM
COVARIANCE ARRAYLIKE SHAPE NFEATURES NFEATURES COVARIANCE MATRIX SHARED BY ALL
CLASSES
EXPLAINEDVARIANCERATIO ARRAY SHAPE NCOMPONENTS PERCENTAGE OF VARIANCE EXPLAINED
BY EACH OF THE SELECTED COMPONENTS IF NCOMPONENTS IS NOT SET THEN ALL COMPONENTS ARE
STORED AND THE SUM OF EXPLAINED VARIANCES IS EQUAL TO 10 ONLY AVAILABLE WHEN EIGEN OR SVD
SOLVER IS USED
MEANS ARRAYLIKE SHAPE NCLASSES NFEATURES CLASS MEANS
PRIORS ARRAYLIKE SHAPE NCLASSES CLASS PRIORS SUM TO 1
SCALINGS ARRAYLIKE SHAPE RANK NCLASSES 1 SCALING OF THE FEATURES IN THE SPACE SPANNED
BY THE CLASS CENTROIDS
XBAR ARRAYLIKE SHAPE NFEATURES OVERALL MEAN
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NANT ANALYSIS
NOTES
THE DEFAULT SOLVER IS ‘SVD’ IT CAN PERFORM BOTH CLASSIFICATION AND TRANSFORM AND IT DOES NOT RELY ON THE CALCU
LATION OF THE COVARIANCE MATRIX THIS CAN BE AN ADVANTAGE IN SITUATIONS WHERE THE NUMBER OF FEATURES IS LARGE
HOWEVER THE ‘SVD’ SOLVER CANNOT BE USED WITH SHRINKAGE
THE ‘LSQR’ SOLVER IS AN EFFICIENT ALGORITHM THAT ONLY WORKS FOR CLASSIFICATION IT SUPPORTS SHRINKAGE
THE ‘EIGEN’ SOLVER IS BASED ON THE OPTIMIZATION OF THE BETWEEN CLASS SCATTER TO WITHIN CLASS SCATTER RATIO IT CAN
BE USED FOR BOTH CLASSIFICATION AND TRANSFORM AND IT SUPPORTS SHRINKAGE HOWEVER THE ‘EIGEN’ SOLVER NEEDS TO
COMPUTE THE COVARIANCE MATRIX SO IT MIGHT NOT BE SUITABLE FOR SITUATIONS WITH A HIGH NUMBER OF FEATURES

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EXAMPLES
IMPORT NUMPY AS NP
FROM SKLEARNDISCRIMINANTANALYSIS IMPORT LINEARDISCRIMINANTANALYSIS
X NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
Y NPARRAY1 1 1 2 2 2
CLF LINEARDISCRIMINANTANALYSIS
CLFFITX Y
LINEARDISCRIMINANTANALYSISNCOMPONENTSNONE PRIORSNONE SHRINKAGENONE
SOLVERSVD STORECOVARIANCEFALSE TOL00001
PRINTCLFPREDICT08 1
1
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GIVEN TRAINING DATA AND PARAMETERS
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASS LABELS FOR SAMPLES IN X
PREDICTLOGPROBA SELF X ESTIMATE LOG PROBABILITY
PREDICTPROBA SELF X ESTIMATE PROBABILITY
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SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X PROJECT DATA TO MAXIMIZE CLASS SEPARATION
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STORECOVARIANCEFALSE TOL00001
DECISIONFUNCTION SELFX
PREDICT CONFIDENCE SCORES FOR SAMPLES
THE CONFIDENCE SCORE FOR A SAMPLE IS THE SIGNED DISTANCE OF THAT SAMPLE TO THE HYPERPLANE
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XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
ARRAY SHAPENSAMPLES IF NCLASSES 2 ELSE NSAMPLES NCLASSES CONFIDENCE
SCORES PER SAMPLE CLASS COMBINATION IN THE BINARY CASE CONFIDENCE SCORE FOR
SELFCLASSES1 WHERE 0 MEANS THIS CLASS WOULD BE PREDICTED
FITSELFXY
FIT LINEARDISCRIMINANTANALYSIS MODEL ACCORDING TO THE GIVEN TRAINING DATA AND PARAMETERS
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CHANGED IN VERSION 019 TOLHAS BEEN MOVED TO MAIN CONSTRUCTOR
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA

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YARRAY SHAPE NSAMPLES TARGET VALUES
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
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DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
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RETURNS
CARRAY SHAPE NSAMPLES PREDICTED CLASS LABEL PER SAMPLE
PREDICTLOGPROBA SELFX
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XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT DATA
RETURNS
CARRAY SHAPE NSAMPLES NCLASSES ESTIMATED LOG PROBABILITIES
PREDICTPROBA SELFX
ESTIMATE PROBABILITY
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT DATA
RETURNS
CARRAY SHAPE NSAMPLES NCLASSES ESTIMATED PROBABILITIES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
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XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
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PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT DATA
RETURNS
XNEW ARRAY SHAPE NSAMPLES NCOMPONENTS TRANSFORMED DATA
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•NORMAL AND SHRINKAGE LINEAR DISCRIMINANT ANALYSIS FOR CLASSIFICATION
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•COMPARISON OF LDA AND PCA 2D PROJECTION OF IRIS DATASET
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
•DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
6102SKLEARNDISCRIMINANTANALYSIS QUADRATICDISCRIMINANTANALYSIS
CLASSSKLEARNDISCRIMINANTANALYSIS QUADRATICDISCRIMINANTANALYSIS PRIORSNONE
REGPARAM00
STORECOVARIANCEFALSE
TOL00001
QUADRATIC DISCRIMINANT ANALYSIS
A CLASSIFIER WITH A QUADRATIC DECISION BOUNDARY GENERATED BY FITTING CLASS CONDITIONAL DENSITIES TO THE DATA AND
USING BAYES’ RULE
THE MODEL FITS A GAUSSIAN DENSITY TO EACH CLASS
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PRIORS ARRAY OPTIONAL SHAPE NCLASSES PRIORS ON CLASSES
REGPARAM FLOAT OPTIONAL REGULARIZES THE COVARIANCE ESTIMATE AS
1REGPARAM SIGMA REGPARAM NPEYENFEATURES
STORECOVARIANCE BOOLEAN IF TRUE THE COVARIANCE MATRICES ARE COMPUTED AND STORED IN THE
SELFCOVARIANCE ATTRIBUTE
NEW IN VERSION 017
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COVARIANCE LIST OF ARRAYLIKE SHAPE NFEATURES NFEATURES COVARIANCE MATRICES OF EACH
CLASS
MEANS ARRAYLIKE SHAPE NCLASSES NFEATURES CLASS MEANS
PRIORS ARRAYLIKE SHAPE NCLASSES CLASS PRIORS SUM TO 1
ROTATIONS LIST OF ARRAYS FOR EACH CLASS K AN ARRAY OF SHAPE NFEATURES NK WITH NK
MINNFEATURES NUMBER OF ELEMENTS IN CLASS K IT IS THE ROTATION OF THE
GAUSSIAN DISTRIBUTION IE ITS PRINCIPAL AXIS
SCALINGS LIST OF ARRAYS FOR EACH CLASS K AN ARRAY OF SHAPE NK IT CONTAINS THE SCALING OF THE
GAUSSIAN DISTRIBUTIONS ALONG ITS PRINCIPAL AXES IE THE VARIANCE IN THE ROTATED COORDINATE
SYSTEM
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 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
Y  NPARRAY1 1 1 2 2 2
CLF  QUADRATICDISCRIMINANTANALYSIS
CLFFITX Y

QUADRATICDISCRIMINANTANALYSISPRIORSNONE REGPARAM00
STORECOVARIANCEFALSE TOL00001
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1
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PREDICTPROBA SELF X RETURN POSTERIOR PROBABILITIES OF CLASSIFICATION
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XARRAYLIKE SHAPE NSAMPLES NFEATURES ARRAY OF SAMPLES TEST VECTORS
RETURNS
CARRAY SHAPE NSAMPLES NCLASSES OR NSAMPLES DECISION FUNCTION VALUES RELATED
TO EACH CLASS PER SAMPLE IN THE TWOCLASS CASE THE SHAPE IS NSAMPLES GIVING THE LOG
LIKELIHOOD RATIO OF THE POSITIVE CLASS
FITSELFXY
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CHANGED IN VERSION 019 STORECOVARIANCES HAS BEEN MOVED TO MAIN CONSTRUCTOR AS
STORECOVARIANCE
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XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IS THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAY SHAPE NSAMPLES TARGET VALUES INTEGERS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
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DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
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PREDICTSELFX
PERFORM CLASSIFICATION ON AN ARRAY OF TEST VECTORS X
THE PREDICTED CLASS C FOR EACH SAMPLE IN X IS RETURNED
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XARRAYLIKE SHAPE NSAMPLES NFEATURES
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CARRAY SHAPE NSAMPLES

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XARRAYLIKE SHAPE NSAMPLES NFEATURES ARRAY OF SAMPLESTEST VECTORS
RETURNS
CARRAY SHAPE NSAMPLES NCLASSES POSTERIOR PROBABILITIES OF CLASSIFICATION PER CLASS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
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XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
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SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
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SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
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611SKLEARNDUMMY DUMMY ESTIMATORS
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DUMMYDUMMYCLASSIFIER STRATEGY DUMMYCLASSIFIER IS A CLASSIFIER THAT MAKES PREDICTIONS US
ING SIMPLE RULES
DUMMYDUMMYREGRESSOR STRATEGY CONSTANT DUMMYREGRESSOR IS A REGRESSOR THAT MAKES PREDICTIONS US
ING SIMPLE RULES
6111SKLEARNDUMMY DUMMYCLASSIFIER
CLASSSKLEARNDUMMY DUMMYCLASSIFIER STRATEGY’STRATIFIED’ RANDOMSTATENONE CONSTANTNONE
DUMMYCLASSIFIER IS A CLASSIFIER THAT MAKES PREDICTIONS USING SIMPLE RULES
THIS CLASSIFIER IS USEFUL AS A SIMPLE BASELINE TO COMPARE WITH OTHER REAL CLASSIFIERS DO NOT USE IT FOR REAL
PROBLEMS
READ MORE IN THE USER GUIDE
PARAMETERS
STRATEGY STR DEFAULT”STRATIFIED” STRATEGY TO USE TO GENERATE PREDICTIONS
• “STRATIFIED” GENERATES PREDICTIONS BY RESPECTING THE TRAINING SET’S CLASS DISTRIBUTION
• “MOSTFREQUENT” ALWAYS PREDICTS THE MOST FREQUENT LABEL IN THE TRAINING SET
• “PRIOR” ALWAYS PREDICTS THE CLASS THAT MAXIMIZES THE CLASS PRIOR LIKE “MOSTFREQUENT”
ANDPREDICTPROBA RETURNS THE CLASS PRIOR
• “UNIFORM” GENERATES PREDICTIONS UNIFORMLY AT RANDOM
• “CONSTANT” ALWAYS PREDICTS A CONSTANT LABEL THAT IS PROVIDED BY THE USER THIS IS USEFUL FOR
METRICS THAT EVALUATE A NONMAJORITY CLASS
NEW IN VERSION 017 DUMMY CLASSIFIER NOW SUPPORTS PRIOR FITTING STRATEGY USING PARAM
ETERPRIOR
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
CONSTANT INT OR STR OR ARRAY OF SHAPE NOUTPUTS THE EXPLICIT CONSTANT AS PREDICTED BY THE
“CONSTANT” STRATEGY THIS PARAMETER IS USEFUL ONLY FOR THE “CONSTANT” STRATEGY
ATTRIBUTES
CLASSES ARRAY OR LIST OF ARRAY OF SHAPE NCLASSES CLASS LABELS FOR EACH OUTPUT
NCLASSES ARRAY OR LIST OF ARRAY OF SHAPE NCLASSES NUMBER OF LABEL FOR EACH OUTPUT
CLASSPRIOR ARRAY OR LIST OF ARRAY OF SHAPE NCLASSES PROBABILITY OF EACH CLASS FOR EACH
OUTPUT
NOUTPUTS INT NUMBER OF OUTPUTS
SPARSEOUTPUT BOOL TRUE IF THE ARRAY RETURNED FROM PREDICT IS TO BE IN SPARSE CSC FORMAT
IS AUTOMATICALLY SET TO TRUE IF THE INPUT Y IS PASSED IN SPARSE FORMAT
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PREDICTLOGPROBA SELF X RETURN LOG PROBABILITY ESTIMATES FOR THE TEST VECTORS X
PREDICTPROBA SELF X RETURN PROBABILITY ESTIMATES FOR THE TEST VECTORS X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
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INIT SELFSTRATEGY'STRATIFIED' RANDOMSTATENONE CONSTANTNONE
FITSELFXYSAMPLEWEIGHTNONE
FIT THE RANDOM CLASSIFIER
PARAMETERS
XARRAYLIKE OBJECT WITH FINITE LENGTH OR SHAPE TRAINING DATA REQUIRES LENGTH
NSAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PERFORM CLASSIFICATION ON TEST VECTORS X
PARAMETERS
XARRAYLIKE OBJECT WITH FINITE LENGTH OR SHAPE TRAINING DATA REQUIRES LENGTH
NSAMPLES
RETURNS
YARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS PREDICTED TARGET VALUES FOR X
PREDICTLOGPROBA SELFX
RETURN LOG PROBABILITY ESTIMATES FOR THE TEST VECTORS X
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XARRAYLIKE OBJECT WITH FINITE LENGTH OR SHAPE TRAINING DATA REQUIRES LENGTH
NSAMPLES
RETURNS
PARRAYLIKE OR LIST OF ARRAYLIKE OF SHAPE NSAMPLES NCLASSES RETURNS THE LOG PROBA
BILITY OF THE SAMPLE FOR EACH CLASS IN THE MODEL WHERE CLASSES ARE ORDERED ARITHMETICALLY
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PREDICTPROBA SELFX
RETURN PROBABILITY ESTIMATES FOR THE TEST VECTORS X
PARAMETERS
XARRAYLIKE OBJECT WITH FINITE LENGTH OR SHAPE TRAINING DATA REQUIRES LENGTH
NSAMPLES
RETURNS
PARRAYLIKE OR LIST OF ARRAYLKE OF SHAPE NSAMPLES NCLASSES RETURNS THE PROBABILITY
OF THE SAMPLE FOR EACH CLASS IN THE MODEL WHERE CLASSES ARE ORDERED ARITHMETICALLY FOR
EACH OUTPUT
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE NONE TEST SAMPLES WITH SHAPE NSAMPLES NFEATURES OR NONE PASSING
NONE AS TEST SAMPLES GIVES THE SAME RESULT AS PASSING REAL TEST SAMPLES SINCE DUMMYCLAS
SIFIER OPERATES INDEPENDENTLY OF THE SAMPLED OBSERVATIONS
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
6112SKLEARNDUMMY DUMMYREGRESSOR
CLASSSKLEARNDUMMY DUMMYREGRESSOR STRATEGY’MEAN’ CONSTANTNONE QUANTILENONE
DUMMYREGRESSOR IS A REGRESSOR THAT MAKES PREDICTIONS USING SIMPLE RULES
THIS REGRESSOR IS USEFUL AS A SIMPLE BASELINE TO COMPARE WITH OTHER REAL REGRESSORS DO NOT USE IT FOR REAL
PROBLEMS
READ MORE IN THE USER GUIDE
PARAMETERS
STRATEGY STR STRATEGY TO USE TO GENERATE PREDICTIONS
• “MEAN” ALWAYS PREDICTS THE MEAN OF THE TRAINING SET
• “MEDIAN” ALWAYS PREDICTS THE MEDIAN OF THE TRAINING SET
• “QUANTILE” ALWAYS PREDICTS A SPECIFIED QUANTILE OF THE TRAINING SET PROVIDED WITH THE
QUANTILE PARAMETER

• “CONSTANT” ALWAYS PREDICTS A CONSTANT VALUE THAT IS PROVIDED BY THE USER
CONSTANT INT OR FLOAT OR ARRAY OF SHAPE NOUTPUTS THE EXPLICIT CONSTANT AS PREDICTED BY THE
“CONSTANT” STRATEGY THIS PARAMETER IS USEFUL ONLY FOR THE “CONSTANT” STRATEGY
QUANTILE FLOAT IN 00 10 THE QUANTILE TO PREDICT USING THE “QUANTILE” STRATEGY A QUANTILE OF
05 CORRESPONDS TO THE MEDIAN WHILE 00 TO THE MINIMUM AND 10 TO THE MAXIMUM
ATTRIBUTES
CONSTANT FLOAT OR ARRAY OF SHAPE NOUTPUTS MEAN OR MEDIAN OR QUANTILE OF THE TRAINING TAR
GETS OR CONSTANT VALUE GIVEN BY THE USER
NOUTPUTS INT NUMBER OF OUTPUTS
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE RANDOM REGRESSOR
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X RETURNSTD PERFORM CLASSIFICATION ON TEST VECTORS X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFSTRATEGY’MEAN’ CONSTANTNONE QUANTILENONE
FITSELFXYSAMPLEWEIGHTNONE
FIT THE RANDOM REGRESSOR
PARAMETERS
XARRAYLIKE OBJECT WITH FINITE LENGTH OR SHAPE TRAINING DATA REQUIRES LENGTH
NSAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXRETURNSTDFALSE
PERFORM CLASSIFICATION ON TEST VECTORS X
PARAMETERS
XARRAYLIKE OBJECT WITH FINITE LENGTH OR SHAPE TRAINING DATA REQUIRES LENGTH
NSAMPLES

RETURNSTD BOOLEAN OPTIONAL WHETHER TO RETURN THE STANDARD DEVIATION OF POSTERIOR PREDIC
TION ALL ZEROS IN THIS CASE
RETURNS
YARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS PREDICTED TARGET VALUES FOR X
YSTD ARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS STANDARD DEVIATION OF PREDIC
TIVE DISTRIBUTION OF QUERY POINTS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE NONE TEST SAMPLES WITH SHAPE NSAMPLES NFEATURES OR NONE FOR
SOME ESTIMATORS THIS MAY BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES
NSAMPLESFITTED WHERE NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING
FOR THE ESTIMATOR PASSING NONE AS TEST SAMPLES GIVES THE SAME RESULT AS PASSING REAL TEST
SAMPLES SINCE DUMMYREGRESSOR OPERATES INDEPENDENTLY OF THE SAMPLED OBSERVATIONS
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
612SKLEARNENSEMBLE ENSEMBLE METHODS
THESKLEARNENSEMBLE MODULE INCLUDES ENSEMBLEBASED METHODS FOR CLASSIFICATION REGRESSION AND ANOMALY DE
TECTION
USER GUIDE SEE THE ENSEMBLE METHODS SECTION FOR FURTHER DETAILS
ENSEMBLEADABOOSTCLASSIFIER   AN ADABOOST CLASSIFIER
ENSEMBLEADABOOSTREGRESSOR BASEESTIMATOR
  AN ADABOOST REGRESSOR
ENSEMBLEBAGGINGCLASSIFIER BASEESTIMATOR
  A BAGGING CLASSIFIER
CONTINUED ON NEXT PAGE

TABLE 671 – CONTINUED FROM PREVIOUS PAGE

ENSEMBLEBAGGINGREGRESSOR BASEESTIMATOR	A BAGGING REGRESSOR
ENSEMBLEEXTRATREESCLASSIFIER	AN EXTRATREES CLASSIFIER
ENSEMBLEEXTRATREESREGRESSOR NESTIMATORS	AN EXTRATREES REGRESSOR
ENSEMBLEGRADIENTBOOSTINGCLASSIFIER LOSS	GRADIENT BOOSTING FOR CLASSIFICATION
ENSEMBLEGRADIENTBOOSTINGREGRESSOR LOSS	GRADIENT BOOSTING FOR REGRESSION
ENSEMBLEISOLATIONFOREST NESTIMATORS	ISOLATION FOREST ALGORITHM
ENSEMBLERANDOMFORESTCLASSIFIER	A RANDOM FOREST CLASSIFIER
ENSEMBLERANDOMFORESTREGRESSOR	A RANDOM FOREST REGRESSOR
ENSEMBLERANDOMTREESEMBEDDING	AN ENSEMBLE OF TOTALLY RANDOM TREES
ENSEMBLEVOTINGCLASSIFIER ESTIMATORS	SOFT V OTINGMAJORITY RULE CLASSIFIER FOR UNFITTED ESTIMATORS
ENSEMBLEVOTINGREGRESSOR ESTIMATORS	PREDICTION VOTING REGRESSOR FOR UNFITTED ESTIMATORS
ENSEMBLEHISTGRADIENTBOOSTINGREGRESSOR	HISTOGRAMBASED GRADIENT BOOSTING REGRESSION TREE
ENSEMBLEHISTGRADIENTBOOSTINGCLASSIFIER	HISTOGRAMBASED GRADIENT BOOSTING CLASSIFICATION TREE

6121SKLEARNENSEMBLE ADABOOSTCLASSIFIER

CLASSSKLEARNENSEMBLE ADABOOSTCLASSIFIER BASEESTIMATORNONE NESTIMATORS50 LEARN
INGRATE10 ALGORITHM’SAMMER’ RAN
DOMSTATENONE

AN ADABOOST CLASSIFIER

AN ADABOOST 1 CLASSIFIER IS A METAESTIMATOR THAT BEGINS BY FITTING A CLASSIFIER ON THE ORIGINAL DATASET AND THEN FITS ADDITIONAL COPIES OF THE CLASSIFIER ON THE SAME DATASET BUT WHERE THE WEIGHTS OF INCORRECTLY CLASSIFIED INSTANCES ARE ADJUSTED SUCH THAT SUBSEQUENT CLASSIFIERS FOCUS MORE ON DIFFICULT CASES

THIS CLASS IMPLEMENTS THE ALGORITHM KNOWN AS ADABOOSTSAMME 2

READ MORE IN THE USER GUIDE

PARAMETERS

BASEESTIMATOR OBJECT OPTIONAL DEFAULTNONE THE BASE ESTIMATOR FROM WHICH THE BOOSTED ENSEMBLE IS BUILT SUPPORT FOR SAMPLE WEIGHTING IS REQUIRED AS WELL AS PROPER CLASSES ANDNCLASSES ATTRIBUTES IF NONE THEN THE BASE ESTIMATOR IS DECISIONTREECLASSIFIERMAXDEPTH1

NESTIMATORS INTEGER OPTIONAL DEFAULT50 THE MAXIMUM NUMBER OF ESTIMATORS AT WHICH BOOSTING IS TERMINATED IN CASE OF PERFECT FIT THE LEARNING PROCEDURE IS STOPPED EARLY

LEARNINGRATE FLOAT OPTIONAL DEFAULT1 LEARNING RATE SHRINKS THE CONTRIBUTION OF EACH CLASSIFIER BY LEARNINGRATE THERE IS A TRADEOFF BETWEEN LEARNINGRATE AND NESTIMATORS

ALGORITHM ‘SAMME’ ‘SAMMER’ OPTIONAL DEFAULT’SAMMER’ IF ‘SAMMER’ THEN USE THE SAMMER REAL BOOSTING ALGORITHM BASEESTIMATOR MUST SUPPORT CALCULATION OF CLASS PROBABILITIES IF ‘SAMME’ THEN USE THE SAMME DISCRETE BOOSTING ALGORITHM THE SAMMER ALGORITHM TYPICALLY CONVERGES FASTER THAN SAMME ACHIEVING A LOWER TEST ERROR WITH FEWER BOOSTING ITERATIONS

RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE

RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES
ESTIMATORS LIST OF CLASSIFIERS THE COLLECTION OF FITTED SUBESTIMATORS
CLASSES ARRAY OF SHAPE NCLASSES THE CLASSES LABELS
NCLASSES INT THE NUMBER OF CLASSES
ESTIMATORWEIGHTS ARRAY OF FLOATS WEIGHTS FOR EACH ESTIMATOR IN THE BOOSTED ENSEMBLE
ESTIMATORERRORS ARRAY OF FLOATS CLASSIFICATION ERROR FOR EACH ESTIMATOR IN THE BOOSTED EN
SEMBLE
FEATUREIMPORTANCES ARRAY OF SHAPE NFEATURES RETURN THE FEATURE IMPORTANCES
THE HIGHER THE MORE IMPORTANT THE FEATURE
SEE ALSO
ADABOOSTREGRESSOR GRADIENTBOOSTINGCLASSIFIER
SKLEARNTREEDECISIONTREECLASSIFIER
REFERENCES
R33E4EC8C4AD51 R33E4EC8C4AD52
EXAMPLES
```
 FROM SKLEARNENSEMBLE IMPORT ADABOOSTCLASSIFIER
 FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
X Y  MAKECLASSIFICATIONNSAMPLES1000 NFEATURES4
 NINFORMATIVE2 NREDUNDANT0
 RANDOMSTATE0 SHUFFLE FALSE
CLF  ADABOOSTCLASSIFIERNESTIMATORS100 RANDOMSTATE0
CLFFITX Y
ADABOOSTCLASSIFIERALGORITHMSAMMER BASEESTIMATORNONE
LEARNINGRATE10 NESTIMATORS100 RANDOMSTATE0
CLFFEATUREIMPORTANCES
ARRAY028 042 014 016
CLFPREDICT0 0 0 0
ARRAY1
CLFSCOREX Y
0983
```
METHODS
DECISIONFUNCTION SELF X COMPUTE THE DECISION FUNCTION OF X
FITSELF X Y SAMPLEWEIGHT BUILD A BOOSTED CLASSIFIER FROM THE TRAINING SET X Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASSES FOR X
PREDICTLOGPROBA SELF X PREDICT CLASS LOGPROBABILITIES FOR X
CONTINUED ON NEXT PAGE

TABLE 672 – CONTINUED FROM PREVIOUS PAGE
PREDICTPROBA SELF X PREDICT CLASS PROBABILITIES FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
STAGEDDECISIONFUNCTION SELF X COMPUTE DECISION FUNCTION OF XFOR EACH BOOSTING ITERA
TION
STAGEDPREDICT SELF X RETURN STAGED PREDICTIONS FOR X
STAGEDPREDICTPROBA SELF X PREDICT CLASS PROBABILITIES FOR X
STAGEDSCORE SELF X Y SAMPLEWEIGHT RETURN STAGED SCORES FOR X Y
INIT SELFBASEESTIMATORNONE NESTIMATORS50 LEARNINGRATE10 ALGORITHM’SAMMER’
RANDOMSTATENONE
DECISIONFUNCTION SELFX
COMPUTE THE DECISION FUNCTION OF X
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE
CONVERTED TO CSR
RETURNS
SCORE ARRAY SHAPE NSAMPLES K THE DECISION FUNCTION OF THE INPUT SAMPLES THE ORDER
OF OUTPUTS IS THE SAME OF THAT OF THE CLASSES ATTRIBUTE BINARY CLASSIFICATION IS A SPECIAL
CASES WITHK 1 OTHERWISE KNCLASSES FOR BINARY CLASSIFICATION VALUES CLOSER
TO 1 OR 1 MEAN MORE LIKE THE FIRST OR SECOND CLASS IN CLASSES RESPECTIVELY
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES THE HIGHER THE MORE IMPORTANT THE FEATURE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES
FITSELFXYSAMPLEWEIGHTNONE
BUILD A BOOSTED CLASSIFIER FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE
CONVERTED TO CSR
YARRAYLIKE OF SHAPE NSAMPLES THE TARGET VALUES CLASS LABELS
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS IF NONE THE
SAMPLE WEIGHTS ARE INITIALIZED TO 1 NSAMPLES
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT CLASSES FOR X
THE PREDICTED CLASS OF AN INPUT SAMPLE IS COMPUTED AS THE WEIGHTED MEAN PREDICTION OF THE CLASSIFIERS IN
THE ENSEMBLE
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE
CONVERTED TO CSR
RETURNS
YARRAY OF SHAPE NSAMPLES THE PREDICTED CLASSES
PREDICTLOGPROBA SELFX
PREDICT CLASS LOGPROBABILITIES FOR X
THE PREDICTED CLASS LOGPROBABILITIES OF AN INPUT SAMPLE IS COMPUTED AS THE WEIGHTED MEAN PREDICTED CLASS
LOGPROBABILITIES OF THE CLASSIFIERS IN THE ENSEMBLE
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE
CONVERTED TO CSR
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE
ORDER OF OUTPUTS IS THE SAME OF THAT OF THE CLASSES ATTRIBUTE
PREDICTPROBA SELFX
PREDICT CLASS PROBABILITIES FOR X
THE PREDICTED CLASS PROBABILITIES OF AN INPUT SAMPLE IS COMPUTED AS THE WEIGHTED MEAN PREDICTED CLASS
PROBABILITIES OF THE CLASSIFIERS IN THE ENSEMBLE
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE
CONVERTED TO CSR
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE
ORDER OF OUTPUTS IS THE SAME OF THAT OF THE CLASSES ATTRIBUTE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES

YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
STAGEDDECISIONFUNCTION SELFX
COMPUTE DECISION FUNCTION OF XFOR EACH BOOSTING ITERATION
THIS METHOD ALLOWS MONITORING IE DETERMINE ERROR ON TESTING SET AFTER EACH BOOSTING ITERATION
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE
CONVERTED TO CSR
RETURNS
SCORE GENERATOR OF ARRAY SHAPE NSAMPLES K THE DECISION FUNCTION OF THE INPUT SAM
PLES THE ORDER OF OUTPUTS IS THE SAME OF THAT OF THE CLASSES ATTRIBUTE BINARY CLASSIFICATION
IS A SPECIAL CASES WITH K 1 OTHERWISE KNCLASSES FOR BINARY CLASSIFICATION
VALUES CLOSER TO 1 OR 1 MEAN MORE LIKE THE FIRST OR SECOND CLASS IN CLASSES RESPECTIVELY
STAGEDPREDICT SELFX
RETURN STAGED PREDICTIONS FOR X
THE PREDICTED CLASS OF AN INPUT SAMPLE IS COMPUTED AS THE WEIGHTED MEAN PREDICTION OF THE CLASSIFIERS IN
THE ENSEMBLE
THIS GENERATOR METHOD YIELDS THE ENSEMBLE PREDICTION AFTER EACH ITERATION OF BOOSTING AND THEREFORE ALLOWS
MONITORING SUCH AS TO DETERMINE THE PREDICTION ON A TEST SET AFTER EACH BOOST
PARAMETERS
XARRAYLIKE OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES SPARSE MATRIX CAN BE
CSC CSR COO DOK OR LIL COO DOK AND LIL ARE CONVERTED TO CSR
RETURNS
YGENERATOR OF ARRAY SHAPE NSAMPLES THE PREDICTED CLASSES
STAGEDPREDICTPROBA SELFX
PREDICT CLASS PROBABILITIES FOR X
THE PREDICTED CLASS PROBABILITIES OF AN INPUT SAMPLE IS COMPUTED AS THE WEIGHTED MEAN PREDICTED CLASS
PROBABILITIES OF THE CLASSIFIERS IN THE ENSEMBLE
THIS GENERATOR METHOD YIELDS THE ENSEMBLE PREDICTED CLASS PROBABILITIES AFTER EACH ITERATION OF BOOSTING
AND THEREFORE ALLOWS MONITORING SUCH AS TO DETERMINE THE PREDICTED CLASS PROBABILITIES ON A TEST SET AFTER
EACH BOOST
PARAMETERS

XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE
CONVERTED TO CSR
RETURNS
PGENERATOR OF ARRAY SHAPE NSAMPLES THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE
ORDER OF OUTPUTS IS THE SAME OF THAT OF THE CLASSES ATTRIBUTE
STAGEDSCORE SELFXYSAMPLEWEIGHTNONE
RETURN STAGED SCORES FOR X Y
THIS GENERATOR METHOD YIELDS THE ENSEMBLE SCORE AFTER EACH ITERATION OF BOOSTING AND THEREFORE ALLOWS
MONITORING SUCH AS TO DETERMINE THE SCORE ON A TEST SET AFTER EACH BOOST
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE
CONVERTED TO CSR
YARRAYLIKE SHAPE NSAMPLES LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
ZFLOAT
EXAMPLES USING SKLEARNENSEMBLEADABOOSTCLASSIFIER
•CLASSIFIER COMPARISON
•TWOCLASS ADABOOST
•MULTICLASS ADABOOSTED DECISION TREES
•DISCRETE VERSUS REAL ADABOOST
•PLOT THE DECISION SURFACES OF ENSEMBLES OF TREES ON THE IRIS DATASET
6122SKLEARNENSEMBLE ADABOOSTREGRESSOR
CLASSSKLEARNENSEMBLE ADABOOSTREGRESSOR BASEESTIMATORNONE NESTIMATORS50 LEARN
INGRATE10 LOSS’LINEAR’ RANDOMSTATENONE
AN ADABOOST REGRESSOR
AN ADABOOST 1 REGRESSOR IS A METAESTIMATOR THAT BEGINS BY FITTING A REGRESSOR ON THE ORIGINAL DATASET AND
THEN FITS ADDITIONAL COPIES OF THE REGRESSOR ON THE SAME DATASET BUT WHERE THE WEIGHTS OF INSTANCES ARE ADJUSTED
ACCORDING TO THE ERROR OF THE CURRENT PREDICTION AS SUCH SUBSEQUENT REGRESSORS FOCUS MORE ON DIFFICULT CASES
THIS CLASS IMPLEMENTS THE ALGORITHM KNOWN AS ADABOOSTR2 2
READ MORE IN THE USER GUIDE
PARAMETERS
BASEESTIMATOR OBJECT OPTIONAL DEFAULTNONE THE BASE ESTIMATOR FROM WHICH THE BOOSTED
ENSEMBLE IS BUILT SUPPORT FOR SAMPLE WEIGHTING IS REQUIRED IF NONE THEN THE BASE ESTIMA
TOR ISDECISIONTREEREGRESSORMAXDEPTH3
NESTIMATORS INTEGER OPTIONAL DEFAULT50 THE MAXIMUM NUMBER OF ESTIMATORS AT WHICH
BOOSTING IS TERMINATED IN CASE OF PERFECT FIT THE LEARNING PROCEDURE IS STOPPED EARLY

LEARNINGRATE FLOAT OPTIONAL DEFAULT1 LEARNING RATE SHRINKS THE CONTRIBUTION OF EACH
REGRESSOR BY LEARNINGRATE THERE IS A TRADEOFF BETWEEN LEARNINGRATE AND
NESTIMATORS
LOSS ‘LINEAR’ ‘SQUARE’ ‘EXPONENTIAL’ OPTIONAL DEFAULT’LINEAR’ THE LOSS FUNCTION TO USE
WHEN UPDATING THE WEIGHTS AFTER EACH BOOSTING ITERATION
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES
ESTIMATORS LIST OF CLASSIFIERS THE COLLECTION OF FITTED SUBESTIMATORS
ESTIMATORWEIGHTS ARRAY OF FLOATS WEIGHTS FOR EACH ESTIMATOR IN THE BOOSTED ENSEMBLE
ESTIMATORERRORS ARRAY OF FLOATS REGRESSION ERROR FOR EACH ESTIMATOR IN THE BOOSTED ENSEM
BLE
FEATUREIMPORTANCES ARRAY OF SHAPE NFEATURES RETURN THE FEATURE IMPORTANCES
THE HIGHER THE MORE IMPORTANT THE FEATURE
SEE ALSO
ADABOOSTCLASSIFIER GRADIENTBOOSTINGREGRESSOR
SKLEARNTREEDECISIONTREEREGRESSOR
REFERENCES
R0C261B7DEE9D1 R0C261B7DEE9D2
EXAMPLES
 FROM SKLEARNENSEMBLE IMPORT ADABOOSTREGRESSOR
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y MAKEREGRESSIONNFEATURES4 NINFORMATIVE2
 RANDOMSTATE0 SHUFFLE FALSE
REGR ADABOOSTREGRESSORRANDOMSTATE0 NESTIMATORS100
REGRFITX Y
ADABOOSTREGRESSORBASEESTIMATORNONE LEARNINGRATE10 LOSSLINEAR
NESTIMATORS100 RANDOMSTATE0
REGRFEATUREIMPORTANCES
ARRAY02788 07109 00065 00036
REGRPREDICT0 0 0 0
ARRAY47972
REGRSCOREX Y
09771
METHODS
FITSELF X Y SAMPLEWEIGHT BUILD A BOOSTED REGRESSOR FROM THE TRAINING SET X Y
CONTINUED ON NEXT PAGE

TABLE 673 – CONTINUED FROM PREVIOUS PAGE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT REGRESSION VALUE FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
STAGEDPREDICT SELF X RETURN STAGED PREDICTIONS FOR X
STAGEDSCORE SELF X Y SAMPLEWEIGHT RETURN STAGED SCORES FOR X Y
INIT SELFBASEESTIMATORNONE NESTIMATORS50 LEARNINGRATE10 LOSS'LINEAR' RAN
DOMSTATENONE
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES THE HIGHER THE MORE IMPORTANT THE FEATURE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES
FITSELFXYSAMPLEWEIGHTNONE
BUILD A BOOSTED REGRESSOR FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE
CONVERTED TO CSR
YARRAYLIKE OF SHAPE NSAMPLES THE TARGET VALUES REAL NUMBERS
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS IF NONE THE
SAMPLE WEIGHTS ARE INITIALIZED TO 1 NSAMPLES
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT REGRESSION VALUE FOR X
THE PREDICTED REGRESSION VALUE OF AN INPUT SAMPLE IS COMPUTED AS THE WEIGHTED MEDIAN PREDICTION OF THE
CLASSIFIERS IN THE ENSEMBLE
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE
CONVERTED TO CSR
RETURNS

YARRAY OF SHAPE NSAMPLES THE PREDICTED REGRESSION VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
STAGEDPREDICT SELFX
RETURN STAGED PREDICTIONS FOR X
THE PREDICTED REGRESSION VALUE OF AN INPUT SAMPLE IS COMPUTED AS THE WEIGHTED MEDIAN PREDICTION OF THE
CLASSIFIERS IN THE ENSEMBLE
THIS GENERATOR METHOD YIELDS THE ENSEMBLE PREDICTION AFTER EACH ITERATION OF BOOSTING AND THEREFORE ALLOWS
MONITORING SUCH AS TO DETERMINE THE PREDICTION ON A TEST SET AFTER EACH BOOST
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES
RETURNS
YGENERATOR OF ARRAY SHAPE NSAMPLES THE PREDICTED REGRESSION VALUES

STAGEDSCORE SELFXYSAMPLEWEIGHTNONE
RETURN STAGED SCORES FOR X Y
THIS GENERATOR METHOD YIELDS THE ENSEMBLE SCORE AFTER EACH ITERATION OF BOOSTING AND THEREFORE ALLOWS MONITORING SUCH AS TO DETERMINE THE SCORE ON A TEST SET AFTER EACH BOOST
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES SPARSE MATRIX CAN BE CSC CSR COO DOK OR LIL COO DOK AND LIL ARE CONVERTED TO CSR
YARRAYLIKE SHAPE NSAMPLES LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
ZFLOAT
EXAMPLES USING SKLEARNENSEMBLEADABOOSTREGRESSOR
•DECISION TREE REGRESSION WITH ADABOOST
6123SKLEARNENSEMBLE BAGGINGCLASSIFIER
CLASSSKLEARNENSEMBLE BAGGINGCLASSIFIER BASEESTIMATORNONE NESTIMATORS10 MAXSAMPLES10 MAXFEATURES10 BOOTSTRAPTRUE BOOTSTRAPFEATURESFALSE OOBSCOREFALSE WARMSTARTFALSE NJOBSNONE RANDOMSTATENONE VERBOSE0
A BAGGING CLASSIFIER
A BAGGING CLASSIFIER IS AN ENSEMBLE METAESTIMATOR THAT FITS BASE CLASSIFIERS EACH ON RANDOM SUBSETS OF THE ORIGINAL DATASET AND THEN AGGREGATE THEIR INDIVIDUAL PREDICTIONS EITHER BY VOTING OR BY AVERAGING TO FORM A FINAL PREDICTION SUCH A METAESTIMATOR CAN TYPICALLY BE USED AS A WAY TO REDUCE THE VARIANCE OF A BLACKBOX ESTIMATOR EG A DECISION TREE BY INTRODUCING RANDOMIZATION INTO ITS CONSTRUCTION PROCEDURE AND THEN MAKING AN ENSEMBLE OUT OF IT
THIS ALGORITHM ENCOMPASSES SEVERAL WORKS FROM THE LITERATURE WHEN RANDOM SUBSETS OF THE DATASET ARE DRAWN AS RANDOM SUBSETS OF THE SAMPLES THEN THIS ALGORITHM IS KNOWN AS PASTING RB1846455D0E51 IF SAMPLES ARE DRAWN WITH REPLACEMENT THEN THE METHOD IS KNOWN AS BAGGING RB1846455D0E52 WHEN RANDOM SUBSETS OF THE DATASET ARE DRAWN AS RANDOM SUBSETS OF THE FEATURES THEN THE METHOD IS KNOWN AS RANDOM SUBSPACES RB1846455D0E53 FINALLY WHEN BASE ESTIMATORS ARE BUILT ON SUBSETS OF BOTH SAMPLES AND FEATURES THEN THE METHOD IS KNOWN AS RANDOM PATCHES RB1846455D0E54
READ MORE IN THE USER GUIDE
PARAMETERS
BASEESTIMATOR OBJECT OR NONE OPTIONAL DEFAULTNONE THE BASE ESTIMATOR TO FIT ON RANDOM SUBSETS OF THE DATASET IF NONE THEN THE BASE ESTIMATOR IS A DECISION TREE
NESTIMATORS INT OPTIONAL DEFAULT10 THE NUMBER OF BASE ESTIMATORS IN THE ENSEMBLE
MAXSAMPLES INT OR FLOAT OPTIONAL DEFAULT10 THE NUMBER OF SAMPLES TO DRAW FROM X TO TRAIN EACH BASE ESTIMATOR
• IF INT THEN DRAW MAXSAMPLES SAMPLES
• IF FLOAT THEN DRAW MAXSAMPLES XSHAPE0 SAMPLES

MAXFEATURES INT OR FLOAT OPTIONAL DEFAULT10 THE NUMBER OF FEATURES TO DRAW FROM X TO TRAIN EACH BASE ESTIMATOR

- IF INT THEN DRAW MAXFEATURES FEATURES
- IF FLOAT THEN DRAW MAXFEATURES XSHAPE1 FEATURES

BOOTSTRAP BOOLEAN OPTIONAL DEFAULTTRUE WHETHER SAMPLES ARE DRAWN WITH REPLACEMENT IF FALSE SAMPLING WITHOUT REPLACEMENT IS PERFORMED
BOOTSTRAPFEATURES BOOLEAN OPTIONAL DEFAULTFALSE WHETHER FEATURES ARE DRAWN WITH RE PLACEMENT
OOBSCORE BOOL OPTIONAL DEFAULTFALSE WHETHER TO USE OUTOFBAG SAMPLES TO ESTIMATE THE GENERALIZATION ERROR
WARMSTART BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PRE VIOUS CALL TO FIT AND ADD MORE ESTIMATORS TO THE ENSEMBLE OTHERWISE JUST FIT A WHOLE NEW ENSEMBLE SEE THE GLOSSARY
NEW IN VERSION 017 WARMSTART CONSTRUCTOR PARAMETER
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR BOTH FIT ANDPREDICT NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT 1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
VERBOSE INT OPTIONAL DEFAULT0 CONTROLS THE VERBOSITY WHEN FITTING AND PREDICTING

ATTRIBUTES

BASEESTIMATOR ESTIMATOR THE BASE ESTIMATOR FROM WHICH THE ENSEMBLE IS GROWN
ESTIMATORS LIST OF ESTIMATORS THE COLLECTION OF FITTED BASE ESTIMATORS
ESTIMATORSSAMPLES LIST OF ARRAYS THE SUBSET OF DRAWN SAMPLES FOR EACH BASE ESTIMA TOR
ESTIMATORSFEATURES LIST OF ARRAYS THE SUBSET OF DRAWN FEATURES FOR EACH BASE ESTIMATOR
CLASSES ARRAY OF SHAPE NCLASSES THE CLASSES LABELS
NCLASSES INT OR LIST THE NUMBER OF CLASSES
OOBSCORE FLOAT SCORE OF THE TRAINING DATASET OBTAINED USING AN OUTOFBAG ESTIMATE
OOBDECISIONFUNCTION ARRAY OF SHAPE NSAMPLES NCLASSES DECISION FUNCTION COM PUTED WITH OUTOFBAG ESTIMATE ON THE TRAINING SET IF NESTIMATORS IS SMALL IT MIGHT BE POSSIBLE THAT A DATA POINT WAS NEVER LEFT OUT DURING THE BOOTSTRAP IN THIS CASE OOBDECISIONFUNCTION MIGHT CONTAIN NAN

REFERENCES

RB1846455D0E51 RB1846455D0E52 RB1846455D0E53 RB1846455D0E54

DECISIONFUNCTION SELF X AVERAGE OF THE DECISION FUNCTIONS OF THE BASE CLASSIFIERS
FITSELF X Y SAMPLEWEIGHT BUILD A BAGGING ENSEMBLE OF ESTIMATORS FROM THE TRAIN
ING SET X Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASS FOR X
PREDICTLOGPROBA SELF X PREDICT CLASS LOGPROBABILITIES FOR X
PREDICTPROBA SELF X PREDICT CLASS PROBABILITIES FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFBASEESTIMATORNONE NESTIMATORS10 MAXSAMPLES10 MAXFEATURES10 BOOT
STRAPTRUE BOOTSTRAPFEATURESFALSE OOBSCOREFALSE WARMSTARTFALSE NJOBSNONE
RANDOMSTATENONE VERBOSE0
DECISIONFUNCTION SELFX
AVERAGE OF THE DECISION FUNCTIONS OF THE BASE CLASSIFIERS
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRICES ARE ACCEPTED ONLY IF THEY ARE SUPPORTED BY THE BASE ESTIMATOR
RETURNS
SCORE ARRAY SHAPE NSAMPLES K THE DECISION FUNCTION OF THE INPUT SAMPLES THE
COLUMNS CORRESPOND TO THE CLASSES IN SORTED ORDER AS THEY APPEAR IN THE ATTRIBUTE
CLASSES REGRESSION AND BINARY CLASSIFICATION ARE SPECIAL CASES WITH K 1 OTH
ERWISEKNCLASSES
ESTIMATORSSAMPLES
THE SUBSET OF DRAWN SAMPLES FOR EACH BASE ESTIMATOR
RETURNS A DYNAMICALLY GENERATED LIST OF INDICES IDENTIFYING THE SAMPLES USED FOR FITTING EACH MEMBER OF THE
ENSEMBLE IE THE INBAG SAMPLES
NOTE THE LIST IS RECREATED AT EACH CALL TO THE PROPERTY IN ORDER TO REDUCE THE OBJECT MEMORY FOOTPRINT BY
NOT STORING THE SAMPLING DATA THUS FETCHING THE PROPERTY MAY BE SLOWER THAN EXPECTED
FITSELFXYSAMPLEWEIGHTNONE
BUILD A BAGGING ENSEMBLE OF ESTIMATORS FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRICES ARE ACCEPTED ONLY IF THEY ARE SUPPORTED BY THE BASE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUM
BERS IN REGRESSION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED NOTE THAT THIS IS SUPPORTED ONLY IF THE BASE ESTIMATOR SUP
PORTS SAMPLE WEIGHTING
RETURNS
SELF OBJECT

GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT CLASS FOR X
THE PREDICTED CLASS OF AN INPUT SAMPLE IS COMPUTED AS THE CLASS WITH THE HIGHEST MEAN PREDICTED PROBABILITY
IF BASE ESTIMATORS DO NOT IMPLEMENT A PREDICTPROBA METHOD THEN IT RESORTS TO VOTING
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRICES ARE ACCEPTED ONLY IF THEY ARE SUPPORTED BY THE BASE ESTIMATOR
RETURNS
YARRAY OF SHAPE NSAMPLES THE PREDICTED CLASSES
PREDICTLOGPROBA SELFX
PREDICT CLASS LOGPROBABILITIES FOR X
THE PREDICTED CLASS LOGPROBABILITIES OF AN INPUT SAMPLE IS COMPUTED AS THE LOG OF THE MEAN PREDICTED CLASS
PROBABILITIES OF THE BASE ESTIMATORS IN THE ENSEMBLE
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRICES ARE ACCEPTED ONLY IF THEY ARE SUPPORTED BY THE BASE ESTIMATOR
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES THE CLASS LOGPROBABILITIES OF THE INPUT SAMPLES
THE ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES
PREDICTPROBA SELFX
PREDICT CLASS PROBABILITIES FOR X
THE PREDICTED CLASS PROBABILITIES OF AN INPUT SAMPLE IS COMPUTED AS THE MEAN PREDICTED CLASS PROBABILITIES
OF THE BASE ESTIMATORS IN THE ENSEMBLE IF BASE ESTIMATORS DO NOT IMPLEMENT A PREDICTPROBA METHOD
THEN IT RESORTS TO VOTING AND THE PREDICTED CLASS PROBABILITIES OF AN INPUT SAMPLE REPRESENTS THE PROPORTION
OF ESTIMATORS PREDICTING EACH CLASS
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRICES ARE ACCEPTED ONLY IF THEY ARE SUPPORTED BY THE BASE ESTIMATOR
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE
ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED

PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
6124SKLEARNENSEMBLE BAGGINGREGRESSOR
CLASSSKLEARNENSEMBLE BAGGINGREGRESSOR BASEESTIMATORNONE NESTIMATORS10 MAXSAMPLES10 MAXFEATURES10 BOOTSTRAPTRUE BOOTSTRAPFEATURESFALSE OOBSCOREFALSE WARMSTARTFALSE NJOBSNONE RANDOMSTATENONE VERBOSE0
A BAGGING REGRESSOR
A BAGGING REGRESSOR IS AN ENSEMBLE METAESTIMATOR THAT FITS BASE REGRESSORS EACH ON RANDOM SUBSETS OF THE ORIGINAL DATASET AND THEN AGGREGATE THEIR INDIVIDUAL PREDICTIONS EITHER BY VOTING OR BY AVERAGING TO FORM A FINAL PREDICTION SUCH A METAESTIMATOR CAN TYPICALLY BE USED AS A WAY TO REDUCE THE VARIANCE OF A BLACKBOX ESTIMATOR EG A DECISION TREE BY INTRODUCING RANDOMIZATION INTO ITS CONSTRUCTION PROCEDURE AND THEN MAKING AN ENSEMBLE OUT OF IT
THIS ALGORITHM ENCOMPASSES SEVERAL WORKS FROM THE LITERATURE WHEN RANDOM SUBSETS OF THE DATASET ARE DRAWN AS RANDOM SUBSETS OF THE SAMPLES THEN THIS ALGORITHM IS KNOWN AS PASTING R4D113BA76FC01 IF SAMPLES ARE DRAWN WITH REPLACEMENT THEN THE METHOD IS KNOWN AS BAGGING R4D113BA76FC02 WHEN RANDOM SUBSETS OF THE DATASET ARE DRAWN AS RANDOM SUBSETS OF THE FEATURES THEN THE METHOD IS KNOWN AS RANDOM SUBSPACES R4D113BA76FC03 FINALLY WHEN BASE ESTIMATORS ARE BUILT ON SUBSETS OF BOTH SAMPLES AND FEATURES THEN THE METHOD IS KNOWN AS RANDOM PATCHES R4D113BA76FC04
READ MORE IN THE USER GUIDE
PARAMETERS
BASEESTIMATOR OBJECT OR NONE OPTIONAL DEFAULTNONE THE BASE ESTIMATOR TO FIT ON RANDOM SUBSETS OF THE DATASET IF NONE THEN THE BASE ESTIMATOR IS A DECISION TREE
NESTIMATORS INT OPTIONAL DEFAULT10 THE NUMBER OF BASE ESTIMATORS IN THE ENSEMBLE
MAXSAMPLES INT OR FLOAT OPTIONAL DEFAULT10 THE NUMBER OF SAMPLES TO DRAW FROM X TO TRAIN EACH BASE ESTIMATOR
• IF INT THEN DRAW MAXSAMPLES SAMPLES
• IF FLOAT THEN DRAW MAXSAMPLES XSHAPE0 SAMPLES
MAXFEATURES INT OR FLOAT OPTIONAL DEFAULT10 THE NUMBER OF FEATURES TO DRAW FROM X TO TRAIN EACH BASE ESTIMATOR

• IF INT THEN DRAW MAXFEATURES FEATURES
• IF FLOAT THEN DRAW MAXFEATURES XSHAPE1 FEATURES
BOOTSTRAP BOOLEAN OPTIONAL DEFAULTTRUE WHETHER SAMPLES ARE DRAWN WITH REPLACEMENT IF FALSE SAMPLING WITHOUT REPLACEMENT IS PERFORMED
BOOTSTRAPFEATURES BOOLEAN OPTIONAL DEFAULTFALSE WHETHER FEATURES ARE DRAWN WITH RE PLACEMENT
OOBSCORE BOOL WHETHER TO USE OUTOFBAG SAMPLES TO ESTIMATE THE GENERALIZATION ERROR
WARMSTART BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PRE VIOUS CALL TO FIT AND ADD MORE ESTIMATORS TO THE ENSEMBLE OTHERWISE JUST FIT A WHOLE NEW ENSEMBLE SEE THE GLOSSARY
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR BOTH FIT ANDPREDICT NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT 1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
VERBOSE INT OPTIONAL DEFAULT0 CONTROLS THE VERBOSITY WHEN FITTING AND PREDICTING
ATTRIBUTES
ESTIMATORS LIST OF ESTIMATORS THE COLLECTION OF FITTED SUBESTIMATORS
ESTIMATORSSAMPLES LIST OF ARRAYS THE SUBSET OF DRAWN SAMPLES FOR EACH BASE ESTIMA TOR
ESTIMATORSFEATURES LIST OF ARRAYS THE SUBSET OF DRAWN FEATURES FOR EACH BASE ESTIMATOR
OOBSCORE FLOAT SCORE OF THE TRAINING DATASET OBTAINED USING AN OUTOFBAG ESTIMATE
OOBPREDICTION ARRAY OF SHAPE NSAMPLES PREDICTION COMPUTED WITH OUTOFBAG ESTIMATE ON THE TRAINING SET IF NESTIMATORS IS SMALL IT MIGHT BE POSSIBLE THAT A DATA POINT WAS NEVER LEFT OUT DURING THE BOOTSTRAP IN THIS CASE OOBPREDICTION MIGHT CONTAIN NAN
REFERENCES
R4D113BA76FC01 R4D113BA76FC02 R4D113BA76FC03 R4D113BA76FC04
METHODS
FITSELF X Y SAMPLEWEIGHT BUILD A BAGGING ENSEMBLE OF ESTIMATORS FROM THE TRAIN ING SET X Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT REGRESSION TARGET FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

INIT SELFBASEESTIMATORNONE NESTIMATORS10 MAXSAMPLES10 MAXFEATURES10 BOOT
STRAPTRUE BOOTSTRAPFEATURESFALSE OOBSCOREFALSE WARMSTARTFALSE NJOBSNONE
RANDOMSTATENONE VERBOSE0
ESTIMATORSSAMPLES
THE SUBSET OF DRAWN SAMPLES FOR EACH BASE ESTIMATOR
RETURNS A DYNAMICALLY GENERATED LIST OF INDICES IDENTIFYING THE SAMPLES USED FOR FITTING EACH MEMBER OF THE
ENSEMBLE IE THE INBAG SAMPLES
NOTE THE LIST IS RECREATED AT EACH CALL TO THE PROPERTY IN ORDER TO REDUCE THE OBJECT MEMORY FOOTPRINT BY
NOT STORING THE SAMPLING DATA THUS FETCHING THE PROPERTY MAY BE SLOWER THAN EXPECTED
FITSELFXYSAMPLEWEIGHTNONE
BUILD A BAGGING ENSEMBLE OF ESTIMATORS FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRICES ARE ACCEPTED ONLY IF THEY ARE SUPPORTED BY THE BASE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUM
BERS IN REGRESSION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED NOTE THAT THIS IS SUPPORTED ONLY IF THE BASE ESTIMATOR SUP
PORTS SAMPLE WEIGHTING
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT REGRESSION TARGET FOR X
THE PREDICTED REGRESSION TARGET OF AN INPUT SAMPLE IS COMPUTED AS THE MEAN PREDICTED REGRESSION TARGETS OF
THE ESTIMATORS IN THE ENSEMBLE
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAM
PLES SPARSE MATRICES ARE ACCEPTED ONLY IF THEY ARE SUPPORTED BY THE BASE ESTIMATOR
RETURNS
YARRAY OF SHAPE NSAMPLES THE PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE

IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNENSEMBLEBAGGINGREGRESSOR
•SINGLE ESTIMATOR VERSUS BAGGING BIASVARIANCE DECOMPOSITION
6125SKLEARNENSEMBLE ISOLATIONFOREST
CLASSSKLEARNENSEMBLE ISOLATIONFOREST NESTIMATORS100 MAXSAMPLES’AUTO’ CONTAMINA
TION’LEGACY’ MAXFEATURES10 BOOTSTRAPFALSE
NJOBSNONE BEHAVIOUR’OLD’ RANDOMSTATENONE
VERBOSE0 WARMSTARTFALSE
ISOLATION FOREST ALGORITHM
RETURN THE ANOMALY SCORE OF EACH SAMPLE USING THE ISOLATIONFOREST ALGORITHM
THE ISOLATIONFOREST ‘ISOLATES’ OBSERVATIONS BY RANDOMLY SELECTING A FEATURE AND THEN RANDOMLY SELECTING A SPLIT
VALUE BETWEEN THE MAXIMUM AND MINIMUM VALUES OF THE SELECTED FEATURE
SINCE RECURSIVE PARTITIONING CAN BE REPRESENTED BY A TREE STRUCTURE THE NUMBER OF SPLITTINGS REQUIRED TO ISOLATE A
SAMPLE IS EQUIVALENT TO THE PATH LENGTH FROM THE ROOT NODE TO THE TERMINATING NODE
THIS PATH LENGTH AVERAGED OVER A FOREST OF SUCH RANDOM TREES IS A MEASURE OF NORMALITY AND OUR DECISION
FUNCTION

RANDOM PARTITIONING PRODUCES NOTICEABLY SHORTER PATHS FOR ANOMALIES HENCE WHEN A FOREST OF RANDOM TREES COLLECTIVELY PRODUCE SHORTER PATH LENGTHS FOR PARTICULAR SAMPLES THEY ARE HIGHLY LIKELY TO BE ANOMALIES
READ MORE IN THE USER GUIDE
NEW IN VERSION 018
PARAMETERS
NESTIMATORS INT OPTIONAL DEFAULT100 THE NUMBER OF BASE ESTIMATORS IN THE ENSEMBLE
MAXSAMPLES INT OR FLOAT OPTIONAL DEFAULT"AUTO"
THE NUMBER OF SAMPLES TO DRAW FROM X TO TRAIN EACH BASE ESTIMATOR
• IF INT THEN DRAW MAXSAMPLES SAMPLES
• IF FLOAT THEN DRAW MAXSAMPLES XSHAPE0 SAMPLES
• IF "AUTO" THEN MAXSAMPLESMIN256 NSAMPLES
IF MAXSAMPLES IS LARGER THAN THE NUMBER OF SAMPLES PROVIDED ALL SAMPLES WILL BE USED FOR ALL TREES NO SAMPLING
CONTAMINATION FLOAT IN 0 05 OPTIONAL DEFAULT01 THE AMOUNT OF CONTAMINATION OF THE DATA SET IE THE PROPORTION OF OUTLIERS IN THE DATA SET USED WHEN FITTING TO DEFINE THE THRESHOLD ON THE DECISION FUNCTION IF 'AUTO' THE DECISION FUNCTION THRESHOLD IS DETERMINED AS IN THE ORIGINAL PAPER
CHANGED IN VERSION 020 THE DEFAULT VALUE OF CONTAMINATION WILL CHANGE FROM 01 IN 020 TOAUTO IN 022
MAXFEATURES INT OR FLOAT OPTIONAL DEFAULT10 THE NUMBER OF FEATURES TO DRAW FROM X TO TRAIN EACH BASE ESTIMATOR
• IF INT THEN DRAW MAXFEATURES FEATURES
• IF FLOAT THEN DRAW MAXFEATURES XSHAPE1 FEATURES
BOOTSTRAP BOOLEAN OPTIONAL DEFAULTFALSE IF TRUE INDIVIDUAL TREES ARE FIT ON RANDOM SUBSETS OF THE TRAINING DATA SAMPLED WITH REPLACEMENT IF FALSE SAMPLING WITHOUT REPLACEMENT IS PERFORMED
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR BOTH FIT ANDPREDICT NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT 1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
BEHAVIOUR STR DEFAULT'OLD' BEHAVIOUR OF THE DECISIONFUNCTION WHICH CAN BE EI THER 'OLD' OR 'NEW' PASSING BEHAVIOURNEW MAKES THE DECISIONFUNCTION CHANGE TO MATCH OTHER ANOMALY DETECTION ALGORITHM API WHICH WILL BE THE DEFAULT BE HAVIOUR IN THE FUTURE AS EXPLAINED IN DETAILS IN THE OFFSET ATTRIBUTE DOCUMENTATION THEDECISIONFUNCTION BECOMES DEPENDENT ON THE CONTAMINATION PARAMETER IN SUCH A WAY THAT 0 BECOMES ITS NATURAL THRESHOLD TO DETECT OUTLIERS
NEW IN VERSION 020 BEHAVIOUR IS ADDED IN 020 FOR BACKCOMPATIBILITY PURPOSE
DEPRECATED SINCE VERSION 020 BEHAVIOUROLD IS DEPRECATED IN 020 AND WILL NOT BE POSSIBLE IN 022
DEPRECATED SINCE VERSION 022 BEHAVIOUR PARAMETER WILL BE DEPRECATED IN 022 AND RE MOVED IN 024
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE

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RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
VERBOSE INT OPTIONAL DEFAULT0 CONTROLS THE VERBOSITY OF THE TREE BUILDING PROCESS
WARMSTART BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PRE
VIOUS CALL TO FIT AND ADD MORE ESTIMATORS TO THE ENSEMBLE OTHERWISE JUST FIT A WHOLE NEW
FOREST SEE THE GLOSSARY
NEW IN VERSION 021
ATTRIBUTES
ESTIMATORS LIST OF DECISIONTREECLASSIFIER THE COLLECTION OF FITTED SUBESTIMATORS
ESTIMATORSSAMPLES LIST OF ARRAYS THE SUBSET OF DRAWN SAMPLES FOR EACH BASE ESTIMA
TOR
MAXSAMPLES INTEGER THE ACTUAL NUMBER OF SAMPLES
OFFSET FLOAT OFFSET USED TO DEFINE THE DECISION FUNCTION FROM THE RAW SCORES WE HAVE THE
RELATIONDECISIONFUNCTION SCORESAMPLES OFFSET ASSUMING BE
HAVIOUR 'NEW' OFFSET IS DEFINED AS FOLLOWS WHEN THE CONTAMINATION PARAMETER
IS SET TO "AUTO" THE OFFSET IS EQUAL TO 05 AS THE SCORES OF INLIERS ARE CLOSE TO 0 AND THE
SCORES OF OUTLIERS ARE CLOSE TO 1 WHEN A CONTAMINATION PARAMETER DIFFERENT THAN "AUTO"
IS PROVIDED THE OFFSET IS DEFINED IN SUCH A WAY WE OBTAIN THE EXPECTED NUMBER OF OUTLIERS
SAMPLES WITH DECISION FUNCTION 0 IN TRAINING ASSUMING THE BEHAVIOUR PARAMETER IS SET
TO 'OLD' WE ALWAYS HAVE OFFSET 05 MAKING THE DECISION FUNCTION INDEPENDENT
FROM THE CONTAMINATION PARAMETER
NOTES
THE IMPLEMENTATION IS BASED ON AN ENSEMBLE OF EXTRATREEREGRESSOR THE MAXIMUM DEPTH OF EACH TREE IS SET TO
CEILLOG2N WHERE IS THE NUMBER OF SAMPLES USED TO BUILD THE TREE SEE LIU ET AL 2008 FOR MORE
DETAILS
REFERENCES
RD7AE0A2AE6881 RD7AE0A2AE6882
METHODS
DECISIONFUNCTION SELF X AVERAGE ANOMALY SCORE OF X OF THE BASE CLASSIFIERS
FITSELF X Y SAMPLEWEIGHT FIT ESTIMATOR
FITPREDICT SELF X Y PERFORMS FIT ON X AND RETURNS LABELS FOR X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT IF A PARTICULAR SAMPLE IS AN OUTLIER OR NOT
SCORESAMPLES SELF X OPPOSITE OF THE ANOMALY SCORE DEFINED IN THE ORIGINAL
PAPER
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNESTIMATORS100 MAXSAMPLES'AUTO' CONTAMINATION'LEGACY' MAXFEATURES10
BOOTSTRAPFALSE NJOBSNONE BEHAVIOUR'OLD' RANDOMSTATENONE VERBOSE0
WARMSTARTFALSE
612SKLEARNENSEMBLE ENSEMBLE METHODS 1709

DECISIONFUNCTION SELFX
AVERAGE ANOMALY SCORE OF X OF THE BASE CLASSIFIERS
THE ANOMALY SCORE OF AN INPUT SAMPLE IS COMPUTED AS THE MEAN ANOMALY SCORE OF THE TREES IN THE FOREST
THE MEASURE OF NORMALITY OF AN OBSERVATION GIVEN A TREE IS THE DEPTH OF THE LEAF CONTAINING THIS OBSERVATION
WHICH IS EQUIVALENT TO THE NUMBER OF SPLITTINGS REQUIRED TO ISOLATE THIS POINT IN CASE OF SEVERAL OBSERVATIONS
NLEFT IN THE LEAF THE AVERAGE PATH LENGTH OF A NLEFT SAMPLES ISOLATION TREE IS ADDED
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTERNALLY
IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO A SPARSE
CSRMATRIX
RETURNS
SCORES ARRAY SHAPE NSAMPLES THE ANOMALY SCORE OF THE INPUT SAMPLES THE LOWER THE
MORE ABNORMAL NEGATIVE SCORES REPRESENT OUTLIERS POSITIVE SCORES REPRESENT INLIERS
ESTIMATORSSAMPLES
THE SUBSET OF DRAWN SAMPLES FOR EACH BASE ESTIMATOR
RETURNS A DYNAMICALLY GENERATED LIST OF INDICES IDENTIFYING THE SAMPLES USED FOR FITTING EACH MEMBER OF THE
ENSEMBLE IE THE INBAG SAMPLES
NOTE THE LIST IS RECREATED AT EACH CALL TO THE PROPERTY IN ORDER TO REDUCE THE OBJECT MEMORY FOOTPRINT BY
NOT STORING THE SAMPLING DATA THUS FETCHING THE PROPERTY MAY BE SLOWER THAN EXPECTED
FITSELFXYNONE SAMPLEWEIGHTNONE
FIT ESTIMATOR
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES USE
DTYPENPFLOAT32 FOR MAXIMUM EFFICIENCY SPARSE MATRICES ARE ALSO SUPPORTED USE
SPARSECSCMATRIX FOR MAXIMUM EFFICIENCY
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
SELF OBJECT
FITPREDICT SELFXYNONE
PERFORMS FIT ON X AND RETURNS LABELS FOR X
RETURNS 1 FOR OUTLIERS AND 1 FOR INLIERS
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES INPUT DATA
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
YNDARRAY SHAPE NSAMPLES 1 FOR INLIERS 1 FOR OUTLIERS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT IF A PARTICULAR SAMPLE IS AN OUTLIER OR NOT
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTERNALLY
IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO A SPARSE
CSRMATRIX
RETURNS
ISINLIER ARRAY SHAPE NSAMPLES FOR EACH OBSERVATION TELLS WHETHER OR NOT 1 OR 1 IT
SHOULD BE CONSIDERED AS AN INLIER ACCORDING TO THE FITTED MODEL
SCORESAMPLES SELFX
OPPOSITE OF THE ANOMALY SCORE DEFINED IN THE ORIGINAL PAPER
THE ANOMALY SCORE OF AN INPUT SAMPLE IS COMPUTED AS THE MEAN ANOMALY SCORE OF THE TREES IN THE FOREST
THE MEASURE OF NORMALITY OF AN OBSERVATION GIVEN A TREE IS THE DEPTH OF THE LEAF CONTAINING THIS OBSERVATION
WHICH IS EQUIVALENT TO THE NUMBER OF SPLITTINGS REQUIRED TO ISOLATE THIS POINT IN CASE OF SEVERAL OBSERVATIONS
NLEFT IN THE LEAF THE AVERAGE PATH LENGTH OF A NLEFT SAMPLES ISOLATION TREE IS ADDED
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
SCORES ARRAY SHAPE NSAMPLES THE ANOMALY SCORE OF THE INPUT SAMPLES THE LOWER THE
MORE ABNORMAL
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNENSEMBLEISOLATIONFOREST
•COMPARING ANOMALY DETECTION ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS
•ISOLATIONFOREST EXAMPLE

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6126SKLEARNENSEMBLE RANDOMTREESEMBEDDING
CLASSSKLEARNENSEMBLE RANDOMTREESEMBEDDING NESTIMATORS’WARN’ MAXDEPTH5
MINSAMPLESSPLIT2 MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00
MAXLEAFNODESNONE
MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE SPARSEOUTPUTTRUE
NJOBSNONE RANDOMSTATENONE VERBOSE0
WARMSTARTFALSE
AN ENSEMBLE OF TOTALLY RANDOM TREES
AN UNSUPERVISED TRANSFORMATION OF A DATASET TO A HIGHDIMENSIONAL SPARSE REPRESENTATION A DATAPOINT IS CODED
ACCORDING TO WHICH LEAF OF EACH TREE IT IS SORTED INTO USING A ONEHOT ENCODING OF THE LEAVES THIS LEADS TO A
BINARY CODING WITH AS MANY ONES AS THERE ARE TREES IN THE FOREST
THE DIMENSIONALITY OF THE RESULTING REPRESENTATION IS NOUT NESTIMATORS MAXLEAFNODES
IFMAXLEAFNODES NONE THE NUMBER OF LEAF NODES IS AT MOST NESTIMATORS 2
MAXDEPTH
READ MORE IN THE USER GUIDE
PARAMETERS
NESTIMATORS INTEGER OPTIONAL DEFAULT10 NUMBER OF TREES IN THE FOREST
CHANGED IN VERSION 020 THE DEFAULT VALUE OF NESTIMATORS WILL CHANGE FROM 10 IN
VERSION 020 TO 100 IN VERSION 022
MAXDEPTH INTEGER OPTIONAL DEFAULT5 THE MAXIMUM DEPTH OF EACH TREE IF NONE
THEN NODES ARE EXPANDED UNTIL ALL LEAVES ARE PURE OR UNTIL ALL LEAVES CONTAIN LESS THAN
MINSAMPLESSPLIT SAMPLES
MINSAMPLESSPLIT INT FLOAT OPTIONAL DEFAULT2 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT
NSAMPLES IS THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST
MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY
HAVE THE EFFECT OF SMOOTHING THE MODEL ESPECIALLY IN REGRESSION
• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF
NSAMPLES IS THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE
SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE
EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULTNONE GROW TREES WITH MAXLEAFNODES
IN BESTFIRST FASHION BEST NODES ARE DEFINED AS RELATIVE REDUCTION IN IMPURITY IF NONE THEN
UNLIMITED NUMBER OF LEAF NODES

MINIMPURITYDECREASE FLOAT OPTIONAL DEFAULT0 A NODE WILL BE SPLIT IF THIS SPLIT INDUCES
A DECREASE OF THE IMPURITY GREATER THAN OR EQUAL TO THIS VALUE
THE WEIGHTED IMPURITY DECREASE EQUATION IS THE FOLLOWING
NT N IMPURITY NTR NT RIGHTIMPURITY
 NTL NT LEFTIMPURITY
WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE
NTL IS THE NUMBER OF SAMPLES IN THE LEFT CHILD AND NTR IS THE NUMBER OF SAMPLES IN
THE RIGHT CHILD
NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED
NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE
WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
DEPRECATED SINCE VERSION 019 MINIMPURITYSPLIT HAS BEEN DEPRECATED IN FAVOR OF
MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT
WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE
MINIMPURITYDECREASE INSTEAD
SPARSEOUTPUT BOOL OPTIONAL DEFAULTTRUE WHETHER OR NOT TO RETURN A SPARSE CSR MATRIX
AS DEFAULT BEHAVIOR OR TO RETURN A DENSE ARRAY COMPATIBLE WITH DENSE PIPELINE OPERATORS
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR BOTH
FIT ANDPREDICT NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT
1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
VERBOSE INT OPTIONAL DEFAULT0 CONTROLS THE VERBOSITY WHEN FITTING AND PREDICTING
WARMSTART BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PRE
VIOUS CALL TO FIT AND ADD MORE ESTIMATORS TO THE ENSEMBLE OTHERWISE JUST FIT A WHOLE NEW
FOREST SEE THE GLOSSARY
ATTRIBUTES
ESTIMATORS LIST OF DECISIONTREECLASSIFIER THE COLLECTION OF FITTED SUBESTIMATORS
REFERENCES
R6E47E53BACBD1 R6E47E53BACBD2
METHODS
APPLY SELF X APPLY TREES IN THE FOREST TO X RETURN LEAF INDICES
DECISIONPATH SELF X RETURN THE DECISION PATH IN THE FOREST
FITSELF X Y SAMPLEWEIGHT FIT ESTIMATOR
FITTRANSFORM SELF X Y SAMPLEWEIGHT FIT ESTIMATOR AND TRANSFORM DATASET
CONTINUED ON NEXT PAGE

TABLE 677 – CONTINUED FROM PREVIOUS PAGE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM DATASET
INIT SELFNESTIMATORS'WARN' MAXDEPTH5 MINSAMPLESSPLIT2 MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00 MAXLEAFNODESNONE MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE SPARSEOUTPUTTRUE NJOBSNONE RANDOMSTATENONE
VERBOSE0 WARMSTARTFALSE
APPLYSELFX
APPLY TREES IN THE FOREST TO X RETURN LEAF INDICES
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES NESTIMATORS FOR EACH DATAPOINT X IN X AND FOR
EACH TREE IN THE FOREST RETURN THE INDEX OF THE LEAF X ENDS UP IN
DECISIONPATH SELFX
RETURN THE DECISION PATH IN THE FOREST
NEW IN VERSION 018
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY ITS DTYPE WILL BE CONVERTED TO DTYPENPFLOAT32 IF A SPARSE MATRIX IS PROVIDED
IT WILL BE CONVERTED INTO A SPARSE CSRMATRIX
RETURNS
INDICATOR SPARSE CSR ARRAY SHAPE NSAMPLES NNODES RETURN A NODE INDICATOR MATRIX
WHERE NON ZERO ELEMENTS INDICATES THAT THE SAMPLES GOES THROUGH THE NODES
NNODESPTR ARRAY OF SIZE NESTIMATORS 1 THE COLUMNS FROM INDICA
TORNNODESPTRINNODESPTRI1 GIVES THE INDICATOR VALUE FOR THE ITH ESTIMATOR
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES THE HIGHER THE MORE IMPORTANT THE FEATURE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES THE VALUES OF THIS ARRAY SUM TO 1 UNLESS
ALL TREES ARE SINGLE NODE TREES CONSISTING OF ONLY THE ROOT NODE IN WHICH CASE IT WILL BE AN
ARRAY OF ZEROS
FITSELFXYNONE SAMPLEWEIGHTNONE
FIT ESTIMATOR
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPENSAMPLES NFEATURES THE INPUT SAMPLES USE
DTYPENPFLOAT32 FOR MAXIMUM EFFICIENCY SPARSE MATRICES ARE ALSO SUPPORTED USE
SPARSECSCMATRIX FOR MAXIMUM EFFICIENCY

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SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEG
ATIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE IN THE CASE OF CLASSIFI
CATION SPLITS ARE ALSO IGNORED IF THEY WOULD RESULT IN ANY SINGLE CLASS CARRYING A NEGATIVE
WEIGHT IN EITHER CHILD NODE
RETURNS
SELF OBJECT
FITTRANSFORM SELFXYNONE SAMPLEWEIGHTNONE
FIT ESTIMATOR AND TRANSFORM DATASET
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPENSAMPLES NFEATURES INPUT DATA USED TO BUILD
FORESTS USE DTYPENPFLOAT32 FOR MAXIMUM EFFICIENCY
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEG
ATIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE IN THE CASE OF CLASSIFI
CATION SPLITS ARE ALSO IGNORED IF THEY WOULD RESULT IN ANY SINGLE CLASS CARRYING A NEGATIVE
WEIGHT IN EITHER CHILD NODE
RETURNS
XTRANSFORMED SPARSE MATRIX SHAPENSAMPLES NOUT TRANSFORMED DATASET
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM DATASET
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPENSAMPLES NFEATURES INPUT DATA TO BE TRANSFORMED
USEDTYPENPFLOAT32 FOR MAXIMUM EFFICIENCY SPARSE MATRICES ARE ALSO SUPPORTED
USE SPARSECSRMATRIX FOR MAXIMUM EFFICIENCY
RETURNS
XTRANSFORMED SPARSE MATRIX SHAPENSAMPLES NOUT TRANSFORMED DATASET

EXAMPLES USING SKLEARNENSEMBLERANDOMTREESEMBEDDING
•HASHING FEATURE TRANSFORMATION USING TOTALLY RANDOM TREES
•FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
6127SKLEARNENSEMBLE VOTINGCLASSIFIER
CLASSSKLEARNENSEMBLE VOTINGCLASSIFIER ESTIMATORS VOTING'HARD' WEIGHTSNONE
NJOBSNONE FLATTENTRANSFORMTRUE
SOFT V OTINGMAJORITY RULE CLASSIFIER FOR UNFITTED ESTIMATORS
NEW IN VERSION 017
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATORS LIST OF STRING ESTIMATOR TUPLES INVOKING THE FIT METHOD ON THE
VOTINGCLASSIFIER WILL FIT CLONES OF THOSE ORIGINAL ESTIMATORS THAT WILL BE STORED
IN THE CLASS ATTRIBUTE SELFESTIMATORS AN ESTIMATOR CAN BE SET TO NONE ORDROP
USINGSETPARAMS
VOTING STR 'HARD' 'SOFT' DEFAULT'HARD' IF 'HARD' USES PREDICTED CLASS LABELS FOR MAJORITY
RULE VOTING ELSE IF 'SOFT' PREDICTS THE CLASS LABEL BASED ON THE ARGMAX OF THE SUMS OF THE PRE
DICTED PROBABILITIES WHICH IS RECOMMENDED FOR AN ENSEMBLE OF WELLCALIBRATED CLASSIFIERS
WEIGHTS ARRAYLIKE SHAPE NCLASSIFIERS OPTIONAL DEFAULT'NONE' SEQUENCE OF WEIGHTS
FLOAT ORINT TO WEIGHT THE OCCURRENCES OF PREDICTED CLASS LABELS HARD VOTING OR CLASS
PROBABILITIES BEFORE AVERAGING SOFT VOTING USES UNIFORM WEIGHTS IF NONE
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR FIT
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL
PROCESSORS SEE GLOSSARY FOR MORE DETAILS
FLATTENTRANSFORM BOOL OPTIONAL DEFAULTTRUE AFFECTS SHAPE OF TRANSFORM OUTPUT ONLY WHEN
VOTING'SOFT' IF VOTING'SOFT' AND FLATTENTRANSFORMTRUE TRANSFORM METHOD RETURNS MA
TRIX WITH SHAPE NSAMPLES NCLASSIFIERS NCLASSES IF FLATTENTRANSFORMFALSE IT RETURNS
NCLASSIFIERS NSAMPLES NCLASSES
ATTRIBUTES
ESTIMATORS LIST OF CLASSIFIERS THE COLLECTION OF FITTED SUBESTIMATORS AS DEFINED IN
ESTIMATORS THAT ARE NOT NONE
NAMEDESTIMATORS BUNCH OBJECT A DICTIONARY WITH ATTRIBUTE ACCESS ATTRIBUTE TO ACCESS ANY
FITTED SUBESTIMATORS BY NAME
NEW IN VERSION 020
CLASSES ARRAYLIKE SHAPE NPREDICTIONS THE CLASSES LABELS
SEE ALSO
VOTINGREGRESSOR PREDICTION VOTING REGRESSOR

EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
 FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
 FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTCLASSIFIER VOTINGCLASSIFIER
CLF1  LOGISTICREGRESSIONSOLVERLBFGS MULTICLASSMULTINOMIAL
 RANDOMSTATE1
CLF2  RANDOMFORESTCLASSIFIERNESTIMATORS50 RANDOMSTATE1
CLF3  GAUSSIANNB
X  NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
Y  NPARRAY1 1 1 2 2 2
ECLF1  VOTINGCLASSIFIERESTIMATORS
 LR CLF1 RF CLF2 GNB CLF3 VOTINGHARD
ECLF1  ECLF1FITX Y
PRINTECLF1PREDICTX
1 1 1 2 2 2
NPARRAYEQUALECLF1NAMEDESTIMATORSLRPREDICTX
 ECLF1NAMEDESTIMATORSLRPREDICTX
TRUE
ECLF2  VOTINGCLASSIFIERESTIMATORS
 LR CLF1 RF CLF2 GNB CLF3
 VOTINGSOFT
ECLF2  ECLF2FITX Y
PRINTECLF2PREDICTX
1 1 1 2 2 2
ECLF3  VOTINGCLASSIFIERESTIMATORS
 LR CLF1 RF CLF2 GNB CLF3
 VOTINGSOFT WEIGHTS211
 FLATTENTRANSFORM TRUE
ECLF3  ECLF3FITX Y
PRINTECLF3PREDICTX
1 1 1 2 2 2
PRINTECLF3TRANSFORMXSHAPE
6 6
```
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE ESTIMATORS
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET THE PARAMETERS OF THE ENSEMBLE ESTIMATOR
PREDICT SELF X PREDICT CLASS LABELS FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SETTING THE PARAMETERS FOR THE ENSEMBLE ESTIMATOR
TRANSFORM SELF X RETURN CLASS LABELS OR PROBABILITIES FOR X FOR EACH ESTI
MATOR
INIT SELFESTIMATORS VOTING’HARD’ WEIGHTSNONE NJOBSNONE FLATTENTRANSFORMTRUE
FITSELFXYSAMPLEWEIGHTNONE
FIT THE ESTIMATORS
PARAMETERS

XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED NOTE THAT THIS IS SUPPORTED ONLY IF ALL UNDERLYING ESTIMATORS
SUPPORT SAMPLE WEIGHTS
RETURNS
SELF OBJECT
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET THE PARAMETERS OF THE ENSEMBLE ESTIMATOR
PARAMETERS
DEEP BOOL SETTING IT TO TRUE GETS THE VARIOUS ESTIMATORS AND THE PARAMETERS OF THE ESTIMATORS
AS WELL
PREDICTSELFX
PREDICT CLASS LABELS FOR X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
MAJ ARRAYLIKE SHAPE NSAMPLES PREDICTED CLASS LABELS
PREDICTPROBA
COMPUTE PROBABILITIES OF POSSIBLE OUTCOMES FOR SAMPLES IN X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
AVG ARRAYLIKE SHAPE NSAMPLES NCLASSES WEIGHTED AVERAGE PROBABILITY FOR EACH CLASS
PER SAMPLE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES

YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SETTING THE PARAMETERS FOR THE ENSEMBLE ESTIMATOR
VALID PARAMETER KEYS CAN BE LISTED WITH GETPARAMS
PARAMETERS
PARAMS KEYWORD ARGUMENTS SPECIFIC PARAMETERS USING EG
SETPARAMSPARAMETERNAMENEWVALUE IN ADDITION TO SETTING THE PARAMETERS OF
THE ENSEMBLE ESTIMATOR THE INDIVIDUAL ESTIMATORS OF THE ENSEMBLE ESTIMATOR CAN ALSO BE
SET OR REPLACED BY SETTING THEM TO NONE
EXAMPLES
 IN THIS EXAMPLE THE RANDOMFORESTCLASSIFIER IS REMOVED CLF1 LOGISTICREGRESSION CLF2 RANDOM
FORESTCLASSIFIER ECLF V OTINGCLASSIFIERESTIMATORS‘LR’ CLF1 ‘RF’ CLF2 ECLFSETPARAMSRFNONE
TRANSFORM SELFX
RETURN CLASS LABELS OR PROBABILITIES FOR X FOR EACH ESTIMATOR
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
RETURNS
PROBABILITIESORLABELS
IFVOTINGSOFT ANDFLATTENTRANSFORMTRUE RETURNS ARRAYLIKE OF SHAPE
NCLASSIFIERS NSAMPLES NCLASSES BEING CLASS PROBABILITIES CALCULATED BY EACH CLAS
SIFIER
IFVOTINGSOFT AND FLATTENTRANSFORMFALSE ARRAYLIKE OF SHAPE
NCLASSIFIERS NSAMPLES NCLASSES
IFVOTINGHARD ARRAYLIKE OF SHAPE NSAMPLES NCLASSIFIERS BEING CLASS LABELS
PREDICTED BY EACH CLASSIFIER
EXAMPLES USING SKLEARNENSEMBLEVOTINGCLASSIFIER
•PLOT THE DECISION BOUNDARIES OF A VOTINGCLASSIFIER
•PLOT CLASS PROBABILITIES CALCULATED BY THE VOTINGCLASSIFIER
6128SKLEARNENSEMBLE VOTINGREGRESSOR
CLASSSKLEARNENSEMBLE VOTINGREGRESSOR ESTIMATORS WEIGHTSNONE NJOBSNONE
PREDICTION VOTING REGRESSOR FOR UNFITTED ESTIMATORS
NEW IN VERSION 021
612SKLEARNENSEMBLE ENSEMBLE METHODS 1719

A VOTING REGRESSOR IS AN ENSEMBLE METAESTIMATOR THAT FITS BASE REGRESSORS EACH ON THE WHOLE DATASET IT THEN AVERAGES THE INDIVIDUAL PREDICTIONS TO FORM A FINAL PREDICTION
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATORS LIST OF STRING ESTIMATOR TUPLES INVOKING THE FIT METHOD ON THE VOTINGREGRESSOR WILL FIT CLONES OF THOSE ORIGINAL ESTIMATORS THAT WILL BE STORED IN THE CLASS ATTRIBUTE SELFESTIMATORS AN ESTIMATOR CAN BE SET TO NONE ORDROP USINGSETPARAMS
WEIGHTS ARRAYLIKE SHAPE NREGRESSORS OPTIONAL DEFAULT‘NONE‘ SEQUENCE OF WEIGHTS FLOAT ORINT TO WEIGHT THE OCCURRENCES OF PREDICTED VALUES BEFORE AVERAGING USES UNIFORM WEIGHTS IF NONE
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR FIT NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
ATTRIBUTES
ESTIMATORS LIST OF REGRESSORS THE COLLECTION OF FITTED SUBESTIMATORS AS DEFINED IN ESTIMATORS THAT ARE NOT NONE
NAMEDESTIMATORS BUNCH OBJECT A DICTIONARY WITH ATTRIBUTE ACCESS ATTRIBUTE TO ACCESS ANY FITTED SUBESTIMATORS BY NAME
SEE ALSO
VOTINGCLASSIFIER SOFT V OTINGMAJORITY RULE CLASSIFIER
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION
 FROM SKLEARNENSEMBLE IMPORT RANDOMFORESTREGRESSOR
 FROM SKLEARNENSEMBLE IMPORT VOTINGREGRESSOR
R1  LINEARREGRESSION
R2  RANDOMFORESTREGRESSORNESTIMATORS10 RANDOMSTATE1
X  NPARRAY1 1 2 4 3 9 4 16 5 25 6 36
Y  NPARRAY2 6 12 20 30 42
ER  VOTINGREGRESSORLR R1 RF R2
PRINTERFITX YPREDICTX
 33 57 118 197 28 403
```
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE ESTIMATORS
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET THE PARAMETERS OF THE ENSEMBLE ESTIMATOR
PREDICT SELF X PREDICT REGRESSION TARGET FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE DICTION
SETPARAMS SELF PARAMS SETTING THE PARAMETERS FOR THE ENSEMBLE ESTIMATOR
CONTINUED ON NEXT PAGE

TABLE 679 – CONTINUED FROM PREVIOUS PAGE
TRANSFORM SELF X RETURN PREDICTIONS FOR X FOR EACH ESTIMATOR
INIT SELFESTIMATORS WEIGHTSNONE NJOBSNONE
FITSELFXYSAMPLEWEIGHTNONE
FIT THE ESTIMATORS
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED NOTE THAT THIS IS SUPPORTED ONLY IF ALL UNDERLYING ESTIMATORS
SUPPORT SAMPLE WEIGHTS
RETURNS
SELF OBJECT
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET THE PARAMETERS OF THE ENSEMBLE ESTIMATOR
PARAMETERS
DEEP BOOL SETTING IT TO TRUE GETS THE VARIOUS ESTIMATORS AND THE PARAMETERS OF THE ESTIMATORS
AS WELL
PREDICTSELFX
PREDICT REGRESSION TARGET FOR X
THE PREDICTED REGRESSION TARGET OF AN INPUT SAMPLE IS COMPUTED AS THE MEAN PREDICTED REGRESSION TARGETS OF
THE ESTIMATORS IN THE ENSEMBLE
PARAMETERS
XARRAYLIKE SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
YARRAY OF SHAPE NSAMPLES THE PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE

IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SETTING THE PARAMETERS FOR THE ENSEMBLE ESTIMATOR
VALID PARAMETER KEYS CAN BE LISTED WITH GETPARAMS
PARAMETERS
PARAMS KEYWORD ARGUMENTS SPECIFIC PARAMETERS USING EG
SETPARAMSPARAMETERNAMENEWVALUE IN ADDITION TO SETTING THE PARAMETERS OF
THE ENSEMBLE ESTIMATOR THE INDIVIDUAL ESTIMATORS OF THE ENSEMBLE ESTIMATOR CAN ALSO BE
SET OR REPLACED BY SETTING THEM TO NONE
EXAMPLES
 IN THIS EXAMPLE THE RANDOMFORESTCLASSIFIER IS REMOVED CLF1 LOGISTICREGRESSION CLF2 RANDOM
FORESTCLASSIFIER ECLF V OTINGCLASSIFIERESTIMATORS‘LR’ CLF1 ‘RF’ CLF2 ECLFSETPARAMSRFNONE
TRANSFORM SELFX
RETURN PREDICTIONS FOR X FOR EACH ESTIMATOR
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
PREDICTIONS ARRAYLIKE OF SHAPE NSAMPLES NCLASSIFIERS BEING VALUES PREDICTED BY EACH
REGRESSOR
EXAMPLES USING SKLEARNENSEMBLEVOTINGREGRESSOR
•PLOT INDIVIDUAL AND VOTING REGRESSION PREDICTIONS

SCIKITLEARN USER GUIDE RELEASE 0213
6129SKLEARNENSEMBLE HISTGRADIENTBOOSTINGREGRESSOR
CLASSSKLEARNENSEMBLE HISTGRADIENTBOOSTINGREGRESSOR LOSS'LEASTSQUARES' LEARN
INGRATE01 MAXITER100
MAXLEAFNODES31
MAXDEPTHNONE
MINSAMPLESLEAF20
L2REGULARIZATION00
MAXBINS256 SCORINGNONE
VALIDATIONFRACTION01
NITERNOCHANGENONE
TOL1E07 VERBOSE0 RAN
DOMSTATENONE
HISTOGRAMBASED GRADIENT BOOSTING REGRESSION TREE
THIS ESTIMATOR IS MUCH FASTER THAN GRADIENTBOOSTINGREGRESSOR FOR BIG DATASETS NSAMPLES 10 000
THE INPUT DATA XIS PREBINNED INTO INTEGERVALUED BINS WHICH CONSIDERABLY REDUCES THE NUMBER OF SPLITTING
POINTS TO CONSIDER AND ALLOWS THE ALGORITHM TO LEVERAGE INTEGERBASED DATA STRUCTURES FOR SMALL SAMPLE SIZES
GRADIENTBOOSTINGREGRESSOR MIGHT BE PREFERRED SINCE BINNING MAY LEAD TO SPLIT POINTS THAT ARE TOO
APPROXIMATE IN THIS SETTING
THIS IMPLEMENTATION IS INSPIRED BY LIGHTGBM
NOTE THIS ESTIMATOR IS STILL EXPERIMENTAL FOR NOW THE PREDICTIONS AND THE API MIGHT CHANGE WITHOUT ANY
DEPRECATION CYCLE TO USE IT YOU NEED TO EXPLICITLY IMPORT ENABLEHISTGRADIENTBOOSTING
EXPLICITLY REQUIRE THIS EXPERIMENTAL FEATURE
FROM SKLEARNEXPERIMENTAL IMPORT ENABLEHISTGRADIENTBOOSTING NOQA
NOW YOU CAN IMPORT NORMALLY FROM ENSEMBLE
FROM SKLEARNENSEMBLE IMPORT HISTGRADIENTBOOSTINGCLASSIFIER
PARAMETERS
LOSS 'LEASTSQUARES' OPTIONAL DEFAULT'LEASTSQUARES' THE LOSS FUNCTION TO USE IN THE BOOST
ING PROCESS NOTE THAT THE "LEAST SQUARES" LOSS ACTUALLY IMPLEMENTS AN "HALF LEAST SQUARES
LOSS" TO SIMPLIFY THE COMPUTATION OF THE GRADIENT
LEARNINGRATE FLOAT OPTIONAL DEFAULT01 THE LEARNING RATE ALSO KNOWN AS SHRINKAGE THIS
IS USED AS A MULTIPLICATIVE FACTOR FOR THE LEAVES VALUES USE 1FOR NO SHRINKAGE
MAXITER INT OPTIONAL DEFAULT100 THE MAXIMUM NUMBER OF ITERATIONS OF THE BOOSTING PRO
CESS IE THE MAXIMUM NUMBER OF TREES
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULT31 THE MAXIMUM NUMBER OF LEAVES FOR EACH
TREE MUST BE STRICTLY GREATER THAN 1 IF NONE THERE IS NO MAXIMUM LIMIT
MAXDEPTH INT OR NONE OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF EACH TREE THE
DEPTH OF A TREE IS THE NUMBER OF NODES TO GO FROM THE ROOT TO THE DEEPEST LEAF MUST BE
STRICTLY GREATER THAN 1 DEPTH ISN'T CONSTRAINED BY DEFAULT
MINSAMPLESLEAF INT OPTIONAL DEFAULT20 THE MINIMUM NUMBER OF SAMPLES PER LEAF FOR
SMALL DATASETS WITH LESS THAN A FEW HUNDRED SAMPLES IT IS RECOMMENDED TO LOWER THIS VALUE
SINCE ONLY VERY SHALLOW TREES WOULD BE BUILT
L2REGULARIZATION FLOAT OPTIONAL DEFAULT0 THE L2 REGULARIZATION PARAMETER USE 0FOR NO
REGULARIZATION DEFAULT

MAXBINS INT OPTIONAL DEFAULT256 THE MAXIMUM NUMBER OF BINS TO USE BEFORE TRAINING
EACH FEATURE OF THE INPUT ARRAY XIS BINNED INTO AT MOST MAXBINS BINS WHICH ALLOWS FOR A
MUCH FASTER TRAINING STAGE FEATURES WITH A SMALL NUMBER OF UNIQUE VALUES MAY USE LESS THAN
MAXBINS BINS MUST BE NO LARGER THAN 256
SCORING STR OR CALLABLE OR NONE OPTIONAL DEFAULTNONE SCORING PARAMETER TO USE FOR EARLY
STOPPING IT CAN BE A SINGLE STRING SEE THE SCORING PARAMETER DEFINING MODEL EVALUATION
RULES OR A CALLABLE SEE DEFINING YOUR SCORING STRATEGY FROM METRIC FUNCTIONS IF NONE THE
ESTIMATOR’S DEFAULT SCORER IS USED IF SCORINGLOSS EARLY STOPPING IS CHECKED WRT
THE LOSS VALUE ONLY USED IF NITERNOCHANGE IS NOT NONE
VALIDATIONFRACTION INT OR FLOAT OR NONE OPTIONAL DEFAULT01 PROPORTION OR ABSOLUTE SIZE
OF TRAINING DATA TO SET ASIDE AS VALIDATION DATA FOR EARLY STOPPING IF NONE EARLY STOPPING IS
DONE ON THE TRAINING DATA ONLY USED IF NITERNOCHANGE IS NOT NONE
NITERNOCHANGE INT OR NONE OPTIONAL DEFAULTNONE USED TO DETERMINE WHEN TO “EARLY
STOP” THE FITTING PROCESS IS STOPPED WHEN NONE OF THE LAST NITERNOCHANGE SCORES
ARE BETTER THAN THE ‘‘NITERNOCHANGE 1‘‘THTOLAST ONE UP TO SOME TOLERANCE IF NONE OR
0 NO EARLYSTOPPING IS DONE
TOLFLOAT OR NONE OPTIONAL DEFAULT1E7 THE ABSOLUTE TOLERANCE TO USE WHEN COMPARING
SCORES DURING EARLY STOPPING THE HIGHER THE TOLERANCE THE MORE LIKELY WE ARE TO EARLY
STOP HIGHER TOLERANCE MEANS THAT IT WILL BE HARDER FOR SUBSEQUENT ITERATIONS TO BE CONSIDERED
AN IMPROVEMENT UPON THE REFERENCE SCORE
VERBOSE INT OPTIONAL DEFAULT0 THE VERBOSITY LEVEL IF NOT ZERO PRINT SOME INFORMATION
ABOUT THE FITTING PROCESS
RANDOMSTATE INT NPRANDOMRANDOMSTATEINSTANCE OR NONE OPTIONAL DEFAULTNONE
PSEUDORANDOM NUMBER GENERATOR TO CONTROL THE SUBSAMPLING IN THE BINNING PROCESS AND
THE TRAINVALIDATION DATA SPLIT IF EARLY STOPPING IS ENABLED SEE RANDOMSTATE
ATTRIBUTES
NITER INT THE NUMBER OF ITERATIONS AS SELECTED BY EARLY STOPPING IF NITERNOCHANGE IS NOT
NONE OTHERWISE IT CORRESPONDS TO MAXITER
NTREESPERITERATION INT THE NUMBER OF TREE THAT ARE BUILT AT EACH ITERATION FOR REGRESSORS
THIS IS ALWAYS 1
TRAINSCORE NDARRAY SHAPE MAXITER 1 THE SCORES AT EACH ITERATION ON THE TRAINING DATA
THE FIRST ENTRY IS THE SCORE OF THE ENSEMBLE BEFORE THE FIRST ITERATION SCORES ARE COMPUTED
ACCORDING TO THE SCORING PARAMETER IF SCORING IS NOT ‘LOSS’ SCORES ARE COMPUTED ON A
SUBSET OF AT MOST 10 000 SAMPLES EMPTY IF NO EARLY STOPPING
VALIDATIONSCORE NDARRAY SHAPE MAXITER 1 THE SCORES AT EACH ITERATION ON THE HELD
OUT VALIDATION DATA THE FIRST ENTRY IS THE SCORE OF THE ENSEMBLE BEFORE THE FIRST ITERATION
SCORES ARE COMPUTED ACCORDING TO THE SCORING PARAMETER EMPTY IF NO EARLY STOPPING OR
IFVALIDATIONFRACTION IS NONE
EXAMPLES
```
 TO USE THIS EXPERIMENTAL FEATURE WE NEED TO EXPLICITLY ASK FOR IT
 FROM SKLEARNEXPERIMENTAL IMPORT ENABLEHISTGRADIENTBOOSTING  NOQA
 FROM SKLEARNENSEMBLE IMPORT HISTGRADIENTBOOSTINGREGRESSOR
 FROM SKLEARNDATASETS IMPORT LOADBOSTON
X Y  LOADBOSTONRETURNXY TRUE
EST  HISTGRADIENTBOOSTINGREGRESSORFITX Y
```

SCIKITLEARN USER GUIDE RELEASE 0213
ESTSCOREX Y
098
METHODS
FITSELF X Y FIT THE GRADIENT BOOSTING MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT VALUES FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFLOSS'LEASTSQUARES' LEARNINGRATE01 MAXITER100 MAXLEAFNODES31
MAXDEPTHNONE MINSAMPLESLEAF20 L2REGULARIZATION00 MAXBINS256 SCOR
INGNONE VALIDATIONFRACTION01 NITERNOCHANGENONE TOL1E07 VERBOSE0
RANDOMSTATENONE
FITSELFXY
FIT THE GRADIENT BOOSTING MODEL
PARAMETERS
XARRAYLIKE SHAPENSAMPLES NFEATURES THE INPUT SAMPLES
YARRAYLIKE SHAPENSAMPLES TARGET VALUES
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT VALUES FOR X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
YNDARRAY SHAPE NSAMPLES THE PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
612SKLEARNENSEMBLE ENSEMBLE METHODS 1725

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PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
61210SKLEARNENSEMBLE HISTGRADIENTBOOSTINGCLASSIFIER
CLASSSKLEARNENSEMBLE HISTGRADIENTBOOSTINGCLASSIFIER LOSS’AUTO’ LEARN
INGRATE01 MAXITER100
MAXLEAFNODES31
MAXDEPTHNONE
MINSAMPLESLEAF20
L2REGULARIZATION00
MAXBINS256 SCORINGNONE
VALIDATIONFRACTION01
NITERNOCHANGENONE
TOL1E07 VERBOSE0 RAN
DOMSTATENONE
HISTOGRAMBASED GRADIENT BOOSTING CLASSIFICATION TREE
THIS ESTIMATOR IS MUCH FASTER THAN GRADIENTBOOSTINGCLASSIFIER FOR BIG DATASETS NSAMPLES 10
000 THE INPUT DATA XIS PREBINNED INTO INTEGERVALUED BINS WHICH CONSIDERABLY REDUCES THE NUMBER OF SPLITTING
POINTS TO CONSIDER AND ALLOWS THE ALGORITHM TO LEVERAGE INTEGERBASED DATA STRUCTURES FOR SMALL SAMPLE SIZES
GRADIENTBOOSTINGCLASSIFIER MIGHT BE PREFERRED SINCE BINNING MAY LEAD TO SPLIT POINTS THAT ARE TOO
APPROXIMATE IN THIS SETTING
THIS IMPLEMENTATION IS INSPIRED BY LIGHTGBM

NOTE THIS ESTIMATOR IS STILL EXPERIMENTAL FOR NOW THE PREDICTIONS AND THE API MIGHT CHANGE WITHOUT ANY DEPRECATION CYCLE TO USE IT YOU NEED TO EXPLICITLY IMPORT ENABLEHISTGRADIENTBOOSTING

```
EXPLICITLY REQUIRE THIS EXPERIMENTAL FEATURE
FROM SKLEARNEXPERIMENTAL IMPORT ENABLEHISTGRADIENTBOOSTING  NOQA
NOW YOU CAN IMPORT NORMALLY FROM ENSEMBLE
FROM SKLEARNENSEMBLE IMPORT HISTGRADIENTBOOSTINGCLASSIFIER
```

PARAMETERS

LOSS ‘AUTO’ ‘BINARYCROSSENTROPY’ ‘CATEGORICALCROSSENTROPY’ OPTIONAL DEFAULT’AUTO’
THE LOSS FUNCTION TO USE IN THE BOOSTING PROCESS ‘BINARYCROSSENTROPY’ ALSO KNOWN AS LOGISTIC LOSS IS USED FOR BINARY CLASSIFICATION AND GENERALIZES TO ‘CATEGORICALCROSSENTROPY’ FOR MULTICLASS CLASSIFICATION ‘AUTO’ WILL AUTOMATICALLY CHOOSE EITHER LOSS DEPENDING ON THE NATURE OF THE PROBLEM

LEARNINGRATE FLOAT OPTIONAL DEFAULT01 THE LEARNING RATE ALSO KNOWN AS SHRINKAGE THIS IS USED AS A MULTIPLICATIVE FACTOR FOR THE LEAVES VALUES USE 1FOR NO SHRINKAGE

MAXITER INT OPTIONAL DEFAULT100 THE MAXIMUM NUMBER OF ITERATIONS OF THE BOOSTING PRO CESS IE THE MAXIMUM NUMBER OF TREES FOR BINARY CLASSIFICATION FOR MULTICLASS CLASSIFICA TIONNCLASSES TREES PER ITERATION ARE BUILT

MAXLEAFNODES INT OR NONE OPTIONAL DEFAULT31 THE MAXIMUM NUMBER OF LEAVES FOR EACH TREE MUST BE STRICTLY GREATER THAN 1 IF NONE THERE IS NO MAXIMUM LIMIT

MAXDEPTH INT OR NONE OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF EACH TREE THE DEPTH OF A TREE IS THE NUMBER OF NODES TO GO FROM THE ROOT TO THE DEEPEST LEAF MUST BE STRICTLY GREATER THAN 1 DEPTH ISN’T CONSTRAINED BY DEFAULT

MINSAMPLESLEAF INT OPTIONAL DEFAULT20 THE MINIMUM NUMBER OF SAMPLES PER LEAF FOR SMALL DATASETS WITH LESS THAN A FEW HUNDRED SAMPLES IT IS RECOMMENDED TO LOWER THIS VALUE SINCE ONLY VERY SHALLOW TREES WOULD BE BUILT

L2REGULARIZATION FLOAT OPTIONAL DEFAULT0 THE L2 REGULARIZATION PARAMETER USE 0 FOR NO REGULARIZATION

MAXBINS INT OPTIONAL DEFAULT256 THE MAXIMUM NUMBER OF BINS TO USE BEFORE TRAINING EACH FEATURE OF THE INPUT ARRAY XIS BINNED INTO AT MOST MAXBINS BINS WHICH ALLOWS FOR A MUCH FASTER TRAINING STAGE FEATURES WITH A SMALL NUMBER OF UNIQUE VALUES MAY USE LESS THAN MAXBINS BINS MUST BE NO LARGER THAN 256

SCORING STR OR CALLABLE OR NONE OPTIONAL DEFAULTNONE SCORING PARAMETER TO USE FOR EARLY STOPPING IT CAN BE A SINGLE STRING SEE THE SCORING PARAMETER DEFINING MODEL EVALUATION RULES OR A CALLABLE SEE DEFINING YOUR SCORING STRATEGY FROM METRIC FUNCTIONS IF NONE THE ESTIMATOR’S DEFAULT SCORER IS USED IF SCORINGLOSS EARLY STOPPING IS CHECKED WRT THE LOSS VALUE ONLY USED IF NITERNOCHANGE IS NOT NONE

VALIDATIONFRACTION INT OR FLOAT OR NONE OPTIONAL DEFAULT01 PROPORTION OR ABSOLUTE SIZE OF TRAINING DATA TO SET ASIDE AS VALIDATION DATA FOR EARLY STOPPING IF NONE EARLY STOPPING IS DONE ON THE TRAINING DATA

NITERNOCHANGE INT OR NONE OPTIONAL DEFAULTNONE USED TO DETERMINE WHEN TO “EARLY STOP” THE FITTING PROCESS IS STOPPED WHEN NONE OF THE LAST NITERNOCHANGE SCORES ARE BETTER THAN THE ‘‘NITERNOCHANGE 1‘‘THTOLAST ONE UP TO SOME TOLERANCE IF NONE OR 0 NO EARLYSTOPPING IS DONE

TOLFLOAT OR NONE OPTIONAL DEFAULT1E7 THE ABSOLUTE TOLERANCE TO USE WHEN COMPARING SCORES THE HIGHER THE TOLERANCE THE MORE LIKELY WE ARE TO EARLY STOP HIGHER TOLERANCE MEANS THAT IT WILL BE HARDER FOR SUBSEQUENT ITERATIONS TO BE CONSIDERED AN IMPROVEMENT UPON THE REFERENCE SCORE
VERBOSE INT OPTIONAL DEFAULT0 THE VERBOSITY LEVEL IF NOT ZERO PRINT SOME INFORMATION ABOUT THE FITTING PROCESS
RANDOMSTATE INT NPRANDOMRANDOMSTATEINSTANCE OR NONE OPTIONAL DEFAULTNONE PSEUDORANDOM NUMBER GENERATOR TO CONTROL THE SUBSAMPLING IN THE BINNING PROCESS AND THE TRAINVALIDATION DATA SPLIT IF EARLY STOPPING IS ENABLED SEE RANDOMSTATE
ATTRIBUTES
NITER INT THE NUMBER OF ESTIMATORS AS SELECTED BY EARLY STOPPING IF NITERNOCHANGE IS NOT NONE OTHERWISE IT CORRESPONDS TO MAXITER
NTREESPERITERATION INT THE NUMBER OF TREE THAT ARE BUILT AT EACH ITERATION THIS IS EQUAL TO 1 FOR BINARY CLASSIFICATION AND TO NCLASSES FOR MULTICLASS CLASSIFICATION
TRAINSCORE NDARRAY SHAPE MAXITER 1 THE SCORES AT EACH ITERATION ON THE TRAINING DATA THE FIRST ENTRY IS THE SCORE OF THE ENSEMBLE BEFORE THE FIRST ITERATION SCORES ARE COMPUTED ACCORDING TO THE SCORING PARAMETER IF SCORING IS NOT ‘LOSS’ SCORES ARE COMPUTED ON A SUBSET OF AT MOST 10 000 SAMPLES EMPTY IF NO EARLY STOPPING
VALIDATIONSCORE NDARRAY SHAPE MAXITER 1 THE SCORES AT EACH ITERATION ON THE HELD OUT VALIDATION DATA THE FIRST ENTRY IS THE SCORE OF THE ENSEMBLE BEFORE THE FIRST ITERATION SCORES ARE COMPUTED ACCORDING TO THE SCORING PARAMETER EMPTY IF NO EARLY STOPPING OR IFVALIDATIONFRACTION IS NONE
EXAMPLES
```
 TO USE THIS EXPERIMENTAL FEATURE WE NEED TO EXPLICITLY ASK FOR IT
 FROM SKLEARNEXPERIMENTAL IMPORT ENABLEHISTGRADIENTBOOSTING  NOQA
 FROM SKLEARNENSEMBLE IMPORT HISTGRADIENTBOOSTINGREGRESSOR
 FROM SKLEARNDATASETS IMPORT LOADIRIS
X Y  LOADIRISRETURNXY TRUE
CLF  HISTGRADIENTBOOSTINGCLASSIFIERFITX Y
CLFSCOREX Y
10
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METHODS
DECISIONFUNCTION SELF X COMPUTE THE DECISION FUNCTION OF X
FITSELF X Y FIT THE GRADIENT BOOSTING MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASSES FOR X
PREDICTPROBA SELF X PREDICT CLASS PROBABILITIES FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

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MAXDEPTHNONE MINSAMPLESLEAF20 L2REGULARIZATION00 MAXBINS256 SCOR
INGNONE VALIDATIONFRACTION01 NITERNOCHANGENONE TOL1E07 VERBOSE0
RANDOMSTATENONE
DECISIONFUNCTION SELFX
COMPUTE THE DECISION FUNCTION OF X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
DECISION NDARRAY SHAPE NSAMPLES OR NSAMPLES NTREESPERITERATION THE RAW PRE
DICTED VALUES IE THE SUM OF THE TREES LEAVES FOR EACH SAMPLE NTREESPERITERATION IS
EQUAL TO THE NUMBER OF CLASSES IN MULTICLASS CLASSIFICATION
FITSELFXY
FIT THE GRADIENT BOOSTING MODEL
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XARRAYLIKE SHAPENSAMPLES NFEATURES THE INPUT SAMPLES
YARRAYLIKE SHAPENSAMPLES TARGET VALUES
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
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PREDICT CLASSES FOR X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
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PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
PNDARRAY SHAPE NSAMPLES NCLASSES THE CLASS PROBABILITIES OF THE INPUT SAMPLES
612SKLEARNENSEMBLE ENSEMBLE METHODS 1729

SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
613SKLEARNEXCEPTIONS EXCEPTIONS AND WARNINGS
THESKLEARNEXCEPTIONS MODULE INCLUDES ALL CUSTOM WARNINGS AND ERROR CLASSES USED ACROSS SCIKITLEARN
EXCEPTIONSCHANGEDBEHAVIORWARNING WARNING CLASS USED TO NOTIFY THE USER OF ANY CHANGE IN THE
BEHAVIOR
EXCEPTIONSCONVERGENCEWARNING CUSTOM WARNING TO CAPTURE CONVERGENCE PROBLEMS
EXCEPTIONSDATACONVERSIONWARNING WARNING USED TO NOTIFY IMPLICIT DATA CONVERSIONS HAPPENING
IN THE CODE
EXCEPTIONSDATADIMENSIONALITYWARNING CUSTOM WARNING TO NOTIFY POTENTIAL ISSUES WITH DATA DIMEN
SIONALITY
EXCEPTIONSEFFICIENCYWARNING WARNING USED TO NOTIFY THE USER OF INEFFICIENT COMPUTATION
EXCEPTIONSFITFAILEDWARNING WARNING CLASS USED IF THERE IS AN ERROR WHILE FITTING THE ES
TIMATOR
EXCEPTIONSNOTFITTEDERROR EXCEPTION CLASS TO RAISE IF ESTIMATOR IS USED BEFORE FITTING
EXCEPTIONSNONBLASDOTWARNING WARNING USED WHEN THE DOT OPERATION DOES NOT USE BLAS
EXCEPTIONSUNDEFINEDMETRICWARNING WARNING USED WHEN THE METRIC IS INVALID
6131SKLEARNEXCEPTIONS CHANGEDBEHAVIORWARNING
CLASSSKLEARNEXCEPTIONS CHANGEDBEHAVIORWARNING
WARNING CLASS USED TO NOTIFY THE USER OF ANY CHANGE IN THE BEHAVIOR
CHANGED IN VERSION 018 MOVED FROM SKLEARNBASE
ATTRIBUTES

ARGS
METHODS
WITHTRACEBACK EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK
TO TB AND RETURN SELF
WITHTRACEBACK
EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK TO TB AND RETURN SELF
6132SKLEARNEXCEPTIONS CONVERGENCEWARNING
CLASSSKLEARNEXCEPTIONS CONVERGENCEWARNING
CUSTOM WARNING TO CAPTURE CONVERGENCE PROBLEMS
CHANGED IN VERSION 018 MOVED FROM SKLEARNUTILS
ATTRIBUTES
ARGS
METHODS
WITHTRACEBACK EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK
TO TB AND RETURN SELF
WITHTRACEBACK
EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK TO TB AND RETURN SELF
EXAMPLES USING SKLEARNEXCEPTIONSCONVERGENCEWARNING
•MULTICLASS SPARSE LOGISITIC REGRESSION ON NEWGROUPS20
•EARLY STOPPING OF STOCHASTIC GRADIENT DESCENT
•COMPARE STOCHASTIC LEARNING STRATEGIES FOR MLPCLASSIFIER
•FEATURE DISCRETIZATION
6133SKLEARNEXCEPTIONS DATACONVERSIONWARNING
CLASSSKLEARNEXCEPTIONS DATACONVERSIONWARNING
WARNING USED TO NOTIFY IMPLICIT DATA CONVERSIONS HAPPENING IN THE CODE
THIS WARNING OCCURS WHEN SOME INPUT DATA NEEDS TO BE CONVERTED OR INTERPRETED IN A WAY THAT MAY NOT MATCH THE
USER’S EXPECTATIONS
FOR EXAMPLE THIS WARNING MAY OCCUR WHEN THE USER
• PASSES AN INTEGER ARRAY TO A FUNCTION WHICH EXPECTS FLOAT INPUT AND WILL CONVERT THE INPUT

• REQUESTS A NONCOPYING OPERATION BUT A COPY IS REQUIRED TO MEET THE IMPLEMENTATION'S DATATYPE EX
PECTATIONS
• PASSES AN INPUT WHOSE SHAPE CAN BE INTERPRETED AMBIGUOUSLY
CHANGED IN VERSION 018 MOVED FROM SKLEARNUTILSVALIDATION
ATTRIBUTES
ARGS
METHODS
WITHTRACEBACK EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK
TO TB AND RETURN SELF
WITHTRACEBACK
EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK TO TB AND RETURN SELF
6134SKLEARNEXCEPTIONS DATADIMENSIONALITYWARNING
CLASSSKLEARNEXCEPTIONS DATADIMENSIONALITYWARNING
CUSTOM WARNING TO NOTIFY POTENTIAL ISSUES WITH DATA DIMENSIONALITY
FOR EXAMPLE IN RANDOM PROJECTION THIS WARNING IS RAISED WHEN THE NUMBER OF COMPONENTS WHICH QUANTIFIES
THE DIMENSIONALITY OF THE TARGET PROJECTION SPACE IS HIGHER THAN THE NUMBER OF FEATURES WHICH QUANTIFIES THE
DIMENSIONALITY OF THE ORIGINAL SOURCE SPACE TO IMPLY THAT THE DIMENSIONALITY OF THE PROBLEM WILL NOT BE REDUCED
CHANGED IN VERSION 018 MOVED FROM SKLEARNUTILS
ATTRIBUTES
ARGS
METHODS
WITHTRACEBACK EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK
TO TB AND RETURN SELF
WITHTRACEBACK
EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK TO TB AND RETURN SELF
6135SKLEARNEXCEPTIONS EFFICIENCYWARNING
CLASSSKLEARNEXCEPTIONS EFFICIENCYWARNING
WARNING USED TO NOTIFY THE USER OF INEFFICIENT COMPUTATION
THIS WARNING NOTIFIES THE USER THAT THE EFFICIENCY MAY NOT BE OPTIMAL DUE TO SOME REASON WHICH MAY BE INCLUDED
AS A PART OF THE WARNING MESSAGE THIS MAY BE SUBCLASSED INTO A MORE SPECIFIC WARNING CLASS
NEW IN VERSION 018
ATTRIBUTES

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ARGS
METHODS
WITHTRACEBACK EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK
TO TB AND RETURN SELF
WITHTRACEBACK
EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK TO TB AND RETURN SELF
6136SKLEARNEXCEPTIONS FITFAILEDWARNING
CLASSSKLEARNEXCEPTIONS FITFAILEDWARNING
WARNING CLASS USED IF THERE IS AN ERROR WHILE FITTING THE ESTIMATOR
THIS WARNING IS USED IN META ESTIMATORS GRIDSEARCHCV AND RANDOMIZEDSEARCHCV AND THE CROSSVALIDATION
HELPER FUNCTION CROSSVALSCORE TO WARN WHEN THERE IS AN ERROR WHILE FITTING THE ESTIMATOR
ATTRIBUTES
ARGS
EXAMPLES
 FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
 FROM SKLEARNSVM IMPORT LINEARSVC
 FROM SKLEARNEXCEPTIONS IMPORT FITFAILEDWARNING
 IMPORT WARNINGS
WARNINGSSIMPLEFILTERALWAYS FITFAILEDWARNING
GS GRIDSEARCHCVLINEARSVC C 1 2 ERRORSCORE0 CV2
X Y 1 2 3 4 5 6 7 8 0 0 1 1
 WITH WARNINGSCATCHWARNINGSRECORD TRUEASW
 TRY
 GSFITX Y THIS WILL RAISE A VALUEERROR SINCE C IS 0
 EXCEPT VALUEERROR
 PASS
 PRINTREPRW1MESSAGE

FITFAILEDWARNINGESTIMATOR FIT FAILED THE SCORE ON THIS TRAINTEST
PARTITION FOR THESE PARAMETERS WILL BE SET TO 0000000
DETAILS NVALUEERROR PENALTY TERM MUST BE POSITIVE GOT C2N
CHANGED IN VERSION 018 MOVED FROM SKLEARNCROSSVALIDATION
METHODS
WITHTRACEBACK EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK
TO TB AND RETURN SELF
613SKLEARNEXCEPTIONS EXCEPTIONS AND WARNINGS 1733

WITHTRACEBACK
EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK TO TB AND RETURN SELF
6137SKLEARNEXCEPTIONS NOTFITTEDERROR
CLASSSKLEARNEXCEPTIONS NOTFITTEDERROR
EXCEPTION CLASS TO RAISE IF ESTIMATOR IS USED BEFORE FITTING
THIS CLASS INHERITS FROM BOTH VALUEERROR AND ATTRIBUTEERROR TO HELP WITH EXCEPTION HANDLING AND BACKWARD COMPATIBILITY
ATTRIBUTES
ARGS
EXAMPLES
```
FROM SKLEARNSVM IMPORT LINEARSVC
FROM SKLEARNEXCEPTIONS IMPORT NOTFITTEDERROR
TRY
LINEARSVCPREDICT1 2 2 3 3 4
EXCEPT NOTFITTEDERROR ASE
PRINTREPRE

NOTFITTEDERRORTHIS LINEARSVC INSTANCE IS NOT FITTED YET
```
CHANGED IN VERSION 018 MOVED FROM SKLEARNUTILSVALIDATION
METHODS
WITHTRACEBACK EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK TO TB AND RETURN SELF
WITHTRACEBACK
EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK TO TB AND RETURN SELF
6138SKLEARNEXCEPTIONS NONBLASDOTWARNING
CLASSSKLEARNEXCEPTIONS NONBLASDOTWARNING
WARNING USED WHEN THE DOT OPERATION DOES NOT USE BLAS
THIS WARNING IS USED TO NOTIFY THE USER THAT BLAS WAS NOT USED FOR DOT OPERATION AND HENCE THE EFFICIENCY MAY BE AFFECTED
CHANGED IN VERSION 018 MOVED FROM SKLEARNUTILSVALIDATION EXTENDS EFFICIENCYWARNING
ATTRIBUTES
ARGS

METHODS
WITHTRACEBACK EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK
TO TB AND RETURN SELF
WITHTRACEBACK
EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK TO TB AND RETURN SELF
6139SKLEARNEXCEPTIONS UNDEFINEDMETRICWARNING
CLASSSKLEARNEXCEPTIONS UNDEFINEDMETRICWARNING
WARNING USED WHEN THE METRIC IS INVALID
CHANGED IN VERSION 018 MOVED FROM SKLEARNBASE
ATTRIBUTES
ARGS
METHODS
WITHTRACEBACK EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK
TO TB AND RETURN SELF
WITHTRACEBACK
EXCEPTIONWITHTRACEBACKTB – SET SELFTRACEBACK TO TB AND RETURN SELF
614SKLEARNEXPERIMENTAL EXPERIMENTAL
THESKLEARNEXPERIMENTAL MODULE PROVIDES IMPORTABLE MODULES THAT ENABLE THE USE OF EXPERIMENTAL FEATURES
OR ESTIMATORS
THE FEATURES AND ESTIMATORS THAT ARE EXPERIMENTAL AREN’T SUBJECT TO DEPRECATION CYCLES USE THEM AT YOUR OWN RISKS
EXPERIMENTALENABLEHISTGRADIENTBOOSTING ENABLES HISTOGRAMBASED GRADIENT BOOSTING ESTIMATORS
EXPERIMENTALENABLEITERATIVEIMPUTER ENABLES ITERATIVEIMPUTER
6141 SKLEARNEXPERIMENTALENABLEHISTGRADIENTBOOSTING
ENABLES HISTOGRAMBASED GRADIENT BOOSTING ESTIMATORS
THE API AND RESULTS OF THESE ESTIMATORS MIGHT CHANGE WITHOUT ANY DEPRECATION CYCLE
IMPORTING THIS FILE DYNAMICALLY SETS THE SKLEARNENSEMBLEHISTGRADIENTBOOSTINGCLASSIFIER AND
SKLEARNENSEMBLEHISTGRADIENTBOOSTINGREGRESSOR AS ATTRIBUTES OF THE ENSEMBLE MODULE
 EXPLICITLY REQUIRE THIS EXPERIMENTAL FEATURE
 FROM SKLEARNEXPERIMENTAL IMPORT ENABLEHISTGRADIENTBOOSTING NOQA
 NOW YOU CAN IMPORT NORMALLY FROM ENSEMBLE
614SKLEARNEXPERIMENTAL EXPERIMENTAL 1735

```
 FROM SKLEARNENSEMBLE IMPORT HISTGRADIENTBOOSTINGCLASSIFIER
 FROM SKLEARNENSEMBLE IMPORT HISTGRADIENTBOOSTINGREGRESSOR
```
THE NOQA COMMENT COMMENT CAN BE REMOVED IT JUST TELLS LINTERS LIKE FLAKE8 TO IGNORE THE IMPORT WHICH APPEARS AS UNUSED

6142 SKLEARNEXPERIMENTALENABLEITERATIVEIMPUTER

ENABLES ITERATIVEIMPUTER

THE API AND RESULTS OF THIS ESTIMATOR MIGHT CHANGE WITHOUT ANY DEPRECATION CYCLE

IMPORTING THIS FILE DYNAMICALLY SETS SKLEARNIMPUTEITERATIVEIMPUTER AS AN ATTRIBUTE OF THE IMPUTE MOD ULE

```
 EXPLICITLY REQUIRE THIS EXPERIMENTAL FEATURE
 FROM SKLEARNEXPERIMENTAL IMPORT ENABLEITERATIVEIMPUTER  NOQA
 NOW YOU CAN IMPORT NORMALLY FROM IMPUTE
 FROM SKLEARNIMPUTE IMPORT ITERATIVEIMPUTER
```

615SKLEARNFEATUREEXTRACTION FEATURE EXTRACTION

THESKLEARNFEATUREEXTRACTION MODULE DEALS WITH FEATURE EXTRACTION FROM RAW DATA IT CURRENTLY INCLUDES METHODS TO EXTRACT FEATURES FROM TEXT AND IMAGES

USER GUIDE SEE THE FEATURE EXTRACTION SECTION FOR FURTHER DETAILS

FEATUREEXTRACTIONDICTVECTORIZER DTYPE

   TRANSFORMS LISTS OF FEATUREVALUE MAPPINGS TO VECTORS

FEATUREEXTRACTIONFEATUREHASHER   IMPLEMENTS FEATURE HASHING AKA THE HASHING TRICK

6151SKLEARNFEATUREEXTRACTION DICTVECTORIZER

CLASSSKLEARNFEATUREEXTRACTION DICTVECTORIZER DTYPECLASS ‘NUMPYFLOAT64’ SEPARA TOR’’ SPARSETRUE SORTTRUE

TRANSFORMS LISTS OF FEATUREVALUE MAPPINGS TO VECTORS

THIS TRANSFORMER TURNS LISTS OF MAPPINGS DICTLIKE OBJECTS OF FEATURE NAMES TO FEATURE VALUES INTO NUMPY ARRAYS OR SCIPYSPARSE MATRICES FOR USE WITH SCIKITLEARN ESTIMATORS

WHEN FEATURE VALUES ARE STRINGS THIS TRANSFORMER WILL DO A BINARY ONEHOT AKA ONEOFK CODING ONE BOOLEAN VALUED FEATURE IS CONSTRUCTED FOR EACH OF THE POSSIBLE STRING VALUES THAT THE FEATURE CAN TAKE ON FOR INSTANCE A FEATURE “F” THAT CAN TAKE ON THE VALUES “HAM” AND “SPAM” WILL BECOME TWO FEATURES IN THE OUTPUT ONE SIGNIFYING “FHAM” THE OTHER “FSPAM”

HOWEVER NOTE THAT THIS TRANSFORMER WILL ONLY DO A BINARY ONEHOT ENCODING WHEN FEATURE VALUES ARE OF TYPE STRING IF CATEGORICAL FEATURES ARE REPRESENTED AS NUMERIC VALUES SUCH AS INT THE DICTVECTORIZER CAN BE FOLLOWED BYSKLEARNPREPROCESSINGONEHOTENCODER TO COMPLETE BINARY ONEHOT ENCODING

FEATURES THAT DO NOT OCCUR IN A SAMPLE MAPPING WILL HAVE A ZERO VALUE IN THE RESULTING ARRAYMATRIX

READ MORE IN THE USER GUIDE

PARAMETERS

DTYPE CALLABLE OPTIONAL THE TYPE OF FEATURE VALUES PASSED TO NUMPY ARRAYSCIPYSPARSE MA
TRIX CONSTRUCTORS AS THE DTYPE ARGUMENT
SEPARATOR STRING OPTIONAL SEPARATOR STRING USED WHEN CONSTRUCTING NEW FEATURES FOR ONEHOT
CODING
SPARSE BOOLEAN OPTIONAL WHETHER TRANSFORM SHOULD PRODUCE SCIPYSPARSE MATRICES TRUE BY
DEFAULT
SORT BOOLEAN OPTIONAL WHETHER FEATURENAMES ANDVOCABULARY SHOULD BE SORTED
WHEN FITTING TRUE BY DEFAULT
ATTRIBUTES
VOCABULARY DICT A DICTIONARY MAPPING FEATURE NAMES TO FEATURE INDICES
FEATURENAMES LIST A LIST OF LENGTH NFEATURES CONTAINING THE FEATURE NAMES EG “FHAM”
AND “FSPAM”
SEE ALSO
FEATUREHASHER PERFORMS VECTORIZATION USING ONLY A HASH FUNCTION
SKLEARNPREPROCESSINGORDINALENCODER HANDLES NOMINALCATEGORICAL FEATURES ENCODED AS
COLUMNS OF ARBITRARY DATA TYPES
EXAMPLES
```
 FROM SKLEARNFEATUREEXTRACTION IMPORT DICTVECTORIZER
V  DICTVECTORIZERSPARSE FALSE
D  FOO 1 BAR 2 FOO 3 BAZ 1
X  VFITTRANSFORMD
X
ARRAY2 0 1
0 1 3
VINVERSETRANSFORMX  BAR 20 FOO 10 BAZ 10 FOO
‘→ 30
TRUE
VTRANSFORMFOO 4 UNSEENFEATURE 3
ARRAY0 0 4
```
METHODS
FITSELF X Y LEARN A LIST OF FEATURE NAME INDICES MAPPINGS
FITTRANSFORM SELF X Y LEARN A LIST OF FEATURE NAME INDICES MAPPINGS AND
TRANSFORM X
GETFEATURENAMES SELF RETURNS A LIST OF FEATURE NAMES ORDERED BY THEIR INDICES
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X DICTTYPE TRANSFORM ARRAY OR SPARSE MATRIX X BACK TO FEATURE MAP
PINGS
RESTRICT SELF SUPPORT INDICES RESTRICT THE FEATURES TO THOSE IN SUPPORT USING FEATURE
SELECTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
CONTINUED ON NEXT PAGE

TABLE 695 – CONTINUED FROM PREVIOUS PAGE
TRANSFORM SELF X TRANSFORM FEATUREVALUE DICTS TO ARRAY OR SPARSE MA
TRIX
INIT SELFDTYPECLASS ‘NUMPYFLOAT64’ SEPARATOR’’ SPARSETRUE SORTTRUE
FITSELFXYNONE
LEARN A LIST OF FEATURE NAME INDICES MAPPINGS
PARAMETERS
XMAPPING OR ITERABLE OVER MAPPINGS DICTS OR MAPPINGS FROM FEATURE NAMES ARBITRARY
PYTHON OBJECTS TO FEATURE VALUES STRINGS OR CONVERTIBLE TO DTYPE
YIGNORED
RETURNS
SELF
FITTRANSFORM SELFXYNONE
LEARN A LIST OF FEATURE NAME INDICES MAPPINGS AND TRANSFORM X
LIKE FITX FOLLOWED BY TRANSFORMX BUT DOES NOT REQUIRE MATERIALIZING X IN MEMORY
PARAMETERS
XMAPPING OR ITERABLE OVER MAPPINGS DICTS OR MAPPINGS FROM FEATURE NAMES ARBITRARY
PYTHON OBJECTS TO FEATURE VALUES STRINGS OR CONVERTIBLE TO DTYPE
YIGNORED
RETURNS
XAARRAY SPARSE MATRIX FEATURE VECTORS ALWAYS 2D
GETFEATURENAMES SELF
RETURNS A LIST OF FEATURE NAMES ORDERED BY THEIR INDICES
IF ONEOFK CODING IS APPLIED TO CATEGORICAL FEATURES THIS WILL INCLUDE THE CONSTRUCTED FEATURE NAMES BUT
NOT THE ORIGINAL ONES
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFXDICTTYPECLASS ‘DICT’
TRANSFORM ARRAY OR SPARSE MATRIX X BACK TO FEATURE MAPPINGS
X MUST HAVE BEEN PRODUCED BY THIS DICTVECTORIZER’S TRANSFORM OR FITTRANSFORM METHOD IT MAY ONLY HAVE
PASSED THROUGH TRANSFORMERS THAT PRESERVE THE NUMBER OF FEATURES AND THEIR ORDER
IN THE CASE OF ONEHOTONEOFK CODING THE CONSTRUCTED FEATURE NAMES AND VALUES ARE RETURNED RATHER THAN
THE ORIGINAL ONES
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLE MATRIX

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DICTTYPE CALLABLE OPTIONAL CONSTRUCTOR FOR FEATURE MAPPINGS MUST CONFORM TO THE COL
LECTIONSMAPPING API
RETURNS
DLIST OF DICTTYPE OBJECTS LENGTH NSAMPLES FEATURE MAPPINGS FOR THE SAMPLES IN X
RESTRICT SELFSUPPORT INDICESFALSE
RESTRICT THE FEATURES TO THOSE IN SUPPORT USING FEATURE SELECTION
THIS FUNCTION MODIFIES THE ESTIMATOR INPLACE
PARAMETERS
SUPPORT ARRAYLIKE BOOLEAN MASK OR LIST OF INDICES AS RETURNED BY THE GETSUPPORT MEMBER
OF FEATURE SELECTORS
INDICES BOOLEAN OPTIONAL WHETHER SUPPORT IS A LIST OF INDICES
RETURNS
SELF
EXAMPLES
 FROM SKLEARNFEATUREEXTRACTION IMPORT DICTVECTORIZER
 FROM SKLEARNFEATURESELECTION IMPORT SELECTKBEST CHI2
V DICTVECTORIZER
D FOO 1 BAR 2 FOO 3 BAZ 1
X VFITTRANSFORMD
SUPPORT SELECTKBESTCHI2 K2FITX 0 1
VGETFEATURENAMES
BAR BAZ FOO
VRESTRICTSUPPORTGETSUPPORT

DICTVECTORIZERDTYPE SEPARATOR SORTTRUE
SPARSETRUE
VGETFEATURENAMES
BAR FOO
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM FEATUREVALUE DICTS TO ARRAY OR SPARSE MATRIX
NAMED FEATURES NOT ENCOUNTERED DURING FIT OR FITTRANSFORM WILL BE SILENTLY IGNORED
PARAMETERS
XMAPPING OR ITERABLE OVER MAPPINGS LENGTH NSAMPLES DICTS OR MAPPINGS FROM
FEATURE NAMES ARBITRARY PYTHON OBJECTS TO FEATURE VALUES STRINGS OR CONVERTIBLE TO DTYPE
RETURNS

XAARRAY SPARSE MATRIX FEATURE VECTORS ALWAYS 2D
EXAMPLES USING SKLEARNFEATUREEXTRACTIONDICTVECTORIZER
•COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
•FEATUREHASHER AND DICTVECTORIZER COMPARISON
6152SKLEARNFEATUREEXTRACTION FEATUREHASHER
CLASSSKLEARNFEATUREEXTRACTION FEATUREHASHER NFEATURES1048576 INPUTTYPE'DICT'
DTYPECLASS 'NUMPYFLOAT64' ALTER
NATESIGNTRUE
IMPLEMENTS FEATURE HASHING AKA THE HASHING TRICK
THIS CLASS TURNS SEQUENCES OF SYMBOLIC FEATURE NAMES STRINGS INTO SCIPYSPARSE MATRICES USING A HASH FUNCTION TO COMPUTE THE MATRIX COLUMN CORRESPONDING TO A NAME THE HASH FUNCTION EMPLOYED IS THE SIGNED 32BIT VERSION OF MURMURHASH3
FEATURE NAMES OF TYPE BYTE STRING ARE USED ASIS UNICODE STRINGS ARE CONVERTED TO UTF8 FIRST BUT NO UNICODE NORMALIZATION IS DONE FEATURE VALUES MUST BE FINITE NUMBERS
THIS CLASS IS A LOWMEMORY ALTERNATIVE TO DICTVECTORIZER AND COUNTVECTORIZER INTENDED FOR LARGESCALE ONLINE LEARNING AND SITUATIONS WHERE MEMORY IS TIGHT EG WHEN RUNNING PREDICTION CODE ON EMBEDDED DEVICES
READ MORE IN THE USER GUIDE
PARAMETERS
NFEATURES INTEGER OPTIONAL THE NUMBER OF FEATURES COLUMNS IN THE OUTPUT MATRICES SMALL NUMBERS OF FEATURES ARE LIKELY TO CAUSE HASH COLLISIONS BUT LARGE NUMBERS WILL CAUSE LARGER COEFFICIENT DIMENSIONS IN LINEAR LEARNERS
INPUTTYPE STRING OPTIONAL DEFAULT "DICT" EITHER "DICT" THE DEFAULT TO ACCEPT DICTIONARIES OVER FEATURENAME VALUE "PAIR" TO ACCEPT PAIRS OF FEATURENAME VALUE OR "STRING" TO ACCEPT SINGLE STRINGS FEATURENAME SHOULD BE A STRING WHILE VALUE SHOULD BE A NUMBER IN THE CASE OF "STRING" A VALUE OF 1 IS IMPLIED THE FEATURENAME IS HASHED TO FIND THE APPROPRIATE COLUMN FOR THE FEATURE THE VALUE'S SIGN MIGHT BE FLIPPED IN THE OUTPUT BUT SEE NONNEGATIVE BELOW
DTYPE NUMPY TYPE OPTIONAL DEFAULT NPFLOAT64 THE TYPE OF FEATURE VALUES PASSED TO SCIPYSPARSE MATRIX CONSTRUCTORS AS THE DTYPE ARGUMENT DO NOT SET THIS TO BOOL NPBOOLEAN OR ANY UNSIGNED INTEGER TYPE
ALTERNATESIGN BOOLEAN OPTIONAL DEFAULT TRUE WHEN TRUE AN ALTERNATING SIGN IS ADDED TO THE FEATURES AS TO APPROXIMATELY CONSERVE THE INNER PRODUCT IN THE HASHED SPACE EVEN FOR SMALL NFEATURES THIS APPROACH IS SIMILAR TO SPARSE RANDOM PROJECTION
SEE ALSO
DICTVECTORIZER VECTORIZES STRINGVALUED FEATURES USING A HASH TABLE
SKLEARNPREPROCESSINGONEHOTENCODER HANDLES NOMINALCATEGORICAL FEATURES

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EXAMPLES
FROM SKLEARNFEATUREEXTRACTION IMPORT FEATUREHASHER
H FEATUREHASHERNFEATURES10
D DOG 1 CAT2 ELEPHANT4DOG 2 RUN 5
F HTRANSFORMD
FTOARRAY
ARRAY 0 0 4 1 0 0 0 0 0 2
0 0 0 2 5 0 0 0 0 0
METHODS
FITSELF X Y NOOP
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF RAWX TRANSFORM A SEQUENCE OF INSTANCES TO A SCIPYSPARSE MA
TRIX
INIT SELFNFEATURES1048576 INPUTTYPE'DICT' DTYPECLASS 'NUMPYFLOAT64' ALTER
NATESIGNTRUE
FITSELFXNONE YNONE
NOOP
THIS METHOD DOESN'T DO ANYTHING IT EXISTS PURELY FOR COMPATIBILITY WITH THE SCIKITLEARN TRANSFORMER API
PARAMETERS
XARRAYLIKE
RETURNS
SELF FEATUREHASHER
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
615SKLEARNFEATUREEXTRACTION FEATURE EXTRACTION 1741

PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFRAWX
TRANSFORM A SEQUENCE OF INSTANCES TO A SCIPYSPARSE MATRIX
PARAMETERS
RAWX ITERABLE OVER ITERABLE OVER RAW FEATURES LENGTH NSAMPLES SAMPLES EACH SAMPLE
MUST BE ITERABLE AN EG A LIST OR TUPLE CONTAININGGENERATING FEATURE NAMES AND OPTION
ALLY VALUES SEE THE INPUTTYPE CONSTRUCTOR ARGUMENT WHICH WILL BE HASHED RAWX NEED
NOT SUPPORT THE LEN FUNCTION SO IT CAN BE THE RESULT OF A GENERATOR NSAMPLES IS DETERMINED
ON THE FLY
RETURNS
XSCIPYSPARSE MATRIX SHAPE NSAMPLES SELFNFEATURES FEATURE MATRIX FOR USE WITH
ESTIMATORS OR FURTHER TRANSFORMERS
EXAMPLES USING SKLEARNFEATUREEXTRACTIONFEATUREHASHER
•FEATUREHASHER AND DICTVECTORIZER COMPARISON
6153 FROM IMAGES
THESKLEARNFEATUREEXTRACTIONIMAGE SUBMODULE GATHERS UTILITIES TO EXTRACT FEATURES FROM IMAGES
FEATUREEXTRACTIONIMAGE
EXTRACTPATCHES2D RESHAPE A 2D IMAGE INTO A COLLECTION OF PATCHES
FEATUREEXTRACTIONIMAGE
GRIDTOGRAPH NX NYGRAPH OF THE PIXELTOPIXEL CONNECTIONS
FEATUREEXTRACTIONIMAGE
IMGTOGRAPH IMG GRAPH OF THE PIXELTOPIXEL GRADIENT CONNECTIONS
FEATUREEXTRACTIONIMAGE
RECONSTRUCTFROMPATCHES2D RECONSTRUCT THE IMAGE FROM ALL OF ITS PATCHES
FEATUREEXTRACTIONIMAGE
PATCHEXTRACTOR EXTRACTS PATCHES FROM A COLLECTION OF IMAGES
SKLEARNFEATUREEXTRACTIONIMAGE EXTRACTPATCHES2D
SKLEARNFEATUREEXTRACTIONIMAGE EXTRACTPATCHES2D IMAGE PATCHSIZE
MAXPATCHESNONE RAN
DOMSTATENONE
RESHAPE A 2D IMAGE INTO A COLLECTION OF PATCHES
THE RESULTING PATCHES ARE ALLOCATED IN A DEDICATED ARRAY

READ MORE IN THE USER GUIDE
PARAMETERS
IMAGE ARRAY SHAPE IMAGEHEIGHT IMAGEWIDTH OR IMAGEHEIGHT IMAGEWIDTH
NCHANNELS THE ORIGINAL IMAGE DATA FOR COLOR IMAGES THE LAST DIMENSION SPECIFIES THE
CHANNEL A RGB IMAGE WOULD HAVE NCHANNELS3
PATCHSIZE TUPLE OF INTS PATCHHEIGHT PATCHWIDTH THE DIMENSIONS OF ONE PATCH
MAXPATCHES INTEGER OR FLOAT OPTIONAL DEFAULT IS NONE THE MAXIMUM NUMBER OF PATCHES TO
EXTRACT IF MAXPATCHES IS A FLOAT BETWEEN 0 AND 1 IT IS TAKEN TO BE A PROPORTION OF THE TOTAL
NUMBER OF PATCHES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE PSEUDO NUMBER
GENERATOR STATE USED FOR RANDOM SAMPLING TO USE IF MAXPATCHES IS NOT NONE IF INT
RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE
RANDOMSTATE INSTANCE USED BY NPRANDOM
RETURNS
PATCHES ARRAY SHAPE NPATCHES PATCHHEIGHT PATCHWIDTH OR NPATCHES PATCHHEIGHT
PATCHWIDTH NCHANNELS THE COLLECTION OF PATCHES EXTRACTED FROM THE IMAGE WHERE
NPATCHES IS EITHERMAXPATCHES OR THE TOTAL NUMBER OF PATCHES THAT CAN BE EXTRACTED
EXAMPLES
 FROM SKLEARNDATASETS IMPORT LOADSAMPLEIMAGE
 FROM SKLEARNFEATUREEXTRACTION IMPORT IMAGE
 USE THE ARRAY DATA FROM THE FIRST IMAGE IN THIS DATASET
ONEIMAGE LOADSAMPLEIMAGECHINAJPG
PRINTIMAGE SHAPE FORMATONEIMAGESHAPE
IMAGE SHAPE 427 640 3
PATCHES IMAGEEXTRACTPATCHES2DONEIMAGE 2 2
PRINTPATCHES SHAPE FORMATPATCHESSHAPE
PATCHES SHAPE 272214 2 2 3
 HERE ARE JUST TWO OF THESE PATCHES
PRINTPATCHES1
174 201 231
174 201 231
173 200 230
173 200 230
PRINTPATCHES800
187 214 243
188 215 244
187 214 243
188 215 244
EXAMPLES USING SKLEARNFEATUREEXTRACTIONIMAGEEXTRACTPATCHES2D
•ONLINE LEARNING OF A DICTIONARY OF PARTS OF FACES
•IMAGE DENOISING USING DICTIONARY LEARNING

SKLEARNFEATUREEXTRACTIONIMAGE GRIDTOGRAPH
SKLEARNFEATUREEXTRACTIONIMAGE GRIDTOGRAPH NX NY NZ1
MASKNONE RETURNASCLASS
'SCIPYSPARSECOOCOOMATRIX'
DTYPECLASS 'INT'
GRAPH OF THE PIXELTOPIXEL CONNECTIONS
EDGES EXIST IF 2 VOXELS ARE CONNECTED
PARAMETERS
NX INT DIMENSION IN X AXIS
NY INT DIMENSION IN Y AXIS
NZ INT OPTIONAL DEFAULT 1 DIMENSION IN Z AXIS
MASK NDARRAY OF BOOLEANS OPTIONAL AN OPTIONAL MASK OF THE IMAGE TO CONSIDER ONLY PART OF
THE PIXELS
RETURNAS NPNDARRAY OR A SPARSE MATRIX CLASS OPTIONAL THE CLASS TO USE TO BUILD THE RETURNED
ADJACENCY MATRIX
DTYPE DTYPE OPTIONAL DEFAULT INT THE DATA OF THE RETURNED SPARSE MATRIX BY DEFAULT IT IS INT
NOTES
FOR SCIKITLEARN VERSIONS 0141 AND PRIOR RETURNASNPNDARRAY WAS HANDLED BY RETURNING A DENSE NPMATRIX
INSTANCE GOING FORWARD NPNDARRAY RETURNS AN NPNDARRAY AS EXPECTED
FOR COMPATIBILITY USER CODE RELYING ON THIS METHOD SHOULD WRAP ITS CALLS IN NPASARRAY TO AVOID TYPE ISSUES
SKLEARNFEATUREEXTRACTIONIMAGE IMGTOGRAPH
SKLEARNFEATUREEXTRACTIONIMAGE IMGTOGRAPH IMGMASKNONE RETURNASCLASS
'SCIPYSPARSECOOCOOMATRIX'
DTYPENONE
GRAPH OF THE PIXELTOPIXEL GRADIENT CONNECTIONS
EDGES ARE WEIGHTED WITH THE GRADIENT VALUES
READ MORE IN THE USER GUIDE
PARAMETERS
IMG NDARRAY 2D OR 3D 2D OR 3D IMAGE
MASK NDARRAY OF BOOLEANS OPTIONAL AN OPTIONAL MASK OF THE IMAGE TO CONSIDER ONLY PART OF
THE PIXELS
RETURNAS NPNDARRAY OR A SPARSE MATRIX CLASS OPTIONAL THE CLASS TO USE TO BUILD THE RETURNED
ADJACENCY MATRIX
DTYPE NONE OR DTYPE OPTIONAL THE DATA OF THE RETURNED SPARSE MATRIX BY DEFAULT IT IS THE
DTYPE OF IMG

NOTES
FOR SCIKITLEARN VERSIONS 0141 AND PRIOR RETURNASNPNDARRAY WAS HANDLED BY RETURNING A DENSE NPMATRIX
INSTANCE GOING FORWARD NPNDARRAY RETURNS AN NPNDARRAY AS EXPECTED
FOR COMPATIBILITY USER CODE RELYING ON THIS METHOD SHOULD WRAP ITS CALLS IN NPASARRAY TO AVOID TYPE ISSUES
SKLEARNFEATUREEXTRACTIONIMAGE RECONSTRUCTFROMPATCHES2D
SKLEARNFEATUREEXTRACTIONIMAGE RECONSTRUCTFROMPATCHES2D PATCHES IM
AGESIZE
RECONSTRUCT THE IMAGE FROM ALL OF ITS PATCHES
PATCHES ARE ASSUMED TO OVERLAP AND THE IMAGE IS CONSTRUCTED BY FILLING IN THE PATCHES FROM LEFT TO RIGHT TOP TO
BOTTOM AVERAGING THE OVERLAPPING REGIONS
READ MORE IN THE USER GUIDE
PARAMETERS
PATCHES ARRAY SHAPE NPATCHES PATCHHEIGHT PATCHWIDTH OR NPATCHES PATCHHEIGHT
PATCHWIDTH NCHANNELS THE COMPLETE SET OF PATCHES IF THE PATCHES CONTAIN COLOUR
INFORMATION CHANNELS ARE INDEXED ALONG THE LAST DIMENSION RGB PATCHES WOULD HAVE
NCHANNELS3
IMAGESIZE TUPLE OF INTS IMAGEHEIGHT IMAGEWIDTH OR IMAGEHEIGHT IMAGEWIDTH
NCHANNELS THE SIZE OF THE IMAGE THAT WILL BE RECONSTRUCTED
RETURNS
IMAGE ARRAY SHAPE IMAGESIZE THE RECONSTRUCTED IMAGE
EXAMPLES USING SKLEARNFEATUREEXTRACTIONIMAGERECONSTRUCTFROMPATCHES2D
•IMAGE DENOISING USING DICTIONARY LEARNING
SKLEARNFEATUREEXTRACTIONIMAGE PATCHEXTRACTOR
CLASSSKLEARNFEATUREEXTRACTIONIMAGE PATCHEXTRACTOR PATCHSIZENONE
MAXPATCHESNONE RAN
DOMSTATENONE
EXTRACTS PATCHES FROM A COLLECTION OF IMAGES
READ MORE IN THE USER GUIDE
PARAMETERS
PATCHSIZE TUPLE OF INTS PATCHHEIGHT PATCHWIDTH THE DIMENSIONS OF ONE PATCH
MAXPATCHES INTEGER OR FLOAT OPTIONAL DEFAULT IS NONE THE MAXIMUM NUMBER OF PATCHES PER
IMAGE TO EXTRACT IF MAXPATCHES IS A FLOAT IN 0 1 IT IS TAKEN TO MEAN A PROPORTION OF THE
TOTAL NUMBER OF PATCHES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM

EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADSAMPLEIMAGES
 FROM SKLEARNFEATUREEXTRACTION IMPORT IMAGE
 USE THE ARRAY DATA FROM THE SECOND IMAGE IN THIS DATASET
X  LOADSAMPLEIMAGESIMAGES1
PRINTIMAGE SHAPE FORMATXSHAPE
IMAGE SHAPE 427 640 3
PE  IMAGEPATCHEXTRACTORPATCHSIZE2 2
PEFIT  PEFITX
PETRANS  PETRANSFORMX
PRINTPATCHES SHAPE FORMATPETRANSSHAPE
PATCHES SHAPE 545706 2 2
```
METHODS
```
FITSELF X Y DO NOTHING AND RETURN THE ESTIMATOR UNCHANGED
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORMS THE IMAGE SAMPLES IN X INTO A MATRIX OF
PATCH DATA
INIT SELFPATCHSIZENONE MAXPATCHESNONE RANDOMSTATENONE
FITSELFXYNONE
DO NOTHING AND RETURN THE ESTIMATOR UNCHANGED
THIS METHOD IS JUST THERE TO IMPLEMENT THE USUAL API AND HENCE WORK IN PIPELINES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORMS THE IMAGE SAMPLES IN X INTO A MATRIX OF PATCH DATA
```

PARAMETERS
XARRAY SHAPE NSAMPLES IMAGEHEIGHT IMAGEWIDTH OR NSAMPLES IMAGEHEIGHT
IMAGEWIDTH NCHANNELS ARRAY OF IMAGES FROM WHICH TO EXTRACT PATCHES FOR
COLOR IMAGES THE LAST DIMENSION SPECIFIES THE CHANNEL A RGB IMAGE WOULD HAVE
NCHANNELS3
RETURNS
PATCHES ARRAY SHAPE NPATCHES PATCHHEIGHT PATCHWIDTH OR NPATCHES
PATCHHEIGHT PATCHWIDTH NCHANNELS THE COLLECTION OF PATCHES EXTRACTED FROM THE IM
AGES WHERE NPATCHES IS EITHERNSAMPLES MAXPATCHES OR THE TOTAL NUMBER
OF PATCHES THAT CAN BE EXTRACTED
6154 FROM TEXT
THESKLEARNFEATUREEXTRACTIONTEXT SUBMODULE GATHERS UTILITIES TO BUILD FEATURE VECTORS FROM TEXT DOC
UMENTS
FEATUREEXTRACTIONTEXT
COUNTVECTORIZER CONVERT A COLLECTION OF TEXT DOCUMENTS TO A MATRIX OF TOKEN
COUNTS
FEATUREEXTRACTIONTEXT
HASHINGVECTORIZER CONVERT A COLLECTION OF TEXT DOCUMENTS TO A MATRIX OF TOKEN
OCCURRENCES
FEATUREEXTRACTIONTEXT
TFIDFTRANSFORMER TRANSFORM A COUNT MATRIX TO A NORMALIZED TF OR TFIDF REPRE
SENTATION
FEATUREEXTRACTIONTEXT
TFIDFVECTORIZER CONVERT A COLLECTION OF RAW DOCUMENTS TO A MATRIX OF TF
IDF FEATURES
SKLEARNFEATUREEXTRACTIONTEXT COUNTVECTORIZER
CLASSSKLEARNFEATUREEXTRACTIONTEXT COUNTVECTORIZER INPUT’CONTENT’ ENCODING’UTF
8’ DECODEERROR‘STRICT’
STRIPACCENTSNONE LOW
ERCASETRUE PREPROCES
SORNONE TOKENIZERNONE
STOPWORDSNONE TO
KENPATTERN’UBWWB’
NGRAMRANGE1 1 ANA
LYZER’WORD’ MAXDF10
MINDF1 MAXFEATURESNONE
VOCABULARYNONE BINARYFALSE
DTYPECLASS ‘NUMPYINT64’
CONVERT A COLLECTION OF TEXT DOCUMENTS TO A MATRIX OF TOKEN COUNTS
THIS IMPLEMENTATION PRODUCES A SPARSE REPRESENTATION OF THE COUNTS USING SCIPYSPARSECSRMATRIX
IF YOU DO NOT PROVIDE AN APRIORI DICTIONARY AND YOU DO NOT USE AN ANALYZER THAT DOES SOME KIND OF FEATURE
SELECTION THEN THE NUMBER OF FEATURES WILL BE EQUAL TO THE VOCABULARY SIZE FOUND BY ANALYZING THE DATA
READ MORE IN THE USER GUIDE
PARAMETERS
INPUT STRING ‘FILENAME’ ‘FILE’ ‘CONTENT’ IF ‘FILENAME’ THE SEQUENCE PASSED AS AN ARGUMENT TO
FIT IS EXPECTED TO BE A LIST OF FILENAMES THAT NEED READING TO FETCH THE RAW CONTENT TO ANALYZE

IF ‘FILE’ THE SEQUENCE ITEMS MUST HAVE A ‘READ’ METHOD FILELIKE OBJECT THAT IS CALLED TO FETCH
THE BYTES IN MEMORY
OTHERWISE THE INPUT IS EXPECTED TO BE THE SEQUENCE STRINGS OR BYTES ITEMS ARE EXPECTED TO BE
ANALYZED DIRECTLY
ENCODING STRING ‘UTF8’ BY DEFAULT IF BYTES OR FILES ARE GIVEN TO ANALYZE THIS ENCODING IS USED
TO DECODE
DECODEERROR ‘STRICT’ ‘IGNORE’ ‘REPLACE’ INSTRUCTION ON WHAT TO DO IF A BYTE SEQUENCE IS
GIVEN TO ANALYZE THAT CONTAINS CHARACTERS NOT OF THE GIVEN ENCODING BY DEFAULT IT IS
‘STRICT’ MEANING THAT A UNICODEDECODEERROR WILL BE RAISED OTHER VALUES ARE ‘IGNORE’ AND
‘REPLACE’
STRIPACCENTS ‘ASCII’ ‘UNICODE’ NONE REMOVE ACCENTS AND PERFORM OTHER CHARACTER NOR
MALIZATION DURING THE PREPROCESSING STEP ‘ASCII’ IS A FAST METHOD THAT ONLY WORKS ON CHAR
ACTERS THAT HAVE AN DIRECT ASCII MAPPING ‘UNICODE’ IS A SLIGHTLY SLOWER METHOD THAT WORKS
ON ANY CHARACTERS NONE DEFAULT DOES NOTHING
BOTH ‘ASCII’ AND ‘UNICODE’ USE NFKD NORMALIZATION FROM UNICODEDATANORMALIZE
LOWERCASE BOOLEAN TRUE BY DEFAULT CONVERT ALL CHARACTERS TO LOWERCASE BEFORE TOKENIZING
PREPROCESSOR CALLABLE OR NONE DEFAULT OVERRIDE THE PREPROCESSING STRING TRANSFORMATION
STAGE WHILE PRESERVING THE TOKENIZING AND NGRAMS GENERATION STEPS
TOKENIZER CALLABLE OR NONE DEFAULT OVERRIDE THE STRING TOKENIZATION STEP WHILE PRESERVING THE
PREPROCESSING AND NGRAMS GENERATION STEPS ONLY APPLIES IF ANALYZER WORD
STOPWORDS STRING ‘ENGLISH’ LIST OR NONE DEFAULT IF ‘ENGLISH’ A BUILTIN STOP WORD LIST FOR
ENGLISH IS USED THERE ARE SEVERAL KNOWN ISSUES WITH ‘ENGLISH’ AND YOU SHOULD CONSIDER AN
ALTERNATIVE SEE USING STOP WORDS
IF A LIST THAT LIST IS ASSUMED TO CONTAIN STOP WORDS ALL OF WHICH WILL BE REMOVED FROM THE
RESULTING TOKENS ONLY APPLIES IF ANALYZER WORD
IF NONE NO STOP WORDS WILL BE USED MAXDF CAN BE SET TO A VALUE IN THE RANGE 07 10
TO AUTOMATICALLY DETECT AND FILTER STOP WORDS BASED ON INTRA CORPUS DOCUMENT FREQUENCY OF
TERMS
TOKENPATTERN STRING REGULAR EXPRESSION DENOTING WHAT CONSTITUTES A “TOKEN” ONLY USED IF
ANALYZER WORD THE DEFAULT REGEXP SELECT TOKENS OF 2 OR MORE ALPHANUMERIC
CHARACTERS PUNCTUATION IS COMPLETELY IGNORED AND ALWAYS TREATED AS A TOKEN SEPARATOR
NGRAMRANGE TUPLE MINN MAXN THE LOWER AND UPPER BOUNDARY OF THE RANGE OF NVALUES
FOR DIFFERENT NGRAMS TO BE EXTRACTED ALL VALUES OF N SUCH THAT MINN N MAXN WILL
BE USED
ANALYZER STRING ‘WORD’ ‘CHAR’ ‘CHARWB’ OR CALLABLE WHETHER THE FEATURE SHOULD BE MADE
OF WORD OR CHARACTER NGRAMS OPTION ‘CHARWB’ CREATES CHARACTER NGRAMS ONLY FROM TEXT
INSIDE WORD BOUNDARIES NGRAMS AT THE EDGES OF WORDS ARE PADDED WITH SPACE
IF A CALLABLE IS PASSED IT IS USED TO EXTRACT THE SEQUENCE OF FEATURES OUT OF THE RAW UNPROCESSED
INPUT
CHANGED IN VERSION 021
SINCE V021 IF INPUT ISFILENAME ORFILE THE DATA IS FIRST READ FROM THE FILE AND THEN
PASSED TO THE GIVEN CALLABLE ANALYZER
MAXDF FLOAT IN RANGE 00 10 OR INT DEFAULT10 WHEN BUILDING THE VOCABULARY IGNORE TERMS
THAT HAVE A DOCUMENT FREQUENCY STRICTLY HIGHER THAN THE GIVEN THRESHOLD CORPUSSPECIFIC STOP

SCIKITLEARN USER GUIDE RELEASE 0213
WORDS IF FLOAT THE PARAMETER REPRESENTS A PROPORTION OF DOCUMENTS INTEGER ABSOLUTE COUNTS
THIS PARAMETER IS IGNORED IF VOCABULARY IS NOT NONE
MINDF FLOAT IN RANGE 00 10 OR INT DEFAULT1 WHEN BUILDING THE VOCABULARY IGNORE TERMS
THAT HAVE A DOCUMENT FREQUENCY STRICTLY LOWER THAN THE GIVEN THRESHOLD THIS VALUE IS ALSO
CALLED CUTOFF IN THE LITERATURE IF FLOAT THE PARAMETER REPRESENTS A PROPORTION OF DOCUMENTS
INTEGER ABSOLUTE COUNTS THIS PARAMETER IS IGNORED IF VOCABULARY IS NOT NONE
MAXFEATURES INT OR NONE DEFAULTNONE IF NOT NONE BUILD A VOCABULARY THAT ONLY CONSIDER
THE TOP MAXFEATURES ORDERED BY TERM FREQUENCY ACROSS THE CORPUS
THIS PARAMETER IS IGNORED IF VOCABULARY IS NOT NONE
VOCABULARY MAPPING OR ITERABLE OPTIONAL EITHER A MAPPING EG A DICT WHERE KEYS ARE TERMS
AND VALUES ARE INDICES IN THE FEATURE MATRIX OR AN ITERABLE OVER TERMS IF NOT GIVEN A VOCABU
LARY IS DETERMINED FROM THE INPUT DOCUMENTS INDICES IN THE MAPPING SHOULD NOT BE REPEATED
AND SHOULD NOT HAVE ANY GAP BETWEEN 0 AND THE LARGEST INDEX
BINARY BOOLEAN DEFAULTFALSE IF TRUE ALL NON ZERO COUNTS ARE SET TO 1 THIS IS USEFUL FOR
DISCRETE PROBABILISTIC MODELS THAT MODEL BINARY EVENTS RATHER THAN INTEGER COUNTS
DTYPE TYPE OPTIONAL TYPE OF THE MATRIX RETURNED BY FITTRANSFORM OR TRANSFORM
ATTRIBUTES
VOCABULARY DICT A MAPPING OF TERMS TO FEATURE INDICES
STOPWORDS SET TERMS THAT WERE IGNORED BECAUSE THEY EITHER
• OCCURRED IN TOO MANY DOCUMENTS MAXDF
• OCCURRED IN TOO FEW DOCUMENTS MINDF
• WERE CUT OFF BY FEATURE SELECTION MAXFEATURES
THIS IS ONLY AVAILABLE IF NO VOCABULARY WAS GIVEN
SEE ALSO
HASHINGVECTORIZER TFIDFVECTORIZER
NOTES
THESTOPWORDS ATTRIBUTE CAN GET LARGE AND INCREASE THE MODEL SIZE WHEN PICKLING THIS ATTRIBUTE IS PROVIDED
ONLY FOR INTROSPECTION AND CAN BE SAFELY REMOVED USING DELATTR OR SET TO NONE BEFORE PICKLING
EXAMPLES
 FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT COUNTVECTORIZER
CORPUS
 THIS IS THE FIRST DOCUMENT
 THIS DOCUMENT IS THE SECOND DOCUMENT
 AND THIS IS THE THIRD ONE
 IS THIS THE FIRST DOCUMENT

VECTORIZER COUNTVECTORIZER
X VECTORIZERFITTRANSFORMCORPUS
PRINTVECTORIZERGETFEATURENAMES
AND DOCUMENT FIRST IS ONE SECOND THE THIRD THIS
615SKLEARNFEATUREEXTRACTION FEATURE EXTRACTION 1749

PRINTXTOARRAY
0 1 1 1 0 0 1 0 1
0 2 0 1 0 1 1 0 1
1 0 0 1 1 0 1 1 1
0 1 1 1 0 0 1 0 1
METHODS
BUILDANALYZER SELF RETURN A CALLABLE THAT HANDLES PREPROCESSING AND TOK
ENIZATION
BUILDPREPROCESSOR SELF RETURN A FUNCTION TO PREPROCESS THE TEXT BEFORE TOKENIZA
TION
BUILDTOKENIZER SELF RETURN A FUNCTION THAT SPLITS A STRING INTO A SEQUENCE OF
TOKENS
DECODE SELF DOC DECODE THE INPUT INTO A STRING OF UNICODE SYMBOLS
FITSELF RAWDOCUMENTS Y LEARN A VOCABULARY DICTIONARY OF ALL TOKENS IN THE RAW
DOCUMENTS
FITTRANSFORM SELF RAWDOCUMENTS Y LEARN THE VOCABULARY DICTIONARY AND RETURN TERM
DOCUMENT MATRIX
GETFEATURENAMES SELF ARRAY MAPPING FROM FEATURE INTEGER INDICES TO FEATURE
NAME
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSTOPWORDS SELF BUILD OR FETCH THE EFFECTIVE STOP WORDS LIST
INVERSETRANSFORM SELF X RETURN TERMS PER DOCUMENT WITH NONZERO ENTRIES IN X
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF RAWDOCUMENTS TRANSFORM DOCUMENTS TO DOCUMENTTERM MATRIX
INIT SELFINPUT’CONTENT’ ENCODING’UTF8’ DECODEERROR’STRICT’ STRIPACCENTSNONE
LOWERCASETRUE PREPROCESSORNONE TOKENIZERNONE STOPWORDSNONE TO
KENPATTERN’UBWWB’ NGRAMRANGE1 1ANALYZER’WORD’ MAXDF10
MINDF1 MAXFEATURESNONE VOCABULARYNONE BINARYFALSE DTYPECLASS
‘NUMPYINT64’
BUILDANALYZER SELF
RETURN A CALLABLE THAT HANDLES PREPROCESSING AND TOKENIZATION
BUILDPREPROCESSOR SELF
RETURN A FUNCTION TO PREPROCESS THE TEXT BEFORE TOKENIZATION
BUILDTOKENIZER SELF
RETURN A FUNCTION THAT SPLITS A STRING INTO A SEQUENCE OF TOKENS
DECODESELFDOC
DECODE THE INPUT INTO A STRING OF UNICODE SYMBOLS
THE DECODING STRATEGY DEPENDS ON THE VECTORIZER PARAMETERS
PARAMETERS
DOC STRING THE STRING TO DECODE
FITSELFRAWDOCUMENTS YNONE
LEARN A VOCABULARY DICTIONARY OF ALL TOKENS IN THE RAW DOCUMENTS
PARAMETERS

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RAWDOCUMENTS ITERABLE AN ITERABLE WHICH YIELDS EITHER STR UNICODE OR FILE OBJECTS
RETURNS
SELF
FITTRANSFORM SELFRAWDOCUMENTS YNONE
LEARN THE VOCABULARY DICTIONARY AND RETURN TERMDOCUMENT MATRIX
THIS IS EQUIVALENT TO FIT FOLLOWED BY TRANSFORM BUT MORE EFFICIENTLY IMPLEMENTED
PARAMETERS
RAWDOCUMENTS ITERABLE AN ITERABLE WHICH YIELDS EITHER STR UNICODE OR FILE OBJECTS
RETURNS
XARRAY NSAMPLES NFEATURES DOCUMENTTERM MATRIX
GETFEATURENAMES SELF
ARRAY MAPPING FROM FEATURE INTEGER INDICES TO FEATURE NAME
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSTOPWORDS SELF
BUILD OR FETCH THE EFFECTIVE STOP WORDS LIST
INVERSETRANSFORM SELFX
RETURN TERMS PER DOCUMENT WITH NONZERO ENTRIES IN X
PARAMETERS
XARRAY SPARSE MATRIX SHAPE NSAMPLES NFEATURES
RETURNS
XINV LIST OF ARRAYS LEN NSAMPLES LIST OF ARRAYS OF TERMS
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFRAWDOCUMENTS
TRANSFORM DOCUMENTS TO DOCUMENTTERM MATRIX
EXTRACT TOKEN COUNTS OUT OF RAW TEXT DOCUMENTS USING THE VOCABULARY FITTED WITH FIT OR THE ONE PROVIDED TO
THE CONSTRUCTOR
PARAMETERS
RAWDOCUMENTS ITERABLE AN ITERABLE WHICH YIELDS EITHER STR UNICODE OR FILE OBJECTS
615SKLEARNFEATUREEXTRACTION FEATURE EXTRACTION 1751

SCIKITLEARN USER GUIDE RELEASE 0213
RETURNS
XSPARSE MATRIX NSAMPLES NFEATURES DOCUMENTTERM MATRIX
EXAMPLES USING SKLEARNFEATUREEXTRACTIONTEXTCOUNTVECTORIZER
•TOPIC EXTRACTION WITH NONNEGATIVE MATRIX FACTORIZATION AND LATENT DIRICHLET ALLOCATION
•SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
SKLEARNFEATUREEXTRACTIONTEXT HASHINGVECTORIZER
CLASSSKLEARNFEATUREEXTRACTIONTEXT HASHINGVECTORIZER INPUT'CONTENT'
ENCODING'UTF8' DE
CODEERROR'STRICT'
STRIPACCENTSNONE LOW
ERCASETRUE PREPROCES
SORNONE TOKENIZERNONE
STOPWORDSNONE TO
KENPATTERN'UBWWB'
NGRAMRANGE1
1 ANALYZER'WORD'
NFEATURES1048576 BI
NARYFALSE NORM'L2'
ALTERNATESIGNTRUE
DTYPECLASS
'NUMPYFLOAT64'
CONVERT A COLLECTION OF TEXT DOCUMENTS TO A MATRIX OF TOKEN OCCURRENCES
IT TURNS A COLLECTION OF TEXT DOCUMENTS INTO A SCIPYSPARSE MATRIX HOLDING TOKEN OCCURRENCE COUNTS OR BINARY OCCURRENCE INFORMATION POSSIBLY NORMALIZED AS TOKEN FREQUENCIES IF NORM'L1' OR PROJECTED ON THE EUCLIDEAN UNIT SPHERE IF NORM'L2'
THIS TEXT VECTORIZER IMPLEMENTATION USES THE HASHING TRICK TO FIND THE TOKEN STRING NAME TO FEATURE INTEGER INDEX MAPPING
THIS STRATEGY HAS SEVERAL ADVANTAGES
• IT IS VERY LOW MEMORY SCALABLE TO LARGE DATASETS AS THERE IS NO NEED TO STORE A VOCABULARY DICTIONARY IN MEMORY
• IT IS FAST TO PICKLE AND UNPICKLE AS IT HOLDS NO STATE BESIDES THE CONSTRUCTOR PARAMETERS
• IT CAN BE USED IN A STREAMING PARTIAL FIT OR PARALLEL PIPELINE AS THERE IS NO STATE COMPUTED DURING FIT
THERE ARE ALSO A COUPLE OF CONS VS USING A COUNTVECTORIZER WITH AN INMEMORY VOCABULARY
• THERE IS NO WAY TO COMPUTE THE INVERSE TRANSFORM FROM FEATURE INDICES TO STRING FEATURE NAMES WHICH CAN BE A PROBLEM WHEN TRYING TO INTROSPECT WHICH FEATURES ARE MOST IMPORTANT TO A MODEL
• THERE CAN BE COLLISIONS DISTINCT TOKENS CAN BE MAPPED TO THE SAME FEATURE INDEX HOWEVER IN PRACTICE THIS IS RARELY AN ISSUE IF NFEATURES IS LARGE ENOUGH EG 2 18 FOR TEXT CLASSIFICATION PROBLEMS
• NO IDF WEIGHTING AS THIS WOULD RENDER THE TRANSFORMER STATEFUL
THE HASH FUNCTION EMPLOYED IS THE SIGNED 32BIT VERSION OF MURMURHASH3
READ MORE IN THE USER GUIDE
PARAMETERS

INPUT STRING ‘FILENAME’ ‘FILE’ ‘CONTENT’ IF ‘FILENAME’ THE SEQUENCE PASSED AS AN ARGUMENT TO FIT IS EXPECTED TO BE A LIST OF FILENAMES THAT NEED READING TO FETCH THE RAW CONTENT TO ANALYZE IF ‘FILE’ THE SEQUENCE ITEMS MUST HAVE A ‘READ’ METHOD FILELIKE OBJECT THAT IS CALLED TO FETCH THE BYTES IN MEMORY
OTHERWISE THE INPUT IS EXPECTED TO BE THE SEQUENCE STRINGS OR BYTES ITEMS ARE EXPECTED TO BE ANALYZED DIRECTLY
ENCODING STRING DEFAULT’UTF8’ IF BYTES OR FILES ARE GIVEN TO ANALYZE THIS ENCODING IS USED TO DECODE
DECODEERROR ‘STRICT’ ‘IGNORE’ ‘REPLACE’ INSTRUCTION ON WHAT TO DO IF A BYTE SEQUENCE IS GIVEN TO ANALYZE THAT CONTAINS CHARACTERS NOT OF THE GIVEN ENCODING BY DEFAULT IT IS ‘STRICT’ MEANING THAT A UNICODEDECODEERROR WILL BE RAISED OTHER VALUES ARE ‘IGNORE’ AND ‘REPLACE’
STRIPACCENTS ‘ASCII’ ‘UNICODE’ NONE REMOVE ACCENTS AND PERFORM OTHER CHARACTER NOR MALIZATION DURING THE PREPROCESSING STEP ‘ASCII’ IS A FAST METHOD THAT ONLY WORKS ON CHAR ACTERS THAT HAVE AN DIRECT ASCII MAPPING ‘UNICODE’ IS A SLIGHTLY SLOWER METHOD THAT WORKS ON ANY CHARACTERS NONE DEFAULT DOES NOTHING
BOTH ‘ASCII’ AND ‘UNICODE’ USE NFKD NORMALIZATION FROM UNICODEDATANORMALIZE
LOWERCASE BOOLEAN DEFAULTTRUE CONVERT ALL CHARACTERS TO LOWERCASE BEFORE TOKENIZING
PREPROCESSOR CALLABLE OR NONE DEFAULT OVERRIDE THE PREPROCESSING STRING TRANSFORMATION STAGE WHILE PRESERVING THE TOKENIZING AND NGRAMS GENERATION STEPS
TOKENIZER CALLABLE OR NONE DEFAULT OVERRIDE THE STRING TOKENIZATION STEP WHILE PRESERVING THE PREPROCESSING AND NGRAMS GENERATION STEPS ONLY APPLIES IF ANALYZER WORD
STOPWORDS STRING ‘ENGLISH’ LIST OR NONE DEFAULT IF ‘ENGLISH’ A BUILTIN STOP WORD LIST FOR ENGLISH IS USED THERE ARE SEVERAL KNOWN ISSUES WITH ‘ENGLISH’ AND YOU SHOULD CONSIDER AN ALTERNATIVE SEE USING STOP WORDS
IF A LIST THAT LIST IS ASSUMED TO CONTAIN STOP WORDS ALL OF WHICH WILL BE REMOVED FROM THE RESULTING TOKENS ONLY APPLIES IF ANALYZER WORD
TOKENPATTERN STRING REGULAR EXPRESSION DENOTING WHAT CONSTITUTES A “TOKEN” ONLY USED IF ANALYZER WORD THE DEFAULT REGEXP SELECTS TOKENS OF 2 OR MORE ALPHANUMERIC CHARACTERS PUNCTUATION IS COMPLETELY IGNORED AND ALWAYS TREATED AS A TOKEN SEPARATOR
NGRAMRANGE TUPLE MINN MAXN DEFAULT1 1 THE LOWER AND UPPER BOUNDARY OF THE RANGE OF NVALUES FOR DIFFERENT NGRAMS TO BE EXTRACTED ALL VALUES OF N SUCH THAT MINN N MAXN WILL BE USED
ANALYZER STRING ‘WORD’ ‘CHAR’ ‘CHARWB’ OR CALLABLE WHETHER THE FEATURE SHOULD BE MADE OF WORD OR CHARACTER NGRAMS OPTION ‘CHARWB’ CREATES CHARACTER NGRAMS ONLY FROM TEXT INSIDE WORD BOUNDARIES NGRAMS AT THE EDGES OF WORDS ARE PADDED WITH SPACE
IF A CALLABLE IS PASSED IT IS USED TO EXTRACT THE SEQUENCE OF FEATURES OUT OF THE RAW UNPROCESSED INPUT
CHANGED IN VERSION 021
SINCE V021 IF INPUT ISFILENAME ORFILE THE DATA IS FIRST READ FROM THE FILE AND THEN PASSED TO THE GIVEN CALLABLE ANALYZER
NFEATURES INTEGER DEFAULT2 20 THE NUMBER OF FEATURES COLUMNS IN THE OUTPUT MATRI CES SMALL NUMBERS OF FEATURES ARE LIKELY TO CAUSE HASH COLLISIONS BUT LARGE NUMBERS WILL CAUSE LARGER COEFFICIENT DIMENSIONS IN LINEAR LEARNERS

BINARY BOOLEAN DEFAULTFALSE IF TRUE ALL NON ZERO COUNTS ARE SET TO 1 THIS IS USEFUL FOR
DISCRETE PROBABILISTIC MODELS THAT MODEL BINARY EVENTS RATHER THAN INTEGER COUNTS
NORM ‘L1’ ‘L2’ OR NONE OPTIONAL NORM USED TO NORMALIZE TERM VECTORS NONE FOR NO NORMAL
IZATION
ALTERNATESIGN BOOLEAN OPTIONAL DEFAULT TRUE WHEN TRUE AN ALTERNATING SIGN IS ADDED TO THE
FEATURES AS TO APPROXIMATELY CONSERVE THE INNER PRODUCT IN THE HASHED SPACE EVEN FOR SMALL
NFEATURES THIS APPROACH IS SIMILAR TO SPARSE RANDOM PROJECTION
NEW IN VERSION 019
DTYPE TYPE OPTIONAL TYPE OF THE MATRIX RETURNED BY FITTRANSFORM OR TRANSFORM
SEE ALSO
COUNTVECTORIZER TFIDFVECTORIZER
EXAMPLES
```
 FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT HASHINGVECTORIZER
CORPUS
 THIS IS THE FIRST DOCUMENT
 THIS DOCUMENT IS THE SECOND DOCUMENT
 AND THIS IS THE THIRD ONE
 IS THIS THE FIRST DOCUMENT

VECTORIZER  HASHINGVECTORIZERNFEATURES2 4
X  VECTORIZERFITTRANSFORMCORPUS
PRINTXSHAPE
4 16
```
METHODS
BUILDANALYZER SELF RETURN A CALLABLE THAT HANDLES PREPROCESSING AND TOK
ENIZATION
BUILDPREPROCESSOR SELF RETURN A FUNCTION TO PREPROCESS THE TEXT BEFORE TOKENIZA
TION
BUILDTOKENIZER SELF RETURN A FUNCTION THAT SPLITS A STRING INTO A SEQUENCE OF
TOKENS
DECODE SELF DOC DECODE THE INPUT INTO A STRING OF UNICODE SYMBOLS
FITSELF X Y DOES NOTHING THIS TRANSFORMER IS STATELESS
FITTRANSFORM SELF X Y TRANSFORM A SEQUENCE OF DOCUMENTS TO A DOCUMENTTERM
MATRIX
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSTOPWORDS SELF BUILD OR FETCH THE EFFECTIVE STOP WORDS LIST
PARTIALFIT SELF X Y DOES NOTHING THIS TRANSFORMER IS STATELESS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM A SEQUENCE OF DOCUMENTS TO A DOCUMENTTERM
MATRIX

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INIT SELFINPUT'CONTENT' ENCODING'UTF8' DECODEERROR'STRICT' STRIPACCENTSNONE
LOWERCASETRUE PREPROCESSORNONE TOKENIZERNONE STOPWORDSNONE TO
KENPATTERN'UBWWB' NGRAMRANGE1 1ANALYZER'WORD' NFEATURES1048576
BINARYFALSE NORM'L2' ALTERNATESIGNTRUE DTYPECLASS 'NUMPYFLOAT64'
BUILDANALYZER SELF
RETURN A CALLABLE THAT HANDLES PREPROCESSING AND TOKENIZATION
BUILDPREPROCESSOR SELF
RETURN A FUNCTION TO PREPROCESS THE TEXT BEFORE TOKENIZATION
BUILDTOKENIZER SELF
RETURN A FUNCTION THAT SPLITS A STRING INTO A SEQUENCE OF TOKENS
DECODESELFDOC
DECODE THE INPUT INTO A STRING OF UNICODE SYMBOLS
THE DECODING STRATEGY DEPENDS ON THE VECTORIZER PARAMETERS
PARAMETERS
DOC STRING THE STRING TO DECODE
FITSELFXYNONE
DOES NOTHING THIS TRANSFORMER IS STATELESS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
FITTRANSFORM SELFXYNONE
TRANSFORM A SEQUENCE OF DOCUMENTS TO A DOCUMENTTERM MATRIX
PARAMETERS
XITERABLE OVER RAW TEXT DOCUMENTS LENGTH NSAMPLES SAMPLES EACH SAMPLE MUST BE A
TEXT DOCUMENT EITHER BYTES OR UNICODE STRINGS FILE NAME OR FILE OBJECT DEPENDING ON THE
CONSTRUCTOR ARGUMENT WHICH WILL BE TOKENIZED AND HASHED
YANY IGNORED THIS PARAMETER EXISTS ONLY FOR COMPATIBILITY WITH SKLEARNPIPELINEPIPELINE
RETURNS
XSCIPYSPARSE MATRIX SHAPE NSAMPLES SELFNFEATURES DOCUMENTTERM MATRIX
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSTOPWORDS SELF
BUILD OR FETCH THE EFFECTIVE STOP WORDS LIST
PARTIALFIT SELFXYNONE
DOES NOTHING THIS TRANSFORMER IS STATELESS
THIS METHOD IS JUST THERE TO MARK THE FACT THAT THIS TRANSFORMER CAN WORK IN A STREAMING SETUP
PARAMETERS
615SKLEARNFEATUREEXTRACTION FEATURE EXTRACTION 1755

XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM A SEQUENCE OF DOCUMENTS TO A DOCUMENTTERM MATRIX
PARAMETERS
XITERABLE OVER RAW TEXT DOCUMENTS LENGTH NSAMPLES SAMPLES EACH SAMPLE MUST BE A TEXT DOCUMENT EITHER BYTES OR UNICODE STRINGS FILE NAME OR FILE OBJECT DEPENDING ON THE CONSTRUCTOR ARGUMENT WHICH WILL BE TOKENIZED AND HASHED
RETURNS
XSCIPYSPARSE MATRIX SHAPE NSAMPLES SELFNFEATURES DOCUMENTTERM MATRIX
EXAMPLES USING SKLEARNFEATUREEXTRACTIONTEXTHASHINGVECTORIZER
•OUTOFCORE CLASSIFICATION OF TEXT DOCUMENTS
•CLUSTERING TEXT DOCUMENTS USING KMEANS
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
SKLEARNFEATUREEXTRACTIONTEXT TFIDFTRANSFORMER
CLASSSKLEARNFEATUREEXTRACTIONTEXT TFIDFTRANSFORMER NORM'L2' USEIDFTRUE SMOOTHIDFTRUE SUBLIN EARTFFALSE
TRANSFORM A COUNT MATRIX TO A NORMALIZED TF OR TFIDF REPRESENTATION
TF MEANS TERMFREQUENCY WHILE TFIDF MEANS TERMFREQUENCY TIMES INVERSE DOCUMENTFREQUENCY THIS IS A COMMON TERM WEIGHTING SCHEME IN INFORMATION RETRIEVAL THAT HAS ALSO FOUND GOOD USE IN DOCUMENT CLASSIFICATION
THE GOAL OF USING TFIDF INSTEAD OF THE RAW FREQUENCIES OF OCCURRENCE OF A TOKEN IN A GIVEN DOCUMENT IS TO SCALE DOWN THE IMPACT OF TOKENS THAT OCCUR VERY FREQUENTLY IN A GIVEN CORPUS AND THAT ARE HENCE EMPIRICALLY LESS INFORMATIVE THAN FEATURES THAT OCCUR IN A SMALL FRACTION OF THE TRAINING CORPUS
THE FORMULA THAT IS USED TO COMPUTE THE TFIDF FOR A TERM T OF A DOCUMENT D IN A DOCUMENT SET IS TFIDFT D TFT D IDFT AND THE IDF IS COMPUTED AS IDFT LOG N DFT 1 IF SMOOTHIDFFALSE WHERE N IS THE TOTAL NUMBER OF DOCUMENTS IN THE DOCUMENT SET AND DFT IS THE DOCUMENT FREQUENCY OF T THE DOCUMENT FREQUENCY IS THE NUMBER OF DOCUMENTS IN THE DOCUMENT SET THAT CONTAIN THE TERM T THE EFFECT OF ADDING "1" TO THE IDF IN THE EQUATION ABOVE IS THAT TERMS WITH ZERO IDF IE TERMS THAT OCCUR IN ALL DOCUMENTS IN A TRAINING SET WILL NOT BE ENTIRELY IGNORED NOTE THAT THE IDF FORMULA ABOVE DIFFERS FROM THE STANDARD TEXTBOOK NOTATION THAT DEFINES THE IDF AS IDFT LOG N DFT 1
IFSMOOTHIDFTRUE THE DEFAULT THE CONSTANT "1" IS ADDED TO THE NUMERATOR AND DENOMINATOR OF THE IDF AS IF AN EXTRA DOCUMENT WAS SEEN CONTAINING EVERY TERM IN THE COLLECTION EXACTLY ONCE WHICH PREVENTS ZERO DIVISIONS IDFD T LOG 1 N 1 DFD T 1

FURTHERMORE THE FORMULAS USED TO COMPUTE TF AND IDF DEPEND ON PARAMETER SETTINGS THAT CORRESPOND TO THE SMART NOTATION USED IN IR AS FOLLOWS
TF IS “N” NATURAL BY DEFAULT “L” LOGARITHMIC WHEN SUBLINEARTFTRUE IDF IS “T” WHEN USEIDF IS GIVEN “N” NONE OTHERWISE NORMALIZATION IS “C” COSINE WHEN NORML2 “N” NONE WHEN NORMNONE
READ MORE IN THE USER GUIDE
PARAMETERS
NORM ‘L1’ ‘L2’ OR NONE OPTIONAL DEFAULT’L2’ EACH OUTPUT ROW WILL HAVE UNIT NORM EITHER ‘L2’ SUM OF SQUARES OF VECTOR ELEMENTS IS 1 THE COSINE SIMILARITY BETWEEN TWO VECTORS IS THEIR DOT PRODUCT WHEN L2 NORM HAS BEEN APPLIED ‘L1’ SUM OF ABSOLUTE VALUES OF VECTOR ELEMENTS IS 1 SEE PREPROCESSINGNORMALIZE
USEIDF BOOLEAN DEFAULTTRUE ENABLE INVERSEDOCUMENTFREQUENCY REWEIGHTING
SMOOTHIDF BOOLEAN DEFAULTTRUE SMOOTH IDF WEIGHTS BY ADDING ONE TO DOCUMENT FREQUENCIES AS IF AN EXTRA DOCUMENT WAS SEEN CONTAINING EVERY TERM IN THE COLLECTION EXACTLY ONCE PREVENTS ZERO DIVISIONS
SUBLINEARTF BOOLEAN DEFAULTFALSE APPLY SUBLINEAR TF SCALING IE REPLACE TF WITH 1 LOGTF
ATTRIBUTES
IDF ARRAY SHAPE NFEATURES THE INVERSE DOCUMENT FREQUENCY IDF VECTOR ONLY DEFINED IF USEIDF IS TRUE
REFERENCES
R1B90AC3CA370YATES2011 R1B90AC3CA370MRS2008
METHODS
FITSELF X Y LEARN THE IDF VECTOR GLOBAL TERM WEIGHTS
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X COPY TRANSFORM A COUNT MATRIX TO A TF OR TFIDF REPRESENTATION
INIT SELFNORM’L2’ USEIDFTRUE SMOOTHIDFTRUE SUBLINEARTFFALSE
FITSELFXYNONE
LEARN THE IDF VECTOR GLOBAL TERM WEIGHTS
PARAMETERS
XSPARSE MATRIX NSAMPLES NFEATURES A MATRIX OF TERMTOKEN COUNTS
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET

YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFXCOPYTRUE
TRANSFORM A COUNT MATRIX TO A TF OR TFIDF REPRESENTATION
PARAMETERS
XSPARSE MATRIX NSAMPLES NFEATURES A MATRIX OF TERMTOKEN COUNTS
COPY BOOLEAN DEFAULT TRUE WHETHER TO COPY X AND OPERATE ON THE COPY OR PERFORM INPLACE
OPERATIONS
RETURNS
VECTORS SPARSE MATRIX NSAMPLES NFEATURES
EXAMPLES USING SKLEARNFEATUREEXTRACTIONTEXTTFIDFTRANSFORMER
•SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
•CLUSTERING TEXT DOCUMENTS USING KMEANS

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SKLEARNFEATUREEXTRACTIONTEXT TFIDFVECTORIZER
CLASSSKLEARNFEATUREEXTRACTIONTEXT TFIDFVECTORIZER INPUT'CONTENT' ENCODING'UTF
8' DECODEERROR'STRICT'
STRIPACCENTSNONE LOW
ERCASETRUE PREPROCES
SORNONE TOKENIZERNONE ANA
LYZER'WORD' STOPWORDSNONE
TOKENPATTERN'UBWWB'
NGRAMRANGE1 1
MAXDF10 MINDF1
MAXFEATURESNONE VOCAB
ULARYNONE BINARYFALSE
DTYPECLASS 'NUMPYFLOAT64'
NORM'L2' USEIDFTRUE
SMOOTHIDFTRUE SUBLIN
EARTFFALSE
CONVERT A COLLECTION OF RAW DOCUMENTS TO A MATRIX OF TFIDF FEATURES
EQUIVALENT TO COUNTVECTORIZER FOLLOWED BY TFIDFTRANSFORMER
READ MORE IN THE USER GUIDE
PARAMETERS
INPUT STRING 'FILENAME' 'FILE' 'CONTENT' IF 'FILENAME' THE SEQUENCE PASSED AS AN ARGUMENT TO
FIT IS EXPECTED TO BE A LIST OF FILENAMES THAT NEED READING TO FETCH THE RAW CONTENT TO ANALYZE
IF 'FILE' THE SEQUENCE ITEMS MUST HAVE A 'READ' METHOD FILELIKE OBJECT THAT IS CALLED TO FETCH
THE BYTES IN MEMORY
OTHERWISE THE INPUT IS EXPECTED TO BE THE SEQUENCE STRINGS OR BYTES ITEMS ARE EXPECTED TO BE
ANALYZED DIRECTLY
ENCODING STRING 'UTF8' BY DEFAULT IF BYTES OR FILES ARE GIVEN TO ANALYZE THIS ENCODING IS USED
TO DECODE
DECODEERROR 'STRICT' 'IGNORE' 'REPLACE' DEFAULT'STRICT' INSTRUCTION ON WHAT TO DO IF A
BYTE SEQUENCE IS GIVEN TO ANALYZE THAT CONTAINS CHARACTERS NOT OF THE GIVEN ENCODING BY
DEFAULT IT IS 'STRICT' MEANING THAT A UNICODEDECODEERROR WILL BE RAISED OTHER VALUES ARE
'IGNORE' AND 'REPLACE'
STRIPACCENTS 'ASCII' 'UNICODE' NONE DEFAULTNONE REMOVE ACCENTS AND PERFORM OTHER
CHARACTER NORMALIZATION DURING THE PREPROCESSING STEP 'ASCII' IS A FAST METHOD THAT ONLY
WORKS ON CHARACTERS THAT HAVE AN DIRECT ASCII MAPPING 'UNICODE' IS A SLIGHTLY SLOWER
METHOD THAT WORKS ON ANY CHARACTERS NONE DEFAULT DOES NOTHING
BOTH 'ASCII' AND 'UNICODE' USE NFKD NORMALIZATION FROM UNICODEDATANORMALIZE
LOWERCASE BOOLEAN DEFAULTTRUE CONVERT ALL CHARACTERS TO LOWERCASE BEFORE TOKENIZING
PREPROCESSOR CALLABLE OR NONE DEFAULTNONE OVERRIDE THE PREPROCESSING STRING TRANSFORMA
TION STAGE WHILE PRESERVING THE TOKENIZING AND NGRAMS GENERATION STEPS
TOKENIZER CALLABLE OR NONE DEFAULTNONE OVERRIDE THE STRING TOKENIZATION STEP WHILE PRE
SERVING THE PREPROCESSING AND NGRAMS GENERATION STEPS ONLY APPLIES IF ANALYZER
WORD
ANALYZER STRING 'WORD' 'CHAR' 'CHARWB' OR CALLABLE WHETHER THE FEATURE SHOULD BE MADE
OF WORD OR CHARACTER NGRAMS OPTION 'CHARWB' CREATES CHARACTER NGRAMS ONLY FROM TEXT
INSIDE WORD BOUNDARIES NGRAMS AT THE EDGES OF WORDS ARE PADDED WITH SPACE
615SKLEARNFEATUREEXTRACTION FEATURE EXTRACTION 1759

IF A CALLABLE IS PASSED IT IS USED TO EXTRACT THE SEQUENCE OF FEATURES OUT OF THE RAW UNPROCESSED INPUT
CHANGED IN VERSION 021
SINCE V021 IF INPUT ISFILENAME ORFILE THE DATA IS FIRST READ FROM THE FILE AND THEN PASSED TO THE GIVEN CALLABLE ANALYZER
STOPWORDS STRING ‘ENGLISH’ LIST OR NONE DEFAULTNONE IF A STRING IT IS PASSED TO CHECKSTOPLIST AND THE APPROPRIATE STOP LIST IS RETURNED ‘ENGLISH’ IS CURRENTLY THE ONLY SUPPORTED STRING VALUE THERE ARE SEVERAL KNOWN ISSUES WITH ‘ENGLISH’ AND YOU SHOULD CON SIDER AN ALTERNATIVE SEE USING STOP WORDS
IF A LIST THAT LIST IS ASSUMED TO CONTAIN STOP WORDS ALL OF WHICH WILL BE REMOVED FROM THE RESULTING TOKENS ONLY APPLIES IF ANALYZER WORD
IF NONE NO STOP WORDS WILL BE USED MAXDF CAN BE SET TO A VALUE IN THE RANGE 07 10 TO AUTOMATICALLY DETECT AND FILTER STOP WORDS BASED ON INTRA CORPUS DOCUMENT FREQUENCY OF TERMS
TOKENPATTERN STRING REGULAR EXPRESSION DENOTING WHAT CONSTITUTES A “TOKEN” ONLY USED IF ANALYZER WORD THE DEFAULT REGEXP SELECTS TOKENS OF 2 OR MORE ALPHANUMERIC CHARACTERS PUNCTUATION IS COMPLETELY IGNORED AND ALWAYS TREATED AS A TOKEN SEPARATOR
NGRAMRANGE TUPLE MINN MAXN DEFAULT1 1 THE LOWER AND UPPER BOUNDARY OF THE RANGE OF NVALUES FOR DIFFERENT NGRAMS TO BE EXTRACTED ALL VALUES OF N SUCH THAT MINN N MAXN WILL BE USED
MAXDF FLOAT IN RANGE 00 10 OR INT DEFAULT10 WHEN BUILDING THE VOCABULARY IGNORE TERMS THAT HAVE A DOCUMENT FREQUENCY STRICTLY HIGHER THAN THE GIVEN THRESHOLD CORPUS SPECIFIC STOP WORDS IF FLOAT THE PARAMETER REPRESENTS A PROPORTION OF DOCUMENTS INTEGER ABSOLUTE COUNTS THIS PARAMETER IS IGNORED IF VOCABULARY IS NOT NONE
MINDF FLOAT IN RANGE 00 10 OR INT DEFAULT1 WHEN BUILDING THE VOCABULARY IGNORE TERMS THAT HAVE A DOCUMENT FREQUENCY STRICTLY LOWER THAN THE GIVEN THRESHOLD THIS VALUE IS ALSO CALLED CUTOFF IN THE LITERATURE IF FLOAT THE PARAMETER REPRESENTS A PROPORTION OF DOCUMENTS INTEGER ABSOLUTE COUNTS THIS PARAMETER IS IGNORED IF VOCABULARY IS NOT NONE
MAXFEATURES INT OR NONE DEFAULTNONE IF NOT NONE BUILD A VOCABULARY THAT ONLY CONSIDER THE TOP MAXFEATURES ORDERED BY TERM FREQUENCY ACROSS THE CORPUS
THIS PARAMETER IS IGNORED IF VOCABULARY IS NOT NONE
VOCABULARY MAPPING OR ITERABLE OPTIONAL DEFAULTNONE EITHER A MAPPING EG A DICT WHERE KEYS ARE TERMS AND VALUES ARE INDICES IN THE FEATURE MATRIX OR AN ITERABLE OVER TERMS IF NOT GIVEN A VOCABULARY IS DETERMINED FROM THE INPUT DOCUMENTS
BINARY BOOLEAN DEFAULTFALSE IF TRUE ALL NONZERO TERM COUNTS ARE SET TO 1 THIS DOES NOT MEAN OUTPUTS WILL HAVE ONLY 01 VALUES ONLY THAT THE TF TERM IN TFIDF IS BINARY SET IDF AND NORMALIZATION TO FALSE TO GET 01 OUTPUTS
DTYPE TYPE OPTIONAL DEFAULTFLOAT64 TYPE OF THE MATRIX RETURNED BY FITTRANSFORM OR TRANS FORM
NORM ‘L1’ ‘L2’ OR NONE OPTIONAL DEFAULT’L2’ EACH OUTPUT ROW WILL HAVE UNIT NORM EITHER ‘L2’ SUM OF SQUARES OF VECTOR ELEMENTS IS 1 THE COSINE SIMILARITY BETWEEN TWO VECTORS IS THEIR DOT PRODUCT WHEN L2 NORM HAS BEEN APPLIED ‘L1’ SUM OF ABSOLUTE VALUES OF VECTOR ELEMENTS IS 1 SEE PREPROCESSINGNORMALIZE
USEIDF BOOLEAN DEFAULTTRUE ENABLE INVERSEDOCUMENTFREQUENCY REWEIGHTING

SMOOTHIDF BOOLEAN DEFAULTTRUE SMOOTH IDF WEIGHTS BY ADDING ONE TO DOCUMENT FREQUEN
CIES AS IF AN EXTRA DOCUMENT WAS SEEN CONTAINING EVERY TERM IN THE COLLECTION EXACTLY ONCE
PREVENTS ZERO DIVISIONS
SUBLINEARTF BOOLEAN DEFAULTFALSE APPLY SUBLINEAR TF SCALING IE REPLACE TF WITH 1
LOGTF
ATTRIBUTES
VOCABULARY DICT A MAPPING OF TERMS TO FEATURE INDICES
IDF ARRAY SHAPE NFEATURES THE INVERSE DOCUMENT FREQUENCY IDF VECTOR ONLY DEFINED IF
USEIDF IS TRUE
STOPWORDS SET TERMS THAT WERE IGNORED BECAUSE THEY EITHER
• OCCURRED IN TOO MANY DOCUMENTS MAXDF
• OCCURRED IN TOO FEW DOCUMENTS MINDF
• WERE CUT OFF BY FEATURE SELECTION MAXFEATURES
THIS IS ONLY AVAILABLE IF NO VOCABULARY WAS GIVEN
SEE ALSO
COUNTVECTORIZER TRANSFORMS TEXT INTO A SPARSE MATRIX OF NGRAM COUNTS
TFIDFTRANSFORMER PERFORMS THE TFIDF TRANSFORMATION FROM A PROVIDED MATRIX OF COUNTS
NOTES
THESTOPWORDS ATTRIBUTE CAN GET LARGE AND INCREASE THE MODEL SIZE WHEN PICKLING THIS ATTRIBUTE IS PROVIDED
ONLY FOR INTROSPECTION AND CAN BE SAFELY REMOVED USING DELATTR OR SET TO NONE BEFORE PICKLING
EXAMPLES
 FROM SKLEARNFEATUREEXTRACTIONTEXT IMPORT TFIDFVECTORIZER
CORPUS
 THIS IS THE FIRST DOCUMENT
 THIS DOCUMENT IS THE SECOND DOCUMENT
 AND THIS IS THE THIRD ONE
 IS THIS THE FIRST DOCUMENT

VECTORIZER TFIDFVECTORIZER
X VECTORIZERFITTRANSFORMCORPUS
PRINTVECTORIZERGETFEATURENAMES
AND DOCUMENT FIRST IS ONE SECOND THE THIRD THIS
PRINTXSHAPE
4 9
METHODS
BUILDANALYZER SELF RETURN A CALLABLE THAT HANDLES PREPROCESSING AND TOK
ENIZATION
CONTINUED ON NEXT PAGE

TABLE 6103 – CONTINUED FROM PREVIOUS PAGE
BUILDPREPROCESSOR SELF RETURN A FUNCTION TO PREPROCESS THE TEXT BEFORE TOKENIZA
TION
BUILDTOKENIZER SELF RETURN A FUNCTION THAT SPLITS A STRING INTO A SEQUENCE OF
TOKENS
DECODE SELF DOC DECODE THE INPUT INTO A STRING OF UNICODE SYMBOLS
FITSELF RAWDOCUMENTS Y LEARN VOCABULARY AND IDF FROM TRAINING SET
FITTRANSFORM SELF RAWDOCUMENTS Y LEARN VOCABULARY AND IDF RETURN TERMDOCUMENT MATRIX
GETFEATURENAMES SELF ARRAY MAPPING FROM FEATURE INTEGER INDICES TO FEATURE
NAME
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSTOPWORDS SELF BUILD OR FETCH THE EFFECTIVE STOP WORDS LIST
INVERSETRANSFORM SELF X RETURN TERMS PER DOCUMENT WITH NONZERO ENTRIES IN X
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF RAWDOCUMENTS COPY TRANSFORM DOCUMENTS TO DOCUMENTTERM MATRIX
INIT SELFINPUT’CONTENT’ ENCODING’UTF8’ DECODEERROR’STRICT’ STRIPACCENTSNONE LOW
ERCASETRUE PREPROCESSORNONE TOKENIZERNONE ANALYZER’WORD’ STOPWORDSNONE
TOKENPATTERN’UBWWB’ NGRAMRANGE1 1MAXDF10 MINDF1
MAXFEATURESNONE VOCABULARYNONE BINARYFALSE DTYPECLASS ‘NUMPYFLOAT64’
NORM’L2’ USEIDFTRUE SMOOTHIDFTRUE SUBLINEARTFFALSE
BUILDANALYZER SELF
RETURN A CALLABLE THAT HANDLES PREPROCESSING AND TOKENIZATION
BUILDPREPROCESSOR SELF
RETURN A FUNCTION TO PREPROCESS THE TEXT BEFORE TOKENIZATION
BUILDTOKENIZER SELF
RETURN A FUNCTION THAT SPLITS A STRING INTO A SEQUENCE OF TOKENS
DECODESELFDOC
DECODE THE INPUT INTO A STRING OF UNICODE SYMBOLS
THE DECODING STRATEGY DEPENDS ON THE VECTORIZER PARAMETERS
PARAMETERS
DOC STRING THE STRING TO DECODE
FITSELFRAWDOCUMENTS YNONE
LEARN VOCABULARY AND IDF FROM TRAINING SET
PARAMETERS
RAWDOCUMENTS ITERABLE AN ITERABLE WHICH YIELDS EITHER STR UNICODE OR FILE OBJECTS
RETURNS
SELF TFIDFVECTORIZER
FITTRANSFORM SELFRAWDOCUMENTS YNONE
LEARN VOCABULARY AND IDF RETURN TERMDOCUMENT MATRIX
THIS IS EQUIVALENT TO FIT FOLLOWED BY TRANSFORM BUT MORE EFFICIENTLY IMPLEMENTED
PARAMETERS
RAWDOCUMENTS ITERABLE AN ITERABLE WHICH YIELDS EITHER STR UNICODE OR FILE OBJECTS
RETURNS
XSPARSE MATRIX NSAMPLES NFEATURES TFIDFWEIGHTED DOCUMENTTERM MATRIX

GETFEATURENAMES SELF
ARRAY MAPPING FROM FEATURE INTEGER INDICES TO FEATURE NAME
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSTOPWORDS SELF
BUILD OR FETCH THE EFFECTIVE STOP WORDS LIST
INVERSETRANSFORM SELFX
RETURN TERMS PER DOCUMENT WITH NONZERO ENTRIES IN X
PARAMETERS
XARRAY SPARSE MATRIX SHAPE NSAMPLES NFEATURES
RETURNS
XINV LIST OF ARRAYS LEN NSAMPLES LIST OF ARRAYS OF TERMS
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFRAWDOCUMENTS COPYTRUE
TRANSFORM DOCUMENTS TO DOCUMENTTERM MATRIX
USES THE VOCABULARY AND DOCUMENT FREQUENCIES DF LEARNED BY FIT OR FITTRANSFORM
PARAMETERS
RAWDOCUMENTS ITERABLE AN ITERABLE WHICH YIELDS EITHER STR UNICODE OR FILE OBJECTS
COPY BOOLEAN DEFAULT TRUE WHETHER TO COPY X AND OPERATE ON THE COPY OR PERFORM INPLACE
OPERATIONS
RETURNS
XSPARSE MATRIX NSAMPLES NFEATURES TFIDFWEIGHTED DOCUMENTTERM MATRIX
EXAMPLES USING SKLEARNFEATUREEXTRACTIONTEXTTFIDFVECTORIZER
•TOPIC EXTRACTION WITH NONNEGATIVE MATRIX FACTORIZATION AND LATENT DIRICHLET ALLOCATION
•BICLUSTERING DOCUMENTS WITH THE SPECTRAL COCLUSTERING ALGORITHM
•COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
•CLUSTERING TEXT DOCUMENTS USING KMEANS

•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
616SKLEARNFEATURESELECTION FEATURE SELECTION
THESKLEARNFEATURESELECTION MODULE IMPLEMENTS FEATURE SELECTION ALGORITHMS IT CURRENTLY INCLUDES UNI
VARIATE FILTER SELECTION METHODS AND THE RECURSIVE FEATURE ELIMINATION ALGORITHM
USER GUIDE SEE THE FEATURE SELECTION SECTION FOR FURTHER DETAILS
FEATURESELECTION
GENERICUNIVARIATESELECT UNIVARIATE FEATURE SELECTOR WITH CONFIGURABLE STRATEGY
FEATURESELECTIONSELECTPERCENTILE SELECT FEATURES ACCORDING TO A PERCENTILE OF THE HIGHEST
SCORES
FEATURESELECTIONSELECTKBEST SCOREFUNC
KSELECT FEATURES ACCORDING TO THE K HIGHEST SCORES
FEATURESELECTIONSELECTFPR SCOREFUNC AL
PHAFILTER SELECT THE PVALUES BELOW ALPHA BASED ON A FPR TEST
FEATURESELECTIONSELECTFDR SCOREFUNC AL
PHAFILTER SELECT THE PVALUES FOR AN ESTIMATED FALSE DISCOVERY
RATE
FEATURESELECTION
SELECTFROMMODEL ESTIMATORMETATRANSFORMER FOR SELECTING FEATURES BASED ON IMPOR
TANCE WEIGHTS
FEATURESELECTIONSELECTFWE SCOREFUNC AL
PHAFILTER SELECT THE PVALUES CORRESPONDING TO FAMILYWISE
ERROR RATE
FEATURESELECTIONRFE ESTIMATOR FEATURE RANKING WITH RECURSIVE FEATURE ELIMINATION
FEATURESELECTIONRFECV ESTIMATOR STEP FEATURE RANKING WITH RECURSIVE FEATURE ELIMINATION AND
CROSSVALIDATED SELECTION OF THE BEST NUMBER OF FEATURES
FEATURESELECTION
VARIANCETHRESHOLD THRESHOLDFEATURE SELECTOR THAT REMOVES ALL LOWVARIANCE FEATURES
6161SKLEARNFEATURESELECTION GENERICUNIVARIATESELECT
CLASSSKLEARNFEATURESELECTION GENERICUNIVARIATESELECT SCOREFUNCFUNCTION
FCLASSIF MODE’PERCENTILE’
PARAM1E05
UNIVARIATE FEATURE SELECTOR WITH CONFIGURABLE STRATEGY
READ MORE IN THE USER GUIDE
PARAMETERS
SCOREFUNC CALLABLE FUNCTION TAKING TWO ARRAYS X AND Y AND RETURNING A PAIR OF ARRAYS SCORES
PVALUES FOR MODES ‘PERCENTILE’ OR ‘KBEST’ IT CAN RETURN A SINGLE ARRAY SCORES
MODE ‘PERCENTILE’ ‘KBEST’ ‘FPR’ ‘FDR’ ‘FWE’ FEATURE SELECTION MODE
PARAM FLOAT OR INT DEPENDING ON THE FEATURE SELECTION MODE PARAMETER OF THE CORRESPONDING
MODE
ATTRIBUTES
SCORES ARRAYLIKE SHAPENFEATURES SCORES OF FEATURES
PVALUES ARRAYLIKE SHAPENFEATURES PVALUES OF FEATURE SCORES NONE IF SCOREFUNC
RETURNED SCORES ONLY
SEE ALSO

SCIKITLEARN USER GUIDE RELEASE 0213
FCLASSIF ANOV A FVALUE BETWEEN LABELFEATURE FOR CLASSIFICATION TASKS
MUTUALINFOCLASSIF MUTUAL INFORMATION FOR A DISCRETE TARGET
CHI2 CHISQUARED STATS OF NONNEGATIVE FEATURES FOR CLASSIFICATION TASKS
FREGRESSION FVALUE BETWEEN LABELFEATURE FOR REGRESSION TASKS
MUTUALINFOREGRESSION MUTUAL INFORMATION FOR A CONTINUOUS TARGET
SELECTPERCENTILE SELECT FEATURES BASED ON PERCENTILE OF THE HIGHEST SCORES
SELECTKBEST SELECT FEATURES BASED ON THE K HIGHEST SCORES
SELECTFPR SELECT FEATURES BASED ON A FALSE POSITIVE RATE TEST
SELECTFDR SELECT FEATURES BASED ON AN ESTIMATED FALSE DISCOVERY RATE
SELECTFWE SELECT FEATURES BASED ON FAMILYWISE ERROR RATE
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADBREASTCANCER
 FROM SKLEARNFEATURESELECTION IMPORT GENERICUNIVARIATESELECT CHI2
X Y  LOADBREASTCANCERRETURNXY TRUE
XSHAPE
569 30
TRANSFORMER  GENERICUNIVARIATESELECTCHI2 KBEST PARAM20
XNEW  TRANSFORMERFITTRANSFORMX Y
XNEWSHAPE
569 20
```
METHODS
FITSELF X Y RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE
FEATURES
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSUPPORT SELF INDICES GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
INVERSETRANSFORM SELF X REVERSE THE TRANSFORMATION OPERATION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X REDUCE X TO THE SELECTED FEATURES
INIT SELFSCOREFUNCFUNCTION FCLASSIF AT 0X7EFE30BB2158 MODE’PERCENTILE’ PARAM1E
05
FITSELFXY
RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE FEATURES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUM
BERS IN REGRESSION
RETURNS
616SKLEARNFEATURESELECTION FEATURE SELECTION 1765

SELF OBJECT
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSUPPORT SELFINDICESFALSE
GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
PARAMETERS
INDICES BOOLEAN DEFAULT FALSE IF TRUE THE RETURN VALUE WILL BE AN ARRAY OF INTEGERS RATHER
THAN A BOOLEAN MASK
RETURNS
SUPPORT ARRAY AN INDEX THAT SELECTS THE RETAINED FEATURES FROM A FEATURE VECTOR IF
INDICES IS FALSE THIS IS A BOOLEAN ARRAY OF SHAPE INPUT FEATURES IN WHICH AN ELE
MENT IS TRUE IFF ITS CORRESPONDING FEATURE IS SELECTED FOR RETENTION IF INDICES IS TRUE
THIS IS AN INTEGER ARRAY OF SHAPE OUTPUT FEATURES WHOSE VALUES ARE INDICES INTO THE INPUT
FEATURE VECTOR
INVERSETRANSFORM SELFX
REVERSE THE TRANSFORMATION OPERATION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NORIGINALFEATURES XWITH COLUMNS OF ZEROS INSERTED
WHERE FEATURES WOULD HAVE BEEN REMOVED BY TRANSFORM
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF

TRANSFORM SELFX
REDUCE X TO THE SELECTED FEATURES
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES WITH ONLY THE SE
LECTED FEATURES
6162SKLEARNFEATURESELECTION SELECTPERCENTILE
CLASSSKLEARNFEATURESELECTION SELECTPERCENTILE SCOREFUNCFUNCTION FCLASSIF PER
CENTILE10
SELECT FEATURES ACCORDING TO A PERCENTILE OF THE HIGHEST SCORES
READ MORE IN THE USER GUIDE
PARAMETERS
SCOREFUNC CALLABLE FUNCTION TAKING TWO ARRAYS X AND Y AND RETURNING A PAIR OF ARRAYS SCORES
PVALUES OR A SINGLE ARRAY WITH SCORES DEFAULT IS FCLASSIF SEE BELOW “SEE ALSO” THE
DEFAULT FUNCTION ONLY WORKS WITH CLASSIFICATION TASKS
PERCENTILE INT OPTIONAL DEFAULT10 PERCENT OF FEATURES TO KEEP
ATTRIBUTES
SCORES ARRAYLIKE SHAPENFEATURES SCORES OF FEATURES
PVALUES ARRAYLIKE SHAPENFEATURES PVALUES OF FEATURE SCORES NONE IF SCOREFUNC
RETURNED ONLY SCORES
SEE ALSO
FCLASSIF ANOV A FVALUE BETWEEN LABELFEATURE FOR CLASSIFICATION TASKS
MUTUALINFOCLASSIF MUTUAL INFORMATION FOR A DISCRETE TARGET
CHI2 CHISQUARED STATS OF NONNEGATIVE FEATURES FOR CLASSIFICATION TASKS
FREGRESSION FVALUE BETWEEN LABELFEATURE FOR REGRESSION TASKS
MUTUALINFOREGRESSION MUTUAL INFORMATION FOR A CONTINUOUS TARGET
SELECTKBEST SELECT FEATURES BASED ON THE K HIGHEST SCORES
SELECTFPR SELECT FEATURES BASED ON A FALSE POSITIVE RATE TEST
SELECTFDR SELECT FEATURES BASED ON AN ESTIMATED FALSE DISCOVERY RATE
SELECTFWE SELECT FEATURES BASED ON FAMILYWISE ERROR RATE
GENERICUNIVARIATESELECT UNIVARIATE FEATURE SELECTOR WITH CONFIGURABLE MODE
NOTES
TIES BETWEEN FEATURES WITH EQUAL SCORES WILL BE BROKEN IN AN UNSPECIFIED WAY

EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADDIGITS
 FROM SKLEARNFEATURESELECTION IMPORT SELECTPERCENTILE CHI2
X Y  LOADDIGITSRETURNXY TRUE
XSHAPE
1797 64
XNEW  SELECTPERCENTILECHI2 PERCENTILE10FITTRANSFORMX Y
XNEWSHAPE
1797 7
```
METHODS
FITSELF X Y RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE
FEATURES
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSUPPORT SELF INDICES GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
INVERSETRANSFORM SELF X REVERSE THE TRANSFORMATION OPERATION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X REDUCE X TO THE SELECTED FEATURES
INIT SELFSCOREFUNCFUNCTION FCLASSIF AT 0X7F3C10E93840 PERCENTILE10
FITSELFXY
RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE FEATURES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUM
BERS IN REGRESSION
RETURNS
SELF OBJECT
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSUPPORT SELFINDICESFALSE
GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
PARAMETERS
INDICES BOOLEAN DEFAULT FALSE IF TRUE THE RETURN VALUE WILL BE AN ARRAY OF INTEGERS RATHER
THAN A BOOLEAN MASK
RETURNS
SUPPORT ARRAY AN INDEX THAT SELECTS THE RETAINED FEATURES FROM A FEATURE VECTOR IF
INDICES IS FALSE THIS IS A BOOLEAN ARRAY OF SHAPE INPUT FEATURES IN WHICH AN ELE
MENT IS TRUE IFF ITS CORRESPONDING FEATURE IS SELECTED FOR RETENTION IF INDICES IS TRUE
THIS IS AN INTEGER ARRAY OF SHAPE OUTPUT FEATURES WHOSE VALUES ARE INDICES INTO THE INPUT
FEATURE VECTOR
INVERSETRANSFORM SELFX
REVERSE THE TRANSFORMATION OPERATION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NORIGINALFEATURES XWITH COLUMNS OF ZEROS INSERTED
WHERE FEATURES WOULD HAVE BEEN REMOVED BY TRANSFORM
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
REDUCE X TO THE SELECTED FEATURES
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES WITH ONLY THE SE
LECTED FEATURES
EXAMPLES USING SKLEARNFEATURESELECTIONSELECTPERCENTILE
•FEATURE AGGLOMERATION VS UNIVARIATE SELECTION
•UNIVARIATE FEATURE SELECTION
•SVMANOVA SVM WITH UNIVARIATE FEATURE SELECTION

6163SKLEARNFEATURESELECTION SELECTKBEST
CLASSSKLEARNFEATURESELECTION SELECTKBEST SCOREFUNCFUNCTION FCLASSIF K10
SELECT FEATURES ACCORDING TO THE K HIGHEST SCORES
READ MORE IN THE USER GUIDE
PARAMETERS
SCOREFUNC CALLABLE FUNCTION TAKING TWO ARRAYS X AND Y AND RETURNING A PAIR OF ARRAYS SCORES
PVALUES OR A SINGLE ARRAY WITH SCORES DEFAULT IS FCLASSIF SEE BELOW “SEE ALSO” THE
DEFAULT FUNCTION ONLY WORKS WITH CLASSIFICATION TASKS
KINT OR “ALL” OPTIONAL DEFAULT10 NUMBER OF TOP FEATURES TO SELECT THE “ALL” OPTION BYPASSES
SELECTION FOR USE IN A PARAMETER SEARCH
ATTRIBUTES
SCORES ARRAYLIKE SHAPENFEATURES SCORES OF FEATURES
PVALUES ARRAYLIKE SHAPENFEATURES PVALUES OF FEATURE SCORES NONE IF SCOREFUNC
RETURNED ONLY SCORES
SEE ALSO
FCLASSIF ANOV A FVALUE BETWEEN LABELFEATURE FOR CLASSIFICATION TASKS
MUTUALINFOCLASSIF MUTUAL INFORMATION FOR A DISCRETE TARGET
CHI2 CHISQUARED STATS OF NONNEGATIVE FEATURES FOR CLASSIFICATION TASKS
FREGRESSION FVALUE BETWEEN LABELFEATURE FOR REGRESSION TASKS
MUTUALINFOREGRESSION MUTUAL INFORMATION FOR A CONTINUOUS TARGET
SELECTPERCENTILE SELECT FEATURES BASED ON PERCENTILE OF THE HIGHEST SCORES
SELECTFPR SELECT FEATURES BASED ON A FALSE POSITIVE RATE TEST
SELECTFDR SELECT FEATURES BASED ON AN ESTIMATED FALSE DISCOVERY RATE
SELECTFWE SELECT FEATURES BASED ON FAMILYWISE ERROR RATE
GENERICUNIVARIATESELECT UNIVARIATE FEATURE SELECTOR WITH CONFIGURABLE MODE
NOTES
TIES BETWEEN FEATURES WITH EQUAL SCORES WILL BE BROKEN IN AN UNSPECIFIED WAY
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADDIGITS
 FROM SKLEARNFEATURESELECTION IMPORT SELECTKBEST CHI2
X Y  LOADDIGITSRETURNXY TRUE
XSHAPE
1797 64
XNEW  SELECTKBESTCHI2 K20FITTRANSFORMX Y
XNEWSHAPE
1797 20
```

METHODS
FITSELF X Y RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE
FEATURES
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSUPPORT SELF INDICES GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
INVERSETRANSFORM SELF X REVERSE THE TRANSFORMATION OPERATION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X REDUCE X TO THE SELECTED FEATURES
INIT SELFSCOREFUNCFUNCTION FCLASSIF AT 0X7F3C10E93840 K10
FITSELFXY
RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE FEATURES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUM
BERS IN REGRESSION
RETURNS
SELF OBJECT
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSUPPORT SELFINDICESFALSE
GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
PARAMETERS
INDICES BOOLEAN DEFAULT FALSE IF TRUE THE RETURN VALUE WILL BE AN ARRAY OF INTEGERS RATHER
THAN A BOOLEAN MASK
RETURNS

SUPPORT ARRAY AN INDEX THAT SELECTS THE RETAINED FEATURES FROM A FEATURE VECTOR IF
INDICES IS FALSE THIS IS A BOOLEAN ARRAY OF SHAPE INPUT FEATURES IN WHICH AN ELE
MENT IS TRUE IFF ITS CORRESPONDING FEATURE IS SELECTED FOR RETENTION IF INDICES IS TRUE
THIS IS AN INTEGER ARRAY OF SHAPE OUTPUT FEATURES WHOSE VALUES ARE INDICES INTO THE INPUT
FEATURE VECTOR
INVERSETRANSFORM SELFX
REVERSE THE TRANSFORMATION OPERATION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NORIGINALFEATURES XWITH COLUMNS OF ZEROS INSERTED
WHERE FEATURES WOULD HAVE BEEN REMOVED BY TRANSFORM
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
REDUCE X TO THE SELECTED FEATURES
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES WITH ONLY THE SE
LECTED FEATURES
EXAMPLES USING SKLEARNFEATURESELECTIONSELECTKBEST
•CONCATENATING MULTIPLE FEATURE EXTRACTION METHODS
•SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV
•PIPELINE ANOVA SVM
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
6164SKLEARNFEATURESELECTION SELECTFPR
CLASSSKLEARNFEATURESELECTION SELECTFPR SCOREFUNCFUNCTION FCLASSIF ALPHA005
FILTER SELECT THE PVALUES BELOW ALPHA BASED ON A FPR TEST
FPR TEST STANDS FOR FALSE POSITIVE RATE TEST IT CONTROLS THE TOTAL AMOUNT OF FALSE DETECTIONS
READ MORE IN THE USER GUIDE
PARAMETERS

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SCOREFUNC CALLABLE FUNCTION TAKING TWO ARRAYS X AND Y AND RETURNING A PAIR OF ARRAYS SCORES
PVALUES DEFAULT IS FCLASSIF SEE BELOW “SEE ALSO” THE DEFAULT FUNCTION ONLY WORKS WITH
CLASSIFICATION TASKS
ALPHA FLOAT OPTIONAL THE HIGHEST PVALUE FOR FEATURES TO BE KEPT
ATTRIBUTES
SCORES ARRAYLIKE SHAPENFEATURES SCORES OF FEATURES
PVALUES ARRAYLIKE SHAPENFEATURES PVALUES OF FEATURE SCORES
SEE ALSO
FCLASSIF ANOV A FVALUE BETWEEN LABELFEATURE FOR CLASSIFICATION TASKS
CHI2 CHISQUARED STATS OF NONNEGATIVE FEATURES FOR CLASSIFICATION TASKS
MUTUALINFOCLASSIF
FREGRESSION FVALUE BETWEEN LABELFEATURE FOR REGRESSION TASKS
MUTUALINFOREGRESSION MUTUAL INFORMATION BETWEEN FEATURES AND THE TARGET
SELECTPERCENTILE SELECT FEATURES BASED ON PERCENTILE OF THE HIGHEST SCORES
SELECTKBEST SELECT FEATURES BASED ON THE K HIGHEST SCORES
SELECTFDR SELECT FEATURES BASED ON AN ESTIMATED FALSE DISCOVERY RATE
SELECTFWE SELECT FEATURES BASED ON FAMILYWISE ERROR RATE
GENERICUNIVARIATESELECT UNIVARIATE FEATURE SELECTOR WITH CONFIGURABLE MODE
EXAMPLES
 FROM SKLEARNDATASETS IMPORT LOADBREASTCANCER
 FROM SKLEARNFEATURESELECTION IMPORT SELECTFPR CHI2
X Y LOADBREASTCANCERRETURNXY TRUE
XSHAPE
569 30
XNEW SELECTFPRCHI2 ALPHA001FITTRANSFORMX Y
XNEWSHAPE
569 16
METHODS
FITSELF X Y RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE
FEATURES
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSUPPORT SELF INDICES GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
INVERSETRANSFORM SELF X REVERSE THE TRANSFORMATION OPERATION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X REDUCE X TO THE SELECTED FEATURES
INIT SELFSCOREFUNCFUNCTION FCLASSIF AT 0X7EFE30BB2158 ALPHA005
616SKLEARNFEATURESELECTION FEATURE SELECTION 1773

FITSELFXY
RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE FEATURES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUM
BERS IN REGRESSION
RETURNS
SELF OBJECT
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSUPPORT SELFINDICESFALSE
GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
PARAMETERS
INDICES BOOLEAN DEFAULT FALSE IF TRUE THE RETURN VALUE WILL BE AN ARRAY OF INTEGERS RATHER
THAN A BOOLEAN MASK
RETURNS
SUPPORT ARRAY AN INDEX THAT SELECTS THE RETAINED FEATURES FROM A FEATURE VECTOR IF
INDICES IS FALSE THIS IS A BOOLEAN ARRAY OF SHAPE INPUT FEATURES IN WHICH AN ELE
MENT IS TRUE IFF ITS CORRESPONDING FEATURE IS SELECTED FOR RETENTION IF INDICES IS TRUE
THIS IS AN INTEGER ARRAY OF SHAPE OUTPUT FEATURES WHOSE VALUES ARE INDICES INTO THE INPUT
FEATURE VECTOR
INVERSETRANSFORM SELFX
REVERSE THE TRANSFORMATION OPERATION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES
RETURNS

SCIKITLEARN USER GUIDE RELEASE 0213
XR ARRAY OF SHAPE NSAMPLES NORIGINALFEATURES XWITH COLUMNS OF ZEROS INSERTED
WHERE FEATURES WOULD HAVE BEEN REMOVED BY TRANSFORM
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
REDUCE X TO THE SELECTED FEATURES
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES WITH ONLY THE SE
LECTED FEATURES
6165SKLEARNFEATURESELECTION SELECTFDR
CLASSSKLEARNFEATURESELECTION SELECTFDR SCOREFUNCFUNCTION FCLASSIF ALPHA005
FILTER SELECT THE PVALUES FOR AN ESTIMATED FALSE DISCOVERY RATE
THIS USES THE BENJAMINIHOCHBERG PROCEDURE ALPHA IS AN UPPER BOUND ON THE EXPECTED FALSE DISCOVERY RATE
READ MORE IN THE USER GUIDE
PARAMETERS
SCOREFUNC CALLABLE FUNCTION TAKING TWO ARRAYS X AND Y AND RETURNING A PAIR OF ARRAYS SCORES
PVALUES DEFAULT IS FCLASSIF SEE BELOW "SEE ALSO" THE DEFAULT FUNCTION ONLY WORKS WITH
CLASSIFICATION TASKS
ALPHA FLOAT OPTIONAL THE HIGHEST UNCORRECTED PVALUE FOR FEATURES TO KEEP
ATTRIBUTES
SCORES ARRAYLIKE SHAPENFEATURES SCORES OF FEATURES
PVALUES ARRAYLIKE SHAPENFEATURES PVALUES OF FEATURE SCORES
SEE ALSO
FCLASSIF ANOV A FVALUE BETWEEN LABELFEATURE FOR CLASSIFICATION TASKS
MUTUALINFOCLASSIF MUTUAL INFORMATION FOR A DISCRETE TARGET
CHI2 CHISQUARED STATS OF NONNEGATIVE FEATURES FOR CLASSIFICATION TASKS
FREGRESSION FVALUE BETWEEN LABELFEATURE FOR REGRESSION TASKS
MUTUALINFOREGRESSION MUTUAL INFORMATION FOR A CONTNUOUS TARGET
SELECTPERCENTILE SELECT FEATURES BASED ON PERCENTILE OF THE HIGHEST SCORES
SELECTKBEST SELECT FEATURES BASED ON THE K HIGHEST SCORES
SELECTFPR SELECT FEATURES BASED ON A FALSE POSITIVE RATE TEST
616SKLEARNFEATURESELECTION FEATURE SELECTION 1775

SELECTFWE SELECT FEATURES BASED ON FAMILYWISE ERROR RATE
GENERICUNIVARIATESELECT UNIVARIATE FEATURE SELECTOR WITH CONFIGURABLE MODE
REFERENCES
HTTPSENWIKIPEDIAORGWIKIFALSEDISCOVERYRATE
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADBREASTCANCER
 FROM SKLEARNFEATURESELECTION IMPORT SELECTFDR CHI2
X Y  LOADBREASTCANCERRETURNXY TRUE
XSHAPE
569 30
XNEW  SELECTFDRCHI2 ALPHA001FITTRANSFORMX Y
XNEWSHAPE
569 16
```
METHODS
FITSELF X Y RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE
FEATURES
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSUPPORT SELF INDICES GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
INVERSETRANSFORM SELF X REVERSE THE TRANSFORMATION OPERATION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X REDUCE X TO THE SELECTED FEATURES
INIT SELFSCOREFUNCFUNCTION FCLASSIF AT 0X7EFE30BB2158 ALPHA005
FITSELFXY
RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE FEATURES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUM
BERS IN REGRESSION
RETURNS
SELF OBJECT
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET

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YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSUPPORT SELFINDICESFALSE
GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
PARAMETERS
INDICES BOOLEAN DEFAULT FALSE IF TRUE THE RETURN VALUE WILL BE AN ARRAY OF INTEGERS RATHER
THAN A BOOLEAN MASK
RETURNS
SUPPORT ARRAY AN INDEX THAT SELECTS THE RETAINED FEATURES FROM A FEATURE VECTOR IF
INDICES IS FALSE THIS IS A BOOLEAN ARRAY OF SHAPE INPUT FEATURES IN WHICH AN ELE
MENT IS TRUE IFF ITS CORRESPONDING FEATURE IS SELECTED FOR RETENTION IF INDICES IS TRUE
THIS IS AN INTEGER ARRAY OF SHAPE OUTPUT FEATURES WHOSE VALUES ARE INDICES INTO THE INPUT
FEATURE VECTOR
INVERSETRANSFORM SELFX
REVERSE THE TRANSFORMATION OPERATION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NORIGINALFEATURES XWITH COLUMNS OF ZEROS INSERTED
WHERE FEATURES WOULD HAVE BEEN REMOVED BY TRANSFORM
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
REDUCE X TO THE SELECTED FEATURES
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
616SKLEARNFEATURESELECTION FEATURE SELECTION 1777

XR ARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES WITH ONLY THE SE
LECTED FEATURES
6166SKLEARNFEATURESELECTION SELECTFROMMODEL
CLASSSKLEARNFEATURESELECTION SELECTFROMMODEL ESTIMATOR THRESHOLDNONE PREFITFALSE
NORMORDER1 MAXFEATURESNONE
METATRANSFORMER FOR SELECTING FEATURES BASED ON IMPORTANCE WEIGHTS
NEW IN VERSION 017
PARAMETERS
ESTIMATOR OBJECT THE BASE ESTIMATOR FROM WHICH THE TRANSFORMER IS BUILT THIS CAN BE BOTH A
FITTED IFPREFIT IS SET TO TRUE OR A NONFITTED ESTIMATOR THE ESTIMATOR MUST HAVE EITHER A
FEATUREIMPORTANCES ORCOEF ATTRIBUTE AFTER FITTING
THRESHOLD STRING FLOAT OPTIONAL DEFAULT NONE THE THRESHOLD VALUE TO USE FOR FEATURE SELECTION
FEATURES WHOSE IMPORTANCE IS GREATER OR EQUAL ARE KEPT WHILE THE OTHERS ARE DISCARDED IF
“MEDIAN” RESP “MEAN” THEN THE THRESHOLD VALUE IS THE MEDIAN RESP THE MEAN OF THE
FEATURE IMPORTANCES A SCALING FACTOR EG “125MEAN” MAY ALSO BE USED IF NONE AND
IF THE ESTIMATOR HAS A PARAMETER PENALTY SET TO L1 EITHER EXPLICITLY OR IMPLICITLY EG LASSO
THE THRESHOLD USED IS 1E5 OTHERWISE “MEAN” IS USED BY DEFAULT
PREFIT BOOL DEFAULT FALSE WHETHER A PREFIT MODEL IS EXPECTED TO BE PASSED INTO THE CONSTRUCTOR
DIRECTLY OR NOT IF TRUE TRANSFORM MUST BE CALLED DIRECTLY AND SELECTFROMMODEL CAN
NOT BE USED WITH CROSSVALSCORE GRIDSEARCHCV AND SIMILAR UTILITIES THAT CLONE
THE ESTIMATOR OTHERWISE TRAIN THE MODEL USING FIT AND THENTRANSFORM TO DO FEATURE
SELECTION
NORMORDER NONZERO INT INF INF DEFAULT 1 ORDER OF THE NORM USED TO FILTER THE VECTORS OF
COEFFICIENTS BELOW THRESHOLD IN THE CASE WHERE THE COEF ATTRIBUTE OF THE ESTIMATOR IS
OF DIMENSION 2
MAXFEATURES INT OR NONE OPTIONAL THE MAXIMUM NUMBER OF FEATURES SELECTED SCORING ABOVE
THRESHOLD TO DISABLE THRESHOLD AND ONLY SELECT BASED ON MAXFEATURES SET
THRESHOLDNPINF
NEW IN VERSION 020
ATTRIBUTES
ESTIMATOR AN ESTIMATOR THE BASE ESTIMATOR FROM WHICH THE TRANSFORMER IS BUILT THIS IS STORED
ONLY WHEN A NONFITTED ESTIMATOR IS PASSED TO THE SELECTFROMMODEL IE WHEN PREFIT IS
FALSE
THRESHOLD FLOAT THE THRESHOLD VALUE USED FOR FEATURE SELECTION
METHODS
FITSELF X Y FIT THE SELECTFROMMODEL METATRANSFORMER
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSUPPORT SELF INDICES GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
INVERSETRANSFORM SELF X REVERSE THE TRANSFORMATION OPERATION
PARTIALFIT SELF X Y FIT THE SELECTFROMMODEL METATRANSFORMER ONLY ONCE
CONTINUED ON NEXT PAGE

TABLE 6110 – CONTINUED FROM PREVIOUS PAGE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X REDUCE X TO THE SELECTED FEATURES
INIT SELFESTIMATOR THRESHOLDNONE PREFITFALSE NORMORDER1 MAXFEATURESNONE
FITSELFXYNONE FITPARAMS
FIT THE SELECTFROMMODEL METATRANSFORMER
PARAMETERS
XARRAYLIKE OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES INTEGERS THAT CORRESPOND TO CLASSES IN
CLASSIFICATION REAL NUMBERS IN REGRESSION
FITPARAMS OTHER ESTIMATOR SPECIFIC PARAMETERS
RETURNS
SELF OBJECT
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSUPPORT SELFINDICESFALSE
GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
PARAMETERS
INDICES BOOLEAN DEFAULT FALSE IF TRUE THE RETURN VALUE WILL BE AN ARRAY OF INTEGERS RATHER
THAN A BOOLEAN MASK
RETURNS
SUPPORT ARRAY AN INDEX THAT SELECTS THE RETAINED FEATURES FROM A FEATURE VECTOR IF
INDICES IS FALSE THIS IS A BOOLEAN ARRAY OF SHAPE INPUT FEATURES IN WHICH AN ELE
MENT IS TRUE IFF ITS CORRESPONDING FEATURE IS SELECTED FOR RETENTION IF INDICES IS TRUE
THIS IS AN INTEGER ARRAY OF SHAPE OUTPUT FEATURES WHOSE VALUES ARE INDICES INTO THE INPUT
FEATURE VECTOR

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INVERSETRANSFORM SELFX
REVERSE THE TRANSFORMATION OPERATION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NORIGINALFEATURES XWITH COLUMNS OF ZEROS INSERTED
WHERE FEATURES WOULD HAVE BEEN REMOVED BY TRANSFORM
PARTIALFIT SELFXYNONE FITPARAMS
FIT THE SELECTFROMMODEL METATRANSFORMER ONLY ONCE
PARAMETERS
XARRAYLIKE OF SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES INTEGERS THAT CORRESPOND TO CLASSES IN
CLASSIFICATION REAL NUMBERS IN REGRESSION
FITPARAMS OTHER ESTIMATOR SPECIFIC PARAMETERS
RETURNS
SELF OBJECT
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
REDUCE X TO THE SELECTED FEATURES
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES WITH ONLY THE SE
LECTED FEATURES
EXAMPLES USING SKLEARNFEATURESELECTIONSELECTFROMMODEL
•FEATURE SELECTION USING SELECTFROMMODEL AND LASSOCV
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
6167SKLEARNFEATURESELECTION SELECTFWE
CLASSSKLEARNFEATURESELECTION SELECTFWE SCOREFUNCFUNCTION FCLASSIF ALPHA005
FILTER SELECT THE PVALUES CORRESPONDING TO FAMILYWISE ERROR RATE
READ MORE IN THE USER GUIDE
1780 CHAPTER 6 API REFERENCE

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PARAMETERS
SCOREFUNC CALLABLE FUNCTION TAKING TWO ARRAYS X AND Y AND RETURNING A PAIR OF ARRAYS SCORES
PVALUES DEFAULT IS FCLASSIF SEE BELOW “SEE ALSO” THE DEFAULT FUNCTION ONLY WORKS WITH
CLASSIFICATION TASKS
ALPHA FLOAT OPTIONAL THE HIGHEST UNCORRECTED PVALUE FOR FEATURES TO KEEP
ATTRIBUTES
SCORES ARRAYLIKE SHAPENFEATURES SCORES OF FEATURES
PVALUES ARRAYLIKE SHAPENFEATURES PVALUES OF FEATURE SCORES
SEE ALSO
FCLASSIF ANOV A FVALUE BETWEEN LABELFEATURE FOR CLASSIFICATION TASKS
CHI2 CHISQUARED STATS OF NONNEGATIVE FEATURES FOR CLASSIFICATION TASKS
FREGRESSION FVALUE BETWEEN LABELFEATURE FOR REGRESSION TASKS
SELECTPERCENTILE SELECT FEATURES BASED ON PERCENTILE OF THE HIGHEST SCORES
SELECTKBEST SELECT FEATURES BASED ON THE K HIGHEST SCORES
SELECTFPR SELECT FEATURES BASED ON A FALSE POSITIVE RATE TEST
SELECTFDR SELECT FEATURES BASED ON AN ESTIMATED FALSE DISCOVERY RATE
GENERICUNIVARIATESELECT UNIVARIATE FEATURE SELECTOR WITH CONFIGURABLE MODE
EXAMPLES
 FROM SKLEARNDATASETS IMPORT LOADBREASTCANCER
 FROM SKLEARNFEATURESELECTION IMPORT SELECTFWE CHI2
X Y LOADBREASTCANCERRETURNXY TRUE
XSHAPE
569 30
XNEW SELECTFWECHI2 ALPHA001FITTRANSFORMX Y
XNEWSHAPE
569 15
METHODS
FITSELF X Y RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE
FEATURES
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSUPPORT SELF INDICES GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
INVERSETRANSFORM SELF X REVERSE THE TRANSFORMATION OPERATION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X REDUCE X TO THE SELECTED FEATURES
INIT SELFSCOREFUNCFUNCTION FCLASSIF AT 0X7EFE30BB2158 ALPHA005
FITSELFXY
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RUN SCORE FUNCTION ON X Y AND GET THE APPROPRIATE FEATURES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUM
BERS IN REGRESSION
RETURNS
SELF OBJECT
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSUPPORT SELFINDICESFALSE
GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
PARAMETERS
INDICES BOOLEAN DEFAULT FALSE IF TRUE THE RETURN VALUE WILL BE AN ARRAY OF INTEGERS RATHER
THAN A BOOLEAN MASK
RETURNS
SUPPORT ARRAY AN INDEX THAT SELECTS THE RETAINED FEATURES FROM A FEATURE VECTOR IF
INDICES IS FALSE THIS IS A BOOLEAN ARRAY OF SHAPE INPUT FEATURES IN WHICH AN ELE
MENT IS TRUE IFF ITS CORRESPONDING FEATURE IS SELECTED FOR RETENTION IF INDICES IS TRUE
THIS IS AN INTEGER ARRAY OF SHAPE OUTPUT FEATURES WHOSE VALUES ARE INDICES INTO THE INPUT
FEATURE VECTOR
INVERSETRANSFORM SELFX
REVERSE THE TRANSFORMATION OPERATION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NORIGINALFEATURES XWITH COLUMNS OF ZEROS INSERTED
WHERE FEATURES WOULD HAVE BEEN REMOVED BY TRANSFORM

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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
REDUCE X TO THE SELECTED FEATURES
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES WITH ONLY THE SE
LECTED FEATURES
6168SKLEARNFEATURESELECTION RFE
CLASSSKLEARNFEATURESELECTION RFEESTIMATOR NFEATURESTOSELECTNONE STEP1 VERBOSE0
FEATURE RANKING WITH RECURSIVE FEATURE ELIMINATION
GIVEN AN EXTERNAL ESTIMATOR THAT ASSIGNS WEIGHTS TO FEATURES EG THE COEFFICIENTS OF A LINEAR MODEL THE GOAL OF
RECURSIVE FEATURE ELIMINATION RFE IS TO SELECT FEATURES BY RECURSIVELY CONSIDERING SMALLER AND SMALLER SETS OF
FEATURES FIRST THE ESTIMATOR IS TRAINED ON THE INITIAL SET OF FEATURES AND THE IMPORTANCE OF EACH FEATURE IS OBTAINED
EITHER THROUGH A COEF ATTRIBUTE OR THROUGH A FEATUREIMPORTANCES ATTRIBUTE THEN THE LEAST IMPORTANT
FEATURES ARE PRUNED FROM CURRENT SET OF FEATURES THAT PROCEDURE IS RECURSIVELY REPEATED ON THE PRUNED SET UNTIL
THE DESIRED NUMBER OF FEATURES TO SELECT IS EVENTUALLY REACHED
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR OBJECT A SUPERVISED LEARNING ESTIMATOR WITH A FIT METHOD THAT PROVIDES IN
FORMATION ABOUT FEATURE IMPORTANCE EITHER THROUGH A COEF ATTRIBUTE OR THROUGH A
FEATUREIMPORTANCES ATTRIBUTE
NFEATURESTOSELECT INT OR NONE DEFAULTNONE THE NUMBER OF FEATURES TO SELECT IF NONE
HALF OF THE FEATURES ARE SELECTED
STEP INT OR FLOAT OPTIONAL DEFAULT1 IF GREATER THAN OR EQUAL TO 1 THEN STEP CORRESPONDS TO
THE INTEGER NUMBER OF FEATURES TO REMOVE AT EACH ITERATION IF WITHIN 00 10 THEN STEP
CORRESPONDS TO THE PERCENTAGE ROUNDED DOWN OF FEATURES TO REMOVE AT EACH ITERATION
VERBOSE INT DEFAULT0 CONTROLS VERBOSITY OF OUTPUT
ATTRIBUTES
NFEATURES INT THE NUMBER OF SELECTED FEATURES
SUPPORT ARRAY OF SHAPE NFEATURES THE MASK OF SELECTED FEATURES
RANKING ARRAY OF SHAPE NFEATURES THE FEATURE RANKING SUCH THAT RANKINGI CORRE
SPONDS TO THE RANKING POSITION OF THE ITH FEATURE SELECTED IE ESTIMATED BEST FEATURES ARE
ASSIGNED RANK 1
ESTIMATOR OBJECT THE EXTERNAL ESTIMATOR FIT ON THE REDUCED DATASET
616SKLEARNFEATURESELECTION FEATURE SELECTION 1783

SEE ALSO
RFECV RECURSIVE FEATURE ELIMINATION WITH BUILTIN CROSSVALIDATED SELECTION OF THE BEST NUMBER OF FEATURES
REFERENCES
RE310F679C81E1
EXAMPLES
THE FOLLOWING EXAMPLE SHOWS HOW TO RETRIEVE THE 5 RIGHT INFORMATIVE FEATURES IN THE FRIEDMAN 1 DATASET
```
 FROM SKLEARNDATASETS IMPORT MAKEFRIEDMAN1
 FROM SKLEARNFEATURESELECTION IMPORT RFE
 FROM SKLEARNSVM IMPORT SVR
X Y  MAKEFRIEDMAN1NSAMPLES50 NFEATURES10 RANDOMSTATE0
ESTIMATOR  SVRKERNELLINEAR
SELECTOR  RFEESTIMATOR 5 STEP1
SELECTOR  SELECTORFITX Y
SELECTORSUPPORT
ARRAY TRUE TRUE TRUE TRUE TRUE FALSE FALSE FALSE FALSE
FALSE
SELECTORRANKING
ARRAY1 1 1 1 1 6 4 3 2 5
```
METHODS
DECISIONFUNCTION SELF X COMPUTE THE DECISION FUNCTION OF X
FITSELF X Y FIT THE RFE MODEL AND THEN THE UNDERLYING ESTIMATOR ON
THE SELECTED FEATURES
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSUPPORT SELF INDICES GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
INVERSETRANSFORM SELF X REVERSE THE TRANSFORMATION OPERATION
PREDICT SELF X REDUCE X TO THE SELECTED FEATURES AND THEN PREDICT USING
THE UNDERLYING ESTIMATOR
PREDICTLOGPROBA SELF X PREDICT CLASS LOGPROBABILITIES FOR X
PREDICTPROBA SELF X PREDICT CLASS PROBABILITIES FOR X
SCORE SELF X Y REDUCE X TO THE SELECTED FEATURES AND THEN RETURN THE
SCORE OF THE UNDERLYING ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X REDUCE X TO THE SELECTED FEATURES
INIT SELFESTIMATOR NFEATURESTOSELECTNONE STEP1 VERBOSE0
DECISIONFUNCTION SELFX
COMPUTE THE DECISION FUNCTION OF X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO

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A SPARSECSRMATRIX
RETURNS
SCORE ARRAY SHAPE NSAMPLES NCLASSES OR NSAMPLES THE DECISION FUNCTION OF THE
INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES RE
GRESSION AND BINARY CLASSIFICATION PRODUCE AN ARRAY OF SHAPE NSAMPLES
FITSELFXY
FIT THE RFE MODEL AND THEN THE UNDERLYING ESTIMATOR ON THE SELECTED FEATURES
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSUPPORT SELFINDICESFALSE
GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
PARAMETERS
INDICES BOOLEAN DEFAULT FALSE IF TRUE THE RETURN VALUE WILL BE AN ARRAY OF INTEGERS RATHER
THAN A BOOLEAN MASK
RETURNS
SUPPORT ARRAY AN INDEX THAT SELECTS THE RETAINED FEATURES FROM A FEATURE VECTOR IF
INDICES IS FALSE THIS IS A BOOLEAN ARRAY OF SHAPE INPUT FEATURES IN WHICH AN ELE
MENT IS TRUE IFF ITS CORRESPONDING FEATURE IS SELECTED FOR RETENTION IF INDICES IS TRUE
THIS IS AN INTEGER ARRAY OF SHAPE OUTPUT FEATURES WHOSE VALUES ARE INDICES INTO THE INPUT
FEATURE VECTOR
INVERSETRANSFORM SELFX
REVERSE THE TRANSFORMATION OPERATION
PARAMETERS
616SKLEARNFEATURESELECTION FEATURE SELECTION 1785

XARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NORIGINALFEATURES XWITH COLUMNS OF ZEROS INSERTED
WHERE FEATURES WOULD HAVE BEEN REMOVED BY TRANSFORM
PREDICTSELFX
REDUCE X TO THE SELECTED FEATURES AND THEN PREDICT USING THE UNDERLYING ESTIMATOR
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
YARRAY OF SHAPE NSAMPLES THE PREDICTED TARGET VALUES
PREDICTLOGPROBA SELFX
PREDICT CLASS LOGPROBABILITIES FOR X
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES THE CLASS LOGPROBABILITIES OF THE INPUT SAMPLES
THE ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES
PREDICTPROBA SELFX
PREDICT CLASS PROBABILITIES FOR X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE
ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES
SCORESELFXY
REDUCE X TO THE SELECTED FEATURES AND THEN RETURN THE SCORE OF THE UNDERLYING ESTIMATOR
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
YARRAY OF SHAPE NSAMPLES THE TARGET VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF

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TRANSFORM SELFX
REDUCE X TO THE SELECTED FEATURES
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES WITH ONLY THE SE
LECTED FEATURES
EXAMPLES USING SKLEARNFEATURESELECTIONRFE
•RECURSIVE FEATURE ELIMINATION
6169SKLEARNFEATURESELECTION RFECV
CLASSSKLEARNFEATURESELECTION RFECVESTIMATOR STEP1 MINFEATURESTOSELECT1 CV'WARN'
SCORINGNONE VERBOSE0 NJOBSNONE
FEATURE RANKING WITH RECURSIVE FEATURE ELIMINATION AND CROSSVALIDATED SELECTION OF THE BEST NUMBER OF FEATURES
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR OBJECT A SUPERVISED LEARNING ESTIMATOR WITH A FIT METHOD THAT PROVIDES IN
FORMATION ABOUT FEATURE IMPORTANCE EITHER THROUGH A COEF ATTRIBUTE OR THROUGH A
FEATUREIMPORTANCES ATTRIBUTE
STEP INT OR FLOAT OPTIONAL DEFAULT1 IF GREATER THAN OR EQUAL TO 1 THEN STEP CORRESPONDS
TO THE INTEGER NUMBER OF FEATURES TO REMOVE AT EACH ITERATION IF WITHIN 00 10 THEN
STEP CORRESPONDS TO THE PERCENTAGE ROUNDED DOWN OF FEATURES TO REMOVE AT EACH ITERA
TION NOTE THAT THE LAST ITERATION MAY REMOVE FEWER THAN STEP FEATURES IN ORDER TO REACH
MINFEATURESTOSELECT
MINFEATURESTOSELECT INT DEFAULT1 THE MINIMUM NUMBER OF FEATURES TO BE SELECTED
THIS NUMBER OF FEATURES WILL ALWAYS BE SCORED EVEN IF THE DIFFERENCE BETWEEN THE ORIGI
NAL FEATURE COUNT AND MINFEATURESTOSELECT ISN'T DIVISIBLE BY STEP
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF YIS BINARY OR MULTICLASS SKLEARNMODELSELECTION
STRATIFIEDKFOLD IS USED IF THE ESTIMATOR IS A CLASSIFIER OR IF YIS NEITHER BINARY NOR
MULTICLASS SKLEARNMODELSELECTIONKFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE OF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
616SKLEARNFEATURESELECTION FEATURE SELECTION 1787

SCIKITLEARN USER GUIDE RELEASE 0213
SCORING STRING CALLABLE OR NONE OPTIONAL DEFAULTNONE A STRING SEE MODEL EVALUATION DOC
UMENTATION OR A SCORER CALLABLE OBJECT FUNCTION WITH SIGNATURE SCORERESTIMATOR
X Y
VERBOSE INT DEFAULT0 CONTROLS VERBOSITY OF OUTPUT
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CORES TO RUN IN PARALLEL WHILE FITTING
ACROSS FOLDS NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1
MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
ATTRIBUTES
NFEATURES INT THE NUMBER OF SELECTED FEATURES WITH CROSSVALIDATION
SUPPORT ARRAY OF SHAPE NFEATURES THE MASK OF SELECTED FEATURES
RANKING ARRAY OF SHAPE NFEATURES THE FEATURE RANKING SUCH THAT RANKINGI CORRE
SPONDS TO THE RANKING POSITION OF THE ITH FEATURE SELECTED IE ESTIMATED BEST FEATURES ARE
ASSIGNED RANK 1
GRIDSCORES ARRAY OF SHAPE NSUBSETSOFFEATURES THE CROSSVALIDATION SCORES SUCH THAT
GRIDSCORESI CORRESPONDS TO THE CV SCORE OF THE ITH SUBSET OF FEATURES
ESTIMATOR OBJECT THE EXTERNAL ESTIMATOR FIT ON THE REDUCED DATASET
SEE ALSO
RFE RECURSIVE FEATURE ELIMINATION
NOTES
THE SIZE OF GRIDSCORES IS EQUAL TO CEILNFEATURES MINFEATURESTOSELECT
STEP 1 WHERE STEP IS THE NUMBER OF FEATURES REMOVED AT EACH ITERATION
REFERENCES
R6F4D61CEB4111
EXAMPLES
THE FOLLOWING EXAMPLE SHOWS HOW TO RETRIEVE THE APRIORI NOT KNOWN 5 INFORMATIVE FEATURES IN THE FRIEDMAN 1
DATASET
 FROM SKLEARNDATASETS IMPORT MAKEFRIEDMAN1
 FROM SKLEARNFEATURESELECTION IMPORT RFECV
 FROM SKLEARNSVM IMPORT SVR
X Y MAKEFRIEDMAN1NSAMPLES50 NFEATURES10 RANDOMSTATE0
ESTIMATOR SVRKERNELLINEAR
SELECTOR RFECVESTIMATOR STEP1 CV5
SELECTOR SELECTORFITX Y
SELECTORSUPPORT
ARRAY TRUE TRUE TRUE TRUE TRUE FALSE FALSE FALSE FALSE
FALSE
SELECTORRANKING
ARRAY1 1 1 1 1 6 4 3 2 5

METHODS
DECISIONFUNCTION SELF X COMPUTE THE DECISION FUNCTION OF X
FITSELF X Y GROUPS FIT THE RFE MODEL AND AUTOMATICALLY TUNE THE NUMBER
OF SELECTED FEATURES
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSUPPORT SELF INDICES GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
INVERSETRANSFORM SELF X REVERSE THE TRANSFORMATION OPERATION
PREDICT SELF X REDUCE X TO THE SELECTED FEATURES AND THEN PREDICT USING
THE UNDERLYING ESTIMATOR
PREDICTLOGPROBA SELF X PREDICT CLASS LOGPROBABILITIES FOR X
PREDICTPROBA SELF X PREDICT CLASS PROBABILITIES FOR X
SCORE SELF X Y REDUCE X TO THE SELECTED FEATURES AND THEN RETURN THE
SCORE OF THE UNDERLYING ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X REDUCE X TO THE SELECTED FEATURES
INIT SELFESTIMATOR STEP1 MINFEATURESTOSELECT1 CV'WARN' SCORINGNONE VERBOSE0
NJOBSNONE
DECISIONFUNCTION SELFX
COMPUTE THE DECISION FUNCTION OF X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
SCORE ARRAY SHAPE NSAMPLES NCLASSES OR NSAMPLES THE DECISION FUNCTION OF THE
INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES RE
GRESSION AND BINARY CLASSIFICATION PRODUCE AN ARRAY OF SHAPE NSAMPLES
FITSELFXYGROUPSNONE
FIT THE RFE MODEL AND AUTOMATICALLY TUNE THE NUMBER OF SELECTED FEATURES
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE TOTAL NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES INTEGERS FOR CLASSIFICATION REAL NUMBERS
FOR REGRESSION
GROUPS ARRAYLIKE SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED WHILE
SPLITTING THE DATASET INTO TRAINTEST SET ONLY USED IN CONJUNCTION WITH A "GROUP" CVINSTANCE
EGGROUPKFOLD
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS

XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSUPPORT SELFINDICESFALSE
GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
PARAMETERS
INDICES BOOLEAN DEFAULT FALSE IF TRUE THE RETURN VALUE WILL BE AN ARRAY OF INTEGERS RATHER
THAN A BOOLEAN MASK
RETURNS
SUPPORT ARRAY AN INDEX THAT SELECTS THE RETAINED FEATURES FROM A FEATURE VECTOR IF
INDICES IS FALSE THIS IS A BOOLEAN ARRAY OF SHAPE INPUT FEATURES IN WHICH AN ELE
MENT IS TRUE IFF ITS CORRESPONDING FEATURE IS SELECTED FOR RETENTION IF INDICES IS TRUE
THIS IS AN INTEGER ARRAY OF SHAPE OUTPUT FEATURES WHOSE VALUES ARE INDICES INTO THE INPUT
FEATURE VECTOR
INVERSETRANSFORM SELFX
REVERSE THE TRANSFORMATION OPERATION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NORIGINALFEATURES XWITH COLUMNS OF ZEROS INSERTED
WHERE FEATURES WOULD HAVE BEEN REMOVED BY TRANSFORM
PREDICTSELFX
REDUCE X TO THE SELECTED FEATURES AND THEN PREDICT USING THE UNDERLYING ESTIMATOR
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XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
YARRAY OF SHAPE NSAMPLES THE PREDICTED TARGET VALUES
PREDICTLOGPROBA SELFX
PREDICT CLASS LOGPROBABILITIES FOR X
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES

RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES THE CLASS LOGPROBABILITIES OF THE INPUT SAMPLES
THE ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES
PREDICTPROBA SELFX
PREDICT CLASS PROBABILITIES FOR X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE
ORDER OF THE CLASSES CORRESPONDS TO THAT IN THE ATTRIBUTE CLASSES
SCORESELFXY
REDUCE X TO THE SELECTED FEATURES AND THEN RETURN THE SCORE OF THE UNDERLYING ESTIMATOR
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
YARRAY OF SHAPE NSAMPLES THE TARGET VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
REDUCE X TO THE SELECTED FEATURES
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES WITH ONLY THE SE
LECTED FEATURES
EXAMPLES USING SKLEARNFEATURESELECTIONRFECV
•RECURSIVE FEATURE ELIMINATION WITH CROSSVALIDATION
61610SKLEARNFEATURESELECTION VARIANCETHRESHOLD
CLASSSKLEARNFEATURESELECTION VARIANCETHRESHOLD THRESHOLD00
FEATURE SELECTOR THAT REMOVES ALL LOWVARIANCE FEATURES
616SKLEARNFEATURESELECTION FEATURE SELECTION 1791

THIS FEATURE SELECTION ALGORITHM LOOKS ONLY AT THE FEATURES X NOT THE DESIRED OUTPUTS Y AND CAN THUS BE USED FOR UNSUPERVISED LEARNING
READ MORE IN THE USER GUIDE
PARAMETERS
THRESHOLD FLOAT OPTIONAL FEATURES WITH A TRAININGSET VARIANCE LOWER THAN THIS THRESHOLD WILL BE REMOVED THE DEFAULT IS TO KEEP ALL FEATURES WITH NONZERO VARIANCE IE REMOVE THE FEATURES THAT HAVE THE SAME VALUE IN ALL SAMPLES
ATTRIBUTES
VARIANCES ARRAY SHAPE NFEATURES VARIANCES OF INDIVIDUAL FEATURES
EXAMPLES
THE FOLLOWING DATASET HAS INTEGER FEATURES TWO OF WHICH ARE THE SAME IN EVERY SAMPLE THESE ARE REMOVED WITH THE DEFAULT SETTING FOR THRESHOLD
X 0 2 0 3 0 1 4 3 0 1 1 3
SELECTOR VARIANCETHRESHOLD
SELECTORFITTRANSFORMX
ARRAY2 0
1 4
1 1
METHODS
FITSELF X Y LEARN EMPIRICAL VARIANCES FROM X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETSUPPORT SELF INDICES GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
INVERSETRANSFORM SELF X REVERSE THE TRANSFORMATION OPERATION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X REDUCE X TO THE SELECTED FEATURES
INIT SELFTHRESHOLD00
FITSELFXYNONE
LEARN EMPIRICAL VARIANCES FROM X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLE VECTORS FROM WHICH TO COMPUTE VARIANCES
YANY IGNORED THIS PARAMETER EXISTS ONLY FOR COMPATIBILITY WITH SKLEARNPIPELINEPIPELINE
RETURNS
SELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X

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XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETSUPPORT SELFINDICESFALSE
GET A MASK OR INTEGER INDEX OF THE FEATURES SELECTED
PARAMETERS
INDICES BOOLEAN DEFAULT FALSE IF TRUE THE RETURN VALUE WILL BE AN ARRAY OF INTEGERS RATHER
THAN A BOOLEAN MASK
RETURNS
SUPPORT ARRAY AN INDEX THAT SELECTS THE RETAINED FEATURES FROM A FEATURE VECTOR IF
INDICES IS FALSE THIS IS A BOOLEAN ARRAY OF SHAPE INPUT FEATURES IN WHICH AN ELE
MENT IS TRUE IFF ITS CORRESPONDING FEATURE IS SELECTED FOR RETENTION IF INDICES IS TRUE
THIS IS AN INTEGER ARRAY OF SHAPE OUTPUT FEATURES WHOSE VALUES ARE INDICES INTO THE INPUT
FEATURE VECTOR
INVERSETRANSFORM SELFX
REVERSE THE TRANSFORMATION OPERATION
PARAMETERS
XARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES
RETURNS
XR ARRAY OF SHAPE NSAMPLES NORIGINALFEATURES XWITH COLUMNS OF ZEROS INSERTED
WHERE FEATURES WOULD HAVE BEEN REMOVED BY TRANSFORM
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
REDUCE X TO THE SELECTED FEATURES
PARAMETERS
XARRAY OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES
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RETURNS
XR ARRAY OF SHAPE NSAMPLES NSELECTEDFEATURES THE INPUT SAMPLES WITH ONLY THE SE
LECTED FEATURES
FEATURESELECTIONCHI2 X Y COMPUTE CHISQUARED STATS BETWEEN EACH NONNEGATIVE FEA
TURE AND CLASS
FEATURESELECTIONFCLASSIF X Y COMPUTE THE ANOV A FVALUE FOR THE PROVIDED SAMPLE
FEATURESELECTIONFREGRESSION X Y CEN
TERUNIVARIATE LINEAR REGRESSION TESTS
FEATURESELECTION
MUTUALINFOCLASSIF X YESTIMATE MUTUAL INFORMATION FOR A DISCRETE TARGET VARIABLE
FEATURESELECTION
MUTUALINFOREGRESSION X YESTIMATE MUTUAL INFORMATION FOR A CONTINUOUS TARGET VARI
ABLE
61611SKLEARNFEATURESELECTION CHI2
SKLEARNFEATURESELECTION CHI2XY
COMPUTE CHISQUARED STATS BETWEEN EACH NONNEGATIVE FEATURE AND CLASS
THIS SCORE CAN BE USED TO SELECT THE NFEATURES FEATURES WITH THE HIGHEST VALUES FOR THE TEST CHISQUARED STATISTIC
FROM X WHICH MUST CONTAIN ONLY NONNEGATIVE FEATURES SUCH AS BOOLEANS OR FREQUENCIES EG TERM COUNTS IN
DOCUMENT CLASSIFICATION RELATIVE TO THE CLASSES
RECALL THAT THE CHISQUARE TEST MEASURES DEPENDENCE BETWEEN STOCHASTIC VARIABLES SO USING THIS FUNCTION “WEEDS
OUT” THE FEATURES THAT ARE THE MOST LIKELY TO BE INDEPENDENT OF CLASS AND THEREFORE IRRELEVANT FOR CLASSIFICATION
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURESIN SAMPLE VECTORS
YARRAYLIKE SHAPE NSAMPLES TARGET VECTOR CLASS LABELS
RETURNS
CHI2 ARRAY SHAPE NFEATURES CHI2 STATISTICS OF EACH FEATURE
PVAL ARRAY SHAPE NFEATURES PVALUES OF EACH FEATURE
SEE ALSO
FCLASSIF ANOV A FVALUE BETWEEN LABELFEATURE FOR CLASSIFICATION TASKS
FREGRESSION FVALUE BETWEEN LABELFEATURE FOR REGRESSION TASKS
NOTES
COMPLEXITY OF THIS ALGORITHM IS ONCLASSES NFEATURES
EXAMPLES USING SKLEARNFEATURESELECTIONCHI2
•SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV
•SVMANOVA SVM WITH UNIVARIATE FEATURE SELECTION
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES

61612SKLEARNFEATURESELECTION FCLASSIF
SKLEARNFEATURESELECTION FCLASSIF XY
COMPUTE THE ANOV A FVALUE FOR THE PROVIDED SAMPLE
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE SET OF REGRESSORS THAT WILL
BE TESTED SEQUENTIALLY
YARRAY OF SHAPENSAMPLES THE DATA MATRIX
RETURNS
FARRAY SHAPE NFEATURES THE SET OF F VALUES
PVAL ARRAY SHAPE NFEATURES THE SET OF PVALUES
SEE ALSO
CHI2 CHISQUARED STATS OF NONNEGATIVE FEATURES FOR CLASSIFICATION TASKS
FREGRESSION FVALUE BETWEEN LABELFEATURE FOR REGRESSION TASKS
EXAMPLES USING SKLEARNFEATURESELECTIONFCLASSIF
•UNIVARIATE FEATURE SELECTION
61613SKLEARNFEATURESELECTION FREGRESSION
SKLEARNFEATURESELECTION FREGRESSION XYCENTERTRUE
UNIVARIATE LINEAR REGRESSION TESTS
LINEAR MODEL FOR TESTING THE INDIVIDUAL EFFECT OF EACH OF MANY REGRESSORS THIS IS A SCORING FUNCTION TO BE USED
IN A FEATURE SELECTION PROCEDURE NOT A FREE STANDING FEATURE SELECTION PROCEDURE
THIS IS DONE IN 2 STEPS
1 THE CORRELATION BETWEEN EACH REGRESSOR AND THE TARGET IS COMPUTED THAT IS X I MEANX I Y
MEANY STDX I STDY
2 IT IS CONVERTED TO AN F SCORE THEN TO A PVALUE
FOR MORE ON USAGE SEE THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE SET OF REGRESSORS THAT WILL
BE TESTED SEQUENTIALLY
YARRAY OF SHAPENSAMPLES THE DATA MATRIX
CENTER TRUE BOOL IF TRUE X AND Y WILL BE CENTERED
RETURNS
FARRAY SHAPENFEATURES F VALUES OF FEATURES
PVAL ARRAY SHAPENFEATURES PVALUES OF FSCORES
SEE ALSO

MUTUALINFOREGRESSION MUTUAL INFORMATION FOR A CONTINUOUS TARGET
FCLASSIF ANOV A FVALUE BETWEEN LABELFEATURE FOR CLASSIFICATION TASKS
CHI2 CHISQUARED STATS OF NONNEGATIVE FEATURES FOR CLASSIFICATION TASKS
SELECTKBEST SELECT FEATURES BASED ON THE K HIGHEST SCORES
SELECTFPR SELECT FEATURES BASED ON A FALSE POSITIVE RATE TEST
SELECTFDR SELECT FEATURES BASED ON AN ESTIMATED FALSE DISCOVERY RATE
SELECTFWE SELECT FEATURES BASED ON FAMILYWISE ERROR RATE
SELECTPERCENTILE SELECT FEATURES BASED ON PERCENTILE OF THE HIGHEST SCORES
EXAMPLES USING SKLEARNFEATURESELECTIONFREGRESSION
•FEATURE AGGLOMERATION VS UNIVARIATE SELECTION
•COMPARISON OF FTEST AND MUTUAL INFORMATION
•PIPELINE ANOVA SVM
61614SKLEARNFEATURESELECTION MUTUALINFOCLASSIF
SKLEARNFEATURESELECTION MUTUALINFOCLASSIF X Y DISCRETEFEATURES'AUTO'
NNEIGHBORS3 COPYTRUE RAN
DOMSTATENONE
ESTIMATE MUTUAL INFORMATION FOR A DISCRETE TARGET VARIABLE
MUTUAL INFORMATION MI 1BETWEEN TWO RANDOM VARIABLES IS A NONNEGATIVE VALUE WHICH MEASURES THE DEPEN
DENCY BETWEEN THE VARIABLES IT IS EQUAL TO ZERO IF AND ONLY IF TWO RANDOM VARIABLES ARE INDEPENDENT AND HIGHER
VALUES MEAN HIGHER DEPENDENCY
THE FUNCTION RELIES ON NONPARAMETRIC METHODS BASED ON ENTROPY ESTIMATION FROM KNEAREST NEIGHBORS DISTANCES
AS DESCRIBED IN 2AND3 BOTH METHODS ARE BASED ON THE IDEA ORIGINALLY PROPOSED IN 4
IT CAN BE USED FOR UNIVARIATE FEATURES SELECTION READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES FEATURE MATRIX
YARRAYLIKE SHAPE NSAMPLES TARGET VECTOR
DISCRETEFEATURES 'AUTO' BOOL ARRAYLIKE DEFAULT 'AUTO' IF BOOL THEN DETERMINES WHETHER
TO CONSIDER ALL FEATURES DISCRETE OR CONTINUOUS IF ARRAY THEN IT SHOULD BE EITHER A BOOLEAN
MASK WITH SHAPE NFEATURES OR ARRAY WITH INDICES OF DISCRETE FEATURES IF 'AUTO' IT IS
ASSIGNED TO FALSE FOR DENSE XAND TO TRUE FOR SPARSE X
NNEIGHBORS INT DEFAULT 3 NUMBER OF NEIGHBORS TO USE FOR MI ESTIMATION FOR CONTINUOUS VARI
ABLES SEE 2AND3 HIGHER VALUES REDUCE VARIANCE OF THE ESTIMATION BUT COULD INTRODUCE
A BIAS
COPY BOOL DEFAULT TRUE WHETHER TO MAKE A COPY OF THE GIVEN DATA IF SET TO FALSE THE INITIAL
DATA WILL BE OVERWRITTEN
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR FOR ADDING SMALL NOISE TO CONTINUOUS VARIABLES IN ORDER
TO REMOVE REPEATED VALUES IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER

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GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE
THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
RETURNS
MINDARRAY SHAPE NFEATURES ESTIMATED MUTUAL INFORMATION BETWEEN EACH FEATURE AND THE
TARGET
NOTES
1 THE TERM “DISCRETE FEATURES” IS USED INSTEAD OF NAMING THEM “CATEGORICAL” BECAUSE IT DESCRIBES THE ESSENCE
MORE ACCURATELY FOR EXAMPLE PIXEL INTENSITIES OF AN IMAGE ARE DISCRETE FEATURES BUT HARDLY CATEGORICAL
AND YOU WILL GET BETTER RESULTS IF MARK THEM AS SUCH ALSO NOTE THAT TREATING A CONTINUOUS VARIABLE AS
DISCRETE AND VICE VERSA WILL USUALLY GIVE INCORRECT RESULTS SO BE ATTENTIVE ABOUT THAT
2 TRUE MUTUAL INFORMATION CAN’T BE NEGATIVE IF ITS ESTIMATE TURNS OUT TO BE NEGATIVE IT IS REPLACED BY ZERO
REFERENCES
1234
61615SKLEARNFEATURESELECTION MUTUALINFOREGRESSION
SKLEARNFEATURESELECTION MUTUALINFOREGRESSION XY DISCRETEFEATURES’AUTO’
NNEIGHBORS3 COPYTRUE RAN
DOMSTATENONE
ESTIMATE MUTUAL INFORMATION FOR A CONTINUOUS TARGET VARIABLE
MUTUAL INFORMATION MI 1BETWEEN TWO RANDOM VARIABLES IS A NONNEGATIVE VALUE WHICH MEASURES THE DEPEN
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COPY BOOL DEFAULT TRUE WHETHER TO MAKE A COPY OF THE GIVEN DATA IF SET TO FALSE THE INITIAL
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PSEUDO RANDOM NUMBER GENERATOR FOR ADDING SMALL NOISE TO CONTINUOUS VARIABLES IN ORDER
TO REMOVE REPEATED VALUES IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER
616SKLEARNFEATURESELECTION FEATURE SELECTION 1797

GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE
THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
RETURNS
MINDARRAY SHAPE NFEATURES ESTIMATED MUTUAL INFORMATION BETWEEN EACH FEATURE AND THE
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NOTES
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•COMPARISON OF FTEST AND MUTUAL INFORMATION
617SKLEARNGAUSSIANPROCESS GAUSSIAN PROCESSES
THESKLEARNGAUSSIANPROCESS MODULE IMPLEMENTS GAUSSIAN PROCESS BASED REGRESSION AND CLASSIFICATION
USER GUIDE SEE THE GAUSSIAN PROCESSES SECTION FOR FURTHER DETAILS
GAUSSIANPROCESSGAUSSIANPROCESSCLASSIFIER GAUSSIAN PROCESS CLASSIFICATION GPC BASED ON LAPLACE
APPROXIMATION
GAUSSIANPROCESSGAUSSIANPROCESSREGRESSOR GAUSSIAN PROCESS REGRESSION GPR
6171SKLEARNGAUSSIANPROCESS GAUSSIANPROCESSCLASSIFIER
CLASSSKLEARNGAUSSIANPROCESS GAUSSIANPROCESSCLASSIFIER KERNELNONE OPTI
MIZER’FMINLBFGSB’
NRESTARTSOPTIMIZER0
MAXITERPREDICT100
WARMSTARTFALSE
COPYXTRAINTRUE
RANDOMSTATENONE
MULTICLASS’ONEVSREST’
NJOBSNONE
GAUSSIAN PROCESS CLASSIFICATION GPC BASED ON LAPLACE APPROXIMATION
THE IMPLEMENTATION IS BASED ON ALGORITHM 31 32 AND 51 OF GAUSSIAN PROCESSES FOR MACHINE LEARNING
GPML BY RASMUSSEN AND WILLIAMS

INTERNALLY THE LAPLACE APPROXIMATION IS USED FOR APPROXIMATING THE NONGAUSSIAN POSTERIOR BY A GAUSSIAN
CURRENTLY THE IMPLEMENTATION IS RESTRICTED TO USING THE LOGISTIC LINK FUNCTION FOR MULTICLASS CLASSIFICATION
SEVERAL BINARY ONEVERSUS REST CLASSIFIERS ARE FITTED NOTE THAT THIS CLASS THUS DOES NOT IMPLEMENT A TRUE MULTI
CLASS LAPLACE APPROXIMATION
PARAMETERS
KERNEL KERNEL OBJECT THE KERNEL SPECIFYING THE COVARIANCE FUNCTION OF THE GP IF NONE IS
PASSED THE KERNEL “10 RBF10” IS USED AS DEFAULT NOTE THAT THE KERNEL’S HYPERPA
RAMETERS ARE OPTIMIZED DURING FITTING
OPTIMIZER STRING OR CALLABLE OPTIONAL DEFAULT “FMINLBFGSB” CAN EITHER BE ONE OF THE
INTERNALLY SUPPORTED OPTIMIZERS FOR OPTIMIZING THE KERNEL’S PARAMETERS SPECIFIED BY A STRING
OR AN EXTERNALLY DEFINED OPTIMIZER PASSED AS A CALLABLE IF A CALLABLE IS PASSED IT MUST HAVE
THE SIGNATURE
DEFOPTIMIZEROBJFUNC INITIALTHETA BOUNDS
OBJFUNC IS THE OBJECTIVE FUNCTION TO BE MAXIMIZED WHICH
 TAKES THE HYPERPARAMETERS THETA AS PARAMETER AND AN
 OPTIONAL FLAG EVALGRADIENT WHICH DETERMINES IF THE
 GRADIENT IS RETURNED ADDITIONALLY TO THE FUNCTION VALUE
INITIALTHETA THE INITIAL VALUE FOR THETA WHICH CAN BE
 USED BY LOCAL OPTIMIZERS
BOUNDS THE BOUNDS ON THE VALUES OF THETA

 RETURNED ARE THE BEST FOUND HYPERPARAMETERS THETA AND
 THE CORRESPONDING VALUE OF THE TARGET FUNCTION
RETURNTHETAOPT FUNCMIN
PER DEFAULT THE ‘FMINLBFGSB’ ALGORITHM FROM SCIPYOPTIMIZE IS USED IF NONE IS PASSED
THE KERNEL’S PARAMETERS ARE KEPT FIXED AVAILABLE INTERNAL OPTIMIZERS ARE
FMINLBFGSB
NRESTARTSOPTIMIZER INT OPTIONAL DEFAULT 0 THE NUMBER OF RESTARTS OF THE OPTIMIZER FOR
FINDING THE KERNEL’S PARAMETERS WHICH MAXIMIZE THE LOGMARGINAL LIKELIHOOD THE FIRST RUN
OF THE OPTIMIZER IS PERFORMED FROM THE KERNEL’S INITIAL PARAMETERS THE REMAINING ONES IF
ANY FROM THETAS SAMPLED LOGUNIFORM RANDOMLY FROM THE SPACE OF ALLOWED THETAVALUES IF
GREATER THAN 0 ALL BOUNDS MUST BE FINITE NOTE THAT NRESTARTSOPTIMIZER0 IMPLIES THAT ONE
RUN IS PERFORMED
MAXITERPREDICT INT OPTIONAL DEFAULT 100 THE MAXIMUM NUMBER OF ITERATIONS IN NEW
TON’S METHOD FOR APPROXIMATING THE POSTERIOR DURING PREDICT SMALLER VALUES WILL REDUCE
COMPUTATION TIME AT THE COST OF WORSE RESULTS
WARMSTART BOOL OPTIONAL DEFAULT FALSE IF WARMSTARTS ARE ENABLED THE SOLUTION OF THE LAST
NEWTON ITERATION ON THE LAPLACE APPROXIMATION OF THE POSTERIOR MODE IS USED AS INITIALIZA
TION FOR THE NEXT CALL OF POSTERIORMODE THIS CAN SPEED UP CONVERGENCE WHEN POSTE
RIORMODE IS CALLED SEVERAL TIMES ON SIMILAR PROBLEMS AS IN HYPERPARAMETER OPTIMIZATION
SEETHE GLOSSARY
COPYXTRAIN BOOL OPTIONAL DEFAULT TRUE IF TRUE A PERSISTENT COPY OF THE TRAINING DATA IS
STORED IN THE OBJECT OTHERWISE JUST A REFERENCE TO THE TRAINING DATA IS STORED WHICH MIGHT
CAUSE PREDICTIONS TO CHANGE IF THE DATA IS MODIFIED EXTERNALLY
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE GENERATOR
USED TO INITIALIZE THE CENTERS IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER

GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE
THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
MULTICLASS STRING DEFAULT SPECIFIES HOW MULTICLASS CLASSIFICATION PROBLEMS ARE HANDLED
SUPPORTED ARE “ONEVSREST” AND “ONEVSONE” IN “ONEVSREST” ONE BINARY GAUSSIAN
PROCESS CLASSIFIER IS FITTED FOR EACH CLASS WHICH IS TRAINED TO SEPARATE THIS CLASS FROM THE REST
IN “ONEVSONE” ONE BINARY GAUSSIAN PROCESS CLASSIFIER IS FITTED FOR EACH PAIR OF CLASSES
WHICH IS TRAINED TO SEPARATE THESE TWO CLASSES THE PREDICTIONS OF THESE BINARY PREDICTORS ARE
COMBINED INTO MULTICLASS PREDICTIONS NOTE THAT “ONEVSONE” DOES NOT SUPPORT PREDICTING
PROBABILITY ESTIMATES
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL
PROCESSORS SEE GLOSSARY FOR MORE DETAILS
ATTRIBUTES
KERNEL KERNEL OBJECT THE KERNEL USED FOR PREDICTION IN CASE OF BINARY CLASSIFICATION THE
STRUCTURE OF THE KERNEL IS THE SAME AS THE ONE PASSED AS PARAMETER BUT WITH OPTIMIZED HY
PERPARAMETERS IN CASE OF MULTICLASS CLASSIFICATION A COMPOUNDKERNEL IS RETURNED WHICH
CONSISTS OF THE DIFFERENT KERNELS USED IN THE ONEVERSUSREST CLASSIFIERS
LOGMARGINALLIKELIHOODVALUE FLOAT THE LOGMARGINALLIKELIHOOD OF SELFKERNEL
THETA
CLASSES ARRAYLIKE SHAPE NCLASSES UNIQUE CLASS LABELS
NCLASSES INT THE NUMBER OF CLASSES IN THE TRAINING DATA
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSCLASSIFIER
 FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT RBF
X Y  LOADIRISRETURNXY TRUE
KERNEL  10 RBF10
GPC  GAUSSIANPROCESSCLASSIFIERKERNELKERNEL
 RANDOMSTATE0FITX Y
GPCSCOREX Y
09866
GPCPREDICTPROBAX2
ARRAY083548752 003228706 013222543
079064206 006525643 014410151
```
NEW IN VERSION 018
METHODS
FITSELF X Y FIT GAUSSIAN PROCESS CLASSIFICATION MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
LOGMARGINALLIKELIHOOD SELF THETA RETURNS LOGMARGINAL LIKELIHOOD OF THETA FOR TRAINING
DATA
PREDICT SELF X PERFORM CLASSIFICATION ON AN ARRAY OF TEST VECTORS X
PREDICTPROBA SELF X RETURN PROBABILITY ESTIMATES FOR THE TEST VECTOR X
CONTINUED ON NEXT PAGE

TABLE 6117 – CONTINUED FROM PREVIOUS PAGE
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELF KERNELNONE OPTIMIZER'FMINLBFGSB' NRESTARTSOPTIMIZER0
MAXITERPREDICT100 WARMSTARTFALSE COPYXTRAINTRUE RANDOMSTATENONE
MULTICLASS'ONEVSREST' NJOBSNONE
FITSELFXY
FIT GAUSSIAN PROCESS CLASSIFICATION MODEL
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES MUST BE BINARY
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
LOGMARGINALLIKELIHOOD SELFTHETANONE EVALGRADIENTFALSE
RETURNS LOGMARGINAL LIKELIHOOD OF THETA FOR TRAINING DATA
IN THE CASE OF MULTICLASS CLASSIFICATION THE MEAN LOGMARGINAL LIKELIHOOD OF THE ONEVERSUSREST CLASSIFIERS
ARE RETURNED
PARAMETERS
THETA ARRAYLIKE SHAPE NKERNELPARAMS OR NONE KERNEL HYPERPARAMETERS FOR WHICH
THE LOGMARGINAL LIKELIHOOD IS EVALUATED IN THE CASE OF MULTICLASS CLASSIFICATION THETA MAY
BE THE HYPERPARAMETERS OF THE COMPOUND KERNEL OR OF AN INDIVIDUAL KERNEL IN THE LATTER
CASE ALL INDIVIDUAL KERNEL GET ASSIGNED THE SAME THETA VALUES IF NONE THE PRECOMPUTED
LOGMARGINALLIKELIHOOD OF SELFKERNELTHETA IS RETURNED
EVALGRADIENT BOOL DEFAULT FALSE IF TRUE THE GRADIENT OF THE LOGMARGINAL LIKELIHOOD WITH
RESPECT TO THE KERNEL HYPERPARAMETERS AT POSITION THETA IS RETURNED ADDITIONALLY NOTE THAT
GRADIENT COMPUTATION IS NOT SUPPORTED FOR NONBINARY CLASSIFICATION IF TRUE THETA MUST NOT
BE NONE
RETURNS
LOGLIKELIHOOD FLOAT LOGMARGINAL LIKELIHOOD OF THETA FOR TRAINING DATA
LOGLIKELIHOODGRADIENT ARRAY SHAPE NKERNELPARAMS OPTIONAL GRADIENT OF THE LOG
MARGINAL LIKELIHOOD WITH RESPECT TO THE KERNEL HYPERPARAMETERS AT POSITION THETA ONLY
RETURNED WHEN EVALGRADIENT IS TRUE
PREDICTSELFX
PERFORM CLASSIFICATION ON AN ARRAY OF TEST VECTORS X

PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
CARRAY SHAPE NSAMPLES PREDICTED TARGET VALUES FOR X VALUES ARE FROM CLASSES
PREDICTPROBA SELFX
RETURN PROBABILITY ESTIMATES FOR THE TEST VECTOR X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
CARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE PROBABILITY OF THE SAMPLES FOR
EACH CLASS IN THE MODEL THE COLUMNS CORRESPOND TO THE CLASSES IN SORTED ORDER AS THEY
APPEAR IN THE ATTRIBUTE CLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNGAUSSIANPROCESSGAUSSIANPROCESSCLASSIFIER
•PLOT CLASSIFICATION PROBABILITY
•CLASSIFIER COMPARISON
•ILLUSTRATION OF GAUSSIAN PROCESS CLASSIFICATION GPC ON THE XOR DATASET
•GAUSSIAN PROCESS CLASSIFICATION GPC ON IRIS DATASET
•ISOPROBABILITY LINES FOR GAUSSIAN PROCESSES CLASSIFICATION GPC
•PROBABILISTIC PREDICTIONS WITH GAUSSIAN PROCESS CLASSIFICATION GPC

SCIKITLEARN USER GUIDE RELEASE 0213
6172SKLEARNGAUSSIANPROCESS GAUSSIANPROCESSREGRESSOR
CLASSSKLEARNGAUSSIANPROCESS GAUSSIANPROCESSREGRESSOR KERNELNONE ALPHA1E10
OPTIMIZER'FMINLBFGSB'
NRESTARTSOPTIMIZER0
NORMALIZEYFALSE
COPYXTRAINTRUE RAN
DOMSTATENONE
GAUSSIAN PROCESS REGRESSION GPR
THE IMPLEMENTATION IS BASED ON ALGORITHM 21 OF GAUSSIAN PROCESSES FOR MACHINE LEARNING GPML BY RAS
MUSSEN AND WILLIAMS
IN ADDITION TO STANDARD SCIKITLEARN ESTIMATOR API GAUSSIANPROCESSREGRESSOR
• ALLOWS PREDICTION WITHOUT PRIOR FITTING BASED ON THE GP PRIOR
• PROVIDES AN ADDITIONAL METHOD SAMPLEYX WHICH EVALUATES SAMPLES DRAWN FROM THE GPR PRIOR OR POS
TERIOR AT GIVEN INPUTS
• EXPOSES A METHOD LOGMARGINALLIKELIHOODTHETA WHICH CAN BE USED EXTERNALLY FOR OTHER WAYS OF SELECTING
HYPERPARAMETERS EG VIA MARKOV CHAIN MONTE CARLO
READ MORE IN THE USER GUIDE
NEW IN VERSION 018
PARAMETERS
KERNEL KERNEL OBJECT THE KERNEL SPECIFYING THE COVARIANCE FUNCTION OF THE GP IF NONE IS
PASSED THE KERNEL "10 RBF10" IS USED AS DEFAULT NOTE THAT THE KERNEL'S HYPERPA
RAMETERS ARE OPTIMIZED DURING FITTING
ALPHA FLOAT OR ARRAYLIKE OPTIONAL DEFAULT 1E10 VALUE ADDED TO THE DIAGONAL OF THE KERNEL
MATRIX DURING FITTING LARGER VALUES CORRESPOND TO INCREASED NOISE LEVEL IN THE OBSERVATIONS
THIS CAN ALSO PREVENT A POTENTIAL NUMERICAL ISSUE DURING FITTING BY ENSURING THAT THE CALCU
LATED VALUES FORM A POSITIVE DEFINITE MATRIX IF AN ARRAY IS PASSED IT MUST HAVE THE SAME
NUMBER OF ENTRIES AS THE DATA USED FOR FITTING AND IS USED AS DATAPOINTDEPENDENT NOISE LEVEL
NOTE THAT THIS IS EQUIVALENT TO ADDING A WHITEKERNEL WITH CALPHA ALLOWING TO SPECIFY THE
NOISE LEVEL DIRECTLY AS A PARAMETER IS MAINLY FOR CONVENIENCE AND FOR CONSISTENCY WITH RIDGE
OPTIMIZER STRING OR CALLABLE OPTIONAL DEFAULT "FMINLBFGSB" CAN EITHER BE ONE OF THE
INTERNALLY SUPPORTED OPTIMIZERS FOR OPTIMIZING THE KERNEL'S PARAMETERS SPECIFIED BY A STRING
OR AN EXTERNALLY DEFINED OPTIMIZER PASSED AS A CALLABLE IF A CALLABLE IS PASSED IT MUST HAVE
THE SIGNATURE
DEFOPTIMIZEROBJFUNC INITIALTHETA BOUNDS
OBJFUNC IS THE OBJECTIVE FUNCTION TO BE MINIMIZED WHICH
 TAKES THE HYPERPARAMETERS THETA AS PARAMETER AND AN
 OPTIONAL FLAG EVALGRADIENT WHICH DETERMINES IF THE
 GRADIENT IS RETURNED ADDITIONALLY TO THE FUNCTION VALUE
INITIALTHETA THE INITIAL VALUE FOR THETA WHICH CAN BE
 USED BY LOCAL OPTIMIZERS
BOUNDS THE BOUNDS ON THE VALUES OF THETA

 RETURNED ARE THE BEST FOUND HYPERPARAMETERS THETA AND
 THE CORRESPONDING VALUE OF THE TARGET FUNCTION
RETURNTHETAOPT FUNCMIN
PER DEFAULT THE 'FMINLBFGSB' ALGORITHM FROM SCIPYOPTIMIZE IS USED IF NONE IS PASSED
THE KERNEL'S PARAMETERS ARE KEPT FIXED AVAILABLE INTERNAL OPTIMIZERS ARE
617SKLEARNGAUSSIANPROCESS GAUSSIAN PROCESSES 1803

FMINLBFGSB
NRESTARTSOPTIMIZER INT OPTIONAL DEFAULT 0 THE NUMBER OF RESTARTS OF THE OPTIMIZER FOR FINDING THE KERNEL'S PARAMETERS WHICH MAXIMIZE THE LOGMARGINAL LIKELIHOOD THE FIRST RUN OF THE OPTIMIZER IS PERFORMED FROM THE KERNEL'S INITIAL PARAMETERS THE REMAINING ONES IF ANY FROM THETAS SAMPLED LOGUNIFORM RANDOMLY FROM THE SPACE OF ALLOWED THETAVALUES IF GREATER THAN 0 ALL BOUNDS MUST BE FINITE NOTE THAT NRESTARTSOPTIMIZER 0 IMPLIES THAT ONE RUN IS PERFORMED
NORMALIZEY BOOLEAN OPTIONAL DEFAULT FALSE WHETHER THE TARGET VALUES Y ARE NORMALIZED IE THE MEAN OF THE OBSERVED TARGET VALUES BECOME ZERO THIS PARAMETER SHOULD BE SET TO TRUE IF THE TARGET VALUES' MEAN IS EXPECTED TO DIFFER CONSIDERABLE FROM ZERO WHEN ENABLED THE NORMALIZATION EFFECTIVELY MODIFIES THE GP'S PRIOR BASED ON THE DATA WHICH CONTRADICTS THE LIKELIHOOD PRINCIPLE NORMALIZATION IS THUS DISABLED PER DEFAULT
COPYXTRAIN BOOL OPTIONAL DEFAULT TRUE IF TRUE A PERSISTENT COPY OF THE TRAINING DATA IS STORED IN THE OBJECT OTHERWISE JUST A REFERENCE TO THE TRAINING DATA IS STORED WHICH MIGHT CAUSE PREDICTIONS TO CHANGE IF THE DATA IS MODIFIED EXTERNALLY
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE GENERATOR USED TO INITIALIZE THE CENTERS IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES
XTRAIN ARRAYLIKE SHAPE NSAMPLES NFEATURES FEATURE VALUES IN TRAINING DATA ALSO REQUIRED FOR PREDICTION
YTRAIN ARRAYLIKE SHAPE NSAMPLES NOUTPUTDIMS TARGET VALUES IN TRAINING DATA ALSO REQUIRED FOR PREDICTION
KERNEL KERNEL OBJECT THE KERNEL USED FOR PREDICTION THE STRUCTURE OF THE KERNEL IS THE SAME AS THE ONE PASSED AS PARAMETER BUT WITH OPTIMIZED HYPERPARAMETERS
LARRAYLIKE SHAPE NSAMPLES NSAMPLES LOWERTRIANGULAR CHOLESKY DECOMPOSITION OF THE KERNEL IN XTRAIN
ALPHA ARRAYLIKE SHAPE NSAMPLES DUAL COEFFICIENTS OF TRAINING DATA POINTS IN KERNEL SPACE
LOGMARGINALLIKELIHOODVALUE FLOAT THE LOGMARGINALLIKELIHOOD OF SELFKERNEL THETA
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT MAKEFRIEDMAN2
 FROM SKLEARNGAUSSIANPROCESS IMPORT GAUSSIANPROCESSREGRESSOR
 FROM SKLEARNGAUSSIANPROCESSKERNELS IMPORT DOTPRODUCT WHITEKERNEL
X Y  MAKEFRIEDMAN2NSAMPLES500 NOISE0 RANDOMSTATE0
KERNEL  DOTPRODUCT  WHITEKERNEL
GPR  GAUSSIANPROCESSREGRESSORKERNELKERNEL
 RANDOMSTATE0FITX Y
GPRSCOREX Y
03680
GPRPREDICTX2 RETURNSTD TRUE
ARRAY6530 5921 ARRAY3166 3166
```

METHODS
FITSELF X Y FIT GAUSSIAN PROCESS REGRESSION MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
LOGMARGINALLIKELIHOOD SELF THETA RETURNS LOGMARGINAL LIKELIHOOD OF THETA FOR TRAINING DATA
PREDICT SELF X RETURNSTD RETURNCOV PREDICT USING THE GAUSSIAN PROCESS REGRESSION MODEL
SAMPLEY SELF X NSAMPLES RANDOMSTATE DRAW SAMPLES FROM GAUSSIAN PROCESS AND EVALUATE AT X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFKERNELNONE ALPHA1E10 OPTIMIZER'FMINLBFGSB' NRESTARTSOPTIMIZER0 NOR MALIZEYFALSE COPYXTRAINTRUE RANDOMSTATENONE
FITSELFXY
FIT GAUSSIAN PROCESS REGRESSION MODEL
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES NOUTPUTDIMS TARGET VALUES
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
LOGMARGINALLIKELIHOOD SELFTHETANONE EVALGRADIENTFALSE
RETURNS LOGMARGINAL LIKELIHOOD OF THETA FOR TRAINING DATA
PARAMETERS
THETA ARRAYLIKE SHAPE NKERNELPARAMS OR NONE KERNEL HYPERPARAMETERS FOR WHICH THE LOGMARGINAL LIKELIHOOD IS EVALUATED IF NONE THE PRECOMPUTED LOGMARGINALLIKELIHOOD OF SELFKERNELTHETA IS RETURNED
EVALGRADIENT BOOL DEFAULT FALSE IF TRUE THE GRADIENT OF THE LOGMARGINAL LIKELIHOOD WITH RESPECT TO THE KERNEL HYPERPARAMETERS AT POSITION THETA IS RETURNED ADDITIONALLY IF TRUE THETA MUST NOT BE NONE
RETURNS
LOGLIKELIHOOD FLOAT LOGMARGINAL LIKELIHOOD OF THETA FOR TRAINING DATA
LOGLIKELIHOODGRADIENT ARRAY SHAPE NKERNELPARAMS OPTIONAL GRADIENT OF THE LOG MARGINAL LIKELIHOOD WITH RESPECT TO THE KERNEL HYPERPARAMETERS AT POSITION THETA ONLY RETURNED WHEN EVALGRADIENT IS TRUE

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PREDICTSELFXRETURNSTDFALSE RETURNCOVFALSE
PREDICT USING THE GAUSSIAN PROCESS REGRESSION MODEL
WE CAN ALSO PREDICT BASED ON AN UNFITTED MODEL BY USING THE GP PRIOR IN ADDITION TO THE MEAN OF THE PRE
DICTIVE DISTRIBUTION ALSO ITS STANDARD DEVIATION RETURNSTDTRUE OR COVARIANCE RETURNCOVTRUE NOTE
THAT AT MOST ONE OF THE TWO CAN BE REQUESTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES QUERY POINTS WHERE THE GP IS EVALUATED
RETURNSTD BOOL DEFAULT FALSE IF TRUE THE STANDARDDEVIATION OF THE PREDICTIVE DISTRIBU
TION AT THE QUERY POINTS IS RETURNED ALONG WITH THE MEAN
RETURNCOV BOOL DEFAULT FALSE IF TRUE THE COVARIANCE OF THE JOINT PREDICTIVE DISTRIBUTION
AT THE QUERY POINTS IS RETURNED ALONG WITH THE MEAN
RETURNS
YMEAN ARRAY SHAPE NSAMPLES NOUTPUTDIMS MEAN OF PREDICTIVE DISTRIBUTION A
QUERY POINTS
YSTD ARRAY SHAPE NSAMPLES OPTIONAL STANDARD DEVIATION OF PREDICTIVE DISTRIBUTION AT
QUERY POINTS ONLY RETURNED WHEN RETURNSTD IS TRUE
YCOV ARRAY SHAPE NSAMPLES NSAMPLES OPTIONAL COVARIANCE OF JOINT PREDICTIVE DIS
TRIBUTION A QUERY POINTS ONLY RETURNED WHEN RETURNCOV IS TRUE
SAMPLEY SELFXNSAMPLES1 RANDOMSTATE0
DRAW SAMPLES FROM GAUSSIAN PROCESS AND EVALUATE AT X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLESX NFEATURES QUERY POINTS WHERE THE GP SAMPLES ARE
EVALUATED
NSAMPLES INT DEFAULT 1 THE NUMBER OF SAMPLES DRAWN FROM THE GAUSSIAN PROCESS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT0 IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
RETURNS
YSAMPLES ARRAY SHAPE NSAMPLESX NOUTPUTDIMS NSAMPLES VALUES OF
NSAMPLES SAMPLES DRAWN FROM GAUSSIAN PROCESS AND EVALUATED AT QUERY POINTS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS

RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNGAUSSIANPROCESSGAUSSIANPROCESSREGRESSOR
•COMPARISON OF KERNEL RIDGE AND GAUSSIAN PROCESS REGRESSION
•ILLUSTRATION OF PRIOR AND POSTERIOR GAUSSIAN PROCESS FOR DIFFERENT KERNELS
•GAUSSIAN PROCESS REGRESSION GPR WITH NOISELEVEL ESTIMATION
•GAUSSIAN PROCESSES REGRESSION BASIC INTRODUCTORY EXAMPLE
•GAUSSIAN PROCESS REGRESSION GPR ON MAUNA LOA CO2 DATA
KERNELS
GAUSSIANPROCESSKERNELS
COMPOUNDKERNEL KERNELSKERNEL WHICH IS COMPOSED OF A SET OF OTHER KERNELS
GAUSSIANPROCESSKERNELS
CONSTANTKERNEL CONSTANT KERNEL
GAUSSIANPROCESSKERNELS
DOTPRODUCT DOTPRODUCT KERNEL
GAUSSIANPROCESSKERNELS
EXPSINESQUARED EXPSINESQUARED KERNEL
GAUSSIANPROCESSKERNELS
EXPONENTIATION EXPONENTIATE KERNEL BY GIVEN EXPONENT
GAUSSIANPROCESSKERNELSHYPERPARAMETER A KERNEL HYPERPARAMETER’S SPECIFICATION IN FORM OF A
NAMEDTUPLE
GAUSSIANPROCESSKERNELSKERNEL BASE CLASS FOR ALL KERNELS
GAUSSIANPROCESSKERNELSMATERN MATERN KERNEL
GAUSSIANPROCESSKERNELS
PAIRWISEKERNEL WRAPPER FOR KERNELS IN SKLEARNMETRICSPAIRWISE
GAUSSIANPROCESSKERNELSPRODUCT K1 K2 PRODUCTKERNEL K1 K2 OF TWO KERNELS K1 AND K2
CONTINUED ON NEXT PAGE

TABLE 6119 – CONTINUED FROM PREVIOUS PAGE
GAUSSIANPROCESSKERNELSRBF LENGTHSCALE
RADIALBASIS FUNCTION KERNEL AKA SQUAREDEXPONENTIAL KER
NEL
GAUSSIANPROCESSKERNELS
RATIONALQUADRATIC RATIONAL QUADRATIC KERNEL
GAUSSIANPROCESSKERNELSSUM K1 K2 SUMKERNEL K1 K2 OF TWO KERNELS K1 AND K2
GAUSSIANPROCESSKERNELS
WHITEKERNEL WHITE KERNEL
6173SKLEARNGAUSSIANPROCESSKERNELS COMPOUNDKERNEL
CLASSSKLEARNGAUSSIANPROCESSKERNELS COMPOUNDKERNEL KERNELS
KERNEL WHICH IS COMPOSED OF A SET OF OTHER KERNELS
NEW IN VERSION 018
PARAMETERS
KERNELS LIST OF KERNEL OBJECTS THE OTHER KERNELS
ATTRIBUTES
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
METHODS
CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS
THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFKERNELS
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
NOTE THAT THIS COMPOUND KERNEL RETURNS THE RESULTS OF ALL SIMPLE KERNEL STACKED ALONG AN ADDITIONAL AXIS
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE
RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD
EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE
SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED
RETURNS

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KARRAY SHAPE NSAMPLESX NSAMPLESY NKERNELS KERNEL KX Y
KGRADIENT ARRAY SHAPE NSAMPLESX NSAMPLESX NDIMS NKERNELS THE GRADIENT
OF THE KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN
EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL'S HYPERPARAM
ETERS THETA
CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
PARAMETERS
THETA ARRAY SHAPE NDIMS THE HYPERPARAMETERS
DIAGSELFX
RETURNS THE DIAGONAL OF THE KERNEL KX X
THE RESULT OF THIS METHOD IS IDENTICAL TO NPDIAGSELFX HOWEVER IT CAN BE EVALUATED MORE EFFICIENTLY
SINCE ONLY THE DIAGONAL IS EVALUATED
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
RETURNS
KDIAG ARRAY SHAPE NSAMPLESX NKERNELS DIAGONAL OF KERNEL KX X
GETPARAMS SELFDEEPTRUE
GET PARAMETERS OF THIS KERNEL
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
HYPERPARAMETERS
RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
ISSTATIONARY SELF
RETURNS WHETHER THE KERNEL IS STATIONARY
NDIMS
RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS KERNEL
THE METHOD WORKS ON SIMPLE KERNELS AS WELL AS ON NESTED KERNELS THE LATTER HAVE PARAMETERS OF THE FORM
COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
617SKLEARNGAUSSIANPROCESS GAUSSIAN PROCESSES 1809

THETA
RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
NOTE THAT THETA ARE TYPICALLY THE LOGTRANSFORMED VALUES OF THE KERNEL'S HYPERPARAMETERS AS THIS REPRESENTA
TION OF THE SEARCH SPACE IS MORE AMENABLE FOR HYPERPARAMETER SEARCH AS HYPERPARAMETERS LIKE LENGTHSCALES
NATURALLY LIVE ON A LOGSCALE
RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL
6174SKLEARNGAUSSIANPROCESSKERNELS CONSTANTKERNEL
CLASSSKLEARNGAUSSIANPROCESSKERNELS CONSTANTKERNEL CONSTANTVALUE10
CONSTANTVALUEBOUNDS1E
051000000
CONSTANT KERNEL
CAN BE USED AS PART OF A PRODUCTKERNEL WHERE IT SCALES THE MAGNITUDE OF THE OTHER FACTOR KERNEL OR AS PART OF A
SUMKERNEL WHERE IT MODIFIES THE MEAN OF THE GAUSSIAN PROCESS
KX1 X2 CONSTANTVALUE FOR ALL X1 X2
NEW IN VERSION 018
PARAMETERS
CONSTANTVALUE FLOAT DEFAULT 10 THE CONSTANT VALUE WHICH DEFINES THE COVARIANCE KX1
X2 CONSTANTVALUE
CONSTANTVALUEBOUNDS PAIR OF FLOATS 0 DEFAULT 1E5 1E5 THE LOWER AND UPPER BOUND
ON CONSTANTVALUE
ATTRIBUTES
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERCONSTANTVALUE
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
METHODS
CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS
THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFCONSTANTVALUE10 CONSTANTVALUEBOUNDS1E05 1000000
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT

PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE
RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD
EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE
SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED ONLY SUPPORTED WHEN Y IS NONE
RETURNS
KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
KGRADIENT ARRAY OPT SHAPE NSAMPLESX NSAMPLESX NDIMS THE GRADIENT OF THE
KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN
EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL'S HYPERPARAM
ETERS THETA
CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
PARAMETERS
THETA ARRAY SHAPE NDIMS THE HYPERPARAMETERS
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RETURNS
KDIAG ARRAY SHAPE NSAMPLESX DIAGONAL OF KERNEL KX X
GETPARAMS SELFDEEPTRUE
GET PARAMETERS OF THIS KERNEL
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
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NDIMS
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SETPARAMS SELFPARAMS
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THE METHOD WORKS ON SIMPLE KERNELS AS WELL AS ON NESTED KERNELS THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
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RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL
EXAMPLES USING SKLEARNGAUSSIANPROCESSKERNELSCONSTANTKERNEL
•ILLUSTRATION OF PRIOR AND POSTERIOR GAUSSIAN PROCESS FOR DIFFERENT KERNELS
•ISOPROBABILITY LINES FOR GAUSSIAN PROCESSES CLASSIFICATION GPC
•GAUSSIAN PROCESSES REGRESSION BASIC INTRODUCTORY EXAMPLE
6175SKLEARNGAUSSIANPROCESSKERNELS DOTPRODUCT
CLASSSKLEARNGAUSSIANPROCESSKERNELS DOTPRODUCT SIGMA010 SIGMA0BOUNDS1E 051000000
DOTPRODUCT KERNEL
THE DOTPRODUCT KERNEL IS NONSTATIONARY AND CAN BE OBTAINED FROM LINEAR REGRESSION BY PUTTING N0 1 PRIORS ON THE COEFFICIENTS OF XD D 1 D AND A PRIOR OF N0 SIGMA02 ON THE BIAS THE DOTPRODUCT KERNEL IS INVARIANT TO A ROTATION OF THE COORDINATES ABOUT THE ORIGIN BUT NOT TRANSLATIONS IT IS PARAMETERIZED BY A PARAMETER SIGMA02 FOR SIGMA02 0 THE KERNEL IS CALLED THE HOMOGENEOUS LINEAR KERNEL OTHERWISE IT IS INHOMOGENEOUS THE KERNEL IS GIVEN BY
KXI XJ SIGMA0 2 XI CDOT XJ
THE DOTPRODUCT KERNEL IS COMMONLY COMBINED WITH EXPONENTIATION
NEW IN VERSION 018
PARAMETERS
SIGMA0 FLOAT 0 DEFAULT 10 PARAMETER CONTROLLING THE INHOMOGENITY OF THE KERNEL IF SIGMA00 THE KERNEL IS HOMOGENOUS
SIGMA0BOUNDS PAIR OF FLOATS 0 DEFAULT 1E5 1E5 THE LOWER AND UPPER BOUND ON L
ATTRIBUTES
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERSIGMA0
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL

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DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFSIGMA010 SIGMA0BOUNDS1E05 1000000
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE
RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD
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KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
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BOUNDS
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RETURNS

KDIAG ARRAY SHAPE NSAMPLESX DIAGONAL OF KERNEL KX X
GETPARAMS SELFDEEPTRUE
GET PARAMETERS OF THIS KERNEL
PARAMETERS
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EXAMPLES USING SKLEARNGAUSSIANPROCESSKERNELSDOTPRODUCT
•ILLUSTRATION OF GAUSSIAN PROCESS CLASSIFICATION GPC ON THE XOR DATASET
•ILLUSTRATION OF PRIOR AND POSTERIOR GAUSSIAN PROCESS FOR DIFFERENT KERNELS
•ISOPROBABILITY LINES FOR GAUSSIAN PROCESSES CLASSIFICATION GPC
6176SKLEARNGAUSSIANPROCESSKERNELS EXPSINESQUARED
CLASSSKLEARNGAUSSIANPROCESSKERNELS EXPSINESQUARED LENGTHSCALE10
PERIODICITY10
LENGTHSCALEBOUNDS1E
05 1000000
PERIODICITYBOUNDS1E05
1000000
EXPSINESQUARED KERNEL

THE EXPSINESQUARED KERNEL ALLOWS MODELING PERIODIC FUNCTIONS IT IS PARAMETERIZED BY A LENGTHSCALE PARAMETER LENGTHSCALE0 AND A PERIODICITY PARAMETER PERIODICITY0 ONLY THE ISOTROPIC VARIANT WHERE L IS A SCALAR IS SUPPORTED AT THE MOMENT THE KERNEL GIVEN BY

KXI XJ EXP2 SINPI PERIODICITY DXI XJ LENGTHSCALE 2

NEW IN VERSION 018

PARAMETERS

LENGTHSCALE FLOAT 0 DEFAULT 10 THE LENGTH SCALE OF THE KERNEL

PERIODICITY FLOAT 0 DEFAULT 10 THE PERIODICITY OF THE KERNEL

LENGTHSCALEBOUNDS PAIR OF FLOATS 0 DEFAULT 1E5 1E5 THE LOWER AND UPPER BOUND ON LENGTHSCALE

PERIODICITYBOUNDS PAIR OF FLOATS 0 DEFAULT 1E5 1E5 THE LOWER AND UPPER BOUND ON PERIODICITY

ATTRIBUTES

BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA

HYPERPARAMETERLENGTHSCALE

HYPERPARAMETERPERIODICITY

HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS

NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL

THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS

METHODS

CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT

CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA

DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X

GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL

ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY

SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL

INIT SELFLENGTHSCALE10 PERIODICITY10 LENGTHSCALEBOUNDS1E05 1000000 PERIODICITYBOUNDS1E05 1000000

CALL SELFXYNONE EVALGRADIENTFALSE

RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT

PARAMETERS

XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y

YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD

EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED ONLY SUPPORTED WHEN Y IS NONE

RETURNS

KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
KGRADIENT ARRAY OPT SHAPE NSAMPLESX NSAMPLESX NDIMS THE GRADIENT OF THE
KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN
EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL'S HYPERPARAM
ETERS THETA
CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
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PARAMETERS
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RETURNS
KDIAG ARRAY SHAPE NSAMPLESX DIAGONAL OF KERNEL KX X
GETPARAMS SELFDEEPTRUE
GET PARAMETERS OF THIS KERNEL
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
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NATURALLY LIVE ON A LOGSCALE
RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL
EXAMPLES USING SKLEARNGAUSSIANPROCESSKERNELSEXPSINESQUARED
•COMPARISON OF KERNEL RIDGE AND GAUSSIAN PROCESS REGRESSION
•ILLUSTRATION OF PRIOR AND POSTERIOR GAUSSIAN PROCESS FOR DIFFERENT KERNELS
•GAUSSIAN PROCESS REGRESSION GPR ON MAUNA LOA CO2 DATA
6177SKLEARNGAUSSIANPROCESSKERNELS EXPONENTIATION
CLASSSKLEARNGAUSSIANPROCESSKERNELS EXPONENTIATION KERNEL EXPONENT
EXPONENTIATE KERNEL BY GIVEN EXPONENT
THE RESULTING KERNEL IS DEFINED AS KEXPX Y KX Y EXPONENT
NEW IN VERSION 018
PARAMETERS
KERNEL KERNEL OBJECT THE BASE KERNEL
EXPONENT FLOAT THE EXPONENT FOR THE BASE KERNEL
ATTRIBUTES
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
METHODS
CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS
THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFKERNEL EXPONENT
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT

PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE
RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD
EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE
SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED
RETURNS
KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
KGRADIENT ARRAY OPT SHAPE NSAMPLESX NSAMPLESX NDIMS THE GRADIENT OF THE
KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN
EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL'S HYPERPARAM
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CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
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RETURNS
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GET PARAMETERS OF THIS KERNEL
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
HYPERPARAMETERS
RETURNS A LIST OF ALL HYPERPARAMETER
ISSTATIONARY SELF
RETURNS WHETHER THE KERNEL IS STATIONARY
NDIMS
RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL

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RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL
6178SKLEARNGAUSSIANPROCESSKERNELS HYPERPARAMETER
CLASSSKLEARNGAUSSIANPROCESSKERNELS HYPERPARAMETER
A KERNEL HYPERPARAMETER'S SPECIFICATION IN FORM OF A NAMEDTUPLE
NEW IN VERSION 018
ATTRIBUTES
NAME STRING ALIAS FOR FIELD NUMBER 0
VALUETYPE STRING ALIAS FOR FIELD NUMBER 1
BOUNDS PAIR OF FLOATS 0 OR "FIXED" ALIAS FOR FIELD NUMBER 2
NELEMENTS INT DEFAULT1 ALIAS FOR FIELD NUMBER 3
FIXED BOOL DEFAULT NONE ALIAS FOR FIELD NUMBER 4
METHODS
COUNT
INDEX RAISES VALUEERROR IF THE VALUE IS NOT PRESENT
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
CALL ARGS KWARGS
CALL SELF AS A FUNCTION
BOUNDS
ALIAS FOR FIELD NUMBER 2
COUNT
FIXED
ALIAS FOR FIELD NUMBER 4
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SCIKITLEARN USER GUIDE RELEASE 0213
RAISES VALUEERROR IF THE VALUE IS NOT PRESENT
NELEMENTS
ALIAS FOR FIELD NUMBER 3
NAME
ALIAS FOR FIELD NUMBER 0
VALUETYPE
ALIAS FOR FIELD NUMBER 1
6179SKLEARNGAUSSIANPROCESSKERNELS KERNEL
CLASSSKLEARNGAUSSIANPROCESSKERNELS KERNEL
BASE CLASS FOR ALL KERNELS
NEW IN VERSION 018
ATTRIBUTES
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
METHODS
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THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
CALL SELFXYNONE EVALGRADIENTFALSE
EVALUATE THE KERNEL
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL’S HYPERPARAM
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THETA
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NOTE THAT THETA ARE TYPICALLY THE LOGTRANSFORMED VALUES OF THE KERNEL'S HYPERPARAMETERS AS THIS REPRESENTA
TION OF THE SEARCH SPACE IS MORE AMENABLE FOR HYPERPARAMETER SEARCH AS HYPERPARAMETERS LIKE LENGTHSCALES
NATURALLY LIVE ON A LOGSCALE
RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL
61710SKLEARNGAUSSIANPROCESSKERNELS MATERN
CLASSSKLEARNGAUSSIANPROCESSKERNELS MATERNLENGTHSCALE10 LENGTHSCALEBOUNDS1E
051000000 NU15
MATERN KERNEL
THE CLASS OF MATERN KERNELS IS A GENERALIZATION OF THE RBF AND THE ABSOLUTE EXPONENTIAL KERNEL PARAMETERIZED BY
AN ADDITIONAL PARAMETER NU THE SMALLER NU THE LESS SMOOTH THE APPROXIMATED FUNCTION IS FOR NUINF THE KERNEL
617SKLEARNGAUSSIANPROCESS GAUSSIAN PROCESSES 1821

BECOMES EQUIVALENT TO THE RBF KERNEL AND FOR NU05 TO THE ABSOLUTE EXPONENTIAL KERNEL IMPORTANT INTERMEDIATE
VALUES ARE NU15 ONCE DIFFERENTIABLE FUNCTIONS AND NU25 TWICE DIFFERENTIABLE FUNCTIONS
SEE RASMUSSEN AND WILLIAMS 2006 PP84 FOR DETAILS REGARDING THE DIFFERENT VARIANTS OF THE MATERN KERNEL
NEW IN VERSION 018
PARAMETERS
LENGTHSCALE FLOAT OR ARRAY WITH SHAPE NFEATURES DEFAULT 10 THE LENGTH SCALE OF THE KERNEL
IF A FLOAT AN ISOTROPIC KERNEL IS USED IF AN ARRAY AN ANISOTROPIC KERNEL IS USED WHERE EACH
DIMENSION OF L DEFINES THE LENGTHSCALE OF THE RESPECTIVE FEATURE DIMENSION
LENGTHSCALEBOUNDS PAIR OF FLOATS 0 DEFAULT 1E5 1E5 THE LOWER AND UPPER BOUND ON
LENGTHSCALE
NUFLOAT DEFAULT 15 THE PARAMETER NU CONTROLLING THE SMOOTHNESS OF THE LEARNED FUNCTION
THE SMALLER NU THE LESS SMOOTH THE APPROXIMATED FUNCTION IS FOR NUINF THE KERNEL BE
COMES EQUIVALENT TO THE RBF KERNEL AND FOR NU05 TO THE ABSOLUTE EXPONENTIAL KERNEL IM
PORTANT INTERMEDIATE VALUES ARE NU15 ONCE DIFFERENTIABLE FUNCTIONS AND NU25 TWICE
DIFFERENTIABLE FUNCTIONS NOTE THAT VALUES OF NU NOT IN 05 15 25 INF INCUR A CONSID
ERABLY HIGHER COMPUTATIONAL COST APPR 10 TIMES HIGHER SINCE THEY REQUIRE TO EVALUATE THE
MODIFIED BESSEL FUNCTION FURTHERMORE IN CONTRAST TO L NU IS KEPT FIXED TO ITS INITIAL VALUE
AND NOT OPTIMIZED
ATTRIBUTES
ANISOTROPIC
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERLENGTHSCALE
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
METHODS
CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS
THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFLENGTHSCALE10 LENGTHSCALEBOUNDS1E05 1000000 NU15
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE
RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD

EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE
SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED ONLY SUPPORTED WHEN Y IS NONE
RETURNS
KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
KGRADIENT ARRAY OPT SHAPE NSAMPLESX NSAMPLESX NDIMS THE GRADIENT OF THE
KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN
EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL'S HYPERPARAM
ETERS THETA
CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
PARAMETERS
THETA ARRAY SHAPE NDIMS THE HYPERPARAMETERS
DIAGSELFX
RETURNS THE DIAGONAL OF THE KERNEL KX X
THE RESULT OF THIS METHOD IS IDENTICAL TO NPDIAGSELFX HOWEVER IT CAN BE EVALUATED MORE EFFICIENTLY
SINCE ONLY THE DIAGONAL IS EVALUATED
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
RETURNS
KDIAG ARRAY SHAPE NSAMPLESX DIAGONAL OF KERNEL KX X
GETPARAMS SELFDEEPTRUE
GET PARAMETERS OF THIS KERNEL
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
HYPERPARAMETERS
RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
ISSTATIONARY SELF
RETURNS WHETHER THE KERNEL IS STATIONARY
NDIMS
RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS KERNEL
THE METHOD WORKS ON SIMPLE KERNELS AS WELL AS ON NESTED KERNELS THE LATTER HAVE PARAMETERS OF THE FORM
COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT

RETURNS
SELF
THETA
RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
NOTE THAT THETA ARE TYPICALLY THE LOGTRANSFORMED VALUES OF THE KERNEL'S HYPERPARAMETERS AS THIS REPRESENTA
TION OF THE SEARCH SPACE IS MORE AMENABLE FOR HYPERPARAMETER SEARCH AS HYPERPARAMETERS LIKE LENGTHSCALES
NATURALLY LIVE ON A LOGSCALE
RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL
EXAMPLES USING SKLEARNGAUSSIANPROCESSKERNELSMATERN
•ILLUSTRATION OF PRIOR AND POSTERIOR GAUSSIAN PROCESS FOR DIFFERENT KERNELS
61711SKLEARNGAUSSIANPROCESSKERNELS PAIRWISEKERNEL
CLASSSKLEARNGAUSSIANPROCESSKERNELS PAIRWISEKERNEL GAMMA10
GAMMABOUNDS1E05
1000000 METRIC'LINEAR' PAIR
WISEKERNELSKWARGSNONE
WRAPPER FOR KERNELS IN SKLEARNMETRICSPAIRWISE
A THIN WRAPPER AROUND THE FUNCTIONALITY OF THE KERNELS IN SKLEARNMETRICSPAIRWISE
NOTE EVALUATION OF EVALGRADIENT IS NOT ANALYTIC BUT NUMERIC AND ALL KERNELS SUPPORT ONLY ISOTROPIC DIS
TANCES THE PARAMETER GAMMA IS CONSIDERED TO BE A HYPERPARAMETER AND MAY BE OPTIMIZED THE OTHER
KERNEL PARAMETERS ARE SET DIRECTLY AT INITIALIZATION AND ARE KEPT FIXED
NEW IN VERSION 018
PARAMETERS
GAMMA FLOAT 0 DEFAULT 10 PARAMETER GAMMA OF THE PAIRWISE KERNEL SPECIFIED BY METRIC
GAMMABOUNDS PAIR OF FLOATS 0 DEFAULT 1E5 1E5 THE LOWER AND UPPER BOUND ON
GAMMA
METRIC STRING OR CALLABLE DEFAULT "LINEAR" THE METRIC TO USE WHEN CALCULATING KERNEL BETWEEN
INSTANCES IN A FEATURE ARRAY IF METRIC IS A STRING IT MUST BE ONE OF THE METRICS IN PAIR
WISEPAIRWISEKERNELFUNCTIONS IF METRIC IS "PRECOMPUTED" X IS ASSUMED TO BE
A KERNEL MATRIX ALTERNATIVELY IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF
INSTANCES ROWS AND THE RESULTING VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS FROM
X AS INPUT AND RETURN A VALUE INDICATING THE DISTANCE BETWEEN THEM
PAIRWISEKERNELSKWARGS DICT DEFAULT NONE ALL ENTRIES OF THIS DICT IF ANY ARE PASSED AS
KEYWORD ARGUMENTS TO THE PAIRWISE KERNEL FUNCTION
ATTRIBUTES
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERGAMMA
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL

THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
METHODS
CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS
THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFGAMMA10 GAMMABOUNDS1E05 1000000 METRIC'LINEAR' PAIR
WISEKERNELSKWARGSNONE
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE
RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD
EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE
SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED ONLY SUPPORTED WHEN Y IS NONE
RETURNS
KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
KGRADIENT ARRAY OPT SHAPE NSAMPLESX NSAMPLESX NDIMS THE GRADIENT OF THE
KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN
EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL'S HYPERPARAM
ETERS THETA
CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
PARAMETERS
THETA ARRAY SHAPE NDIMS THE HYPERPARAMETERS
DIAGSELFX
RETURNS THE DIAGONAL OF THE KERNEL KX X
THE RESULT OF THIS METHOD IS IDENTICAL TO NPDIAGSELFX HOWEVER IT CAN BE EVALUATED MORE EFFICIENTLY
SINCE ONLY THE DIAGONAL IS EVALUATED
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y

RETURNS
KDIAG ARRAY SHAPE NSAMPLESX DIAGONAL OF KERNEL KX X
GETPARAMS SELFDEEPTRUE
GET PARAMETERS OF THIS KERNEL
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
HYPERPARAMETERS
RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
ISSTATIONARY SELF
RETURNS WHETHER THE KERNEL IS STATIONARY
NDIMS
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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS KERNEL
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COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
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TION OF THE SEARCH SPACE IS MORE AMENABLE FOR HYPERPARAMETER SEARCH AS HYPERPARAMETERS LIKE LENGTHSCALES
NATURALLY LIVE ON A LOGSCALE
RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL
61712SKLEARNGAUSSIANPROCESSKERNELS PRODUCT
CLASSSKLEARNGAUSSIANPROCESSKERNELS PRODUCTK1K2
PRODUCTKERNEL K1 K2 OF TWO KERNELS K1 AND K2
THE RESULTING KERNEL IS DEFINED AS KPRODX Y K1X Y K2X Y
NEW IN VERSION 018
PARAMETERS
K1KERNEL OBJECT THE FIRST BASEKERNEL OF THE PRODUCTKERNEL
K2KERNEL OBJECT THE SECOND BASEKERNEL OF THE PRODUCTKERNEL
ATTRIBUTES
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER

NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
METHODS
CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS
THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFK1K2
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE
RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD
EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE
SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED
RETURNS
KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
KGRADIENT ARRAY OPT SHAPE NSAMPLESX NSAMPLESX NDIMS THE GRADIENT OF THE
KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN
EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL’S HYPERPARAM
ETERS THETA
CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
PARAMETERS
THETA ARRAY SHAPE NDIMS THE HYPERPARAMETERS
DIAGSELFX
RETURNS THE DIAGONAL OF THE KERNEL KX X
THE RESULT OF THIS METHOD IS IDENTICAL TO NPDIAGSELFX HOWEVER IT CAN BE EVALUATED MORE EFFICIENTLY
SINCE ONLY THE DIAGONAL IS EVALUATED
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y

RETURNS
KDIAG ARRAY SHAPE NSAMPLESX DIAGONAL OF KERNEL KX X
GETPARAMS SELFDEEPTRUE
GET PARAMETERS OF THIS KERNEL
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
HYPERPARAMETERS
RETURNS A LIST OF ALL HYPERPARAMETER
ISSTATIONARY SELF
RETURNS WHETHER THE KERNEL IS STATIONARY
NDIMS
RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS KERNEL
THE METHOD WORKS ON SIMPLE KERNELS AS WELL AS ON NESTED KERNELS THE LATTER HAVE PARAMETERS OF THE FORM
COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
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TION OF THE SEARCH SPACE IS MORE AMENABLE FOR HYPERPARAMETER SEARCH AS HYPERPARAMETERS LIKE LENGTHSCALES
NATURALLY LIVE ON A LOGSCALE
RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL
61713SKLEARNGAUSSIANPROCESSKERNELS RBF
CLASSSKLEARNGAUSSIANPROCESSKERNELS RBFLENGTHSCALE10 LENGTHSCALEBOUNDS1E05
1000000
RADIALBASIS FUNCTION KERNEL AKA SQUAREDEXPONENTIAL KERNEL
THE RBF KERNEL IS A STATIONARY KERNEL IT IS ALSO KNOWN AS THE "SQUARED EXPONENTIAL" KERNEL IT IS PARAMETERIZED
BY A LENGTHSCALE PARAMETER LENGTHSCALE0 WHICH CAN EITHER BE A SCALAR ISOTROPIC VARIANT OF THE KERNEL OR A
VECTOR WITH THE SAME NUMBER OF DIMENSIONS AS THE INPUTS X ANISOTROPIC VARIANT OF THE KERNEL THE KERNEL IS
GIVEN BY
KXI XJ EXP1 2 DXI LENGTHSCALE XJ LENGTHSCALE2
THIS KERNEL IS INFINITELY DIFFERENTIABLE WHICH IMPLIES THAT GPS WITH THIS KERNEL AS COVARIANCE FUNCTION HAVE MEAN
SQUARE DERIVATIVES OF ALL ORDERS AND ARE THUS VERY SMOOTH
NEW IN VERSION 018

PARAMETERS
LENGTHSCALE FLOAT OR ARRAY WITH SHAPE NFEATURES DEFAULT 10 THE LENGTH SCALE OF THE KERNEL
IF A FLOAT AN ISOTROPIC KERNEL IS USED IF AN ARRAY AN ANISOTROPIC KERNEL IS USED WHERE EACH
DIMENSION OF L DEFINES THE LENGTHSCALE OF THE RESPECTIVE FEATURE DIMENSION
LENGTHSCALEBOUNDS PAIR OF FLOATS 0 DEFAULT 1E5 1E5 THE LOWER AND UPPER BOUND ON
LENGTHSCALE
ATTRIBUTES
ANISOTROPIC
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERLENGTHSCALE
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
METHODS
CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS
THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFLENGTHSCALE10 LENGTHSCALEBOUNDS1E05 1000000
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE
RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD
EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE
SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED ONLY SUPPORTED WHEN Y IS NONE
RETURNS
KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
KGRADIENT ARRAY OPT SHAPE NSAMPLESX NSAMPLESX NDIMS THE GRADIENT OF THE
KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN
EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS

BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL'S HYPERPARAM
ETERS THETA
CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
PARAMETERS
THETA ARRAY SHAPE NDIMS THE HYPERPARAMETERS
DIAGSELFX
RETURNS THE DIAGONAL OF THE KERNEL KX X
THE RESULT OF THIS METHOD IS IDENTICAL TO NPDIAGSELFX HOWEVER IT CAN BE EVALUATED MORE EFFICIENTLY
SINCE ONLY THE DIAGONAL IS EVALUATED
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
RETURNS
KDIAG ARRAY SHAPE NSAMPLESX DIAGONAL OF KERNEL KX X
GETPARAMS SELFDEEPTRUE
GET PARAMETERS OF THIS KERNEL
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
HYPERPARAMETERS
RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
ISSTATIONARY SELF
RETURNS WHETHER THE KERNEL IS STATIONARY
NDIMS
RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS KERNEL
THE METHOD WORKS ON SIMPLE KERNELS AS WELL AS ON NESTED KERNELS THE LATTER HAVE PARAMETERS OF THE FORM
COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
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TION OF THE SEARCH SPACE IS MORE AMENABLE FOR HYPERPARAMETER SEARCH AS HYPERPARAMETERS LIKE LENGTHSCALES
NATURALLY LIVE ON A LOGSCALE
RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL

EXAMPLES USING SKLEARNGAUSSIANPROCESSKERNELSRBF
•PLOT CLASSIFICATION PROBABILITY
•CLASSIFIER COMPARISON
•ILLUSTRATION OF GAUSSIAN PROCESS CLASSIFICATION GPC ON THE XOR DATASET
•GAUSSIAN PROCESS CLASSIFICATION GPC ON IRIS DATASET
•ILLUSTRATION OF PRIOR AND POSTERIOR GAUSSIAN PROCESS FOR DIFFERENT KERNELS
•PROBABILISTIC PREDICTIONS WITH GAUSSIAN PROCESS CLASSIFICATION GPC
•GAUSSIAN PROCESS REGRESSION GPR WITH NOISELEVEL ESTIMATION
•GAUSSIAN PROCESSES REGRESSION BASIC INTRODUCTORY EXAMPLE
•GAUSSIAN PROCESS REGRESSION GPR ON MAUNA LOA CO2 DATA
61714SKLEARNGAUSSIANPROCESSKERNELS RATIONALQUADRATIC
CLASSSKLEARNGAUSSIANPROCESSKERNELS RATIONALQUADRATIC LENGTHSCALE10
ALPHA10
LENGTHSCALEBOUNDS1E
05 1000000
ALPHABOUNDS1E05
1000000
RATIONAL QUADRATIC KERNEL
THE RATIONALQUADRATIC KERNEL CAN BE SEEN AS A SCALE MIXTURE AN INFINITE SUM OF RBF KERNELS WITH DIFFERENT CHARACTERISTIC LENGTHSCALES IT IS PARAMETERIZED BY A LENGTHSCALE PARAMETER LENGTHSCALE0 AND A SCALE MIXTURE PARAMETER ALPHA0 ONLY THE ISOTROPIC VARIANT WHERE LENGTHSCALE IS A SCALAR IS SUPPORTED AT THE MOMENT THE KERNEL GIVEN BY
KXI XJ 1 DXI XJ2 2ALPHA LENGTHSCALE2ALPHA
NEW IN VERSION 018
PARAMETERS
LENGTHSCALE FLOAT 0 DEFAULT 10 THE LENGTH SCALE OF THE KERNEL
ALPHA FLOAT 0 DEFAULT 10 SCALE MIXTURE PARAMETER
LENGTHSCALEBOUNDS PAIR OF FLOATS 0 DEFAULT 1E5 1E5 THE LOWER AND UPPER BOUND ON LENGTHSCALE
ALPHABOUNDS PAIR OF FLOATS 0 DEFAULT 1E5 1E5 THE LOWER AND UPPER BOUND ON ALPHA
ATTRIBUTES
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERALPHA
HYPERPARAMETERLENGTHSCALE
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS

METHODS
CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS
THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELF LENGTHSCALE10 ALPHA10 LENGTHSCALEBOUNDS1E05 1000000
ALPHABOUNDS1E05 1000000
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE
RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD
EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE
SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED ONLY SUPPORTED WHEN Y IS NONE
RETURNS
KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
KGRADIENT ARRAY OPT SHAPE NSAMPLESX NSAMPLESX NDIMS THE GRADIENT OF THE
KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN
EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL'S HYPERPARAM
ETERS THETA
CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
PARAMETERS
THETA ARRAY SHAPE NDIMS THE HYPERPARAMETERS
DIAGSELFX
RETURNS THE DIAGONAL OF THE KERNEL KX X
THE RESULT OF THIS METHOD IS IDENTICAL TO NPDIAGSELFX HOWEVER IT CAN BE EVALUATED MORE EFFICIENTLY
SINCE ONLY THE DIAGONAL IS EVALUATED
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
RETURNS
KDIAG ARRAY SHAPE NSAMPLESX DIAGONAL OF KERNEL KX X

GETPARAMS SELFDEEPTRUE
GET PARAMETERS OF THIS KERNEL
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
HYPERPARAMETERS
RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
ISSTATIONARY SELF
RETURNS WHETHER THE KERNEL IS STATIONARY
NDIMS
RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS KERNEL
THE METHOD WORKS ON SIMPLE KERNELS AS WELL AS ON NESTED KERNELS THE LATTER HAVE PARAMETERS OF THE FORM
COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
THETA
RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
NOTE THAT THETA ARE TYPICALLY THE LOGTRANSFORMED VALUES OF THE KERNEL'S HYPERPARAMETERS AS THIS REPRESENTA
TION OF THE SEARCH SPACE IS MORE AMENABLE FOR HYPERPARAMETER SEARCH AS HYPERPARAMETERS LIKE LENGTHSCALES
NATURALLY LIVE ON A LOGSCALE
RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL
EXAMPLES USING SKLEARNGAUSSIANPROCESSKERNELSRATIONALQUADRATIC
•ILLUSTRATION OF PRIOR AND POSTERIOR GAUSSIAN PROCESS FOR DIFFERENT KERNELS
•GAUSSIAN PROCESS REGRESSION GPR ON MAUNA LOA CO2 DATA
61715SKLEARNGAUSSIANPROCESSKERNELS SUM
CLASSSKLEARNGAUSSIANPROCESSKERNELS SUMK1K2
SUMKERNEL K1 K2 OF TWO KERNELS K1 AND K2
THE RESULTING KERNEL IS DEFINED AS KSUMX Y K1X Y K2X Y
NEW IN VERSION 018
PARAMETERS
K1KERNEL OBJECT THE FIRST BASEKERNEL OF THE SUMKERNEL
K2KERNEL OBJECT THE SECOND BASEKERNEL OF THE SUMKERNEL
617SKLEARNGAUSSIANPROCESS GAUSSIAN PROCESSES 1833

ATTRIBUTES
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
METHODS
CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS
THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFK1K2
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE
RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD
EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE
SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED
RETURNS
KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
KGRADIENT ARRAY OPT SHAPE NSAMPLESX NSAMPLESX NDIMS THE GRADIENT OF THE
KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN
EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL’S HYPERPARAM
ETERS THETA
CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
PARAMETERS
THETA ARRAY SHAPE NDIMS THE HYPERPARAMETERS
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RETURNS
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GET PARAMETERS OF THIS KERNEL
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
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RETURNS WHETHER THE KERNEL IS STATIONARY
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COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
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NATURALLY LIVE ON A LOGSCALE
RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL
61716SKLEARNGAUSSIANPROCESSKERNELS WHITEKERNEL
CLASSSKLEARNGAUSSIANPROCESSKERNELS WHITEKERNEL NOISELEVEL10
NOISELEVELBOUNDS1E05
1000000
WHITE KERNEL
THE MAIN USECASE OF THIS KERNEL IS AS PART OF A SUMKERNEL WHERE IT EXPLAINS THE NOISECOMPONENT OF THE SIGNAL
TUNING ITS PARAMETER CORRESPONDS TO ESTIMATING THE NOISELEVEL
KX1 X2 NOISELEVEL IF X1 X2 ELSE 0
617SKLEARNGAUSSIANPROCESS GAUSSIAN PROCESSES 1835

NEW IN VERSION 018
PARAMETERS
NOISELEVEL FLOAT DEFAULT 10 PARAMETER CONTROLLING THE NOISE LEVEL
NOISELEVELBOUNDS PAIR OF FLOATS 0 DEFAULT 1E5 1E5 THE LOWER AND UPPER BOUND ON NOISELEVEL
ATTRIBUTES
BOUNDS RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
HYPERPARAMETERNOISELEVEL
HYPERPARAMETERS RETURNS A LIST OF ALL HYPERPARAMETER SPECIFICATIONS
NDIMS RETURNS THE NUMBER OF NONFIXED HYPERPARAMETERS OF THE KERNEL
THETA RETURNS THE FLATTENED LOGTRANSFORMED NONFIXED HYPERPARAMETERS
METHODS
CALL SELF X Y EVALGRADIENT RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
CLONEWITHTHETA SELF THETA RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
DIAG SELF X RETURNS THE DIAGONAL OF THE KERNEL KX X
GETPARAMS SELF DEEP GET PARAMETERS OF THIS KERNEL
ISSTATIONARY SELF RETURNS WHETHER THE KERNEL IS STATIONARY
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS KERNEL
INIT SELFNOISELEVEL10 NOISELEVELBOUNDS1E05 1000000
CALL SELFXYNONE EVALGRADIENTFALSE
RETURN THE KERNEL KX Y AND OPTIONALLY ITS GRADIENT
PARAMETERS
XARRAY SHAPE NSAMPLESX NFEATURES LEFT ARGUMENT OF THE RETURNED KERNEL KX Y
YARRAY SHAPE NSAMPLESY NFEATURES OPTIONAL DEFAULTNONE RIGHT ARGUMENT OF THE RETURNED KERNEL KX Y IF NONE KX X IF EVALUATED INSTEAD
EVALGRADIENT BOOL OPTIONAL DEFAULTFALSE DETERMINES WHETHER THE GRADIENT WITH RE SPECT TO THE KERNEL HYPERPARAMETER IS DETERMINED ONLY SUPPORTED WHEN Y IS NONE
RETURNS
KARRAY SHAPE NSAMPLESX NSAMPLESY KERNEL KX Y
KGRADIENT ARRAY OPT SHAPE NSAMPLESX NSAMPLESX NDIMS THE GRADIENT OF THE KERNEL KX X WITH RESPECT TO THE HYPERPARAMETER OF THE KERNEL ONLY RETURNED WHEN EVALGRADIENT IS TRUE
BOUNDS
RETURNS THE LOGTRANSFORMED BOUNDS ON THE THETA
RETURNS
BOUNDS ARRAY SHAPE NDIMS 2 THE LOGTRANSFORMED BOUNDS ON THE KERNEL’S HYPERPARAM ETERS THETA

CLONEWITHTHETA SELFTHETA
RETURNS A CLONE OF SELF WITH GIVEN HYPERPARAMETERS THETA
PARAMETERS
THETA ARRAY SHAPE NDIMS THE HYPERPARAMETERS
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PARAMETERS
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NATURALLY LIVE ON A LOGSCALE
RETURNS
THETA ARRAY SHAPE NDIMS THE NONFIXED LOGTRANSFORMED HYPERPARAMETERS OF THE KERNEL

EXAMPLES USING SKLEARNGAUSSIANPROCESSKERNELSWHITEKERNEL
•COMPARISON OF KERNEL RIDGE AND GAUSSIAN PROCESS REGRESSION
•GAUSSIAN PROCESS REGRESSION GPR WITH NOISELEVEL ESTIMATION
•GAUSSIAN PROCESS REGRESSION GPR ON MAUNA LOA CO2 DATA
618SKLEARNISOTONIC ISOTONIC REGRESSION
USER GUIDE SEE THE ISOTONIC REGRESSION SECTION FOR FURTHER DETAILS
ISOTONICISOTONICREGRESSION YMIN YMAX
ISOTONIC REGRESSION MODEL
6181SKLEARNISOTONIC ISOTONICREGRESSION
CLASSSKLEARNISOTONIC ISOTONICREGRESSION YMINNONE YMAXNONE INCREASINGTRUE
OUTOFBOUNDS'NAN'
ISOTONIC REGRESSION MODEL
THE ISOTONIC REGRESSION OPTIMIZATION PROBLEM IS DEFINED BY
MIN SUM WI YI YI 2
SUBJECT TO YI YJ WHENEVER XI XJ
ANDMINY YMIN MAXY YMAX
WHERE
•YI ARE INPUTS REAL NUMBERS
•YI ARE FITTED
•XSPECIFIES THE ORDER IF XIS NONDECREASING THEN YIS NONDECREASING
•WI ARE OPTIONAL STRICTLY POSITIVE WEIGHTS DEFAULT TO 10
READ MORE IN THE USER GUIDE
PARAMETERS
YMIN OPTIONAL DEFAULT NONE IF NOT NONE SET THE LOWEST VALUE OF THE FIT TO YMIN
YMAX OPTIONAL DEFAULT NONE IF NOT NONE SET THE HIGHEST VALUE OF THE FIT TO YMAX
INCREASING BOOLEAN OR STRING OPTIONAL DEFAULT TRUE IF BOOLEAN WHETHER OR NOT TO FIT THE ISOTONIC REGRESSION WITH Y INCREASING OR DECREASING
THE STRING VALUE "AUTO" DETERMINES WHETHER Y SHOULD INCREASE OR DECREASE BASED ON THE SPEARMAN CORRELATION ESTIMATE'S SIGN
OUTOFBOUNDS STRING OPTIONAL DEFAULT "NAN" THE OUTOFBOUNDS PARAMETER HANDLES HOW XVALUES OUTSIDE OF THE TRAINING DOMAIN ARE HANDLED WHEN SET TO "NAN" PREDICTED YVALUES WILL BE NAN WHEN SET TO "CLIP" PREDICTED YVALUES WILL BE SET TO THE VALUE CORRE SPONDING TO THE NEAREST TRAIN INTERVAL ENDPOINT WHEN SET TO "RAISE" ALLOW INTERP1D TO THROW VALUEERROR

SCIKITLEARN USER GUIDE RELEASE 0213
ATTRIBUTES
XMIN FLOAT MINIMUM VALUE OF INPUT ARRAY XFOR LEFT BOUND
XMAX FLOAT MAXIMUM VALUE OF INPUT ARRAY XFOR RIGHT BOUND
FFUNCTION THE STEPWISE INTERPOLATING FUNCTION THAT COVERS THE INPUT DOMAIN X
NOTES
TIES ARE BROKEN USING THE SECONDARY METHOD FROM LEEUW 1977
REFERENCES
ISOTONIC MEDIAN REGRESSION A LINEAR PROGRAMMING APPROACH NILOTPAL CHAKRAVARTI MATHEMATICS OF OPERATIONS RESEARCH V OL 14 NO 2 MAY 1989 PP 303308
ISOTONE OPTIMIZATION IN R POOLADJACENTVIOLATORS ALGORITHM PA V A AND ACTIVE SET METHODS LEEUW HORNIK MAIR JOURNAL OF STATISTICAL SOFTWARE 2009
CORRECTNESS OF KRUSKAL'S ALGORITHMS FOR MONOTONE REGRESSION WITH TIES LEEUW PSYCHOMETRICA 1977
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
 FROM SKLEARNISOTONIC IMPORT ISOTONICREGRESSION
X Y  MAKEREGRESSIONNSAMPLES10 NFEATURES1 RANDOMSTATE41
ISOREG  ISOTONICREGRESSIONFITXFLATTEN Y
ISOREGPREDICT1 2
ARRAY18628 37256
```
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE MODEL USING X Y AS TRAINING DATA
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF T PREDICT NEW DATA BY LINEAR INTERPOLATION
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF T TRANSFORM NEW DATA BY LINEAR INTERPOLATION
INIT SELFYMINNONE YMAXNONE INCREASINGTRUE OUTOFBOUNDS'NAN'
FITSELFXYSAMPLEWEIGHTNONE
FIT THE MODEL USING X Y AS TRAINING DATA
PARAMETERS
XARRAYLIKE SHAPENSAMPLES TRAINING DATA
YARRAYLIKE SHAPENSAMPLES TRAINING TARGET

SAMPLEWEIGHT ARRAYLIKE SHAPENSAMPLES OPTIONAL DEFAULT NONE WEIGHTS IF SET TO
NONE ALL WEIGHTS WILL BE SET TO 1 EQUAL WEIGHTS
RETURNS
SELF OBJECT RETURNS AN INSTANCE OF SELF
NOTES
X IS STORED FOR FUTURE USE AS TRANSFORM NEEDS X TO INTERPOLATE NEW INPUT DATA
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFT
PREDICT NEW DATA BY LINEAR INTERPOLATION
PARAMETERS
TARRAYLIKE SHAPENSAMPLES DATA TO TRANSFORM
RETURNS
TARRAY SHAPENSAMPLES TRANSFORMED DATA
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X

SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFT
TRANSFORM NEW DATA BY LINEAR INTERPOLATION
PARAMETERS
TARRAYLIKE SHAPENSAMPLES DATA TO TRANSFORM
RETURNS
TARRAY SHAPENSAMPLES THE TRANSFORMED DATA
EXAMPLES USING SKLEARNISOTONICISOTONICREGRESSION
•ISOTONIC REGRESSION
ISOTONICCHECKINCREASING X Y DETERMINE WHETHER Y IS MONOTONICALLY CORRELATED WITH X
ISOTONICISOTONICREGRESSION Y   SOLVE THE ISOTONIC REGRESSION MODEL
6182SKLEARNISOTONIC CHECKINCREASING
SKLEARNISOTONIC CHECKINCREASING XY
DETERMINE WHETHER Y IS MONOTONICALLY CORRELATED WITH X
Y IS FOUND INCREASING OR DECREASING WITH RESPECT TO X BASED ON A SPEARMAN CORRELATION TEST
PARAMETERS
XARRAYLIKE SHAPENSAMPLES TRAINING DATA
YARRAYLIKE SHAPENSAMPLES TRAINING TARGET
RETURNS

SCIKITLEARN USER GUIDE RELEASE 0213
INCREASINGBOOL BOOLEAN WHETHER THE RELATIONSHIP IS INCREASING OR DECREASING
NOTES
THE SPEARMAN CORRELATION COEFFICIENT IS ESTIMATED FROM THE DATA AND THE SIGN OF THE RESULTING ESTIMATE IS USED AS THE RESULT
IN THE EVENT THAT THE 95 CONFIDENCE INTERVAL BASED ON FISHER TRANSFORM SPANS ZERO A WARNING IS RAISED
REFERENCES
FISHER TRANSFORMATION WIKIPEDIA HTTPSENWIKIPEDIAORGWIKIFISHERTRANSFORMATION
6183SKLEARNISOTONIC ISOTONICREGRESSION
SKLEARNISOTONIC ISOTONICREGRESSION YSAMPLEWEIGHTNONE YMINNONE YMAXNONE
INCREASINGTRUE
SOLVE THE ISOTONIC REGRESSION MODEL
MIN SUM WI YI YI 2
SUBJECT TO YMIN Y1 Y2   YN YMAX
WHERE
• YI ARE INPUTS REAL NUMBERS
• YI ARE FITTED
• WI ARE OPTIONAL STRICTLY POSITIVE WEIGHTS DEFAULT TO 10
READ MORE IN THE USER GUIDE
PARAMETERS
YITERABLE OF FLOATS THE DATA
SAMPLEWEIGHT ITERABLE OF FLOATS OPTIONAL DEFAULT NONE WEIGHTS ON EACH POINT OF THE REGRES
SION IF NONE WEIGHT IS SET TO 1 EQUAL WEIGHTS
YMIN OPTIONAL DEFAULT NONE IF NOT NONE SET THE LOWEST VALUE OF THE FIT TO YMIN
YMAX OPTIONAL DEFAULT NONE IF NOT NONE SET THE HIGHEST VALUE OF THE FIT TO YMAX
INCREASING BOOLEAN OPTIONAL DEFAULT TRUE WHETHER TO COMPUTE YIS INCREASING IF SET TO
TRUE OR DECREASING IF SET TO FALSE
RETURNS
YLIST OF FLOATS ISOTONIC FIT OF Y
REFERENCES
“ACTIVE SET ALGORITHMS FOR ISOTONIC REGRESSION A UNIFYING FRAMEWORK” BY MICHAEL J BEST AND NILOTPAL
CHAKRAVARTI SECTION 3
1842 CHAPTER 6 API REFERENCE

619SKLEARNIMPUTE IMPUTE
TRANSFORMERS FOR MISSING VALUE IMPUTATION
USER GUIDE SEE THE IMPUTATION OF MISSING VALUES SECTION FOR FURTHER DETAILS
IMPUTESIMPLEIMPUTER MISSINGVALUES IMPUTATION TRANSFORMER FOR COMPLETING MISSING VALUES
IMPUTEITERATIVEIMPUTER ESTIMATOR MULTIVARIATE IMPUTER THAT ESTIMATES EACH FEATURE FROM ALL THE OTHERS
IMPUTEMISSINGINDICATOR MISSINGVALUES BINARY INDICATORS FOR MISSING VALUES
6191SKLEARNIMPUTE SIMPLEIMPUTER
CLASSSKLEARNIMPUTE SIMPLEIMPUTER MISSINGVALUESNAN STRATEGY’MEAN’ FILLVALUENONE VERBOSE0 COPYTRUE ADDINDICATORFALSE
IMPUTATION TRANSFORMER FOR COMPLETING MISSING VALUES
READ MORE IN THE USER GUIDE
PARAMETERS
MISSINGVALUES NUMBER STRING NPNAN DEFAULT OR NONE THE PLACEHOLDER FOR THE MISSING VALUES ALL OCCURRENCES OF MISSINGVALUES WILL BE IMPUTED
STRATEGY STRING OPTIONAL DEFAULT”MEAN” THE IMPUTATION STRATEGY
• IF “MEAN” THEN REPLACE MISSING VALUES USING THE MEAN ALONG EACH COLUMN CAN ONLY BE USED WITH NUMERIC DATA
• IF “MEDIAN” THEN REPLACE MISSING VALUES USING THE MEDIAN ALONG EACH COLUMN CAN ONLY BE USED WITH NUMERIC DATA
• IF “MOSTFREQUENT” THEN REPLACE MISSING USING THE MOST FREQUENT VALUE ALONG EACH COLUMN CAN BE USED WITH STRINGS OR NUMERIC DATA
• IF “CONSTANT” THEN REPLACE MISSING VALUES WITH FILLVALUE CAN BE USED WITH STRINGS OR NUMERIC DATA
NEW IN VERSION 020 STRATEGY”CONSTANT” FOR FIXED VALUE IMPUTATION
FILLVALUE STRING OR NUMERICAL VALUE OPTIONAL DEFAULTNONE WHEN STRATEGY “CONSTANT” FILLVALUE IS USED TO REPLACE ALL OCCURRENCES OF MISSINGVALUES IF LEFT TO THE DEFAULT FILLVALUE WILL BE 0 WHEN IMPUTING NUMERICAL DATA AND “MISSINGVALUE” FOR STRINGS OR OBJECT DATA TYPES
VERBOSE INTEGER OPTIONAL DEFAULT0 CONTROLS THE VERBOSITY OF THE IMPUTER
COPY BOOLEAN OPTIONAL DEFAULTTRUE IF TRUE A COPY OF X WILL BE CREATED IF FALSE IMPUTATION WILL BE DONE INPLACE WHENEVER POSSIBLE NOTE THAT IN THE FOLLOWING CASES A NEW COPY WILL ALWAYS BE MADE EVEN IF COPYFALSE
• IF X IS NOT AN ARRAY OF FLOATING VALUES
• IF X IS ENCODED AS A CSR MATRIX
• IF ADDINDICATORTRUE
ADDINDICATOR BOOLEAN OPTIONAL DEFAULTFALSE IF TRUE A MISSINGINDICATOR TRANSFORM WILL STACK ONTO OUTPUT OF THE IMPUTER’S TRANSFORM THIS ALLOWS A PREDICTIVE ESTIMATOR TO ACCOUNT FOR MISSINGNESS DESPITE IMPUTATION IF A FEATURE HAS NO MISSING VALUES AT FITTRAIN

TIME THE FEATURE WON’T APPEAR ON THE MISSING INDICATOR EVEN IF THERE ARE MISSING VALUES AT
TRANSFORMTEST TIME
ATTRIBUTES
STATISTICS ARRAY OF SHAPE NFEATURES THE IMPUTATION FILL VALUE FOR EACH FEATURE
INDICATOR SKLEARNIMPUTEMISSINGINDICATOR INDICATOR USED TO ADD BINARY INDI
CATORS FOR MISSING VALUES NONE IF ADDINDICATOR IS FALSE
SEE ALSO
ITERATIVEIMPUTER MULTIVARIATE IMPUTATION OF MISSING VALUES
NOTES
COLUMNS WHICH ONLY CONTAINED MISSING VALUES AT FIT ARE DISCARDED UPON TRANSFORM IF STRATEGY IS NOT “CON
STANT”
EXAMPLES
 IMPORT NUMPY AS NP
 FROM SKLEARNIMPUTE IMPORT SIMPLEIMPUTER
IMPMEAN SIMPLEIMPUTERMISSINGVALUESNPNAN STRATEGYMEAN
IMPMEANFIT7 2 3 4 NPNAN 6 10 5 9

SIMPLEIMPUTERADDINDICATORFALSE COPYTRUE FILLVALUENONE
MISSINGVALUESNAN STRATEGYMEAN VERBOSE0
X NPNAN 2 3 4 NPNAN 6 10 NPNAN 9
PRINTIMPMEANTRANSFORMX

 7 2 3
 4 35 6
10 35 9
METHODS
FITSELF X Y FIT THE IMPUTER ON X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X IMPUTE ALL MISSING VALUES IN X
INIT SELFMISSINGVALUESNAN STRATEGY’MEAN’ FILLVALUENONE VERBOSE0 COPYTRUE
ADDINDICATORFALSE
FITSELFXYNONE
FIT THE IMPUTER ON X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES INPUT DATA WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES

RETURNS
SELF SIMPLEIMPUTER
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
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SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
IMPUTE ALL MISSING VALUES IN X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA TO COMPLETE
EXAMPLES USING SKLEARNIMPUTESIMPLEIMPUTER
•COLUMN TRANSFORMER WITH MIXED TYPES
•IMPUTING MISSING VALUES WITH VARIANTS OF ITERATIVEIMPUTER
•IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR

6192SKLEARNIMPUTE ITERATIVEIMPUTER
CLASSSKLEARNIMPUTE ITERATIVEIMPUTER ESTIMATORNONE MISSINGVALUESNAN SAM
PLEPOSTERIORFALSE MAXITER10 TOL0001
NNEARESTFEATURESNONE INITIALSTRATEGY'MEAN'
IMPUTATIONORDER'ASCENDING' MINVALUENONE
MAXVALUENONE VERBOSE0 RANDOMSTATENONE
ADDINDICATORFALSE
MULTIVARIATE IMPUTER THAT ESTIMATES EACH FEATURE FROM ALL THE OTHERS
A STRATEGY FOR IMPUTING MISSING VALUES BY MODELING EACH FEATURE WITH MISSING VALUES AS A FUNCTION OF OTHER
FEATURES IN A ROUNDROBIN FASHION
READ MORE IN THE USER GUIDE
NOTE THIS ESTIMATOR IS STILL EXPERIMENTAL FOR NOW THE PREDICTIONS AND THE API MIGHT CHANGE WITHOUT ANY
DEPRECATION CYCLE TO USE IT YOU NEED TO EXPLICITLY IMPORT ENABLEITERATIVEIMPUTER
 EXPLICITLY REQUIRE THIS EXPERIMENTAL FEATURE
 FROM SKLEARNEXPERIMENTAL IMPORT ENABLEITERATIVEIMPUTER NOQA
 NOW YOU CAN IMPORT NORMALLY FROM SKLEARNIMPUTE
 FROM SKLEARNIMPUTE IMPORT ITERATIVEIMPUTER
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT DEFAULTBAYESIANRIDGE THE ESTIMATOR TO USE AT EACH STEP OF
THE ROUNDROBIN IMPUTATION IF SAMPLEPOSTERIOR IS TRUE THE ESTIMATOR MUST SUPPORT
RETURNSTD IN ITSPREDICT METHOD
MISSINGVALUES INT NPNAN OPTIONAL DEFAULTNPNAN THE PLACEHOLDER FOR THE MISSING VALUES
ALL OCCURRENCES OF MISSINGVALUES WILL BE IMPUTED
SAMPLEPOSTERIOR BOOLEAN DEFAULTFALSE WHETHER TO SAMPLE FROM THE GAUSSIAN PREDICTIVE
POSTERIOR OF THE FITTED ESTIMATOR FOR EACH IMPUTATION ESTIMATOR MUST SUPPORT RETURNSTD
IN ITSPREDICT METHOD IF SET TO TRUE SET TOTRUE IF USINGITERATIVEIMPUTER FOR
MULTIPLE IMPUTATIONS
MAXITER INT OPTIONAL DEFAULT10 MAXIMUM NUMBER OF IMPUTATION ROUNDS TO PERFORM
BEFORE RETURNING THE IMPUTATIONS COMPUTED DURING THE FINAL ROUND A ROUND IS A SIN
GLE IMPUTATION OF EACH FEATURE WITH MISSING VALUES THE STOPPING CRITERION IS MET
ONCEABSMAXXT XT1ABSMAXXKNOWNVALS TOL WHERE
XT ISXAT ITERATION T NOTE THAT EARLY STOPPING IS ONLY APPLIED IF
SAMPLEPOSTERIORFALSE
TOLFLOAT OPTIONAL DEFAULT1E3 TOLERANCE OF THE STOPPING CONDITION
NNEARESTFEATURES INT OPTIONAL DEFAULTNONE NUMBER OF OTHER FEATURES TO USE TO ESTIMATE
THE MISSING VALUES OF EACH FEATURE COLUMN NEARNESS BETWEEN FEATURES IS MEASURED USING
THE ABSOLUTE CORRELATION COEFFICIENT BETWEEN EACH FEATURE PAIR AFTER INITIAL IMPUTATION TO
ENSURE COVERAGE OF FEATURES THROUGHOUT THE IMPUTATION PROCESS THE NEIGHBOR FEATURES ARE
NOT NECESSARILY NEAREST BUT ARE DRAWN WITH PROBABILITY PROPORTIONAL TO CORRELATION FOR EACH
IMPUTED TARGET FEATURE CAN PROVIDE SIGNIFICANT SPEEDUP WHEN THE NUMBER OF FEATURES IS
HUGE IFNONE ALL FEATURES WILL BE USED
INITIALSTRATEGY STR OPTIONAL DEFAULT"MEAN" WHICH STRATEGY TO USE TO INITIALIZE THE MISSING
VALUES SAME AS THE STRATEGY PARAMETER IN SKLEARNIMPUTESIMPLEIMPUTER
VALID VALUES "MEAN" "MEDIAN" "MOSTFREQUENT" OR "CONSTANT"

IMPUTATIONORDER STR OPTIONAL DEFAULT”ASCENDING” THE ORDER IN WHICH THE FEATURES WILL BE IMPUTED POSSIBLE VALUES
“ASCENDING” FROM FEATURES WITH FEWEST MISSING VALUES TO MOST
“DESCENDING” FROM FEATURES WITH MOST MISSING VALUES TO FEWEST
“ROMAN” LEFT TO RIGHT
“ARABIC” RIGHT TO LEFT
“RANDOM” A RANDOM ORDER FOR EACH ROUND
MINVALUE FLOAT OPTIONAL DEFAULTNONE MINIMUM POSSIBLE IMPUTED VALUE DEFAULT OF NONE WILL SET MINIMUM TO NEGATIVE INFINITY
MAXVALUE FLOAT OPTIONAL DEFAULTNONE MAXIMUM POSSIBLE IMPUTED VALUE DEFAULT OF NONE WILL SET MAXIMUM TO POSITIVE INFINITY
VERBOSE INT OPTIONAL DEFAULT0 VERBOSITY FLAG CONTROLS THE DEBUG MESSAGES THAT ARE ISSUED AS FUNCTIONS ARE EVALUATED THE HIGHER THE MORE VERBOSE CAN BE 0 1 OR 2
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE PSEUDO RANDOM NUMBER GENERATOR TO USE RANDOMIZES SELECTION OF ESTIMATOR FEATURES IF NNEARESTFEATURES IS NOT NONE THE IMPUTATIONORDER IFRANDOM AND THE SAMPLING FROM POSTERIOR IF SAMPLEPOSTERIOR IS TRUE USE AN INTEGER FOR DETERMINISM SEE THE GLOSSARY
ADDINDICATOR BOOLEAN OPTIONAL DEFAULTFALSE IF TRUE A MISSINGINDICATOR TRANSFORM WILL STACK ONTO OUTPUT OF THE IMPUTER’S TRANSFORM THIS ALLOWS A PREDICTIVE ESTIMATOR TO ACCOUNT FOR MISSINGNESS DESPITE IMPUTATION IF A FEATURE HAS NO MISSING VALUES AT FITTRAIN TIME THE FEATURE WON’T APPEAR ON THE MISSING INDICATOR EVEN IF THERE ARE MISSING VALUES AT TRANSFORMTEST TIME
ATTRIBUTES
INITIALIMPUTER OBJECT OF TYPE SKLEARNIMPUTESIMPLEIMPUTER IMPUTER USED TO INITIALIZE THE MISSING VALUES
IMPUTATIONSEQUENCE LIST OF TUPLES EACH TUPLE HAS FEATIDX NEIGHBORFEATIDX ESTIMATOR WHEREFEATIDX IS THE CURRENT FEATURE TO BE IMPUTED NEIGHBORFEATIDX IS THE ARRAY OF OTHER FEATURES USED TO IMPUTE THE CURRENT FEATURE AND ESTIMATOR IS THE TRAINED ESTIMATOR USED FOR THE IMPUTATION LENGTH ISSELFNFEATURESWITHMISSING SELFNITER
NITER INT NUMBER OF ITERATION ROUNDS THAT OCCURRED WILL BE LESS THAN SELFMAXITER IF EARLY STOPPING CRITERION WAS REACHED
NFEATURESWITHMISSING INT NUMBER OF FEATURES WITH MISSING VALUES
INDICATOR SKLEARNIMPUTEMISSINGINDICATOR INDICATOR USED TO ADD BINARY INDI CATORS FOR MISSING VALUES NONE IF ADDINDICATOR IS FALSE
SEE ALSO
SIMPLEIMPUTER UNIVARIATE IMPUTATION OF MISSING VALUES
NOTES
TO SUPPORT IMPUTATION IN INDUCTIVE MODE WE STORE EACH FEATURE’S ESTIMATOR DURING THE FIT PHASE AND PREDICT WITHOUT REFITTING IN ORDER DURING THE TRANSFORM PHASE

FEATURES WHICH CONTAIN ALL MISSING VALUES AT FIT ARE DISCARDED UPON TRANSFORM
FEATURES WITH MISSING VALUES DURING TRANSFORM WHICH DID NOT HAVE ANY MISSING VALUES DURING FIT WILL BE IMPUTED WITH THE INITIAL IMPUTATION METHOD ONLY
REFERENCES
RCD31B817A31E1 RCD31B817A31E2
METHODS
FITSELF X Y FITS THE IMPUTER ON X AND RETURN SELF
FITTRANSFORM SELF X Y FITS THE IMPUTER ON X AND RETURN THE TRANSFORMED X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X IMPUTES ALL MISSING VALUES IN X
INIT SELFESTIMATORNONE MISSINGVALUESNAN SAMPLEPOSTERIORFALSE MAXITER10
TOL0001 NNEARESTFEATURESNONE INITIALSTRATEGY'MEAN' IMPUTA
TIONORDER'ASCENDING' MINVALUENONE MAXVALUENONE VERBOSE0 RAN
DOMSTATENONE ADDINDICATORFALSE
FITSELFXYNONE
FITS THE IMPUTER ON X AND RETURN SELF
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT DATA WHERE "NSAMPLES" IS THE NUMBER OF SAMPLES AND "NFEATURES" IS THE NUMBER OF FEATURES
YIGNORED
RETURNS
SELF OBJECT RETURNS SELF
FITTRANSFORM SELFXYNONE
FITS THE IMPUTER ON X AND RETURN THE TRANSFORMED X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT DATA WHERE "NSAMPLES" IS THE NUMBER OF SAMPLES AND "NFEATURES" IS THE NUMBER OF FEATURES
YIGNORED
RETURNS
XTARRAYLIKE SHAPE NSAMPLES NFEATURES THE IMPUTED INPUT DATA
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED SUBOBJECTS THAT ARE ESTIMATORS
RETURNS

PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
IMPUTES ALL MISSING VALUES IN X
NOTE THAT THIS IS STOCHASTIC AND THAT IF RANDOMSTATE IS NOT FIXED REPEATED CALLS OR PERMUTED INPUT WILL
YIELD DIFFERENT RESULTS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE INPUT DATA TO COMPLETE
RETURNS
XTARRAYLIKE SHAPE NSAMPLES NFEATURES THE IMPUTED INPUT DATA
EXAMPLES USING SKLEARNIMPUTEITERATIVEIMPUTER
•IMPUTING MISSING VALUES WITH VARIANTS OF ITERATIVEIMPUTER
•IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR
6193SKLEARNIMPUTE MISSINGINDICATOR
CLASSSKLEARNIMPUTE MISSINGINDICATOR MISSINGVALUESNAN FEATURES'MISSINGONLY'
SPARSE'AUTO' ERRORONNEWTRUE
BINARY INDICATORS FOR MISSING VALUES
NOTE THAT THIS COMPONENT TYPICALLY SHOULD NOT BE USED IN A VANILLA PIPELINE CONSISTING OF TRANSFORMERS AND A
CLASSIFIER BUT RATHER COULD BE ADDED USING A FEATUREUNION ORCOLUMNTRANSFORMER
READ MORE IN THE USER GUIDE
PARAMETERS
MISSINGVALUES NUMBER STRING NPNAN DEFAULT OR NONE THE PLACEHOLDER FOR THE MISSING
VALUES ALL OCCURRENCES OF MISSINGVALUES WILL BE INDICATED TRUE IN THE OUTPUT ARRAY
THE OTHER VALUES WILL BE MARKED AS FALSE
FEATURES STR OPTIONAL WHETHER THE IMPUTER MASK SHOULD REPRESENT ALL OR A SUBSET OF FEATURES
• IF "MISSINGONLY" DEFAULT THE IMPUTER MASK WILL ONLY REPRESENT FEATURES CONTAINING
MISSING VALUES DURING FIT TIME
• IF "ALL" THE IMPUTER MASK WILL REPRESENT ALL FEATURES
SPARSE BOOLEAN OR "AUTO" OPTIONAL WHETHER THE IMPUTER MASK FORMAT SHOULD BE SPARSE OR
DENSE
• IF "AUTO" DEFAULT THE IMPUTER MASK WILL BE OF SAME TYPE AS INPUT
• IF TRUE THE IMPUTER MASK WILL BE A SPARSE MATRIX
619SKLEARNIMPUTE IMPUTE 1849

• IF FALSE THE IMPUTER MASK WILL BE A NUMPY ARRAY
ERRORONNEW BOOLEAN OPTIONAL IF TRUE DEFAULT TRANSFORM WILL RAISE AN ERROR WHEN THERE ARE FEATURES WITH MISSING VALUES IN TRANSFORM THAT HAVE NO MISSING VALUES IN FIT THIS IS APPLICABLE ONLY WHEN FEATURESMISSINGONLY
ATTRIBUTES
FEATURES NDARRAY SHAPE NMISSINGFEATURES OR NFEATURES THE FEATURES INDICES WHICH WILL BE RETURNED WHEN CALLING TRANSFORM THEY ARE COMPUTED DURING FIT FOR FEATURESALL IT IS TORANGENFEATURES
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNIMPUTE IMPORT MISSINGINDICATOR
X1  NPARRAYNPNAN 1 3
 4 0 NPNAN
 8 1 0
X2  NPARRAY5 1 NPNAN
 NPNAN 2 3
 2 4 0
INDICATOR  MISSINGINDICATOR
INDICATORFITX1
MISSINGINDICATORERRORONNEWTRUE FEATURESMISSINGONLY
MISSINGVALUESNAN SPARSEAUTO
X2TR  INDICATORTRANSFORMX2
X2TR
ARRAYFALSE TRUE
 TRUE FALSE
FALSE FALSE
```
METHODS
FITSELF X Y FIT THE TRANSFORMER ON X
FITTRANSFORM SELF X Y GENERATE MISSING VALUES INDICATOR FOR X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X GENERATE MISSING VALUES INDICATOR FOR X
INIT SELFMISSINGVALUESNAN FEATURES’MISSINGONLY’ SPARSE’AUTO’ ERRORONNEWTRUE
FITSELFXYNONE
FIT THE TRANSFORMER ON X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES INPUT DATA WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
RETURNS
SELF OBJECT RETURNS SELF
FITTRANSFORM SELFXYNONE
GENERATE MISSING VALUES INDICATOR FOR X

PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA TO COMPLETE
RETURNS
XTNDARRAY OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE MISSING INDICATOR FOR
INPUT DATA THE DATA TYPE OF XTWILL BE BOOLEAN
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
GENERATE MISSING VALUES INDICATOR FOR X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA TO COMPLETE
RETURNS
XTNDARRAY OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE MISSING INDICATOR FOR
INPUT DATA THE DATA TYPE OF XTWILL BE BOOLEAN
EXAMPLES USING SKLEARNIMPUTEMISSINGINDICATOR
•IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR
620SKLEARNKERNELAPPROXIMATION KERNEL APPROXIMATION
THESKLEARNKERNELAPPROXIMATION MODULE IMPLEMENTS SEVERAL APPROXIMATE KERNEL FEATURE MAPS BASE ON
FOURIER TRANSFORMS
USER GUIDE SEE THE KERNEL APPROXIMATION SECTION FOR FURTHER DETAILS
KERNELAPPROXIMATION
ADDITIVECHI2SAMPLER APPROXIMATE FEATURE MAP FOR ADDITIVE CHI2 KERNEL
KERNELAPPROXIMATIONNYSTROEM KERNEL APPROXIMATE A KERNEL MAP USING A SUBSET OF THE TRAINING
DATA
CONTINUED ON NEXT PAGE

TABLE 6141 – CONTINUED FROM PREVIOUS PAGE
KERNELAPPROXIMATIONRBFSAMPLER GAMMA
APPROXIMATES FEATURE MAP OF AN RBF KERNEL BY MONTE
CARLO APPROXIMATION OF ITS FOURIER TRANSFORM
KERNELAPPROXIMATION
SKEWEDCHI2SAMPLER APPROXIMATES FEATURE MAP OF THE “SKEWED CHISQUARED”
KERNEL BY MONTE CARLO APPROXIMATION OF ITS FOURIER TRANS
FORM
6201SKLEARNKERNELAPPROXIMATION ADDITIVECHI2SAMPLER
CLASSSKLEARNKERNELAPPROXIMATION ADDITIVECHI2SAMPLER SAMPLESTEPS2 SAM
PLEINTERVALNONE
APPROXIMATE FEATURE MAP FOR ADDITIVE CHI2 KERNEL
USES SAMPLING THE FOURIER TRANSFORM OF THE KERNEL CHARACTERISTIC AT REGULAR INTERVALS
SINCE THE KERNEL THAT IS TO BE APPROXIMATED IS ADDITIVE THE COMPONENTS OF THE INPUT VECTORS CAN BE TREATED
SEPARATELY EACH ENTRY IN THE ORIGINAL SPACE IS TRANSFORMED INTO 2SAMPLESTEPS1 FEATURES WHERE SAMPLESTEPS
IS A PARAMETER OF THE METHOD TYPICAL VALUES OF SAMPLESTEPS INCLUDE 1 2 AND 3
OPTIMAL CHOICES FOR THE SAMPLING INTERVAL FOR CERTAIN DATA RANGES CAN BE COMPUTED SEE THE REFERENCE THE
DEFAULT VALUES SHOULD BE REASONABLE
READ MORE IN THE USER GUIDE
PARAMETERS
SAMPLESTEPS INT OPTIONAL GIVES THE NUMBER OF COMPLEX SAMPLING POINTS
SAMPLEINTERVAL FLOAT OPTIONAL SAMPLING INTERVAL MUST BE SPECIFIED WHEN SAMPLESTEPS NOT
IN 123
SEE ALSO
SKEWEDCHI2SAMPLER A FOURIERAPPROXIMATION TO A NONADDITIVE VARIANT OF THE CHI SQUARED KERNEL
SKLEARNMETRICSPAIRWISECHI2KERNEL THE EXACT CHI SQUARED KERNEL
SKLEARNMETRICSPAIRWISEADDITIVECHI2KERNEL THE EXACT ADDITIVE CHI SQUARED KERNEL
NOTES
THIS ESTIMATOR APPROXIMATES A SLIGHTLY DIFFERENT VERSION OF THE ADDITIVE CHI SQUARED KERNEL THEN METRIC
ADDITIVECHI2 COMPUTES
REFERENCES
SEE “EFFICIENT ADDITIVE KERNELS VIA EXPLICIT FEATURE MAPS” A VEDALDI AND A ZISSERMAN PATTERN ANALYSIS AND
MACHINE INTELLIGENCE 2011
EXAMPLES
FROM SKLEARNDATASETS IMPORT LOADDIGITS
FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
FROM SKLEARNKERNELAPPROXIMATION IMPORT ADDITIVECHI2SAMPLER
X Y LOADDIGITSRETURNXY TRUE

SCIKITLEARN USER GUIDE RELEASE 0213
CHI2SAMPLER ADDITIVECHI2SAMPLERSAMPLESTEPS2
XTRANSFORMED CHI2SAMPLERFITTRANSFORMX Y
CLF SGDCLASSIFIERMAXITER5 RANDOMSTATE0 TOL1E3
CLFFITXTRANSFORMED Y
SGDCLASSIFIERALPHA00001 AVERAGEFALSE CLASSWEIGHTNONE
EARLYSTOPPINGFALSE EPSILON01 ETA000 FITINTERCEPTTRUE
L1RATIO015 LEARNINGRATEOPTIMAL LOSSHINGE MAXITER5
NITERNOCHANGE5 NJOBSNONE PENALTYL2 POWERT05
RANDOMSTATE0 SHUFFLETRUE TOL0001 VALIDATIONFRACTION01
VERBOSE0 WARMSTARTFALSE
CLFSCOREXTRANSFORMED Y
09499
METHODS
FITSELF X Y SET THE PARAMETERS
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X APPLY APPROXIMATE FEATURE MAP TO X
INIT SELFSAMPLESTEPS2 SAMPLEINTERVALNONE
FITSELFXYNONE
SET THE PARAMETERS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IN THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
RETURNS
SELF OBJECT RETURNS THE TRANSFORMER
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
620SKLEARNKERNELAPPROXIMATION KERNEL APPROXIMATION 1853

PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
APPLY APPROXIMATE FEATURE MAP TO X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES
RETURNS
XNEW ARRAY SPARSE MATRIX SHAPE NSAMPLES NFEATURES 2SAMPLESTEPS 1
WHETHER THE RETURN VALUE IS AN ARRAY OF SPARSE MATRIX DEPENDS ON THE TYPE OF THE INPUT X
6202SKLEARNKERNELAPPROXIMATION NYSTROEM
CLASSSKLEARNKERNELAPPROXIMATION NYSTROEM KERNEL'RBF' GAMMANONE COEF0NONE
DEGREENONE KERNELPARAMSNONE
NCOMPONENTS100 RANDOMSTATENONE
APPROXIMATE A KERNEL MAP USING A SUBSET OF THE TRAINING DATA
CONSTRUCTS AN APPROXIMATE FEATURE MAP FOR AN ARBITRARY KERNEL USING A SUBSET OF THE DATA AS BASIS
READ MORE IN THE USER GUIDE
PARAMETERS
KERNEL STRING OR CALLABLE DEFAULT"RBF" KERNEL MAP TO BE APPROXIMATED A CALLABLE SHOULD
ACCEPT TWO ARGUMENTS AND THE KEYWORD ARGUMENTS PASSED TO THIS OBJECT AS KERNELPARAMS
AND SHOULD RETURN A FLOATING POINT NUMBER
GAMMA FLOAT DEFAULTNONE GAMMA PARAMETER FOR THE RBF LAPLACIAN POLYNOMIAL EXPONEN
TIAL CHI2 AND SIGMOID KERNELS INTERPRETATION OF THE DEFAULT VALUE IS LEFT TO THE KERNEL SEE THE
DOCUMENTATION FOR SKLEARNMETRICSPAIRWISE IGNORED BY OTHER KERNELS
COEF0 FLOAT DEFAULTNONE ZERO COEFFICIENT FOR POLYNOMIAL AND SIGMOID KERNELS IGNORED BY
OTHER KERNELS
DEGREE FLOAT DEFAULTNONE DEGREE OF THE POLYNOMIAL KERNEL IGNORED BY OTHER KERNELS
KERNELPARAMS MAPPING OF STRING TO ANY OPTIONAL ADDITIONAL PARAMETERS KEYWORD ARGU
MENTS FOR KERNEL FUNCTION PASSED AS CALLABLE OBJECT
NCOMPONENTS INT NUMBER OF FEATURES TO CONSTRUCT HOW MANY DATA POINTS WILL BE USED TO
CONSTRUCT THE MAPPING
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES

COMPONENTS ARRAY SHAPE NCOMPONENTS NFEATURES SUBSET OF TRAINING POINTS USED TO CON
STRUCT THE FEATURE MAP
COMPONENTINDICES ARRAY SHAPE NCOMPONENTS INDICES OF COMPONENTS IN THE TRAINING
SET
NORMALIZATION ARRAY SHAPE NCOMPONENTS NCOMPONENTS NORMALIZATION MATRIX NEEDED
FOR EMBEDDING SQUARE ROOT OF THE KERNEL MATRIX ON COMPONENTS
SEE ALSO
RBFSAMPLER AN APPROXIMATION TO THE RBF KERNEL USING RANDOM FOURIER FEATURES
SKLEARNMETRICSPAIRWISEKERNELMETRICS LIST OF BUILTIN KERNELS
REFERENCES
• WILLIAMS CKI AND SEEGER M “USING THE NYSTROEM METHOD TO SPEED UP KERNEL MACHINES” ADVANCES IN
NEURAL INFORMATION PROCESSING SYSTEMS 2001
• T YANG Y LI M MAHDAVI R JIN AND Z ZHOU “NYSTROEM METHOD VS RANDOM FOURIER FEATURES A
THEORETICAL AND EMPIRICAL COMPARISON” ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS 2012
EXAMPLES
```
 FROM SKLEARN IMPORT DATASETS SVM
 FROM SKLEARNKERNELAPPROXIMATION IMPORT NYSTROEM
DIGITS  DATASETSLOADDIGITSNCLASS9
DATA  DIGITSDATA  16
CLF  SVMLINEARSVC
FEATUREMAPNYSTROEM  NYSTROEMGAMMA2
 RANDOMSTATE1
 NCOMPONENTS300
DATATRANSFORMED  FEATUREMAPNYSTROEMFITTRANSFORMDATA
CLFFITDATATRANSFORMED DIGITSTARGET

LINEARSVCC10 CLASSWEIGHTNONE DUALTRUE FITINTERCEPTTRUE
INTERCEPTSCALING1 LOSSSQUAREDHINGE MAXITER1000
MULTICLASSOVR PENALTYL2 RANDOMSTATENONE TOL00001
VERBOSE0
CLFSCOREDATATRANSFORMED DIGITSTARGET
09987
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METHODS
FITSELF X Y FIT ESTIMATOR TO DATA
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X APPLY FEATURE MAP TO X
INIT SELFKERNEL’RBF’ GAMMANONE COEF0NONE DEGREENONE KERNELPARAMSNONE
NCOMPONENTS100 RANDOMSTATENONE

FITSELFXYNONE
FIT ESTIMATOR TO DATA
SAMPLES A SUBSET OF TRAINING POINTS COMPUTES KERNEL ON THESE AND COMPUTES NORMALIZATION MATRIX
PARAMETERS
XARRAYLIKE SHAPENSAMPLES NFEATURE TRAINING DATA
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
APPLY FEATURE MAP TO X
COMPUTES AN APPROXIMATE FEATURE MAP USING THE KERNEL BETWEEN SOME TRAINING POINTS AND X
PARAMETERS
XARRAYLIKE SHAPENSAMPLES NFEATURES DATA TO TRANSFORM
RETURNS
XTRANSFORMED ARRAY SHAPENSAMPLES NCOMPONENTS TRANSFORMED DATA
EXAMPLES USING SKLEARNKERNELAPPROXIMATIONNYSTROEM
•EXPLICIT FEATURE MAP APPROXIMATION FOR RBF KERNELS

6203SKLEARNKERNELAPPROXIMATION RBFSAMPLER
CLASSSKLEARNKERNELAPPROXIMATION RBFSAMPLER GAMMA10 NCOMPONENTS100 RAN
DOMSTATENONE
APPROXIMATES FEATURE MAP OF AN RBF KERNEL BY MONTE CARLO APPROXIMATION OF ITS FOURIER TRANSFORM
IT IMPLEMENTS A VARIANT OF RANDOM KITCHEN SINKS1
READ MORE IN THE USER GUIDE
PARAMETERS
GAMMA FLOAT PARAMETER OF RBF KERNEL EXPGAMMA X2
NCOMPONENTS INT NUMBER OF MONTE CARLO SAMPLES PER ORIGINAL FEATURE EQUALS THE DIMEN
SIONALITY OF THE COMPUTED FEATURE SPACE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
NOTES
SEE “RANDOM FEATURES FOR LARGESCALE KERNEL MACHINES” BY A RAHIMI AND BENJAMIN RECHT
1 “WEIGHTED SUMS OF RANDOM KITCHEN SINKS REPLACING MINIMIZATION WITH RANDOMIZATION IN LEARNING” BY A
RAHIMI AND BENJAMIN RECHT HTTPSPEOPLEEECSBERKELEYEDUBRECHTPAPERS08RAHRECNIPSPDF
EXAMPLES
 FROM SKLEARNKERNELAPPROXIMATION IMPORT RBFSAMPLER
 FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
X 0 0 1 1 1 0 0 1
Y 0 0 1 1
RBFFEATURE RBFSAMPLERGAMMA1 RANDOMSTATE1
XFEATURES RBFFEATUREFITTRANSFORMX
CLF SGDCLASSIFIERMAXITER5 TOL1E3
CLFFITXFEATURES Y

SGDCLASSIFIERALPHA00001 AVERAGEFALSE CLASSWEIGHTNONE
EARLYSTOPPINGFALSE EPSILON01 ETA000 FITINTERCEPTTRUE
L1RATIO015 LEARNINGRATEOPTIMAL LOSSHINGE MAXITER5
NITERNOCHANGE5 NJOBSNONE PENALTYL2 POWERT05
RANDOMSTATENONE SHUFFLETRUE TOL0001 VALIDATIONFRACTION01
VERBOSE0 WARMSTARTFALSE
CLFSCOREXFEATURES Y
10
METHODS
FITSELF X Y FIT THE MODEL WITH X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
CONTINUED ON NEXT PAGE

TABLE 6144 – CONTINUED FROM PREVIOUS PAGE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X APPLY THE APPROXIMATE FEATURE MAP TO X
INIT SELFGAMMA10 NCOMPONENTS100 RANDOMSTATENONE
FITSELFXYNONE
FIT THE MODEL WITH X
SAMPLES RANDOM PROJECTION ACCORDING TO NFEATURES
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE
NSAMPLES IN THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
RETURNS
SELF OBJECT RETURNS THE TRANSFORMER
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
APPLY THE APPROXIMATE FEATURE MAP TO X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NEW DATA WHERE NSAMPLES
IN THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES

RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
EXAMPLES USING SKLEARNKERNELAPPROXIMATIONRBFSAMPLER
•EXPLICIT FEATURE MAP APPROXIMATION FOR RBF KERNELS
6204SKLEARNKERNELAPPROXIMATION SKEWEDCHI2SAMPLER
CLASSSKLEARNKERNELAPPROXIMATION SKEWEDCHI2SAMPLER SKEWEDNESS10
NCOMPONENTS100 RAN
DOMSTATENONE
APPROXIMATES FEATURE MAP OF THE “SKEWED CHISQUARED” KERNEL BY MONTE CARLO APPROXIMATION OF ITS FOURIER
TRANSFORM
READ MORE IN THE USER GUIDE
PARAMETERS
SKEWEDNESS FLOAT “SKEWEDNESS” PARAMETER OF THE KERNEL NEEDS TO BE CROSSVALIDATED
NCOMPONENTS INT NUMBER OF MONTE CARLO SAMPLES PER ORIGINAL FEATURE EQUALS THE DIMEN
SIONALITY OF THE COMPUTED FEATURE SPACE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
SEE ALSO
ADDITIVECHI2SAMPLER A DIFFERENT APPROACH FOR APPROXIMATING AN ADDITIVE VARIANT OF THE CHI SQUARED KER
NEL
SKLEARNMETRICSPAIRWISECHI2KERNEL THE EXACT CHI SQUARED KERNEL
REFERENCES
SEE “RANDOM FOURIER APPROXIMATIONS FOR SKEWED MULTIPLICATIVE HISTOGRAM KERNELS” BY FUXIN LI CATALIN
IONESCU AND CRISTIAN SMINCHISESCU
EXAMPLES
```
 FROM SKLEARNKERNELAPPROXIMATION IMPORT SKEWEDCHI2SAMPLER
 FROM SKLEARNLINEARMODEL IMPORT SGDCLASSIFIER
X  0 0 1 1 1 0 0 1
Y  0 0 1 1
CHI2FEATURE  SKEWEDCHI2SAMPLERSKEWEDNESS01
 NCOMPONENTS10
 RANDOMSTATE0
XFEATURES  CHI2FEATUREFITTRANSFORMX Y
CLF  SGDCLASSIFIERMAXITER10 TOL1E3
CLFFITXFEATURES Y
SGDCLASSIFIERALPHA00001 AVERAGEFALSE CLASSWEIGHTNONE
```

SCIKITLEARN USER GUIDE RELEASE 0213
EARLYSTOPPINGFALSE EPSILON01 ETA000 FITINTERCEPTTRUE
L1RATIO015 LEARNINGRATEOPTIMAL LOSSHINGE MAXITER10
NITERNOCHANGE5 NJOBSNONE PENALTYL2 POWERT05
RANDOMSTATENONE SHUFFLETRUE TOL0001 VALIDATIONFRACTION01
VERBOSE0 WARMSTARTFALSE
CLFSCOREXFEATURES Y
10
METHODS
FITSELF X Y FIT THE MODEL WITH X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X APPLY THE APPROXIMATE FEATURE MAP TO X
INIT SELFSKEWEDNESS10 NCOMPONENTS100 RANDOMSTATENONE
FITSELFXYNONE
FIT THE MODEL WITH X
SAMPLES RANDOM PROJECTION ACCORDING TO NFEATURES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IN THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
RETURNS
SELF OBJECT RETURNS THE TRANSFORMER
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES

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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
APPLY THE APPROXIMATE FEATURE MAP TO X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES NEW DATA WHERE NSAMPLES IN THE NUMBER OF
SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES ALL VALUES OF X MUST BE STRICTLY GREATER
THAN "SKEWEDNESS"
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
621SKLEARNKERNELRIDGE KERNEL RIDGE REGRESSION
MODULESKLEARNKERNELRIDGE IMPLEMENTS KERNEL RIDGE REGRESSION
USER GUIDE SEE THE KERNEL RIDGE REGRESSION SECTION FOR FURTHER DETAILS
KERNELRIDGEKERNELRIDGE ALPHA KERNEL KERNEL RIDGE REGRESSION
6211SKLEARNKERNELRIDGE KERNELRIDGE
CLASSSKLEARNKERNELRIDGE KERNELRIDGE ALPHA1 KERNEL'LINEAR' GAMMANONE DEGREE3
COEF01 KERNELPARAMSNONE
KERNEL RIDGE REGRESSION
KERNEL RIDGE REGRESSION KRR COMBINES RIDGE REGRESSION LINEAR LEAST SQUARES WITH L2NORM REGULARIZATION WITH
THE KERNEL TRICK IT THUS LEARNS A LINEAR FUNCTION IN THE SPACE INDUCED BY THE RESPECTIVE KERNEL AND THE DATA FOR
NONLINEAR KERNELS THIS CORRESPONDS TO A NONLINEAR FUNCTION IN THE ORIGINAL SPACE
THE FORM OF THE MODEL LEARNED BY KRR IS IDENTICAL TO SUPPORT VECTOR REGRESSION SVR HOWEVER DIFFERENT LOSS
FUNCTIONS ARE USED KRR USES SQUARED ERROR LOSS WHILE SUPPORT VECTOR REGRESSION USES EPSILONINSENSITIVE LOSS
BOTH COMBINED WITH L2 REGULARIZATION IN CONTRAST TO SVR FITTING A KRR MODEL CAN BE DONE IN CLOSEDFORM AND
IS TYPICALLY FASTER FOR MEDIUMSIZED DATASETS ON THE OTHER HAND THE LEARNED MODEL IS NONSPARSE AND THUS SLOWER
THAN SVR WHICH LEARNS A SPARSE MODEL FOR EPSILON 0 AT PREDICTIONTIME
THIS ESTIMATOR HAS BUILTIN SUPPORT FOR MULTIVARIATE REGRESSION IE WHEN Y IS A 2DARRAY OF SHAPE NSAMPLES
NTARGETS
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA FLOAT ARRAYLIKE SHAPE NTARGETS SMALL POSITIVE VALUES OF ALPHA IMPROVE THE CON
DITIONING OF THE PROBLEM AND REDUCE THE VARIANCE OF THE ESTIMATES ALPHA CORRESPONDS TO
2C1 IN OTHER LINEAR MODELS SUCH AS LOGISTICREGRESSION OR LINEARSVC IF AN ARRAY IS

PASSED PENALTIES ARE ASSUMED TO BE SPECIFIC TO THE TARGETS HENCE THEY MUST CORRESPOND IN NUMBER
KERNEL STRING OR CALLABLE DEFAULT”LINEAR” KERNEL MAPPING USED INTERNALLY A CALLABLE SHOULD ACCEPT TWO ARGUMENTS AND THE KEYWORD ARGUMENTS PASSED TO THIS OBJECT AS KERNELPARAMS AND SHOULD RETURN A FLOATING POINT NUMBER SET TO “PRECOMPUTED” IN ORDER TO PASS A PRECOMPUTED KERNEL MATRIX TO THE ESTIMATOR METHODS INSTEAD OF SAMPLES
GAMMA FLOAT DEFAULTNONE GAMMA PARAMETER FOR THE RBF LAPLACIAN POLYNOMIAL EXPONENTIAL CHI2 AND SIGMOID KERNELS INTERPRETATION OF THE DEFAULT VALUE IS LEFT TO THE KERNEL SEE THE DOCUMENTATION FOR SKLEARNMETRICSPAIRWISE IGNORED BY OTHER KERNELS
DEGREE FLOAT DEFAULT3 DEGREE OF THE POLYNOMIAL KERNEL IGNORED BY OTHER KERNELS
COEF0 FLOAT DEFAULT1 ZERO COEFFICIENT FOR POLYNOMIAL AND SIGMOID KERNELS IGNORED BY OTHER KERNELS
KERNELPARAMS MAPPING OF STRING TO ANY OPTIONAL ADDITIONAL PARAMETERS KEYWORD ARGUMENTS FOR KERNEL FUNCTION PASSED AS CALLABLE OBJECT
ATTRIBUTES
DUALCOEF ARRAY SHAPE NSAMPLES OR NSAMPLES NTARGETS REPRESENTATION OF WEIGHT VECTORS IN KERNEL SPACE
XFIT ARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA WHICH IS ALSO REQUIRED FOR PREDICTION IF KERNEL “PRECOMPUTED” THIS IS INSTEAD THE PRECOMPUTED TRAINING MATRIX SHAPE NSAMPLES NSAMPLES
SEE ALSO
SKLEARNLINEARMODELRIDGE LINEAR RIDGE REGRESSION
SKLEARNSVMSVR SUPPORT VECTOR REGRESSION IMPLEMENTED USING LIBSVM
REFERENCES
• KEVIN P MURPHY “MACHINE LEARNING A PROBABILISTIC PERSPECTIVE” THE MIT PRESS CHAPTER 1443 PP 492493
EXAMPLES
```
 FROM SKLEARNKERNELRIDGE IMPORT KERNELRIDGE
 IMPORT NUMPY AS NP
NSAMPLES NFEATURES  10 5
RNG  NPRANDOMRANDOMSTATE0
Y  RNGRANDNNSAMPLES
X  RNGRANDNNSAMPLES NFEATURES
CLF  KERNELRIDGEALPHA10
CLFFITX Y
KERNELRIDGEALPHA10 COEF01 DEGREE3 GAMMANONE KERNELLINEAR
KERNELPARAMSNONE
```
METHODS

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FITSELF X Y SAMPLEWEIGHT FIT KERNEL RIDGE REGRESSION MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE KERNEL RIDGE MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHA1 KERNEL'LINEAR' GAMMANONE DEGREE3 COEF01 KERNELPARAMSNONE
FITSELFXYNONE SAMPLEWEIGHTNONE
FIT KERNEL RIDGE REGRESSION MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA IF KER
NEL "PRECOMPUTED" THIS IS INSTEAD A PRECOMPUTED KERNEL MATRIX SHAPE NSAMPLES
NSAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
SAMPLEWEIGHT FLOAT OR ARRAYLIKE OF SHAPE NSAMPLES INDIVIDUAL WEIGHTS FOR EACH SAM
PLE IGNORED IF NONE IS PASSED
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE KERNEL RIDGE MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES IF KERNEL
 "PRECOMPUTED" THIS IS INSTEAD A PRECOMPUTED KERNEL MATRIX SHAPE NSAMPLES
NSAMPLESFITTED WHERE NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING
FOR THIS ESTIMATOR
RETURNS
CARRAY SHAPE NSAMPLES OR NSAMPLES NTARGETS RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS

XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNKERNELRIDGEKERNELRIDGE
•COMPARISON OF KERNEL RIDGE REGRESSION AND SVR
•COMPARISON OF KERNEL RIDGE AND GAUSSIAN PROCESS REGRESSION
622SKLEARNLINEARMODEL GENERALIZED LINEAR MODELS
THESKLEARNLINEARMODEL MODULE IMPLEMENTS GENERALIZED LINEAR MODELS IT INCLUDES RIDGE REGRESSION
BAYESIAN REGRESSION LASSO AND ELASTIC NET ESTIMATORS COMPUTED WITH LEAST ANGLE REGRESSION AND COORDINATE DE
SCENT IT ALSO IMPLEMENTS STOCHASTIC GRADIENT DESCENT RELATED ALGORITHMS
USER GUIDE SEE THE GENERALIZED LINEAR MODELS SECTION FOR FURTHER DETAILS
LINEARMODELARDREGRESSION NITER TOL BAYESIAN ARD REGRESSION
LINEARMODELBAYESIANRIDGE NITER TOL BAYESIAN RIDGE REGRESSION
LINEARMODELELASTICNET ALPHA L1RATIO LINEAR REGRESSION WITH COMBINED L1 AND L2 PRIORS AS REGU
LARIZER
LINEARMODELELASTICNETCV L1RATIO EPS ELASTIC NET MODEL WITH ITERATIVE FITTING ALONG A REGULARIZA
TION PATH
LINEARMODELHUBERREGRESSOR EPSILON LINEAR REGRESSION MODEL THAT IS ROBUST TO OUTLIERS
LINEARMODELLARS FITINTERCEPT VERBOSE LEAST ANGLE REGRESSION MODEL AKA
CONTINUED ON NEXT PAGE

TABLE 6148 – CONTINUED FROM PREVIOUS PAGE
LINEARMODELLARSCV FITINTERCEPT CROSSVALIDATED LEAST ANGLE REGRESSION MODEL
LINEARMODELLASSO ALPHA FITINTERCEPT LINEAR MODEL TRAINED WITH L1 PRIOR AS REGULARIZER AKA THE LASSO
LINEARMODELLASSOCV EPS NALPHAS LASSO LINEAR MODEL WITH ITERATIVE FITTING ALONG A REGULARIZATION PATH
LINEARMODELLASSOLARS ALPHA LASSO MODEL FIT WITH LEAST ANGLE REGRESSION AKA
LINEARMODELLASSOLARSCV FITINTERCEPT CROSSVALIDATED LASSO USING THE LARS ALGORITHM
LINEARMODELLASSOLARSIC CRITERION LASSO MODEL FIT WITH LARS USING BIC OR AIC FOR MODEL SELECTION
LINEARMODELLINEARREGRESSION ORDINARY LEAST SQUARES LINEAR REGRESSION
LINEARMODELLOGISTICREGRESSION PENALTY
LOGISTIC REGRESSION AKA LOGIT MAXENT CLASSIFIER
LINEARMODELLOGISTICREGRESSIONCV CS
LOGISTIC REGRESSION CV AKA LOGIT MAXENT CLASSIFIER
LINEARMODELMULTITASKLASSO ALPHA MULTITASK LASSO MODEL TRAINED WITH L1L2 MIXEDNORM AS REGULARIZER
LINEARMODELMULTITASKELASTICNET ALPHA
MULTITASK ELASTICNET MODEL TRAINED WITH L1L2 MIXED NORM AS REGULARIZER
LINEARMODELMULTITASKLASSOCV EPS MULTITASK LASSO MODEL TRAINED WITH L1L2 MIXEDNORM AS REGULARIZER
LINEARMODELMULTITASKELASTICNETCV MULTITASK L1L2 ELASTICNET WITH BUILTIN CROSSVALIDATION
LINEARMODELORTHOGONALMATCHINGPURSUIT ORTHOGONAL MATCHING PURSUIT MODEL OMP
LINEARMODELORTHOGONALMATCHINGPURSUITCV CROSSVALIDATED ORTHOGONAL MATCHING PURSUIT MODEL OMP
LINEARMODELPASSIVEAGGRESSIVECLASSIFIER PASSIVE AGGRESSIVE CLASSIFIER
LINEARMODELPASSIVEAGGRESSIVEREGRESSOR C
PASSIVE AGGRESSIVE REGRESSOR
LINEARMODELPERCEPTRON PENALTY ALPHA READ MORE IN THE USER GUIDE
LINEARMODELRANSACREGRESSOR RANSAC RANDOM SAMPLE CONSENSUS ALGORITHM
LINEARMODELRIDGE ALPHA FITINTERCEPT LINEAR LEAST SQUARES WITH L2 REGULARIZATION
LINEARMODELRIDGECLASSIFIER ALPHA CLASSIFIER USING RIDGE REGRESSION
LINEARMODELRIDGECLASSIFIERCV ALPHAS
RIDGE CLASSIFIER WITH BUILTIN CROSSVALIDATION
LINEARMODELRIDGECV ALPHAS RIDGE REGRESSION WITH BUILTIN CROSSVALIDATION
LINEARMODELSGDCLASSIFIER LOSS PENALTY
LINEAR CLASSIFIERS SVM LOGISTIC REGRESSION AO WITH SGD TRAINING
LINEARMODELSGDREGRESSOR LOSS PENALTY LINEAR MODEL FITTED BY MINIMIZING A REGULARIZED EMPIRICAL LOSS WITH SGD
LINEARMODELTHEILSENREGRESSOR THEILSEN ESTIMATOR ROBUST MULTIVARIATE REGRESSION MODEL
6221SKLEARNLINEARMODEL ARDREGRESSION
CLASSSKLEARNLINEARMODEL ARDREGRESSION NITER300 TOL0001 ALPHA11E06 ALPHA21E06 LAMBDA11E06
LAMBDA21E06 COMPUTESCOREFALSE THRESHOLDLAMBDA100000 FITINTERCEPTTRUE NORMALIZEFALSE COPYXTRUE VERBOSEFALSE
BAYESIAN ARD REGRESSION
FIT THE WEIGHTS OF A REGRESSION MODEL USING AN ARD PRIOR THE WEIGHTS OF THE REGRESSION MODEL ARE ASSUMED TO BE IN GAUSSIAN DISTRIBUTIONS ALSO ESTIMATE THE PARAMETERS LAMBDA PRECISIONS OF THE DISTRIBUTIONS OF THE WEIGHTS AND ALPHA PRECISION OF THE DISTRIBUTION OF THE NOISE THE ESTIMATION IS DONE BY AN ITERATIVE PROCEDURES

EVIDENCE MAXIMIZATION
READ MORE IN THE USER GUIDE
PARAMETERS
NITER INT OPTIONAL MAXIMUM NUMBER OF ITERATIONS DEFAULT IS 300
TOLFLOAT OPTIONAL STOP THE ALGORITHM IF W HAS CONVERGED DEFAULT IS 1E3
ALPHA1 FLOAT OPTIONAL HYPERPARAMETER SHAPE PARAMETER FOR THE GAMMA DISTRIBUTION PRIOR OVER THE ALPHA PARAMETER DEFAULT IS 1E6
ALPHA2 FLOAT OPTIONAL HYPERPARAMETER INVERSE SCALE PARAMETER RATE PARAMETER FOR THE GAMMA DISTRIBUTION PRIOR OVER THE ALPHA PARAMETER DEFAULT IS 1E6
LAMBDA1 FLOAT OPTIONAL HYPERPARAMETER SHAPE PARAMETER FOR THE GAMMA DISTRIBUTION PRIOR OVER THE LAMBDA PARAMETER DEFAULT IS 1E6
LAMBDA2 FLOAT OPTIONAL HYPERPARAMETER INVERSE SCALE PARAMETER RATE PARAMETER FOR THE GAMMA DISTRIBUTION PRIOR OVER THE LAMBDA PARAMETER DEFAULT IS 1E6
COMPUTESCORE BOOLEAN OPTIONAL IF TRUE COMPUTE THE OBJECTIVE FUNCTION AT EACH STEP OF THE MODEL DEFAULT IS FALSE
THRESHOLDLAMBDA FLOAT OPTIONAL THRESHOLD FOR REMOVING PRUNING WEIGHTS WITH HIGH PRECI SION FROM THE COMPUTATION DEFAULT IS 1E4
FITINTERCEPT BOOLEAN OPTIONAL WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED DEFAULT IS TRUE
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
VERBOSE BOOLEAN OPTIONAL DEFAULT FALSE VERBOSE MODE WHEN FITTING THE MODEL
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES COEFFICIENTS OF THE REGRESSION MODEL MEAN OF DISTRIBUTION
ALPHA FLOAT ESTIMATED PRECISION OF THE NOISE
LAMBDA ARRAY SHAPE NFEATURES ESTIMATED PRECISIONS OF THE WEIGHTS
SIGMA ARRAY SHAPE NFEATURES NFEATURES ESTIMATED VARIANCECOVARIANCE MATRIX OF THE WEIGHTS
SCORES FLOAT IF COMPUTED VALUE OF THE OBJECTIVE FUNCTION TO BE MAXIMIZED
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTARDPY

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REFERENCES
D J C MACKAY BAYESIAN NONLINEAR MODELING FOR THE PREDICTION COMPETITION ASHRAE TRANSACTIONS 1994
R SALAKHUTDINOV LECTURE NOTES ON STATISTICAL MACHINE LEARNING HTTPWWWUTSTATTORONTOEDURSALAKHU
STA4273NOTESLECTURE2PDFPAGE15 THEIR BETA IS OUR SELFALPHA THEIR ALPHA IS OUR SELFLAMBDA
ARD IS A LITTLE DIFFERENT THAN THE SLIDE ONLY DIMENSIONSFEATURES FOR WHICH SELFLAMBDA SELF
THRESHOLDLAMBDA ARE KEPT AND THE REST ARE DISCARDED
EXAMPLES
 FROM SKLEARN IMPORT LINEARMODEL
CLF LINEARMODELARDREGRESSION
CLFFIT00 1 1 2 2 0 1 2

ARDREGRESSIONALPHA11E06 ALPHA21E06 COMPUTESCOREFALSE
COPYXTRUE FITINTERCEPTTRUE LAMBDA11E06 LAMBDA21E06
NITER300 NORMALIZEFALSE THRESHOLDLAMBDA100000 TOL0001
VERBOSEFALSE
CLFPREDICT1 1
ARRAY1
METHODS
FITSELF X Y FIT THE ARDREGRESSION MODEL ACCORDING TO THE GIVEN
TRAINING DATA AND PARAMETERS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X RETURNSTD PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNITER300 TOL0001 ALPHA11E06 ALPHA21E06 LAMBDA11E06
LAMBDA21E06 COMPUTESCOREFALSE THRESHOLDLAMBDA100000 FITINTERCEPTTRUE
NORMALIZEFALSE COPYXTRUE VERBOSEFALSE
FITSELFXY
FIT THE ARDREGRESSION MODEL ACCORDING TO THE GIVEN TRAINING DATA AND PARAMETERS
ITERATIVE PROCEDURE TO MAXIMIZE THE EVIDENCE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IN THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAY SHAPE NSAMPLES TARGET VALUES INTEGERS WILL BE CAST TO X’S DTYPE IF NECESSARY
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXRETURNSTDFALSE
PREDICT USING THE LINEAR MODEL
IN ADDITION TO THE MEAN OF THE PREDICTIVE DISTRIBUTION ALSO ITS STANDARD DEVIATION CAN BE RETURNED
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNSTD BOOLEAN OPTIONAL WHETHER TO RETURN THE STANDARD DEVIATION OF POSTERIOR PREDIC
TION
RETURNS
YMEAN ARRAY SHAPE NSAMPLES MEAN OF PREDICTIVE DISTRIBUTION OF QUERY POINTS
YSTD ARRAY SHAPE NSAMPLES STANDARD DEVIATION OF PREDICTIVE DISTRIBUTION OF QUERY
POINTS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT

RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELARDREGRESSION
•AUTOMATIC RELEVANCE DETERMINATION REGRESSION ARD
6222SKLEARNLINEARMODEL BAYESIANRIDGE
CLASSSKLEARNLINEARMODEL BAYESIANRIDGE NITER300 TOL0001 ALPHA11E06
ALPHA21E06 LAMBDA11E06 LAMBDA21E
06 COMPUTESCOREFALSE FITINTERCEPTTRUE
NORMALIZEFALSE COPYXTRUE VERBOSEFALSE
BAYESIAN RIDGE REGRESSION
FIT A BAYESIAN RIDGE MODEL SEE THE NOTES SECTION FOR DETAILS ON THIS IMPLEMENTATION AND THE OPTIMIZATION OF THE
REGULARIZATION PARAMETERS LAMBDA PRECISION OF THE WEIGHTS AND ALPHA PRECISION OF THE NOISE
READ MORE IN THE USER GUIDE
PARAMETERS
NITER INT OPTIONAL MAXIMUM NUMBER OF ITERATIONS DEFAULT IS 300 SHOULD BE GREATER THAN OR
EQUAL TO 1
TOLFLOAT OPTIONAL STOP THE ALGORITHM IF W HAS CONVERGED DEFAULT IS 1E3
ALPHA1 FLOAT OPTIONAL HYPERPARAMETER SHAPE PARAMETER FOR THE GAMMA DISTRIBUTION PRIOR
OVER THE ALPHA PARAMETER DEFAULT IS 1E6
ALPHA2 FLOAT OPTIONAL HYPERPARAMETER INVERSE SCALE PARAMETER RATE PARAMETER FOR THE
GAMMA DISTRIBUTION PRIOR OVER THE ALPHA PARAMETER DEFAULT IS 1E6
LAMBDA1 FLOAT OPTIONAL HYPERPARAMETER SHAPE PARAMETER FOR THE GAMMA DISTRIBUTION PRIOR
OVER THE LAMBDA PARAMETER DEFAULT IS 1E6
LAMBDA2 FLOAT OPTIONAL HYPERPARAMETER INVERSE SCALE PARAMETER RATE PARAMETER FOR THE
GAMMA DISTRIBUTION PRIOR OVER THE LAMBDA PARAMETER DEFAULT IS 1E6
COMPUTESCORE BOOLEAN OPTIONAL IF TRUE COMPUTE THE LOG MARGINAL LIKELIHOOD AT EACH ITERA
TION OF THE OPTIMIZATION DEFAULT IS FALSE
FITINTERCEPT BOOLEAN OPTIONAL DEFAULT TRUE WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL
THE INTERCEPT IS NOT TREATED AS A PROBABILISTIC PARAMETER AND THUS HAS NO ASSOCIATED VARIANCE
IF SET TO FALSE NO INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY
CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
VERBOSE BOOLEAN OPTIONAL DEFAULT FALSE VERBOSE MODE WHEN FITTING THE MODEL
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES COEFFICIENTS OF THE REGRESSION MODEL MEAN OF DISTRIBUTION

INTERCEPT FLOAT INDEPENDENT TERM IN DECISION FUNCTION SET TO 00 IF FITINTERCEPT
FALSE
ALPHA FLOAT ESTIMATED PRECISION OF THE NOISE
LAMBDA FLOAT ESTIMATED PRECISION OF THE WEIGHTS
SIGMA ARRAY SHAPE NFEATURES NFEATURES ESTIMATED VARIANCECOVARIANCE MATRIX OF THE
WEIGHTS
SCORES ARRAY SHAPE NITER 1 IF COMPUTEDSCORE IS TRUE VALUE OF THE LOG MARGINAL
LIKELIHOOD TO BE MAXIMIZED AT EACH ITERATION OF THE OPTIMIZATION THE ARRAY STARTS WITH THE
VALUE OF THE LOG MARGINAL LIKELIHOOD OBTAINED FOR THE INITIAL VALUES OF ALPHA AND LAMBDA AND
ENDS WITH THE VALUE OBTAINED FOR THE ESTIMATED ALPHA AND LAMBDA
NITER INT THE ACTUAL NUMBER OF ITERATIONS TO REACH THE STOPPING CRITERION
NOTES
THERE EXIST SEVERAL STRATEGIES TO PERFORM BAYESIAN RIDGE REGRESSION THIS IMPLEMENTATION IS BASED ON THE ALGO
RITHM DESCRIBED IN APPENDIX A OF TIPPING 2001 WHERE UPDATES OF THE REGULARIZATION PARAMETERS ARE DONE AS
SUGGESTED IN MACKAY 1992 NOTE THAT ACCORDING TO A NEW VIEW OF AUTOMATIC RELEVANCE DETERMINATION WIPF
AND NAGARAJAN 2008 THESE UPDATE RULES DO NOT GUARANTEE THAT THE MARGINAL LIKELIHOOD IS INCREASING BETWEEN TWO
CONSECUTIVE ITERATIONS OF THE OPTIMIZATION
REFERENCES
D J C MACKAY BAYESIAN INTERPOLATION COMPUTATION AND NEURAL SYSTEMS V OL 4 NO 3 1992
M E TIPPING SPARSE BAYESIAN LEARNING AND THE RELEVANCE VECTOR MACHINE JOURNAL OF MACHINE LEARNING
RESEARCH V OL 1 2001
EXAMPLES
```
 FROM SKLEARN IMPORT LINEARMODEL
CLF  LINEARMODELBAYESIANRIDGE
CLFFIT00 1 1 2 2 0 1 2

BAYESIANRIDGEALPHA11E06 ALPHA21E06 COMPUTESCOREFALSE
COPYXTRUE FITINTERCEPTTRUE LAMBDA11E06 LAMBDA21E06
NITER300 NORMALIZEFALSE TOL0001 VERBOSEFALSE
CLFPREDICT1 1
ARRAY1
```
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X RETURNSTD PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
CONTINUED ON NEXT PAGE

TABLE 6150 – CONTINUED FROM PREVIOUS PAGE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNITER300 TOL0001 ALPHA11E06 ALPHA21E06 LAMBDA11E
06LAMBDA21E06 COMPUTESCOREFALSE FITINTERCEPTTRUE NORMALIZEFALSE
COPYXTRUE VERBOSEFALSE
FITSELFXYSAMPLEWEIGHTNONE
FIT THE MODEL
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLESNFEATURES TRAINING DATA
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES WILL BE CAST TO X'S DTYPE IF NECESSARY
SAMPLEWEIGHT NUMPY ARRAY OF SHAPE NSAMPLES INDIVIDUAL WEIGHTS FOR EACH SAMPLE
NEW IN VERSION 020 PARAMETER SAMPLEWEIGHT SUPPORT TO BAYESIANRIDGE
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXRETURNSTDFALSE
PREDICT USING THE LINEAR MODEL
IN ADDITION TO THE MEAN OF THE PREDICTIVE DISTRIBUTION ALSO ITS STANDARD DEVIATION CAN BE RETURNED
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNSTD BOOLEAN OPTIONAL WHETHER TO RETURN THE STANDARD DEVIATION OF POSTERIOR PREDIC
TION
RETURNS
YMEAN ARRAY SHAPE NSAMPLES MEAN OF PREDICTIVE DISTRIBUTION OF QUERY POINTS
YSTD ARRAY SHAPE NSAMPLES STANDARD DEVIATION OF PREDICTIVE DISTRIBUTION OF QUERY
POINTS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS

XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
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TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELBAYESIANRIDGE
•FEATURE AGGLOMERATION VS UNIVARIATE SELECTION
•IMPUTING MISSING VALUES WITH VARIANTS OF ITERATIVEIMPUTER
•BAYESIAN RIDGE REGRESSION
6223SKLEARNLINEARMODEL ELASTICNET
CLASSSKLEARNLINEARMODEL ELASTICNET ALPHA10 L1RATIO05 FITINTERCEPTTRUE NOR
MALIZEFALSE PRECOMPUTEFALSE MAXITER1000
COPYXTRUE TOL00001 WARMSTARTFALSE POSI
TIVEFALSE RANDOMSTATENONE SELECTION’CYCLIC’
LINEAR REGRESSION WITH COMBINED L1 AND L2 PRIORS AS REGULARIZER
MINIMIZES THE OBJECTIVE FUNCTION
1 2NSAMPLES Y XW22
 ALPHA L1RATIO W1
 05ALPHA1 L1RATIO W22
IF YOU ARE INTERESTED IN CONTROLLING THE L1 AND L2 PENALTY SEPARATELY KEEP IN MIND THAT THIS IS EQUIVALENT TO
AL1 BL2

WHERE
ALPHA A B ANDL1RATIO A A B
THE PARAMETER L1RATIO CORRESPONDS TO ALPHA IN THE GLMNET R PACKAGE WHILE ALPHA CORRESPONDS TO THE LAMBDA
PARAMETER IN GLMNET SPECIFICALLY L1RATIO 1 IS THE LASSO PENALTY CURRENTLY L1RATIO 001 IS NOT RELIABLE
UNLESS YOU SUPPLY YOUR OWN SEQUENCE OF ALPHA
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA FLOAT OPTIONAL CONSTANT THAT MULTIPLIES THE PENALTY TERMS DEFAULTS TO 10 SEE THE
NOTES FOR THE EXACT MATHEMATICAL MEANING OF THIS PARAMETER‘‘ALPHA 0‘‘ IS EQUIVALENT TO AN
ORDINARY LEAST SQUARE SOLVED BY THE LINEARREGRESSION OBJECT FOR NUMERICAL REASONS
USINGALPHA 0 WITH THELASSO OBJECT IS NOT ADVISED GIVEN THIS YOU SHOULD USE THE
LINEARREGRESSION OBJECT
L1RATIO FLOAT THE ELASTICNET MIXING PARAMETER WITH 0 L1RATIO 1 FOR
L1RATIO 0 THE PENALTY IS AN L2 PENALTY FOR L1RATIO 1 IT IS AN L1 PENALTY
FOR0 L1RATIO 1 THE PENALTY IS A COMBINATION OF L1 AND L2
FITINTERCEPT BOOL WHETHER THE INTERCEPT SHOULD BE ESTIMATED OR NOT IF FALSE THE DATA IS
ASSUMED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
PRECOMPUTE TRUE FALSE ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO SPEED UP
CALCULATIONS THE GRAM MATRIX CAN ALSO BE PASSED AS ARGUMENT FOR SPARSE INPUT THIS OPTION
IS ALWAYSTRUE TO PRESERVE SPARSITY
MAXITER INT OPTIONAL THE MAXIMUM NUMBER OF ITERATIONS
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
TOLFLOAT OPTIONAL THE TOLERANCE FOR THE OPTIMIZATION IF THE UPDATES ARE SMALLER THAN TOL THE
OPTIMIZATION CODE CHECKS THE DUAL GAP FOR OPTIMALITY AND CONTINUES UNTIL IT IS SMALLER THAN
TOL
WARMSTART BOOL OPTIONAL WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS
INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
POSITIVE BOOL OPTIONAL WHEN SET TO TRUE FORCES THE COEFFICIENTS TO BE POSITIVE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR THAT SELECTS A RANDOM FEATURE TO UPDATE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SELECTION ‘RANDOM’
SELECTION STR DEFAULT ‘CYCLIC’ IF SET TO ‘RANDOM’ A RANDOM COEFFICIENT IS UPDATED EVERY ITERATION
RATHER THAN LOOPING OVER FEATURES SEQUENTIALLY BY DEFAULT THIS SETTING TO ‘RANDOM’ OFTEN
LEADS TO SIGNIFICANTLY FASTER CONVERGENCE ESPECIALLY WHEN TOL IS HIGHER THAN 1E4
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES NTARGETS NFEATURES PARAMETER VECTOR W IN THE COST FUNC
TION FORMULA

SPARSECOEF SCIPYSPARSE MATRIX SHAPE NFEATURES 1 NTARGETS NFEATURES SPARSE
REPRESENTATION OF THE FITTED COEF
INTERCEPT FLOAT ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION
NITER ARRAYLIKE SHAPE NTARGETS NUMBER OF ITERATIONS RUN BY THE COORDINATE DESCENT SOLVER
TO REACH THE SPECIFIED TOLERANCE
SEE ALSO
ELASTICNETCV ELASTIC NET MODEL WITH BEST MODEL SELECTION BY CROSSVALIDATION
SGDREGRESSOR IMPLEMENTS ELASTIC NET REGRESSION WITH INCREMENTAL TRAINING
SGDCLASSIFIER IMPLEMENTS LOGISTIC REGRESSION WITH ELASTIC NET PENALTY
SGDCLASSIFIERLOSSLOG PENALTYELASTICNET
NOTES
TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A
FORTRANCONTIGUOUS NUMPY ARRAY
EXAMPLES
 FROM SKLEARNLINEARMODEL IMPORT ELASTICNET
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y MAKEREGRESSIONNFEATURES2 RANDOMSTATE0
REGR ELASTICNETRANDOMSTATE0
REGRFITX Y
ELASTICNETALPHA10 COPYXTRUE FITINTERCEPTTRUE L1RATIO05
MAXITER1000 NORMALIZEFALSE POSITIVEFALSE PRECOMPUTEFALSE
RANDOMSTATE0 SELECTIONCYCLIC TOL00001 WARMSTARTFALSE
PRINTREGRCOEF
1883816048 6455968825
PRINTREGRINTERCEPT
1451
PRINTREGRPREDICT0 0
1451
METHODS
FITSELF X Y CHECKINPUT FIT MODEL WITH COORDINATE DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PATH X Y L1RATIO EPS NALPHAS   COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

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INIT SELFALPHA10 L1RATIO05 FITINTERCEPTTRUE NORMALIZEFALSE PRECOMPUTEFALSE
MAXITER1000 COPYXTRUE TOL00001 WARMSTARTFALSE POSITIVEFALSE RAN
DOMSTATENONE SELECTION'CYCLIC'
FITSELFXYCHECKINPUTTRUE
FIT MODEL WITH COORDINATE DESCENT
PARAMETERS
XNDARRAY OR SCIPYSPARSE MATRIX NSAMPLES NFEATURES DATA
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET WILL BE CAST TO X'S DTYPE
IF NECESSARY
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON'T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
NOTES
COORDINATE DESCENT IS AN ALGORITHM THAT CONSIDERS EACH COLUMN OF DATA AT A TIME HENCE IT WILL AUTOMATICALLY
CONVERT THE X INPUT AS A FORTRANCONTIGUOUS NUMPY ARRAY IF NECESSARY
TO AVOID MEMORY REALLOCATION IT IS ADVISED TO ALLOCATE THE INITIAL DATA IN MEMORY DIRECTLY USING THAT FORMAT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
STATICPATHXYL1RATIO05 EPS0001 NALPHAS100 ALPHASNONE PRECOMPUTE'AUTO'
XYNONE COPYXTRUE COEFINITNONE VERBOSEFALSE RETURNNITERFALSE POSI
TIVEFALSE CHECKINPUTTRUE PARAMS
COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
THE ELASTIC NET OPTIMIZATION FUNCTION VARIES FOR MONO AND MULTIOUTPUTS
FOR MONOOUTPUT TASKS IT IS
1 2NSAMPLES Y XW22
 ALPHA L1RATIO W1
 05ALPHA1 L1RATIO W22
FOR MULTIOUTPUT TASKS IT IS
1 2 NSAMPLES Y XWFRO2
 ALPHA L1RATIO W21
 05ALPHA1 L1RATIO WFRO2
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
622SKLEARNLINEARMODEL GENERALIZED LINEAR MODELS 1875

PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF YIS MONOOUTPUT THEN X CAN BE SPARSE
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
L1RATIO FLOAT OPTIONAL FLOAT BETWEEN 0 AND 1 PASSED TO ELASTIC NET SCALING BETWEEN L1 AND L2 PENALTIES L1RATIO1 CORRESPONDS TO THE LASSO
EPS FLOAT LENGTH OF THE PATH EPS1E3 MEANS THAT ALPHAMIN ALPHAMAX 1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS NDARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE SET AUTOMATICALLY
PRECOMPUTE TRUE FALSE 'AUTO' ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE PASSED AS ARGUMENT
XYARRAYLIKE OPTIONAL XY NPDOTXT Y THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY WHEN THE GRAM MATRIX IS PRECOMPUTED
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVER WRITTEN
COEFINIT ARRAY SHAPE NFEATURES NONE THE INITIAL VALUES OF THE COEFFICIENTS
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
RETURNNITER BOOL WHETHER TO RETURN THE NUMBER OF ITERATIONS OR NOT
POSITIVE BOOL DEFAULT FALSE IF SET TO TRUE FORCES COEFFICIENTS TO BE POSITIVE ONLY ALLOWED WHENYNDIM 1
CHECKINPUT BOOL DEFAULT TRUE SKIP INPUT VALIDATION CHECKS INCLUDING THE GRAM MATRIX WHEN PROVIDED ASSUMING THERE ARE HANDLED BY THE CALLER WHEN CHECKINPUTFALSE
PARAMS KWARGS KEYWORD ARGUMENTS PASSED TO THE COORDINATE DESCENT SOLVER
RETURNS
ALPHAS ARRAY SHAPE NALPHAS THE ALPHAS ALONG THE PATH WHERE MODELS ARE COMPUTED
COEFS ARRAY SHAPE NFEATURES NALPHAS OR NOUTPUTS NFEATURES NALPHAS COEFFICIENTS ALONG THE PATH
DUALGAPS ARRAY SHAPE NALPHAS THE DUAL GAPS AT THE END OF THE OPTIMIZATION FOR EACH ALPHA
NITERS ARRAYLIKE SHAPE NALPHAS THE NUMBER OF ITERATIONS TAKEN BY THE COORDINATE DESCENT OPTIMIZER TO REACH THE SPECIFIED TOLERANCE FOR EACH ALPHA IS RETURNED WHEN RETURNNITER IS SET TO TRUE
SEE ALSO
MULTITASKELASTICNET
MULTITASKELASTICNETCV
ELASTICNET
ELASTICNETCV

SCIKITLEARN USER GUIDE RELEASE 0213
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOCOORDINATEDESCENTPATHPY
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
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SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
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METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
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DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
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SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SPARSECOEF
SPARSE REPRESENTATION OF THE FITTED COEF
622SKLEARNLINEARMODEL GENERALIZED LINEAR MODELS 1877

EXAMPLES USING SKLEARNLINEARMODELELASTICNET
•LASSO AND ELASTIC NET FOR SPARSE SIGNALS
•TRAIN ERROR VS TEST ERROR
6224SKLEARNLINEARMODEL HUBERREGRESSOR
CLASSSKLEARNLINEARMODEL HUBERREGRESSOR EPSILON135 MAXITER100 ALPHA00001
WARMSTARTFALSE FITINTERCEPTTRUE TOL1E05
LINEAR REGRESSION MODEL THAT IS ROBUST TO OUTLIERS
THE HUBER REGRESSOR OPTIMIZES THE SQUARED LOSS FOR THE SAMPLES WHERE Y XW SIGMA
EPSILON AND THE ABSOLUTE LOSS FOR THE SAMPLES WHERE Y XW SIGMA EPSILON WHERE W
AND SIGMA ARE PARAMETERS TO BE OPTIMIZED THE PARAMETER SIGMA MAKES SURE THAT IF Y IS SCALED UP OR DOWN BY A
CERTAIN FACTOR ONE DOES NOT NEED TO RESCALE EPSILON TO ACHIEVE THE SAME ROBUSTNESS NOTE THAT THIS DOES NOT TAKE
INTO ACCOUNT THE FACT THAT THE DIFFERENT FEATURES OF X MAY BE OF DIFFERENT SCALES
THIS MAKES SURE THAT THE LOSS FUNCTION IS NOT HEAVILY INFLUENCED BY THE OUTLIERS WHILE NOT COMPLETELY IGNORING
THEIR EFFECT
READ MORE IN THE USER GUIDE
NEW IN VERSION 018
PARAMETERS
EPSILON FLOAT GREATER THAN 10 DEFAULT 135 THE PARAMETER EPSILON CONTROLS THE NUMBER OF
SAMPLES THAT SHOULD BE CLASSIFIED AS OUTLIERS THE SMALLER THE EPSILON THE MORE ROBUST IT IS
TO OUTLIERS
MAXITER INT DEFAULT 100 MAXIMUM NUMBER OF ITERATIONS THAT SCIPYOPTIMIZEFMINLBFGSB
SHOULD RUN FOR
ALPHA FLOAT DEFAULT 00001 REGULARIZATION PARAMETER
WARMSTART BOOL DEFAULT FALSE THIS IS USEFUL IF THE STORED ATTRIBUTES OF A PREVIOUSLY USED
MODEL HAS TO BE REUSED IF SET TO FALSE THEN THE COEFFICIENTS WILL BE REWRITTEN FOR EVERY CALL
TO FIT SEE THE GLOSSARY
FITINTERCEPT BOOL DEFAULT TRUE WHETHER OR NOT TO FIT THE INTERCEPT THIS CAN BE SET TO FALSE IF
THE DATA IS ALREADY CENTERED AROUND THE ORIGIN
TOLFLOAT DEFAULT 1E5 THE ITERATION WILL STOP WHEN MAXPROJ GI I 1
NTOL WHERE PGI IS THE ITH COMPONENT OF THE PROJECTED GRADIENT
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES FEATURES GOT BY OPTIMIZING THE HUBER LOSS
INTERCEPT FLOAT BIAS
SCALE FLOAT THE VALUE BY WHICH Y XW C IS SCALED DOWN
NITER INT NUMBER OF ITERATIONS THAT FMINLBFGSB HAS RUN FOR
CHANGED IN VERSION 020 IN SCIPY 100 THE NUMBER OF LBFGS ITERATIONS MAY EXCEED
MAXITER NITER WILL NOW REPORT AT MOST MAXITER
OUTLIERS ARRAY SHAPE NSAMPLES A BOOLEAN MASK WHICH IS SET TO TRUE WHERE THE SAMPLES
ARE IDENTIFIED AS OUTLIERS

REFERENCES
RE4616EF910FB1 RE4616EF910FB2
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNLINEARMODEL IMPORT HUBERREGRESSOR LINEARREGRESSION
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
RNG  NPRANDOMRANDOMSTATE0
X Y COEF  MAKEREGRESSION
 NSAMPLES200 NFEATURES2 NOISE40 COEF TRUE RANDOMSTATE0
X4  RNGUNIFORM10 20 4 2
Y4  RNGUNIFORM10 20 4
HUBER  HUBERREGRESSORFITX Y
HUBERSCOREX Y
7284608623514573
HUBERPREDICTX1
ARRAY8067200
LINEAR  LINEARREGRESSIONFITX Y
PRINTTRUE COEFFICIENTS COEF
TRUE COEFFICIENTS 204923 341698
PRINTHUBER COEFFICIENTS HUBERCOEF
HUBER COEFFICIENTS 177906 310106
PRINTLINEAR REGRESSION COEFFICIENTS LINEARCOEF
LINEAR REGRESSION COEFFICIENTS 19221 70226
```
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFEPSILON135 MAXITER100 ALPHA00001 WARMSTARTFALSE FITINTERCEPTTRUE
TOL1E05
FITSELFXYSAMPLEWEIGHTNONE
FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IN THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES TARGET VECTOR RELATIVE TO X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES WEIGHT GIVEN TO EACH SAMPLE
RETURNS
SELF OBJECT

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GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS

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SELF
EXAMPLES USING SKLEARNLINEARMODELHUBERREGRESSOR
•HUBERREGRESSOR VS RIDGE ON DATASET WITH STRONG OUTLIERS
•ROBUST LINEAR ESTIMATOR FITTING
6225SKLEARNLINEARMODEL LARS
CLASSSKLEARNLINEARMODEL LARSFITINTERCEPTTRUE VERBOSEFALSE NORMALIZETRUE PRECOM
PUTE'AUTO' NNONZEROCOEFS500 EPS2220446049250313E
16COPYXTRUE FITPATHTRUE POSITIVEFALSE
LEAST ANGLE REGRESSION MODEL AKA LAR
READ MORE IN THE USER GUIDE
PARAMETERS
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
VERBOSE BOOLEAN OR INTEGER OPTIONAL SETS THE VERBOSITY AMOUNT
NORMALIZE BOOLEAN OPTIONAL DEFAULT TRUE THIS PARAMETER IS IGNORED WHEN FITINTERCEPT
IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BEFORE REGRESSION BY SUB
TRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO STANDARDIZE PLEASE USE
SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE CALLING FIT ON AN ESTIMATOR
WITHNORMALIZEFALSE
PRECOMPUTE TRUE FALSE 'AUTO' ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO
SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE PASSED
AS ARGUMENT
NNONZEROCOEFS INT OPTIONAL TARGET NUMBER OF NONZERO COEFFICIENTS USE NPINF FOR NO
LIMIT
EPS FLOAT OPTIONAL THE MACHINEPRECISION REGULARIZATION IN THE COMPUTATION OF THE CHOLESKY
DIAGONAL FACTORS INCREASE THIS FOR VERY ILLCONDITIONED SYSTEMS UNLIKE THE TOL PARAMETER IN
SOME ITERATIVE OPTIMIZATIONBASED ALGORITHMS THIS PARAMETER DOES NOT CONTROL THE TOLERANCE
OF THE OPTIMIZATION
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
FITPATH BOOLEAN IF TRUE THE FULL PATH IS STORED IN THE COEFPATH ATTRIBUTE IF YOU COMPUTE
THE SOLUTION FOR A LARGE PROBLEM OR MANY TARGETS SETTING FITPATH TOFALSE WILL LEAD TO
A SPEEDUP ESPECIALLY WITH A SMALL ALPHA
POSITIVE BOOLEAN DEFAULTFALSE RESTRICT COEFFICIENTS TO BE 0 BE AWARE THAT YOU MIGHT
WANT TO REMOVE FITINTERCEPT WHICH IS SET TRUE BY DEFAULT
DEPRECATED SINCE VERSION 020 THE OPTION IS BROKEN AND DEPRECATED IT WILL BE REMOVED IN
V022
ATTRIBUTES
ALPHAS ARRAY SHAPE NALPHAS 1 LIST OF NTARGETS SUCH ARRAYS MAXIMUM OF COVARI
ANCES IN ABSOLUTE VALUE AT EACH ITERATION NALPHAS IS EITHERNNONZEROCOEFS OR
NFEATURES WHICHEVER IS SMALLER

ACTIVE LIST LENGTH NALPHAS LIST OF NTARGETS SUCH LISTS INDICES OF ACTIVE VARIABLES AT THE END
OF THE PATH
COEFPATH ARRAY SHAPE NFEATURES NALPHAS 1 LIST OF NTARGETS SUCH ARRAYS THE VARYING
VALUES OF THE COEFFICIENTS ALONG THE PATH IT IS NOT PRESENT IF THE FITPATH PARAMETER IS
FALSE
COEF ARRAY SHAPE NFEATURES OR NTARGETS NFEATURES PARAMETER VECTOR W IN THE FORMULA
TION FORMULA
INTERCEPT FLOAT ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION
NITER ARRAYLIKE OR INT THE NUMBER OF ITERATIONS TAKEN BY LARSPATH TO FIND THE GRID OF ALPHAS
FOR EACH TARGET
SEE ALSO
LARSPATH LARSCV
SKLEARNDECOMPOSITIONSPARSEENCODE
EXAMPLES
 FROM SKLEARN IMPORT LINEARMODEL
REG LINEARMODELLARSNNONZEROCOEFS1
REGFIT1 1 0 0 1 1 11111 0 11111

LARSCOPYXTRUE EPS FITINTERCEPTTRUE FITPATHTRUE
NNONZEROCOEFS1 NORMALIZETRUE POSITIVEFALSE PRECOMPUTEAUTO
VERBOSEFALSE
PRINTREGCOEF
 0 111
METHODS
FITSELF X Y XY FIT THE MODEL USING X Y AS TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELF FITINTERCEPTTRUE VERBOSEFALSE NORMALIZETRUE PRECOMPUTE’AUTO’
NNONZEROCOEFS500 EPS2220446049250313E16 COPYXTRUE FITPATHTRUE
POSITIVEFALSE
FITSELFXYXYNONE
FIT THE MODEL USING X Y AS TRAINING DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
XYARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS OPTIONAL XY NPDOTXT Y

THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY WHEN THE GRAM MATRIX IS PRECOMPUTED
RETURNS
SELF OBJECT RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
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RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
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THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
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PARAMETERS
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NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR

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PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
6226SKLEARNLINEARMODEL LASSO
CLASSSKLEARNLINEARMODEL LASSOALPHA10 FITINTERCEPTTRUE NORMALIZEFALSE PRECOM
PUTEFALSE COPYXTRUE MAXITER1000 TOL00001
WARMSTARTFALSE POSITIVEFALSE RANDOMSTATENONE SELEC
TION'CYCLIC'
LINEAR MODEL TRAINED WITH L1 PRIOR AS REGULARIZER AKA THE LASSO
THE OPTIMIZATION OBJECTIVE FOR LASSO IS
1 2 NSAMPLES Y XW22 ALPHA W1
TECHNICALLY THE LASSO MODEL IS OPTIMIZING THE SAME OBJECTIVE FUNCTION AS THE ELASTIC NET WITH L1RATIO10
NO L2 PENALTY
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA FLOAT OPTIONAL CONSTANT THAT MULTIPLIES THE L1 TERM DEFAULTS TO 10 ALPHA 0 IS
EQUIVALENT TO AN ORDINARY LEAST SQUARE SOLVED BY THE LINEARREGRESSION OBJECT FOR
NUMERICAL REASONS USING ALPHA 0 WITH THELASSO OBJECT IS NOT ADVISED GIVEN THIS
YOU SHOULD USE THE LINEARREGRESSION OBJECT
FITINTERCEPT BOOLEAN OPTIONAL DEFAULT TRUE WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL
IF SET TO FALSE NO INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY
CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
PRECOMPUTE TRUE FALSE ARRAYLIKE DEFAULTFALSE WHETHER TO USE A PRECOMPUTED GRAM MA
TRIX TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE
PASSED AS ARGUMENT FOR SPARSE INPUT THIS OPTION IS ALWAYS TRUE TO PRESERVE SPARSITY
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
MAXITER INT OPTIONAL THE MAXIMUM NUMBER OF ITERATIONS
TOLFLOAT OPTIONAL THE TOLERANCE FOR THE OPTIMIZATION IF THE UPDATES ARE SMALLER THAN TOL THE
OPTIMIZATION CODE CHECKS THE DUAL GAP FOR OPTIMALITY AND CONTINUES UNTIL IT IS SMALLER THAN
TOL
WARMSTART BOOL OPTIONAL WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS
INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
POSITIVE BOOL OPTIONAL WHEN SET TO TRUE FORCES THE COEFFICIENTS TO BE POSITIVE

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RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR THAT SELECTS A RANDOM FEATURE TO UPDATE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SELECTION 'RANDOM'
SELECTION STR DEFAULT 'CYCLIC' IF SET TO 'RANDOM' A RANDOM COEFFICIENT IS UPDATED EVERY ITERATION
RATHER THAN LOOPING OVER FEATURES SEQUENTIALLY BY DEFAULT THIS SETTING TO 'RANDOM' OFTEN
LEADS TO SIGNIFICANTLY FASTER CONVERGENCE ESPECIALLY WHEN TOL IS HIGHER THAN 1E4
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES NTARGETS NFEATURES PARAMETER VECTOR W IN THE COST FUNC
TION FORMULA
SPARSECOEF SCIPYSPARSE MATRIX SHAPE NFEATURES 1 NTARGETS NFEATURES SPARSE
REPRESENTATION OF THE FITTED COEF
INTERCEPT FLOAT ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION
NITER INT ARRAYLIKE SHAPE NTARGETS NUMBER OF ITERATIONS RUN BY THE COORDINATE DESCENT
SOLVER TO REACH THE SPECIFIED TOLERANCE
SEE ALSO
LARSPATH
LASSOPATH
LASSOLARS
LASSOCV
LASSOLARSCV
SKLEARNDECOMPOSITIONSPARSEENCODE
NOTES
THE ALGORITHM USED TO FIT THE MODEL IS COORDINATE DESCENT
TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A
FORTRANCONTIGUOUS NUMPY ARRAY
EXAMPLES
FROM SKLEARN IMPORT LINEARMODEL
CLF LINEARMODELLASSOALPHA01
CLFFIT00 1 1 2 2 0 1 2

LASSOALPHA01 COPYXTRUE FITINTERCEPTTRUE MAXITER1000
NORMALIZEFALSE POSITIVEFALSE PRECOMPUTEFALSE RANDOMSTATENONE
SELECTIONCYCLIC TOL00001 WARMSTARTFALSE
PRINTCLFCOEF
085 0
PRINTCLFINTERCEPT
015

METHODS
FITSELF X Y CHECKINPUT FIT MODEL WITH COORDINATE DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PATH X Y L1RATIO EPS NALPHAS COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHA10 FITINTERCEPTTRUE NORMALIZEFALSE PRECOMPUTEFALSE COPYXTRUE
MAXITER1000 TOL00001 WARMSTARTFALSE POSITIVEFALSE RANDOMSTATENONE SE
LECTION'CYCLIC'
FITSELFXYCHECKINPUTTRUE
FIT MODEL WITH COORDINATE DESCENT
PARAMETERS
XNDARRAY OR SCIPYSPARSE MATRIX NSAMPLES NFEATURES DATA
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET WILL BE CAST TO X'S DTYPE
IF NECESSARY
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON'T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
NOTES
COORDINATE DESCENT IS AN ALGORITHM THAT CONSIDERS EACH COLUMN OF DATA AT A TIME HENCE IT WILL AUTOMATICALLY
CONVERT THE X INPUT AS A FORTRANCONTIGUOUS NUMPY ARRAY IF NECESSARY
TO AVOID MEMORY REALLOCATION IT IS ADVISED TO ALLOCATE THE INITIAL DATA IN MEMORY DIRECTLY USING THAT FORMAT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
STATICPATHXYL1RATIO05 EPS0001 NALPHAS100 ALPHASNONE PRECOMPUTE'AUTO'
XYNONE COPYXTRUE COEFINITNONE VERBOSEFALSE RETURNNITERFALSE POSI
TIVEFALSE CHECKINPUTTRUE PARAMS
COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
THE ELASTIC NET OPTIMIZATION FUNCTION VARIES FOR MONO AND MULTIOUTPUTS
FOR MONOOUTPUT TASKS IT IS
1 2NSAMPLES Y XW22
 ALPHA L1RATIO W1
 05ALPHA1 L1RATIO W22

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FOR MULTIOUTPUT TASKS IT IS
1 2 NSAMPLES Y XWFRO2
 ALPHA L1RATIO W21
 05ALPHA1 L1RATIO WFRO2
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN
CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF YIS MONOOUTPUT THEN X
CAN BE SPARSE
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
L1RATIO FLOAT OPTIONAL FLOAT BETWEEN 0 AND 1 PASSED TO ELASTIC NET SCALING BETWEEN L1 AND
L2 PENALTIES L1RATIO1 CORRESPONDS TO THE LASSO
EPS FLOAT LENGTH OF THE PATH EPS1E3 MEANS THAT ALPHAMIN ALPHAMAX
1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS NDARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE
SET AUTOMATICALLY
PRECOMPUTE TRUE FALSE ‘AUTO’ ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX
TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE
PASSED AS ARGUMENT
XYARRAYLIKE OPTIONAL XY NPDOTXT Y THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY
WHEN THE GRAM MATRIX IS PRECOMPUTED
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVER
WRITTEN
COEFINIT ARRAY SHAPE NFEATURES   NONE THE INITIAL VALUES OF THE COEFFICIENTS
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
RETURNNITER BOOL WHETHER TO RETURN THE NUMBER OF ITERATIONS OR NOT
POSITIVE BOOL DEFAULT FALSE IF SET TO TRUE FORCES COEFFICIENTS TO BE POSITIVE ONLY ALLOWED
WHENYNDIM 1
CHECKINPUT BOOL DEFAULT TRUE SKIP INPUT VALIDATION CHECKS INCLUDING THE GRAM MATRIX
WHEN PROVIDED ASSUMING THERE ARE HANDLED BY THE CALLER WHEN CHECKINPUTFALSE
PARAMS KWARGS KEYWORD ARGUMENTS PASSED TO THE COORDINATE DESCENT SOLVER
RETURNS
ALPHAS ARRAY SHAPE NALPHAS THE ALPHAS ALONG THE PATH WHERE MODELS ARE COMPUTED
COEFS ARRAY SHAPE NFEATURES NALPHAS OR NOUTPUTS NFEATURES NALPHAS COEFFICIENTS
ALONG THE PATH
622SKLEARNLINEARMODEL GENERALIZED LINEAR MODELS 1887

DUALGAPS ARRAY SHAPE NALPHAS THE DUAL GAPS AT THE END OF THE OPTIMIZATION FOR EACH
ALPHA
NITERS ARRAYLIKE SHAPE NALPHAS THE NUMBER OF ITERATIONS TAKEN BY THE COORDINATE
DESCENT OPTIMIZER TO REACH THE SPECIFIED TOLERANCE FOR EACH ALPHA IS RETURNED WHEN
RETURNNITER IS SET TO TRUE
SEE ALSO
MULTITASKELASTICNET
MULTITASKELASTICNETCV
ELASTICNET
ELASTICNETCV
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOCOORDINATEDESCENTPATHPY
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
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PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
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METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE

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DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
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PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SPARSECOEF
SPARSE REPRESENTATION OF THE FITTED COEF
EXAMPLES USING SKLEARNLINEARMODELLASSO
•COMPRESSIVE SENSING TOMOGRAPHY RECONSTRUCTION WITH L1 PRIOR LASSO
•CROSSVALIDATION ON DIABETES DATASET EXERCISE
•LASSO ON DENSE AND SPARSE DATA
•JOINT FEATURE SELECTION WITH MULTITASK LASSO
•LASSO AND ELASTIC NET FOR SPARSE SIGNALS
6227SKLEARNLINEARMODEL LASSOLARS
CLASSSKLEARNLINEARMODEL LASSOLARS ALPHA10 FITINTERCEPTTRUE VERBOSEFALSE NOR
MALIZETRUE PRECOMPUTE'AUTO' MAXITER500
EPS2220446049250313E16 COPYXTRUE
FITPATHTRUE POSITIVEFALSE
LASSO MODEL FIT WITH LEAST ANGLE REGRESSION AKA LARS
IT IS A LINEAR MODEL TRAINED WITH AN L1 PRIOR AS REGULARIZER
THE OPTIMIZATION OBJECTIVE FOR LASSO IS
1 2 NSAMPLES Y XW22 ALPHA W1
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA FLOAT CONSTANT THAT MULTIPLIES THE PENALTY TERM DEFAULTS TO 10 ALPHA 0 IS EQUIV
ALENT TO AN ORDINARY LEAST SQUARE SOLVED BY LINEARREGRESSION FOR NUMERICAL REASONS
USINGALPHA 0 WITH THE LASSOLARS OBJECT IS NOT ADVISED AND YOU SHOULD PREFER THE LIN
EARREGRESSION OBJECT
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
VERBOSE BOOLEAN OR INTEGER OPTIONAL SETS THE VERBOSITY AMOUNT
NORMALIZE BOOLEAN OPTIONAL DEFAULT TRUE THIS PARAMETER IS IGNORED WHEN FITINTERCEPT
IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BEFORE REGRESSION BY SUB
TRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO STANDARDIZE PLEASE USE
622SKLEARNLINEARMODEL GENERALIZED LINEAR MODELS 1889

SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE CALLING FIT ON AN ESTIMATOR
WITHNORMALIZEFALSE
PRECOMPUTE TRUE FALSE 'AUTO' ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO
SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE PASSED
AS ARGUMENT
MAXITER INTEGER OPTIONAL MAXIMUM NUMBER OF ITERATIONS TO PERFORM
EPS FLOAT OPTIONAL THE MACHINEPRECISION REGULARIZATION IN THE COMPUTATION OF THE CHOLESKY
DIAGONAL FACTORS INCREASE THIS FOR VERY ILLCONDITIONED SYSTEMS UNLIKE THE TOL PARAMETER IN
SOME ITERATIVE OPTIMIZATIONBASED ALGORITHMS THIS PARAMETER DOES NOT CONTROL THE TOLERANCE
OF THE OPTIMIZATION
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
FITPATH BOOLEAN IF TRUE THE FULL PATH IS STORED IN THE COEFPATH ATTRIBUTE IF YOU COMPUTE
THE SOLUTION FOR A LARGE PROBLEM OR MANY TARGETS SETTING FITPATH TOFALSE WILL LEAD TO
A SPEEDUP ESPECIALLY WITH A SMALL ALPHA
POSITIVE BOOLEAN DEFAULTFALSE RESTRICT COEFFICIENTS TO BE 0 BE AWARE THAT YOU MIGHT
WANT TO REMOVE FITINTERCEPT WHICH IS SET TRUE BY DEFAULT UNDER THE POSITIVE RESTRICTION THE
MODEL COEFFICIENTS WILL NOT CONVERGE TO THE ORDINARYLEASTSQUARES SOLUTION FOR SMALL VALUES
OF ALPHA ONLY COEFFICIENTS UP TO THE SMALLEST ALPHA VALUE ALPHASALPHAS 0
MIN WHEN FITPATHTRUE REACHED BY THE STEPWISE LARSLASSO ALGORITHM ARE TYPICALLY IN
CONGRUENCE WITH THE SOLUTION OF THE COORDINATE DESCENT LASSO ESTIMATOR
ATTRIBUTES
ALPHAS ARRAY SHAPE NALPHAS 1 LIST OF NTARGETS SUCH ARRAYS MAXIMUM OF COVARIANCES
IN ABSOLUTE VALUE AT EACH ITERATION NALPHAS IS EITHERMAXITER NFEATURES OR
THE NUMBER OF NODES IN THE PATH WITH CORRELATION GREATER THAN ALPHA WHICHEVER IS SMALLER
ACTIVE LIST LENGTH NALPHAS LIST OF NTARGETS SUCH LISTS INDICES OF ACTIVE VARIABLES AT THE END
OF THE PATH
COEFPATH ARRAY SHAPE NFEATURES NALPHAS 1 OR LIST IF A LIST IS PASSED IT'S EXPECTED TO BE
ONE OF NTARGETS SUCH ARRAYS THE VARYING VALUES OF THE COEFFICIENTS ALONG THE PATH IT IS NOT
PRESENT IF THE FITPATH PARAMETER IS FALSE
COEF ARRAY SHAPE NFEATURES OR NTARGETS NFEATURES PARAMETER VECTOR W IN THE FORMULA
TION FORMULA
INTERCEPT FLOAT ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION
NITER ARRAYLIKE OR INT THE NUMBER OF ITERATIONS TAKEN BY LARSPATH TO FIND THE GRID OF ALPHAS
FOR EACH TARGET
SEE ALSO
LARSPATH
LASSOPATH
LASSO
LASSOCV
LASSOLARSCV
LASSOLARSIC
SKLEARNDECOMPOSITIONSPARSEENCODE

SCIKITLEARN USER GUIDE RELEASE 0213
EXAMPLES
FROM SKLEARN IMPORT LINEARMODEL
REG LINEARMODELLASSOLARSALPHA001
REGFIT1 1 0 0 1 1 1 0 1

LASSOLARSALPHA001 COPYXTRUE EPS FITINTERCEPTTRUE
FITPATHTRUE MAXITER500 NORMALIZETRUE POSITIVEFALSE
PRECOMPUTEAUTO VERBOSEFALSE
PRINTREGCOEF
0 0963257
METHODS
FITSELF X Y XY FIT THE MODEL USING X Y AS TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHA10 FITINTERCEPTTRUE VERBOSEFALSE NORMALIZETRUE PRECOMPUTE'AUTO'
MAXITER500 EPS2220446049250313E16 COPYXTRUE FITPATHTRUE POSI
TIVEFALSE
FITSELFXYXYNONE
FIT THE MODEL USING X Y AS TRAINING DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
XYARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS OPTIONAL XY NPDOTXT Y
THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY WHEN THE GRAM MATRIX IS PRECOMPUTED
RETURNS
SELF OBJECT RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES

RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
6228SKLEARNLINEARMODEL LINEARREGRESSION
CLASSSKLEARNLINEARMODEL LINEARREGRESSION FITINTERCEPTTRUE NORMALIZEFALSE
COPYXTRUE NJOBSNONE
ORDINARY LEAST SQUARES LINEAR REGRESSION
PARAMETERS
FITINTERCEPT BOOLEAN OPTIONAL DEFAULT TRUE WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL
IF SET TO FALSE NO INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY
CENTERED

NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION
THIS WILL ONLY PROVIDE SPEEDUP FOR NTARGETS 1 AND SUFFICIENT LARGE PROBLEMS NONE MEANS
1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES OR NTARGETS NFEATURES ESTIMATED COEFFICIENTS FOR THE LINEAR
REGRESSION PROBLEM IF MULTIPLE TARGETS ARE PASSED DURING THE FIT Y 2D THIS IS A 2D ARRAY OF
SHAPE NTARGETS NFEATURES WHILE IF ONLY ONE TARGET IS PASSED THIS IS A 1D ARRAY OF LENGTH
NFEATURES
INTERCEPT ARRAY INDEPENDENT TERM IN THE LINEAR MODEL
NOTES
FROM THE IMPLEMENTATION POINT OF VIEW THIS IS JUST PLAIN ORDINARY LEAST SQUARES SCIPYLINALGLSTSQ WRAPPED AS
A PREDICTOR OBJECT
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNLINEARMODEL IMPORT LINEARREGRESSION
X  NPARRAY1 1 1 2 2 2 2 3
 Y  1 X0  2 X1  3
Y  NPDOTX NPARRAY1 2  3
REG  LINEARREGRESSIONFITX Y
REGSCOREX Y
10
REGCOEF
ARRAY1 2
REGINTERCEPT
30000
REGPREDICTNPARRAY3 5
ARRAY16
```
METHODS
FITSELF X Y SAMPLEWEIGHT FIT LINEAR MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

INIT SELFFITINTERCEPTTRUE NORMALIZEFALSE COPYXTRUE NJOBSNONE
FITSELFXYSAMPLEWEIGHTNONE
FIT LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES NTARGETS TARGET VALUES WILL BE CAST TO X'S DTYPE IF NEC
ESSARY
SAMPLEWEIGHT NUMPY ARRAY OF SHAPE NSAMPLES INDIVIDUAL WEIGHTS FOR EACH SAMPLE
NEW IN VERSION 017 PARAMETER SAMPLEWEIGHT SUPPORT TO LINEARREGRESSION
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y

NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELLINEARREGRESSION
•ISOTONIC REGRESSION
•FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS
•PLOT INDIVIDUAL AND VOTING REGRESSION PREDICTIONS
•ORDINARY LEAST SQUARES AND RIDGE REGRESSION VARIANCE
•LOGISTIC FUNCTION
•LINEAR REGRESSION EXAMPLE
•ROBUST LINEAR MODEL ESTIMATION USING RANSAC
•SPARSITY EXAMPLE FITTING ONLY FEATURES 1 AND 2
•THEILSEN REGRESSION
•ROBUST LINEAR ESTIMATOR FITTING
•AUTOMATIC RELEVANCE DETERMINATION REGRESSION ARD
•BAYESIAN RIDGE REGRESSION
•PLOTTING CROSSVALIDATED PREDICTIONS
•UNDERFITTING VS OVERFITTING
•USING KBINSDISCRETIZER TO DISCRETIZE CONTINUOUS FEATURES

SCIKITLEARN USER GUIDE RELEASE 0213
6229SKLEARNLINEARMODEL LOGISTICREGRESSION
CLASSSKLEARNLINEARMODEL LOGISTICREGRESSION PENALTY'L2' DUALFALSE TOL00001
C10 FITINTERCEPTTRUE INTER
CEPTSCALING1 CLASSWEIGHTNONE
RANDOMSTATENONE SOLVER'WARN'
MAXITER100 MULTICLASS'WARN' VER
BOSE0 WARMSTARTFALSE NJOBSNONE
L1RATIONONE
LOGISTIC REGRESSION AKA LOGIT MAXENT CLASSIFIER
IN THE MULTICLASS CASE THE TRAINING ALGORITHM USES THE ONEVSREST OVR SCHEME IF THE 'MULTICLASS' OPTION IS SET TO 'OVR' AND USES THE CROSSENTROPY LOSS IF THE 'MULTICLASS' OPTION IS SET TO 'MULTINOMIAL' CURRENTLY THE 'MULTINOMIAL' OPTION IS SUPPORTED ONLY BY THE 'LBFGS' 'SAG' 'SAGA' AND 'NEWTONCG' SOLVERS
THIS CLASS IMPLEMENTS REGULARIZED LOGISTIC REGRESSION USING THE 'LIBLINEAR' LIBRARY 'NEWTONCG' 'SAG' 'SAGA' AND 'LBFGS' SOLVERS NOTE THAT REGULARIZATION IS APPLIED BY DEFAULT IT CAN HANDLE BOTH DENSE AND SPARSE INPUT USE CORDERED ARRAYS OR CSR MATRICES CONTAINING 64BIT FLOATS FOR OPTIMAL PERFORMANCE ANY OTHER INPUT FORMAT WILL BE CONVERTED AND COPIED
THE 'NEWTONCG' 'SAG' AND 'LBFGS' SOLVERS SUPPORT ONLY L2 REGULARIZATION WITH PRIMAL FORMULATION OR NO REG ULARIZATION THE 'LIBLINEAR' SOLVER SUPPORTS BOTH L1 AND L2 REGULARIZATION WITH A DUAL FORMULATION ONLY FOR THE L2 PENALTY THE ELASTICNET REGULARIZATION IS ONLY SUPPORTED BY THE 'SAGA' SOLVER
READ MORE IN THE USER GUIDE
PARAMETERS
PENALTY STR 'L1' 'L2' 'ELASTICNET' OR 'NONE' OPTIONAL DEFAULT'L2' USED TO SPECIFY THE NORM USED IN THE PENALIZATION THE 'NEWTONCG' 'SAG' AND 'LBFGS' SOLVERS SUPPORT ONLY L2 PENAL TIES 'ELASTICNET' IS ONLY SUPPORTED BY THE 'SAGA' SOLVER IF 'NONE' NOT SUPPORTED BY THE LIBLINEAR SOLVER NO REGULARIZATION IS APPLIED
NEW IN VERSION 019 L1 PENALTY WITH SAGA SOLVER ALLOWING 'MULTINOMIAL' L1
DUAL BOOL OPTIONAL DEFAULTFALSE DUAL OR PRIMAL FORMULATION DUAL FORMULATION IS ONLY IMPLEMENTED FOR L2 PENALTY WITH LIBLINEAR SOLVER PREFER DUALFALSE WHEN NSAMPLES NFEATURES
TOLFLOAT OPTIONAL DEFAULT1E4 TOLERANCE FOR STOPPING CRITERIA
CFLOAT OPTIONAL DEFAULT10 INVERSE OF REGULARIZATION STRENGTH MUST BE A POSITIVE FLOAT LIKE IN SUPPORT VECTOR MACHINES SMALLER VALUES SPECIFY STRONGER REGULARIZATION
FITINTERCEPT BOOL OPTIONAL DEFAULTTRUE SPECIFIES IF A CONSTANT AKA BIAS OR INTERCEPT SHOULD BE ADDED TO THE DECISION FUNCTION
INTERCEPTSCALING FLOAT OPTIONAL DEFAULT1 USEFUL ONLY WHEN THE SOLVER 'LIBLINEAR' IS USED AND SELFFITINTERCEPT IS SET TO TRUE IN THIS CASE X BECOMES X SELFINTERCEPTSCALING
IE A "SYNTHETIC" FEATURE WITH CONSTANT VALUE EQUAL TO INTERCEPTSCALING IS AP PENDED TO THE INSTANCE VECTOR THE INTERCEPT BECOMES INTERCEPTSCALING SYNTHETICFEATUREWEIGHT
NOTE THE SYNTHETIC FEATURE WEIGHT IS SUBJECT TO L1L2 REGULARIZATION AS ALL OTHER FEATURES TO LESSEN THE EFFECT OF REGULARIZATION ON SYNTHETIC FEATURE WEIGHT AND THEREFORE ON THE INTERCEPT INTERCEPTSCALING HAS TO BE INCREASED
CLASSWEIGHT DICT OR 'BALANCED' OPTIONAL DEFAULTNONE WEIGHTS ASSOCIATED WITH CLASSES IN THE FORMCLASSLABEL WEIGHT IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT ONE

THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP
BINCOUNTY
NOTE THAT THESE WEIGHTS WILL BE MULTIPLIED WITH SAMPLEWEIGHT PASSED THROUGH THE FIT
METHOD IF SAMPLEWEIGHT IS SPECIFIED
NEW IN VERSION 017 CLASSWEIGHT’BALANCED’
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM USED WHEN SOLVER ‘SAG’ OR ‘LIBLINEAR’
SOLVER STR ‘NEWTONCG’ ‘LBFGS’ ‘LIBLINEAR’ ‘SAG’ ‘SAGA’ OPTIONAL DEFAULT’LIBLINEAR’ AL
GORITHM TO USE IN THE OPTIMIZATION PROBLEM
• FOR SMALL DATASETS ‘LIBLINEAR’ IS A GOOD CHOICE WHEREAS ‘SAG’ AND ‘SAGA’ ARE FASTER FOR
LARGE ONES
• FOR MULTICLASS PROBLEMS ONLY ‘NEWTONCG’ ‘SAG’ ‘SAGA’ AND ‘LBFGS’ HANDLE MULTINOMIAL
LOSS ‘LIBLINEAR’ IS LIMITED TO ONEVERSUSREST SCHEMES
• ‘NEWTONCG’ ‘LBFGS’ ‘SAG’ AND ‘SAGA’ HANDLE L2 OR NO PENALTY
• ‘LIBLINEAR’ AND ‘SAGA’ ALSO HANDLE L1 PENALTY
• ‘SAGA’ ALSO SUPPORTS ‘ELASTICNET’ PENALTY
• ‘LIBLINEAR’ DOES NOT HANDLE NO PENALTY
NOTE THAT ‘SAG’ AND ‘SAGA’ FAST CONVERGENCE IS ONLY GUARANTEED ON FEATURES WITH APPROXI
MATELY THE SAME SCALE YOU CAN PREPROCESS THE DATA WITH A SCALER FROM SKLEARNPREPROCESSING
NEW IN VERSION 017 STOCHASTIC AVERAGE GRADIENT DESCENT SOLVER
NEW IN VERSION 019 SAGA SOLVER
CHANGED IN VERSION 020 DEFAULT WILL CHANGE FROM ‘LIBLINEAR’ TO ‘LBFGS’ IN 022
MAXITER INT OPTIONAL DEFAULT100 MAXIMUM NUMBER OF ITERATIONS TAKEN FOR THE SOLVERS TO
CONVERGE
MULTICLASS STR ‘OVR’ ‘MULTINOMIAL’ ‘AUTO’ OPTIONAL DEFAULT’OVR’ IF THE OPTION CHOSEN
IS ‘OVR’ THEN A BINARY PROBLEM IS FIT FOR EACH LABEL FOR ‘MULTINOMIAL’ THE LOSS MINIMISED
IS THE MULTINOMIAL LOSS FIT ACROSS THE ENTIRE PROBABILITY DISTRIBUTION EVEN WHEN THE DATA IS
BINARY ‘MULTINOMIAL’ IS UNAVAILABLE WHEN SOLVER’LIBLINEAR’ ‘AUTO’ SELECTS ‘OVR’ IF THE DATA
IS BINARY OR IF SOLVER’LIBLINEAR’ AND OTHERWISE SELECTS ‘MULTINOMIAL’
NEW IN VERSION 018 STOCHASTIC AVERAGE GRADIENT DESCENT SOLVER FOR ‘MULTINOMIAL’ CASE
CHANGED IN VERSION 020 DEFAULT WILL CHANGE FROM ‘OVR’ TO ‘AUTO’ IN 022
VERBOSE INT OPTIONAL DEFAULT0 FOR THE LIBLINEAR AND LBFGS SOLVERS SET VERBOSE TO ANY POSITIVE
NUMBER FOR VERBOSITY
WARMSTART BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PRE
VIOUS CALL TO FIT AS INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION USELESS FOR
LIBLINEAR SOLVER SEE THE GLOSSARY
NEW IN VERSION 017 WARMSTART TO SUPPORT LBFGS NEWTONCG SAGSAGA SOLVERS
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CPU CORES USED WHEN PARALLELIZING
OVER CLASSES IF MULTICLASS’OVR’” THIS PARAMETER IS IGNORED WHEN THE SOLVER IS SET TO

‘LIBLINEAR’ REGARDLESS OF WHETHER ‘MULTICLASS’ IS SPECIFIED OR NOT NONE MEANS 1 UNLESS IN
AJOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY
FOR MORE DETAILS
L1RATIO FLOAT OR NONE OPTIONAL DEFAULTNONE THE ELASTICNET MIXING PARAMETER WITH
0 L1RATIO 1 ONLY USED IF PENALTYELASTICNET SETTING
L1RATIO0 IS EQUIVALENT TO USING PENALTYL2 WHILE SETTING L1RATIO1 IS
EQUIVALENT TO USING PENALTYL1 FOR0 L1RATIO 1 THE PENALTY IS A COMBI
NATION OF L1 AND L2
ATTRIBUTES
CLASSES ARRAY SHAPE NCLASSES A LIST OF CLASS LABELS KNOWN TO THE CLASSIFIER
COEF ARRAY SHAPE 1 NFEATURES OR NCLASSES NFEATURES COEFFICIENT OF THE FEATURES IN THE
DECISION FUNCTION
COEF IS OF SHAPE 1 NFEATURES WHEN THE GIVEN PROBLEM IS BINARY IN PARTICULAR WHEN
MULTICLASSMULTINOMIAL COEF CORRESPONDS TO OUTCOME 1 TRUE AND COEF
CORRESPONDS TO OUTCOME 0 FALSE
INTERCEPT ARRAY SHAPE 1 OR NCLASSES INTERCEPT AKA BIAS ADDED TO THE DECISION FUNC
TION
IFFITINTERCEPT IS SET TO FALSE THE INTERCEPT IS SET TO ZERO INTERCEPT
IS OF SHAPE 1 WHEN THE GIVEN PROBLEM IS BINARY IN PARTICULAR WHEN
MULTICLASSMULTINOMIAL INTERCEPT CORRESPONDS TO OUTCOME 1 TRUE AND
INTERCEPT CORRESPONDS TO OUTCOME 0 FALSE
NITER ARRAY SHAPE NCLASSES OR 1 ACTUAL NUMBER OF ITERATIONS FOR ALL CLASSES IF BINARY
OR MULTINOMIAL IT RETURNS ONLY 1 ELEMENT FOR LIBLINEAR SOLVER ONLY THE MAXIMUM NUMBER
OF ITERATION ACROSS ALL CLASSES IS GIVEN
CHANGED IN VERSION 020 IN SCIPY 100 THE NUMBER OF LBFGS ITERATIONS MAY EXCEED
MAXITER NITER WILL NOW REPORT AT MOST MAXITER
SEE ALSO
SGDCLASSIFIER INCREMENTALLY TRAINED LOGISTIC REGRESSION WHEN GIVEN THE PARAMETER LOSSLOG
LOGISTICREGRESSIONCV LOGISTIC REGRESSION WITH BUILTIN CROSS VALIDATION
NOTES
THE UNDERLYING C IMPLEMENTATION USES A RANDOM NUMBER GENERATOR TO SELECT FEATURES WHEN FITTING THE MODEL
IT IS THUS NOT UNCOMMON TO HAVE SLIGHTLY DIFFERENT RESULTS FOR THE SAME INPUT DATA IF THAT HAPPENS TRY WITH A
SMALLER TOL PARAMETER
PREDICT OUTPUT MAY NOT MATCH THAT OF STANDALONE LIBLINEAR IN CERTAIN CASES SEE DIFFERENCES FROM LIBLINEAR IN THE
NARRATIVE DOCUMENTATION
REFERENCES
LIBLINEAR – A LIBRARY FOR LARGE LINEAR CLASSIFICATION HTTPSWWWCSIENTUEDUTWCJLINLIBLINEAR
SAG – MARK SCHMIDT NICOLAS LE ROUX AND FRANCIS BACH MINIMIZING FINITE SUMS WITH THE STOCHASTIC AV
ERAGE GRADIENT HTTPSHALINRIAFRHAL00860051DOCUMENT

SAGA – DEFAZIO A BACH F LACOSTEJULIEN S 2014 SAGA A FAST INCREMENTAL GRADIENT METHOD WITH
SUPPORT FOR NONSTRONGLY CONVEX COMPOSITE OBJECTIVES HTTPSARXIVORGABS14070202
HSIANGFU YU FANGLAN HUANG CHIHJEN LIN 2011 DUAL COORDINATE DESCENT METHODS FOR LOGISTIC RE
GRESSION AND MAXIMUM ENTROPY MODELS MACHINE LEARNING 85124175 HTTPSWWWCSIENTUEDUTW
CJLINPAPERSMAXENTDUALPDF
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNLINEARMODEL IMPORT LOGISTICREGRESSION
X Y  LOADIRISRETURNXY TRUE
CLF  LOGISTICREGRESSIONRANDOMSTATE0 SOLVERLBFGS
 MULTICLASSMULTINOMIALFITX Y
CLFPREDICTX2
ARRAY0 0
CLFPREDICTPROBAX2
ARRAY98E01 18E02 14E08
97E01 28E02 E08
CLFSCOREX Y
097
```
METHODS
DECISIONFUNCTION SELF X PREDICT CONFIDENCE SCORES FOR SAMPLES
DENSIFY SELF CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
FITSELF X Y SAMPLEWEIGHT FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASS LABELS FOR SAMPLES IN X
PREDICTLOGPROBA SELF X LOG OF PROBABILITY ESTIMATES
PREDICTPROBA SELF X PROBABILITY ESTIMATES
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
SPARSIFY SELF CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
INIT SELFPENALTY’L2’ DUALFALSE TOL00001 C10 FITINTERCEPTTRUE INTER
CEPTSCALING1 CLASSWEIGHTNONE RANDOMSTATENONE SOLVER’WARN’ MAXITER100
MULTICLASS’WARN’ VERBOSE0 WARMSTARTFALSE NJOBSNONE L1RATIONONE
DECISIONFUNCTION SELFX
PREDICT CONFIDENCE SCORES FOR SAMPLES
THE CONFIDENCE SCORE FOR A SAMPLE IS THE SIGNED DISTANCE OF THAT SAMPLE TO THE HYPERPLANE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
ARRAY SHAPENSAMPLES IF NCLASSES 2 ELSE NSAMPLES NCLASSES CONFIDENCE
SCORES PER SAMPLE CLASS COMBINATION IN THE BINARY CASE CONFIDENCE SCORE FOR
SELFCLASSES1 WHERE 0 MEANS THIS CLASS WOULD BE PREDICTED

DENSIFYSELF
CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
CONVERTS THE COEF MEMBER BACK TO A NUMPYNDARRAY THIS IS THE DEFAULT FORMAT OF COEF AND IS
REQUIRED FOR FITTING SO CALLING THIS METHOD IS ONLY REQUIRED ON MODELS THAT HAVE PREVIOUSLY BEEN SPARSIFIED
OTHERWISE IT IS A NOOP
RETURNS
SELF ESTIMATOR
FITSELFXYSAMPLEWEIGHTNONE
FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES TARGET VECTOR RELATIVE TO X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL ARRAY OF WEIGHTS THAT ARE ASSIGNED
TO INDIVIDUAL SAMPLES IF NOT PROVIDED THEN EACH SAMPLE IS GIVEN UNIT WEIGHT
NEW IN VERSION 017 SAMPLEWEIGHT SUPPORT TO LOGISTICREGRESSION
RETURNS
SELF OBJECT
NOTES
THE SAGA SOLVER SUPPORTS BOTH FLOAT64 AND FLOAT32 BIT ARRAYS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT CLASS LABELS FOR SAMPLES IN X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES PREDICTED CLASS LABEL PER SAMPLE
PREDICTLOGPROBA SELFX
LOG OF PROBABILITY ESTIMATES
THE RETURNED ESTIMATES FOR ALL CLASSES ARE ORDERED BY THE LABEL OF CLASSES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES

RETURNS
TARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE LOGPROBABILITY OF THE SAMPLE FOR
EACH CLASS IN THE MODEL WHERE CLASSES ARE ORDERED AS THEY ARE IN SELFCLASSES
PREDICTPROBA SELFX
PROBABILITY ESTIMATES
THE RETURNED ESTIMATES FOR ALL CLASSES ARE ORDERED BY THE LABEL OF CLASSES
FOR A MULTICLASS PROBLEM IF MULTICLASS IS SET TO BE “MULTINOMIAL” THE SOFTMAX FUNCTION IS USED TO FIND
THE PREDICTED PROBABILITY OF EACH CLASS ELSE USE A ONEVSREST APPROACH IE CALCULATE THE PROBABILITY OF
EACH CLASS ASSUMING IT TO BE POSITIVE USING THE LOGISTIC FUNCTION AND NORMALIZE THESE VALUES ACROSS ALL THE
CLASSES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
TARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE PROBABILITY OF THE SAMPLE FOR EACH
CLASS IN THE MODEL WHERE CLASSES ARE ORDERED AS THEY ARE IN SELFCLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SPARSIFY SELF
CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
CONVERTS THE COEF MEMBER TO A SCIPYSPARSE MATRIX WHICH FOR L1REGULARIZED MODELS CAN BE MUCH MORE
MEMORY AND STORAGEEFFICIENT THAN THE USUAL NUMPYNDARRAY REPRESENTATION
THEINTERCEPT MEMBER IS NOT CONVERTED
RETURNS
SELF ESTIMATOR

NOTES
FOR NONSPARSE MODELS IE WHEN THERE ARE NOT MANY ZEROS IN COEF THIS MAY ACTUALLY INCREASE MEMORY USAGE SO USE THIS METHOD WITH CARE A RULE OF THUMB IS THAT THE NUMBER OF ZERO ELEMENTS WHICH CAN BE COMPUTED WITH COEF 0SUM MUST BE MORE THAN 50 FOR THIS TO PROVIDE SIGNIFICANT BENEFITS
AFTER CALLING THIS METHOD FURTHER FITTING WITH THE PARTIALFIT METHOD IF ANY WILL NOT WORK UNTIL YOU CALL DENSIFY
EXAMPLES USING SKLEARNLINEARMODELLOGISTICREGRESSION
•COMPACT ESTIMATOR REPRESENTATIONS
•COMPARISON OF CALIBRATION OF CLASSIFIERS
•PROBABILITY CALIBRATION CURVES
•PLOT CLASSIFICATION PROBABILITY
•COLUMN TRANSFORMER WITH MIXED TYPES
•PLOT CLASS PROBABILITIES CALCULATED BY THE VOTINGCLASSIFIER
•FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES
•DIGITS CLASSIFICATION EXERCISE
•REGULARIZATION PATH OF L1 LOGISTIC REGRESSION
•LOGISTIC FUNCTION
•LOGISTIC REGRESSION 3CLASS CLASSIFIER
•COMPARING VARIOUS ONLINE SOLVERS
•MNIST CLASSFIFICATION USING MULTINOMIAL LOGISTIC L1
•PLOT MULTINOMIAL AND ONEVSREST LOGISTIC REGRESSION
•L1 PENALTY AND SPARSITY IN LOGISTIC REGRESSION
•MULTICLASS SPARSE LOGISITIC REGRESSION ON NEWGROUPS20
•CLASSIFIER CHAIN
•RESTRICTED BOLTZMANN MACHINE FEATURES FOR DIGIT CLASSIFICATION
•FEATURE DISCRETIZATION
62210SKLEARNLINEARMODEL MULTITASKLASSO
CLASSSKLEARNLINEARMODEL MULTITASKLASSO ALPHA10 FITINTERCEPTTRUE NORMALIZEFALSE COPYXTRUE MAXITER1000 TOL00001
WARMSTARTFALSE RANDOMSTATENONE SELEC
TION’CYCLIC’
MULTITASK LASSO MODEL TRAINED WITH L1L2 MIXEDNORM AS REGULARIZER
THE OPTIMIZATION OBJECTIVE FOR LASSO IS
1 2 NSAMPLES Y XW2FRO ALPHA W21
WHERE

W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA FLOAT OPTIONAL CONSTANT THAT MULTIPLIES THE L1L2 TERM DEFAULTS TO 10
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
MAXITER INT OPTIONAL THE MAXIMUM NUMBER OF ITERATIONS
TOLFLOAT OPTIONAL THE TOLERANCE FOR THE OPTIMIZATION IF THE UPDATES ARE SMALLER THAN TOL THE
OPTIMIZATION CODE CHECKS THE DUAL GAP FOR OPTIMALITY AND CONTINUES UNTIL IT IS SMALLER THAN
TOL
WARMSTART BOOL OPTIONAL WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS
INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR THAT SELECTS A RANDOM FEATURE TO UPDATE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SELECTION ‘RANDOM’
SELECTION STR DEFAULT ‘CYCLIC’ IF SET TO ‘RANDOM’ A RANDOM COEFFICIENT IS UPDATED EVERY ITERATION
RATHER THAN LOOPING OVER FEATURES SEQUENTIALLY BY DEFAULT THIS SETTING TO ‘RANDOM’ OFTEN
LEADS TO SIGNIFICANTLY FASTER CONVERGENCE ESPECIALLY WHEN TOL IS HIGHER THAN 1E4
ATTRIBUTES
COEF ARRAY SHAPE NTASKS NFEATURES PARAMETER VECTOR W IN THE COST FUNCTION FORMULA
NOTE THATCOEF STORES THE TRANSPOSE OF WWT
INTERCEPT ARRAY SHAPE NTASKS INDEPENDENT TERM IN DECISION FUNCTION
NITER INT NUMBER OF ITERATIONS RUN BY THE COORDINATE DESCENT SOLVER TO REACH THE SPECIFIED
TOLERANCE
SEE ALSO
MULTITASKLASSO MULTITASK L1L2 LASSO WITH BUILTIN CROSSVALIDATION
LASSO
MULTITASKELASTICNET
NOTES
THE ALGORITHM USED TO FIT THE MODEL IS COORDINATE DESCENT

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TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A FORTRANCONTIGUOUS NUMPY ARRAY
EXAMPLES
FROM SKLEARN IMPORT LINEARMODEL
CLF LINEARMODELMULTITASKLASSOALPHA01
CLFFIT00 1 1 2 2 0 0 1 1 2 2

MULTITASKLASSOALPHA01 COPYXTRUE FITINTERCEPTTRUE MAXITER1000
NORMALIZEFALSE RANDOMSTATENONE SELECTIONCYCLIC TOL00001
WARMSTARTFALSE
PRINTCLFCOEF
089393398 0
089393398 0
PRINTCLFINTERCEPT
010606602 010606602
METHODS
FITSELF X Y FIT MULTITASKELASTICNET MODEL WITH COORDINATE DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PATH X Y L1RATIO EPS NALPHAS COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHA10 FITINTERCEPTTRUE NORMALIZEFALSE COPYXTRUE MAXITER1000
TOL00001 WARMSTARTFALSE RANDOMSTATENONE SELECTION’CYCLIC’
FITSELFXY
FIT MULTITASKELASTICNET MODEL WITH COORDINATE DESCENT
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES DATA
YNDARRAY SHAPE NSAMPLES NTASKS TARGET WILL BE CAST TO X’S DTYPE IF NECESSARY
NOTES
COORDINATE DESCENT IS AN ALGORITHM THAT CONSIDERS EACH COLUMN OF DATA AT A TIME HENCE IT WILL AUTOMATICALLY CONVERT THE X INPUT AS A FORTRANCONTIGUOUS NUMPY ARRAY IF NECESSARY
TO AVOID MEMORY REALLOCATION IT IS ADVISED TO ALLOCATE THE INITIAL DATA IN MEMORY DIRECTLY USING THAT FORMAT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED SUBOBJECTS THAT ARE ESTIMATORS

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RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PATHXYL1RATIO05 EPS0001 NALPHAS100 ALPHASNONE PRECOMPUTE’AUTO’ XYNONE
COPYXTRUE COEFINITNONE VERBOSEFALSE RETURNNITERFALSE POSITIVEFALSE
CHECKINPUTTRUE PARAMS
COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
THE ELASTIC NET OPTIMIZATION FUNCTION VARIES FOR MONO AND MULTIOUTPUTS
FOR MONOOUTPUT TASKS IT IS
1 2NSAMPLES Y XW22
 ALPHA L1RATIO W1
 05ALPHA1 L1RATIO W22
FOR MULTIOUTPUT TASKS IT IS
1 2 NSAMPLES Y XWFRO2
 ALPHA L1RATIO W21
 05ALPHA1 L1RATIO WFRO2
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN
CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF YIS MONOOUTPUT THEN X
CAN BE SPARSE
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
L1RATIO FLOAT OPTIONAL FLOAT BETWEEN 0 AND 1 PASSED TO ELASTIC NET SCALING BETWEEN L1 AND
L2 PENALTIES L1RATIO1 CORRESPONDS TO THE LASSO
EPS FLOAT LENGTH OF THE PATH EPS1E3 MEANS THAT ALPHAMIN ALPHAMAX
1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS NDARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE
SET AUTOMATICALLY
PRECOMPUTE TRUE FALSE ‘AUTO’ ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX
TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE
PASSED AS ARGUMENT
XYARRAYLIKE OPTIONAL XY NPDOTXT Y THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY
WHEN THE GRAM MATRIX IS PRECOMPUTED
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVER
WRITTEN
COEFINIT ARRAY SHAPE NFEATURES   NONE THE INITIAL VALUES OF THE COEFFICIENTS
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY

RETURNNITER BOOL WHETHER TO RETURN THE NUMBER OF ITERATIONS OR NOT
POSITIVE BOOL DEFAULT FALSE IF SET TO TRUE FORCES COEFFICIENTS TO BE POSITIVE ONLY ALLOWED
WHENYNDIM 1
CHECKINPUT BOOL DEFAULT TRUE SKIP INPUT VALIDATION CHECKS INCLUDING THE GRAM MATRIX
WHEN PROVIDED ASSUMING THERE ARE HANDLED BY THE CALLER WHEN CHECKINPUTFALSE
PARAMS KWARGS KEYWORD ARGUMENTS PASSED TO THE COORDINATE DESCENT SOLVER
RETURNS
ALPHAS ARRAY SHAPE NALPHAS THE ALPHAS ALONG THE PATH WHERE MODELS ARE COMPUTED
COEFS ARRAY SHAPE NFEATURES NALPHAS OR NOUTPUTS NFEATURES NALPHAS COEFFICIENTS
ALONG THE PATH
DUALGAPS ARRAY SHAPE NALPHAS THE DUAL GAPS AT THE END OF THE OPTIMIZATION FOR EACH
ALPHA
NITERS ARRAYLIKE SHAPE NALPHAS THE NUMBER OF ITERATIONS TAKEN BY THE COORDINATE
DESCENT OPTIMIZER TO REACH THE SPECIFIED TOLERANCE FOR EACH ALPHA IS RETURNED WHEN
RETURNNITER IS SET TO TRUE
SEE ALSO
MULTITASKELASTICNET
MULTITASKELASTICNETCV
ELASTICNET
ELASTICNETCV
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOCOORDINATEDESCENTPATHPY
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X

SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SPARSECOEF
SPARSE REPRESENTATION OF THE FITTED COEF
EXAMPLES USING SKLEARNLINEARMODELMULTITASKLASSO
•JOINT FEATURE SELECTION WITH MULTITASK LASSO
62211SKLEARNLINEARMODEL MULTITASKELASTICNET
CLASSSKLEARNLINEARMODEL MULTITASKELASTICNET ALPHA10 L1RATIO05
FITINTERCEPTTRUE NORMALIZEFALSE
COPYXTRUE MAXITER1000 TOL00001
WARMSTARTFALSE RANDOMSTATENONE
SELECTION’CYCLIC’
MULTITASK ELASTICNET MODEL TRAINED WITH L1L2 MIXEDNORM AS REGULARIZER
THE OPTIMIZATION OBJECTIVE FOR MULTITASKELASTICNET IS
1 2 NSAMPLES Y XWFRO2
 ALPHA L1RATIO W21
 05ALPHA1 L1RATIO WFRO2
WHERE
W21 SUMI SQRTSUMJ WIJ 2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS

ALPHA FLOAT OPTIONAL CONSTANT THAT MULTIPLIES THE L1L2 TERM DEFAULTS TO 10
L1RATIO FLOAT THE ELASTICNET MIXING PARAMETER WITH 0 L1RATIO 1 FOR L1RATIO 1 THE
PENALTY IS AN L1L2 PENALTY FOR L1RATIO 0 IT IS AN L2 PENALTY FOR 0 L1RATIO
1 THE PENALTY IS A COMBINATION OF L1L2 AND L2
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
MAXITER INT OPTIONAL THE MAXIMUM NUMBER OF ITERATIONS
TOLFLOAT OPTIONAL THE TOLERANCE FOR THE OPTIMIZATION IF THE UPDATES ARE SMALLER THAN TOL THE
OPTIMIZATION CODE CHECKS THE DUAL GAP FOR OPTIMALITY AND CONTINUES UNTIL IT IS SMALLER THAN
TOL
WARMSTART BOOL OPTIONAL WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS
INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR THAT SELECTS A RANDOM FEATURE TO UPDATE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SELECTION ‘RANDOM’
SELECTION STR DEFAULT ‘CYCLIC’ IF SET TO ‘RANDOM’ A RANDOM COEFFICIENT IS UPDATED EVERY ITERATION
RATHER THAN LOOPING OVER FEATURES SEQUENTIALLY BY DEFAULT THIS SETTING TO ‘RANDOM’ OFTEN
LEADS TO SIGNIFICANTLY FASTER CONVERGENCE ESPECIALLY WHEN TOL IS HIGHER THAN 1E4
ATTRIBUTES
INTERCEPT ARRAY SHAPE NTASKS INDEPENDENT TERM IN DECISION FUNCTION
COEF ARRAY SHAPE NTASKS NFEATURES PARAMETER VECTOR W IN THE COST FUNCTION FORMULA IF
A 1D Y IS PASSED IN AT FIT NON MULTITASK USAGE COEF IS THEN A 1D ARRAY NOTE THAT COEF
STORES THE TRANSPOSE OF WWT
NITER INT NUMBER OF ITERATIONS RUN BY THE COORDINATE DESCENT SOLVER TO REACH THE SPECIFIED
TOLERANCE
SEE ALSO
MULTITASKELASTICNET MULTITASK L1L2 ELASTICNET WITH BUILTIN CROSSVALIDATION
ELASTICNET
MULTITASKLASSO
NOTES
THE ALGORITHM USED TO FIT THE MODEL IS COORDINATE DESCENT
TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A
FORTRANCONTIGUOUS NUMPY ARRAY

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EXAMPLES
FROM SKLEARN IMPORT LINEARMODEL
CLF LINEARMODELMULTITASKELASTICNETALPHA01
CLFFIT00 1 1 2 2 0 0 1 1 2 2

MULTITASKELASTICNETALPHA01 COPYXTRUE FITINTERCEPTTRUE
L1RATIO05 MAXITER1000 NORMALIZEFALSE RANDOMSTATENONE
SELECTIONCYCLIC TOL00001 WARMSTARTFALSE
PRINTCLFCOEF
045663524 045612256
045663524 045612256
PRINTCLFINTERCEPT
00872422 00872422
METHODS
FITSELF X Y FIT MULTITASKELASTICNET MODEL WITH COORDINATE DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PATH X Y L1RATIO EPS NALPHAS COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHA10 L1RATIO05 FITINTERCEPTTRUE NORMALIZEFALSE COPYXTRUE
MAXITER1000 TOL00001 WARMSTARTFALSE RANDOMSTATENONE SELECTION'CYCLIC'
FITSELFXY
FIT MULTITASKELASTICNET MODEL WITH COORDINATE DESCENT
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES DATA
YNDARRAY SHAPE NSAMPLES NTASKS TARGET WILL BE CAST TO X'S DTYPE IF NECESSARY
NOTES
COORDINATE DESCENT IS AN ALGORITHM THAT CONSIDERS EACH COLUMN OF DATA AT A TIME HENCE IT WILL AUTOMATICALLY
CONVERT THE X INPUT AS A FORTRANCONTIGUOUS NUMPY ARRAY IF NECESSARY
TO AVOID MEMORY REALLOCATION IT IS ADVISED TO ALLOCATE THE INITIAL DATA IN MEMORY DIRECTLY USING THAT FORMAT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES

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PATHXYL1RATIO05 EPS0001 NALPHAS100 ALPHASNONE PRECOMPUTE’AUTO’ XYNONE
COPYXTRUE COEFINITNONE VERBOSEFALSE RETURNNITERFALSE POSITIVEFALSE
CHECKINPUTTRUE PARAMS
COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
THE ELASTIC NET OPTIMIZATION FUNCTION VARIES FOR MONO AND MULTIOUTPUTS
FOR MONOOUTPUT TASKS IT IS
1 2NSAMPLES Y XW22
 ALPHA L1RATIO W1
 05ALPHA1 L1RATIO W22
FOR MULTIOUTPUT TASKS IT IS
1 2 NSAMPLES Y XWFRO2
 ALPHA L1RATIO W21
 05ALPHA1 L1RATIO WFRO2
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN
CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF YIS MONOOUTPUT THEN X
CAN BE SPARSE
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
L1RATIO FLOAT OPTIONAL FLOAT BETWEEN 0 AND 1 PASSED TO ELASTIC NET SCALING BETWEEN L1 AND
L2 PENALTIES L1RATIO1 CORRESPONDS TO THE LASSO
EPS FLOAT LENGTH OF THE PATH EPS1E3 MEANS THAT ALPHAMIN ALPHAMAX
1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS NDARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE
SET AUTOMATICALLY
PRECOMPUTE TRUE FALSE ‘AUTO’ ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX
TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE
PASSED AS ARGUMENT
XYARRAYLIKE OPTIONAL XY NPDOTXT Y THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY
WHEN THE GRAM MATRIX IS PRECOMPUTED
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVER
WRITTEN
COEFINIT ARRAY SHAPE NFEATURES   NONE THE INITIAL VALUES OF THE COEFFICIENTS
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
RETURNNITER BOOL WHETHER TO RETURN THE NUMBER OF ITERATIONS OR NOT
POSITIVE BOOL DEFAULT FALSE IF SET TO TRUE FORCES COEFFICIENTS TO BE POSITIVE ONLY ALLOWED
WHENYNDIM 1

CHECKINPUT BOOL DEFAULT TRUE SKIP INPUT VALIDATION CHECKS INCLUDING THE GRAM MATRIX
WHEN PROVIDED ASSUMING THERE ARE HANDLED BY THE CALLER WHEN CHECKINPUTFALSE
PARAMS KWARGS KEYWORD ARGUMENTS PASSED TO THE COORDINATE DESCENT SOLVER
RETURNS
ALPHAS ARRAY SHAPE NALPHAS THE ALPHAS ALONG THE PATH WHERE MODELS ARE COMPUTED
COEFS ARRAY SHAPE NFEATURES NALPHAS OR NOUTPUTS NFEATURES NALPHAS COEFFICIENTS
ALONG THE PATH
DUALGAPS ARRAY SHAPE NALPHAS THE DUAL GAPS AT THE END OF THE OPTIMIZATION FOR EACH
ALPHA
NITERS ARRAYLIKE SHAPE NALPHAS THE NUMBER OF ITERATIONS TAKEN BY THE COORDINATE
DESCENT OPTIMIZER TO REACH THE SPECIFIED TOLERANCE FOR EACH ALPHA IS RETURNED WHEN
RETURNNITER IS SET TO TRUE
SEE ALSO
MULTITASKELASTICNET
MULTITASKELASTICNETCV
ELASTICNET
ELASTICNETCV
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOCOORDINATEDESCENTPATHPY
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS

SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SPARSECOEF
SPARSE REPRESENTATION OF THE FITTED COEF
62212SKLEARNLINEARMODEL ORTHOGONALMATCHINGPURSUIT
CLASSSKLEARNLINEARMODEL ORTHOGONALMATCHINGPURSUIT NNONZEROCOEFSNONE
TOLNONE FITINTERCEPTTRUE NOR
MALIZETRUE PRECOMPUTE’AUTO’
ORTHOGONAL MATCHING PURSUIT MODEL OMP
READ MORE IN THE USER GUIDE
PARAMETERS
NNONZEROCOEFS INT OPTIONAL DESIRED NUMBER OF NONZERO ENTRIES IN THE SOLUTION IF NONE
BY DEFAULT THIS VALUE IS SET TO 10 OF NFEATURES
TOLFLOAT OPTIONAL MAXIMUM NORM OF THE RESIDUAL IF NOT NONE OVERRIDES NNONZEROCOEFS
FITINTERCEPT BOOLEAN OPTIONAL WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE
NO INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT TRUE THIS PARAMETER IS IGNORED WHEN FITINTERCEPT
IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BEFORE REGRESSION BY SUB
TRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO STANDARDIZE PLEASE USE
SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE CALLING FIT ON AN ESTIMATOR
WITHNORMALIZEFALSE
PRECOMPUTE TRUE FALSE ‘AUTO’ DEFAULT ‘AUTO’ WHETHER TO USE A PRECOMPUTED GRAM AND
XY MATRIX TO SPEED UP CALCULATIONS IMPROVES PERFORMANCE WHEN NTARGETS ORNSAMPLES IS
VERY LARGE NOTE THAT IF YOU ALREADY HAVE SUCH MATRICES YOU CAN PASS THEM DIRECTLY TO THE FIT
METHOD
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES OR NTARGETS NFEATURES PARAMETER VECTOR W IN THE FORMULA
INTERCEPT FLOAT OR ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION

NITER INT OR ARRAYLIKE NUMBER OF ACTIVE FEATURES ACROSS EVERY TARGET
SEE ALSO
ORTHOGONALMP
ORTHOGONALMPGRAM
LARSPATH
LARS
LASSOLARS
DECOMPOSITIONSPARSEENCODE
ORTHOGONALMATCHINGPURSUITCV
NOTES
ORTHOGONAL MATCHING PURSUIT WAS INTRODUCED IN G MALLAT Z ZHANG MATCHING PURSUITS WITH TIMEFREQUENCY
DICTIONARIES IEEE TRANSACTIONS ON SIGNAL PROCESSING V OL 41 NO 12 DECEMBER 1993 PP 33973415
HTTPBLANCHEPOLYTECHNIQUEFRMALLATPAPIERSMALLATPURSUIT93PDF
THIS IMPLEMENTATION IS BASED ON RUBINSTEIN R ZIBULEVSKY M AND ELAD M EFFICIENT IMPLEMENTATION OF
THE KSVD ALGORITHM USING BATCH ORTHOGONAL MATCHING PURSUIT TECHNICAL REPORT CS TECHNION APRIL 2008
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EXAMPLES
```
 FROM SKLEARNLINEARMODEL IMPORT ORTHOGONALMATCHINGPURSUIT
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y  MAKEREGRESSIONNOISE4 RANDOMSTATE0
REG  ORTHOGONALMATCHINGPURSUITFITX Y
REGSCOREX Y
09991
REGPREDICTX1
ARRAY783854
```
METHODS
FITSELF X Y FIT THE MODEL USING X Y AS TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNNONZEROCOEFSNONE TOLNONE FITINTERCEPTTRUE NORMALIZETRUE PRECOM
PUTE‘AUTO’
FITSELFXY
FIT THE MODEL USING X Y AS TRAINING DATA
PARAMETERS

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XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES WILL BE CAST TO
X'S DTYPE IF NECESSARY
RETURNS
SELF OBJECT RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
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METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE

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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELORTHOGONALMATCHINGPURSUIT
•ORTHOGONAL MATCHING PURSUIT
62213SKLEARNLINEARMODEL PASSIVEAGGRESSIVECLASSIFIER
CLASSSKLEARNLINEARMODEL PASSIVEAGGRESSIVECLASSIFIER C10 FITINTERCEPTTRUE
MAXITER1000 TOL0001
EARLYSTOPPINGFALSE
VALIDATIONFRACTION01
NITERNOCHANGE5
SHUFFLETRUE VERBOSE0
LOSS'HINGE' NJOBSNONE
RANDOMSTATENONE
WARMSTARTFALSE
CLASSWEIGHTNONE AVER
AGEFALSE
PASSIVE AGGRESSIVE CLASSIFIER
READ MORE IN THE USER GUIDE
PARAMETERS
CFLOAT MAXIMUM STEP SIZE REGULARIZATION DEFAULTS TO 10
FITINTERCEPT BOOL DEFAULTFALSE WHETHER THE INTERCEPT SHOULD BE ESTIMATED OR NOT IF FALSE
THE DATA IS ASSUMED TO BE ALREADY CENTERED
MAXITER INT OPTIONAL DEFAULT1000 THE MAXIMUM NUMBER OF PASSES OVER THE TRAINING DATA
AKA EPOCHS IT ONLY IMPACTS THE BEHAVIOR IN THE FIT METHOD AND NOT THE PARTIALFIT
NEW IN VERSION 019
TOLFLOAT OR NONE OPTIONAL DEFAULT1E3 THE STOPPING CRITERION IF IT IS NOT NONE THE ITERA
TIONS WILL STOP WHEN LOSS PREVIOUSLOSS TOL
NEW IN VERSION 019
EARLYSTOPPING BOOL DEFAULTFALSE WHETHER TO USE EARLY STOPPING TO TERMINATE TRAINING WHEN
VALIDATION SCORE IS NOT IMPROVING IF SET TO TRUE IT WILL AUTOMATICALLY SET ASIDE A STRATIFIED
FRACTION OF TRAINING DATA AS VALIDATION AND TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT
IMPROVING BY AT LEAST TOL FOR NITERNOCHANGE CONSECUTIVE EPOCHS
NEW IN VERSION 020
VALIDATIONFRACTION FLOAT DEFAULT01 THE PROPORTION OF TRAINING DATA TO SET ASIDE AS VALIDATION
SET FOR EARLY STOPPING MUST BE BETWEEN 0 AND 1 ONLY USED IF EARLYSTOPPING IS TRUE
NEW IN VERSION 020
622SKLEARNLINEARMODEL GENERALIZED LINEAR MODELS 1915

NITERNOCHANGE INT DEFAULT5 NUMBER OF ITERATIONS WITH NO IMPROVEMENT TO WAIT BEFORE
EARLY STOPPING
NEW IN VERSION 020
SHUFFLE BOOL DEFAULTTRUE WHETHER OR NOT THE TRAINING DATA SHOULD BE SHUFFLED AFTER EACH
EPOCH
VERBOSE INTEGER OPTIONAL THE VERBOSITY LEVEL
LOSS STRING OPTIONAL THE LOSS FUNCTION TO BE USED HINGE EQUIVALENT TO PAI IN THE REFERENCE
PAPER SQUAREDHINGE EQUIVALENT TO PAII IN THE REFERENCE PAPER
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF CPUS TO USE TO DO THE OV A ONE
VERSUS ALL FOR MULTICLASS PROBLEMS COMPUTATION NONE MEANS 1 UNLESS IN A JOBLIB
PARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE
DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
WARMSTART BOOL OPTIONAL WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS
INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
REPEATEDLY CALLING FIT OR PARTIALFIT WHEN WARMSTART IS TRUE CAN RESULT IN A DIFFERENT SOLUTION
THAN WHEN CALLING FIT A SINGLE TIME BECAUSE OF THE WAY THE DATA IS SHUFFLED
CLASSWEIGHT DICT CLASSLABEL WEIGHT OR “BALANCED” OR NONE OPTIONAL PRESET FOR THE
CLASSWEIGHT FIT PARAMETER
WEIGHTS ASSOCIATED WITH CLASSES IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT ONE
THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP
BINCOUNTY
NEW IN VERSION 017 PARAMETER CLASSWEIGHT TO AUTOMATICALLY WEIGHT SAMPLES
AVERAGE BOOL OR INT OPTIONAL WHEN SET TO TRUE COMPUTES THE AVERAGED SGD WEIGHTS AND
STORES THE RESULT IN THE COEF ATTRIBUTE IF SET TO AN INT GREATER THAN 1 AVERAGING WILL BEGIN
ONCE THE TOTAL NUMBER OF SAMPLES SEEN REACHES AVERAGE SO AVERAGE10 WILL BEGIN AVERAGING
AFTER SEEING 10 SAMPLES
NEW IN VERSION 019 PARAMETER AVERAGE TO USE WEIGHTS AVERAGING IN SGD
ATTRIBUTES
COEF ARRAY SHAPE 1 NFEATURES IF NCLASSES 2 ELSE NCLASSES NFEATURES WEIGHTS
ASSIGNED TO THE FEATURES
INTERCEPT ARRAY SHAPE 1 IF NCLASSES 2 ELSE NCLASSES CONSTANTS IN DECISION FUNCTION
NITER INT THE ACTUAL NUMBER OF ITERATIONS TO REACH THE STOPPING CRITERION FOR MULTICLASS FITS
IT IS THE MAXIMUM OVER EVERY BINARY FIT
SEE ALSO
SGDCLASSIFIER
PERCEPTRON

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REFERENCES
ONLINE PASSIVEAGGRESSIVE ALGORITHMS HTTPJMLRCSAILMITEDUPAPERSVOLUME7CRAMMER06ACRAMMER06A
PDF K CRAMMER O DEKEL J KESHAT S SHALEVSHWARTZ Y SINGER JMLR 2006
EXAMPLES
 FROM SKLEARNLINEARMODEL IMPORT PASSIVEAGGRESSIVECLASSIFIER
 FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
X Y MAKECLASSIFICATIONNFEATURES4 RANDOMSTATE0
CLF PASSIVEAGGRESSIVECLASSIFIERMAXITER1000 RANDOMSTATE0
TOL1E3
CLFFITX Y
PASSIVEAGGRESSIVECLASSIFIERC10 AVERAGEFALSE CLASSWEIGHTNONE
EARLYSTOPPINGFALSE FITINTERCEPTTRUE LOSSHINGE
MAXITER1000 NITERNOCHANGE5 NJOBSNONE
RANDOMSTATE0 SHUFFLETRUE TOL0001
VALIDATIONFRACTION01 VERBOSE0 WARMSTARTFALSE
PRINTCLFCOEF
026642044 045070924 067251877 064185414
PRINTCLFINTERCEPT
184127814
PRINTCLFPREDICT0 0 0 0
1
METHODS
DECISIONFUNCTION SELF X PREDICT CONFIDENCE SCORES FOR SAMPLES
DENSIFY SELF CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
FITSELF X Y COEFINIT INTERCEPTINIT FIT LINEAR MODEL WITH PASSIVE AGGRESSIVE ALGORITHM
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y CLASSES FIT LINEAR MODEL WITH PASSIVE AGGRESSIVE ALGORITHM
PREDICT SELF X PREDICT CLASS LABELS FOR SAMPLES IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF ARGS KWARGS
SPARSIFY SELF CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
INIT SELFC10 FITINTERCEPTTRUE MAXITER1000 TOL0001 EARLYSTOPPINGFALSE VAL
IDATIONFRACTION01 NITERNOCHANGE5 SHUFFLETRUE VERBOSE0 LOSS‘HINGE’
NJOBSNONE RANDOMSTATENONE WARMSTARTFALSE CLASSWEIGHTNONE AVER
AGEFALSE
DECISIONFUNCTION SELFX
PREDICT CONFIDENCE SCORES FOR SAMPLES
THE CONFIDENCE SCORE FOR A SAMPLE IS THE SIGNED DISTANCE OF THAT SAMPLE TO THE HYPERPLANE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES

RETURNS
ARRAY SHAPENSAMPLES IF NCLASSES 2 ELSE NSAMPLES NCLASSES CONFIDENCE
SCORES PER SAMPLE CLASS COMBINATION IN THE BINARY CASE CONFIDENCE SCORE FOR
SELFCLASSES1 WHERE 0 MEANS THIS CLASS WOULD BE PREDICTED
DENSIFYSELF
CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
CONVERTS THE COEF MEMBER BACK TO A NUMPYNDARRAY THIS IS THE DEFAULT FORMAT OF COEF AND IS
REQUIRED FOR FITTING SO CALLING THIS METHOD IS ONLY REQUIRED ON MODELS THAT HAVE PREVIOUSLY BEEN SPARSIFIED
OTHERWISE IT IS A NOOP
RETURNS
SELF ESTIMATOR
FITSELFXYCOEFINITNONE INTERCEPTINITNONE
FIT LINEAR MODEL WITH PASSIVE AGGRESSIVE ALGORITHM
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
COEFINIT ARRAY SHAPE NCLASSESNFEATURES THE INITIAL COEFFICIENTS TO WARMSTART THE
OPTIMIZATION
INTERCEPTINIT ARRAY SHAPE NCLASSES THE INITIAL INTERCEPT TO WARMSTART THE OPTIMIZA
TION
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYCLASSESNONE
FIT LINEAR MODEL WITH PASSIVE AGGRESSIVE ALGORITHM
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SUBSET OF THE TRAINING DATA
YNUMPY ARRAY OF SHAPE NSAMPLES SUBSET OF THE TARGET VALUES
CLASSES ARRAY SHAPE NCLASSES CLASSES ACROSS ALL CALLS TO PARTIALFIT CAN BE OBTAINED
BY VIANPUNIQUEYALL WHERE YALL IS THE TARGET VECTOR OF THE ENTIRE DATASET THIS
ARGUMENT IS REQUIRED FOR THE FIRST CALL TO PARTIALFIT AND CAN BE OMITTED IN THE SUBSEQUENT
CALLS NOTE THAT Y DOESN’T NEED TO CONTAIN ALL LABELS IN CLASSES
RETURNS
SELF RETURNS AN INSTANCE OF SELF

PREDICTSELFX
PREDICT CLASS LABELS FOR SAMPLES IN X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES PREDICTED CLASS LABEL PER SAMPLE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SPARSIFY SELF
CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
CONVERTS THE COEF MEMBER TO A SCIPYSPARSE MATRIX WHICH FOR L1REGULARIZED MODELS CAN BE MUCH MORE MEMORY AND STORAGEEFFICIENT THAN THE USUAL NUMPYNDARRAY REPRESENTATION
THEINTERCEPT MEMBER IS NOT CONVERTED
RETURNS
SELF ESTIMATOR
NOTES
FOR NONSPARSE MODELS IE WHEN THERE ARE NOT MANY ZEROS IN COEF THIS MAY ACTUALLY INCREASE MEMORY USAGE SO USE THIS METHOD WITH CARE A RULE OF THUMB IS THAT THE NUMBER OF ZERO ELEMENTS WHICH CAN BE COMPUTED WITH COEF 0SUM MUST BE MORE THAN 50 FOR THIS TO PROVIDE SIGNIFICANT BENEFITS
AFTER CALLING THIS METHOD FURTHER FITTING WITH THE PARTIALFIT METHOD IF ANY WILL NOT WORK UNTIL YOU CALL DENSIFY
EXAMPLES USING SKLEARNLINEARMODELPASSIVEAGGRESSIVECLASSIFIER
•OUTOFCORE CLASSIFICATION OF TEXT DOCUMENTS
•COMPARING VARIOUS ONLINE SOLVERS
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES

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62214SKLEARNLINEARMODEL PASSIVEAGGRESSIVEREGRESSOR
CLASSSKLEARNLINEARMODEL PASSIVEAGGRESSIVEREGRESSOR C10 FITINTERCEPTTRUE
MAXITER1000 TOL0001
EARLYSTOPPINGFALSE
VALIDATIONFRACTION01
NITERNOCHANGE5 SHUF
FLETRUE VERBOSE0
LOSS'EPSILONINSENSITIVE' EP
SILON01 RANDOMSTATENONE
WARMSTARTFALSE AVER
AGEFALSE
PASSIVE AGGRESSIVE REGRESSOR
READ MORE IN THE USER GUIDE
PARAMETERS
CFLOAT MAXIMUM STEP SIZE REGULARIZATION DEFAULTS TO 10
FITINTERCEPT BOOL WHETHER THE INTERCEPT SHOULD BE ESTIMATED OR NOT IF FALSE THE DATA IS
ASSUMED TO BE ALREADY CENTERED DEFAULTS TO TRUE
MAXITER INT OPTIONAL DEFAULT1000 THE MAXIMUM NUMBER OF PASSES OVER THE TRAINING DATA
AKA EPOCHS IT ONLY IMPACTS THE BEHAVIOR IN THE FIT METHOD AND NOT THE PARTIALFIT
NEW IN VERSION 019
TOLFLOAT OR NONE OPTIONAL DEFAULT1E3 THE STOPPING CRITERION IF IT IS NOT NONE THE ITERA
TIONS WILL STOP WHEN LOSS PREVIOUSLOSS TOL
NEW IN VERSION 019
EARLYSTOPPING BOOL DEFAULTFALSE WHETHER TO USE EARLY STOPPING TO TERMINATE TRAINING WHEN
VALIDATION SCORE IS NOT IMPROVING IF SET TO TRUE IT WILL AUTOMATICALLY SET ASIDE A FRACTION OF
TRAINING DATA AS VALIDATION AND TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT IMPROVING BY
AT LEAST TOL FOR NITERNOCHANGE CONSECUTIVE EPOCHS
NEW IN VERSION 020
VALIDATIONFRACTION FLOAT DEFAULT01 THE PROPORTION OF TRAINING DATA TO SET ASIDE AS VALIDATION
SET FOR EARLY STOPPING MUST BE BETWEEN 0 AND 1 ONLY USED IF EARLYSTOPPING IS TRUE
NEW IN VERSION 020
NITERNOCHANGE INT DEFAULT5 NUMBER OF ITERATIONS WITH NO IMPROVEMENT TO WAIT BEFORE
EARLY STOPPING
NEW IN VERSION 020
SHUFFLE BOOL DEFAULTTRUE WHETHER OR NOT THE TRAINING DATA SHOULD BE SHUFFLED AFTER EACH
EPOCH
VERBOSE INTEGER OPTIONAL THE VERBOSITY LEVEL
LOSS STRING OPTIONAL THE LOSS FUNCTION TO BE USED EPSILONINSENSITIVE EQUIVALENT TO PAI IN
THE REFERENCE PAPER SQUAREDEPSILONINSENSITIVE EQUIVALENT TO PAII IN THE REFERENCE PAPER
EPSILON FLOAT IF THE DIFFERENCE BETWEEN THE CURRENT PREDICTION AND THE CORRECT LABEL IS BELOW
THIS THRESHOLD THE MODEL IS NOT UPDATED
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
1920 CHAPTER 6 API REFERENCE

THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
WARMSTART BOOL OPTIONAL WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS
INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
REPEATEDLY CALLING FIT OR PARTIALFIT WHEN WARMSTART IS TRUE CAN RESULT IN A DIFFERENT SOLUTION
THAN WHEN CALLING FIT A SINGLE TIME BECAUSE OF THE WAY THE DATA IS SHUFFLED
AVERAGE BOOL OR INT OPTIONAL WHEN SET TO TRUE COMPUTES THE AVERAGED SGD WEIGHTS AND
STORES THE RESULT IN THE COEF ATTRIBUTE IF SET TO AN INT GREATER THAN 1 AVERAGING WILL BEGIN
ONCE THE TOTAL NUMBER OF SAMPLES SEEN REACHES AVERAGE SO AVERAGE10 WILL BEGIN AVERAGING
AFTER SEEING 10 SAMPLES
NEW IN VERSION 019 PARAMETER AVERAGE TO USE WEIGHTS AVERAGING IN SGD
ATTRIBUTES
COEF ARRAY SHAPE 1 NFEATURES IF NCLASSES 2 ELSE NCLASSES NFEATURES WEIGHTS
ASSIGNED TO THE FEATURES
INTERCEPT ARRAY SHAPE 1 IF NCLASSES 2 ELSE NCLASSES CONSTANTS IN DECISION FUNCTION
NITER INT THE ACTUAL NUMBER OF ITERATIONS TO REACH THE STOPPING CRITERION
SEE ALSO
SGDREGRESSOR
REFERENCES
ONLINE PASSIVEAGGRESSIVE ALGORITHMS HTTPJMLRCSAILMITEDUPAPERSVOLUME7CRAMMER06ACRAMMER06A
PDF K CRAMMER O DEKEL J KESHAT S SHALEVSHWARTZ Y SINGER JMLR 2006
EXAMPLES
 FROM SKLEARNLINEARMODEL IMPORT PASSIVEAGGRESSIVEREGRESSOR
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y MAKEREGRESSIONNFEATURES4 RANDOMSTATE0
REGR PASSIVEAGGRESSIVEREGRESSORMAXITER100 RANDOMSTATE0
TOL1E3
REGRFITX Y
PASSIVEAGGRESSIVEREGRESSORC10 AVERAGEFALSE EARLYSTOPPINGFALSE
EPSILON01 FITINTERCEPTTRUE LOSSEPSILONINSENSITIVE
MAXITER100 NITERNOCHANGE5 RANDOMSTATE0
SHUFFLETRUE TOL0001 VALIDATIONFRACTION01
VERBOSE0 WARMSTARTFALSE
PRINTREGRCOEF
2048736655 3418818427 6759122734 8794731329
PRINTREGRINTERCEPT
002306214
PRINTREGRPREDICT0 0 0 0
002306214

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METHODS
DENSIFY SELF CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
FITSELF X Y COEFINIT INTERCEPTINIT FIT LINEAR MODEL WITH PASSIVE AGGRESSIVE ALGORITHM
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y FIT LINEAR MODEL WITH PASSIVE AGGRESSIVE ALGORITHM
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF ARGS KWARGS
SPARSIFY SELF CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
INIT SELFC10 FITINTERCEPTTRUE MAXITER1000 TOL0001 EARLYSTOPPINGFALSE
VALIDATIONFRACTION01 NITERNOCHANGE5 SHUFFLETRUE VERBOSE0
LOSS'EPSILONINSENSITIVE' EPSILON01 RANDOMSTATENONE WARMSTARTFALSE AV
ERAGEFALSE
DENSIFYSELF
CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
CONVERTS THE COEF MEMBER BACK TO A NUMPYNDARRAY THIS IS THE DEFAULT FORMAT OF COEF AND IS
REQUIRED FOR FITTING SO CALLING THIS METHOD IS ONLY REQUIRED ON MODELS THAT HAVE PREVIOUSLY BEEN SPARSIFIED
OTHERWISE IT IS A NOOP
RETURNS
SELF ESTIMATOR
FITSELFXYCOEFINITNONE INTERCEPTINITNONE
FIT LINEAR MODEL WITH PASSIVE AGGRESSIVE ALGORITHM
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
COEFINIT ARRAY SHAPE NFEATURES THE INITIAL COEFFICIENTS TO WARMSTART THE OPTIMIZATION
INTERCEPTINIT ARRAY SHAPE 1 THE INITIAL INTERCEPT TO WARMSTART THE OPTIMIZATION
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXY
FIT LINEAR MODEL WITH PASSIVE AGGRESSIVE ALGORITHM
PARAMETERS

XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SUBSET OF TRAINING DATA
YNUMPY ARRAY OF SHAPE NSAMPLES SUBSET OF TARGET VALUES
RETURNS
SELF RETURNS AN INSTANCE OF SELF
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES
RETURNS
ARRAY SHAPE NSAMPLES PREDICTED TARGET VALUES PER ELEMENT IN X
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SPARSIFY SELF
CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
CONVERTS THE COEF MEMBER TO A SCIPYSPARSE MATRIX WHICH FOR L1REGULARIZED MODELS CAN BE MUCH MORE
MEMORY AND STORAGEEFFICIENT THAN THE USUAL NUMPYNDARRAY REPRESENTATION
THEINTERCEPT MEMBER IS NOT CONVERTED
RETURNS
SELF ESTIMATOR

NOTES
FOR NONSPARSE MODELS IE WHEN THERE ARE NOT MANY ZEROS IN COEF THIS MAY ACTUALLY INCREASE MEMORY USAGE SO USE THIS METHOD WITH CARE A RULE OF THUMB IS THAT THE NUMBER OF ZERO ELEMENTS WHICH CAN BE COMPUTED WITH COEF 0SUM MUST BE MORE THAN 50 FOR THIS TO PROVIDE SIGNIFICANT BENEFITS
AFTER CALLING THIS METHOD FURTHER FITTING WITH THE PARTIALFIT METHOD IF ANY WILL NOT WORK UNTIL YOU CALL DENSIFY
62215SKLEARNLINEARMODEL PERCEPTRON
CLASSSKLEARNLINEARMODEL PERCEPTRON PENALTYNONE ALPHA00001 FITINTERCEPTTRUE MAXITER1000 TOL0001 SHUFFLETRUE VER BOSE0 ETA010 NJOBSNONE RANDOMSTATE0 EARLYSTOPPINGFALSE VALIDATIONFRACTION01 NITERNOCHANGE5 CLASSWEIGHTNONE WARMSTARTFALSE
READ MORE IN THE USER GUIDE
PARAMETERS
PENALTY NONE ‘L2’ OR ‘L1’ OR ‘ELASTICNET’ THE PENALTY AKA REGULARIZATION TERM TO BE USED DEFAULTS TO NONE
ALPHA FLOAT CONSTANT THAT MULTIPLIES THE REGULARIZATION TERM IF REGULARIZATION IS USED DEFAULTS TO 00001
FITINTERCEPT BOOL WHETHER THE INTERCEPT SHOULD BE ESTIMATED OR NOT IF FALSE THE DATA IS ASSUMED TO BE ALREADY CENTERED DEFAULTS TO TRUE
MAXITER INT OPTIONAL DEFAULT1000 THE MAXIMUM NUMBER OF PASSES OVER THE TRAINING DATA AKA EPOCHS IT ONLY IMPACTS THE BEHAVIOR IN THE FIT METHOD AND NOT THE PARTIALFIT
NEW IN VERSION 019
TOLFLOAT OR NONE OPTIONAL DEFAULT1E3 THE STOPPING CRITERION IF IT IS NOT NONE THE ITERA TIONS WILL STOP WHEN LOSS PREVIOUSLOSS TOL
NEW IN VERSION 019
SHUFFLE BOOL OPTIONAL DEFAULT TRUE WHETHER OR NOT THE TRAINING DATA SHOULD BE SHUFFLED AFTER EACH EPOCH
VERBOSE INTEGER OPTIONAL THE VERBOSITY LEVEL
ETA0 DOUBLE CONSTANT BY WHICH THE UPDATES ARE MULTIPLIED DEFAULTS TO 1
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF CPUS TO USE TO DO THE OV A ONE VERSUS ALL FOR MULTICLASS PROBLEMS COMPUTATION NONE MEANS 1 UNLESS IN A JOBLIB PARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
EARLYSTOPPING BOOL DEFAULTFALSE WHETHER TO USE EARLY STOPPING TO TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT IMPROVING IF SET TO TRUE IT WILL AUTOMATICALLY SET ASIDE A STRATIFIED

FRACTION OF TRAINING DATA AS VALIDATION AND TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT IMPROVING BY AT LEAST TOL FOR NITERNOCHANGE CONSECUTIVE EPOCHS
NEW IN VERSION 020
VALIDATIONFRACTION FLOAT DEFAULT01 THE PROPORTION OF TRAINING DATA TO SET ASIDE AS VALIDATION SET FOR EARLY STOPPING MUST BE BETWEEN 0 AND 1 ONLY USED IF EARLYSTOPPING IS TRUE
NEW IN VERSION 020
NITERNOCHANGE INT DEFAULT5 NUMBER OF ITERATIONS WITH NO IMPROVEMENT TO WAIT BEFORE EARLY STOPPING
NEW IN VERSION 020
CLASSWEIGHT DICT CLASSLABEL WEIGHT OR “BALANCED” OR NONE OPTIONAL PRESET FOR THE CLASSWEIGHT FIT PARAMETER
WEIGHTS ASSOCIATED WITH CLASSES IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT ONE THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP BINCOUNTY
WARMSTART BOOL OPTIONAL WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
ATTRIBUTES
COEF ARRAY SHAPE 1 NFEATURES IF NCLASSES 2 ELSE NCLASSES NFEATURES WEIGHTS ASSIGNED TO THE FEATURES
INTERCEPT ARRAY SHAPE 1 IF NCLASSES 2 ELSE NCLASSES CONSTANTS IN DECISION FUNCTION
NITER INT THE ACTUAL NUMBER OF ITERATIONS TO REACH THE STOPPING CRITERION FOR MULTICLASS FITS IT IS THE MAXIMUM OVER EVERY BINARY FIT
SEE ALSO
SGDCLASSIFIER
NOTES
PERCEPTRON IS A CLASSIFICATION ALGORITHM WHICH SHARES THE SAME UNDERLYING IMPLEMENTATION WITH SGDCLASSIFIER IN FACTPERCEPTRON IS EQUIVALENT TO SGDCLASSIFIERLOSSPERCEPTRON ETA01 LEARNINGRATECONSTANT PENALTYNONE
REFERENCES
HTTPSENWIKIPEDIAORGWIKIPERCEPTRON AND REFERENCES THEREIN
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADDIGITS
 FROM SKLEARNLINEARMODEL IMPORT PERCEPTRON
X Y  LOADDIGITSRETURNXY TRUE
CLF  PERCEPTRONTOL1E3 RANDOMSTATE0
CLFFITX Y
```

SCIKITLEARN USER GUIDE RELEASE 0213
PERCEPTRONALPHA00001 CLASSWEIGHTNONE EARLYSTOPPINGFALSE ETA010
FITINTERCEPTTRUE MAXITER1000 NITERNOCHANGE5 NJOBSNONE
PENALTYNONE RANDOMSTATE0 SHUFFLETRUE TOL0001
VALIDATIONFRACTION01 VERBOSE0 WARMSTARTFALSE
CLFSCOREX Y
0939
METHODS
DECISIONFUNCTION SELF X PREDICT CONFIDENCE SCORES FOR SAMPLES
DENSIFY SELF CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
FITSELF X Y COEFINIT INTERCEPTINIT FIT LINEAR MODEL WITH STOCHASTIC GRADIENT DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y CLASSES SAMPLEWEIGHT PERFORM ONE EPOCH OF STOCHASTIC GRADIENT DESCENT ON
GIVEN SAMPLES
PREDICT SELF X PREDICT CLASS LABELS FOR SAMPLES IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF ARGS KWARGS
SPARSIFY SELF CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
INIT SELFPENALTYNONE ALPHA00001 FITINTERCEPTTRUE MAXITER1000 TOL0001 SHUF
FLETRUE VERBOSE0 ETA010 NJOBSNONE RANDOMSTATE0 EARLYSTOPPINGFALSE VAL
IDATIONFRACTION01 NITERNOCHANGE5 CLASSWEIGHTNONE WARMSTARTFALSE
DECISIONFUNCTION SELFX
PREDICT CONFIDENCE SCORES FOR SAMPLES
THE CONFIDENCE SCORE FOR A SAMPLE IS THE SIGNED DISTANCE OF THAT SAMPLE TO THE HYPERPLANE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
ARRAY SHAPENSAMPLES IF NCLASSES 2 ELSE NSAMPLES NCLASSES CONFIDENCE
SCORES PER SAMPLE CLASS COMBINATION IN THE BINARY CASE CONFIDENCE SCORE FOR
SELFCLASSES1 WHERE 0 MEANS THIS CLASS WOULD BE PREDICTED
DENSIFYSELF
CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
CONVERTS THE COEF MEMBER BACK TO A NUMPYNDARRAY THIS IS THE DEFAULT FORMAT OF COEF AND IS
REQUIRED FOR FITTING SO CALLING THIS METHOD IS ONLY REQUIRED ON MODELS THAT HAVE PREVIOUSLY BEEN SPARSIFIED
OTHERWISE IT IS A NOOP
RETURNS
SELF ESTIMATOR
FITSELFXYCOEFINITNONE INTERCEPTINITNONE SAMPLEWEIGHTNONE
FIT LINEAR MODEL WITH STOCHASTIC GRADIENT DESCENT
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA

YNUMPY ARRAY SHAPE NSAMPLES TARGET VALUES
COEFINIT ARRAY SHAPE NCLASSES NFEATURES THE INITIAL COEFFICIENTS TO WARMSTART THE OP
TIMIZATION
INTERCEPTINIT ARRAY SHAPE NCLASSES THE INITIAL INTERCEPT TO WARMSTART THE OPTIMIZA
TION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL WEIGHTS APPLIED TO INDIVIDUAL
SAMPLES IF NOT PROVIDED UNIFORM WEIGHTS ARE ASSUMED THESE WEIGHTS WILL BE MULTIPLIED
WITH CLASSWEIGHT PASSED THROUGH THE CONSTRUCTOR IF CLASSWEIGHT IS SPECIFIED
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYCLASSESNONE SAMPLEWEIGHTNONE
PERFORM ONE EPOCH OF STOCHASTIC GRADIENT DESCENT ON GIVEN SAMPLES
INTERNALLY THIS METHOD USES MAXITER 1 THEREFORE IT IS NOT GUARANTEED THAT A MINIMUM OF THE COST
FUNCTION IS REACHED AFTER CALLING IT ONCE MATTERS SUCH AS OBJECTIVE CONVERGENCE AND EARLY STOPPING SHOULD
BE HANDLED BY THE USER
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SUBSET OF THE TRAINING DATA
YNUMPY ARRAY SHAPE NSAMPLES SUBSET OF THE TARGET VALUES
CLASSES ARRAY SHAPE NCLASSES CLASSES ACROSS ALL CALLS TO PARTIALFIT CAN BE OBTAINED BY
VIANPUNIQUEYALL WHERE YALL IS THE TARGET VECTOR OF THE ENTIRE DATASET THIS
ARGUMENT IS REQUIRED FOR THE FIRST CALL TO PARTIALFIT AND CAN BE OMITTED IN THE SUBSEQUENT
CALLS NOTE THAT Y DOESN’T NEED TO CONTAIN ALL LABELS IN CLASSES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL WEIGHTS APPLIED TO INDIVIDUAL
SAMPLES IF NOT PROVIDED UNIFORM WEIGHTS ARE ASSUMED
RETURNS
SELF RETURNS AN INSTANCE OF SELF
PREDICTSELFX
PREDICT CLASS LABELS FOR SAMPLES IN X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES PREDICTED CLASS LABEL PER SAMPLE

SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SPARSIFY SELF
CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
CONVERTS THE COEF MEMBER TO A SCIPYSPARSE MATRIX WHICH FOR L1REGULARIZED MODELS CAN BE MUCH MORE MEMORY AND STORAGEEFFICIENT THAN THE USUAL NUMPYNDARRAY REPRESENTATION
THEINTERCEPT MEMBER IS NOT CONVERTED
RETURNS
SELF ESTIMATOR
NOTES
FOR NONSPARSE MODELS IE WHEN THERE ARE NOT MANY ZEROS IN COEF THIS MAY ACTUALLY INCREASE MEMORY USAGE SO USE THIS METHOD WITH CARE A RULE OF THUMB IS THAT THE NUMBER OF ZERO ELEMENTS WHICH CAN BE COMPUTED WITH COEF 0SUM MUST BE MORE THAN 50 FOR THIS TO PROVIDE SIGNIFICANT BENEFITS
AFTER CALLING THIS METHOD FURTHER FITTING WITH THE PARTIALFIT METHOD IF ANY WILL NOT WORK UNTIL YOU CALL DENSIFY
EXAMPLES USING SKLEARNLINEARMODELPERCEPTRON
•OUTOFCORE CLASSIFICATION OF TEXT DOCUMENTS
•COMPARING VARIOUS ONLINE SOLVERS
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
62216SKLEARNLINEARMODEL RANSACREGRESSOR
CLASSSKLEARNLINEARMODEL RANSACREGRESSOR BASEESTIMATORNONE MINSAMPLESNONE RESIDUALTHRESHOLDNONE ISDATAVALIDNONE ISMODELVALIDNONE MAXTRIALS100
MAXSKIPSINF STOPNINLIERSINF
STOPSCOREINF STOPPROBABILITY099
LOSS‘ABSOLUTELOSS’ RANDOMSTATENONE
RANSAC RANDOM SAMPLE CONSENSUS ALGORITHM
RANSAC IS AN ITERATIVE ALGORITHM FOR THE ROBUST ESTIMATION OF PARAMETERS FROM A SUBSET OF INLIERS FROM THE COMPLETE DATA SET MORE INFORMATION CAN BE FOUND IN THE GENERAL DOCUMENTATION OF LINEAR MODELS

A DETAILED DESCRIPTION OF THE ALGORITHM CAN BE FOUND IN THE DOCUMENTATION OF THE LINEARMODEL SUBPACKAGE
READ MORE IN THE USER GUIDE
PARAMETERS
BASEESTIMATOR OBJECT OPTIONAL BASE ESTIMATOR OBJECT WHICH IMPLEMENTS THE FOLLOWING METH
ODS
•FITX Y FIT MODEL TO GIVEN TRAINING DATA AND TARGET VALUES
•SCOREX Y RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA WHICH IS USED FOR THE
STOP CRITERION DEFINED BY STOPSCORE ADDITIONALLY THE SCORE IS USED TO DECIDE WHICH
OF TWO EQUALLY LARGE CONSENSUS SETS IS CHOSEN AS THE BETTER ONE
•PREDICTX RETURNS PREDICTED VALUES USING THE LINEAR MODEL WHICH IS USED TO COM
PUTE RESIDUAL ERROR USING LOSS FUNCTION
IFBASEESTIMATOR IS NONE THEN BASEESTIMATORSKLEARNLINEARMODEL
LINEARREGRESSION IS USED FOR TARGET VALUES OF DTYPE FLOAT
NOTE THAT THE CURRENT IMPLEMENTATION ONLY SUPPORTS REGRESSION ESTIMATORS
MINSAMPLES INT 1 OR FLOAT 0 1 OPTIONAL MINIMUM NUMBER OF SAMPLES CHO
SEN RANDOMLY FROM ORIGINAL DATA TREATED AS AN ABSOLUTE NUMBER OF SAMPLES FOR
MINSAMPLES 1 TREATED AS A RELATIVE NUMBER CEILMINSAMPLES X
SHAPE0 FORMINSAMPLES 1 THIS IS TYPICALLY CHOSEN AS THE MINIMAL NUMBER
OF SAMPLES NECESSARY TO ESTIMATE THE GIVEN BASEESTIMATOR BY DEFAULT A SKLEARN
LINEARMODELLINEARREGRESSION ESTIMATOR IS ASSUMED AND MINSAMPLES IS
CHOSEN ASXSHAPE1 1
RESIDUALTHRESHOLD FLOAT OPTIONAL MAXIMUM RESIDUAL FOR A DATA SAMPLE TO BE CLASSIFIED AS AN
INLIER BY DEFAULT THE THRESHOLD IS CHOSEN AS THE MAD MEDIAN ABSOLUTE DEVIATION OF THE
TARGET VALUES Y
ISDATAVALID CALLABLE OPTIONAL THIS FUNCTION IS CALLED WITH THE RANDOMLY SELECTED DATA BEFORE
THE MODEL IS FITTED TO IT ISDATAVALIDX Y IF ITS RETURN VALUE IS FALSE THE CURRENT
RANDOMLY CHOSEN SUBSAMPLE IS SKIPPED
ISMODELVALID CALLABLE OPTIONAL THIS FUNCTION IS CALLED WITH THE ESTIMATED MODEL AND THE
RANDOMLY SELECTED DATA ISMODELVALIDMODEL X Y IF ITS RETURN VALUE IS FALSE
THE CURRENT RANDOMLY CHOSEN SUBSAMPLE IS SKIPPED REJECTING SAMPLES WITH THIS FUNCTION IS
COMPUTATIONALLY COSTLIER THAN WITH ISDATAVALID ISMODELVALID SHOULD THERE
FORE ONLY BE USED IF THE ESTIMATED MODEL IS NEEDED FOR MAKING THE REJECTION DECISION
MAXTRIALS INT OPTIONAL MAXIMUM NUMBER OF ITERATIONS FOR RANDOM SAMPLE SELECTION
MAXSKIPS INT OPTIONAL MAXIMUM NUMBER OF ITERATIONS THAT CAN BE SKIPPED DUE TO FINDING
ZERO INLIERS OR INVALID DATA DEFINED BY ISDATAVALID OR INVALID MODELS DEFINED BY
ISMODELVALID
NEW IN VERSION 019
STOPNINLIERS INT OPTIONAL STOP ITERATION IF AT LEAST THIS NUMBER OF INLIERS ARE FOUND
STOPSCORE FLOAT OPTIONAL STOP ITERATION IF SCORE IS GREATER EQUAL THAN THIS THRESHOLD
STOPPROBABILITY FLOAT IN RANGE 0 1 OPTIONAL RANSAC ITERATION STOPS IF AT LEAST ONE OUTLIER
FREE SET OF THE TRAINING DATA IS SAMPLED IN RANSAC THIS REQUIRES TO GENERATE AT LEAST N
SAMPLES ITERATIONS
N LOG1 PROBABILITY LOG1 E M

WHERE THE PROBABILITY CONFIDENCE IS TYPICALLY SET TO HIGH VALUE SUCH AS 099 THE DEFAULT
AND E IS THE CURRENT FRACTION OF INLIERS WRT THE TOTAL NUMBER OF SAMPLES
LOSS STRING CALLABLE OPTIONAL DEFAULT “ABSOLUTELOSS” STRING INPUTS “ABSOLUTELOSS” AND
“SQUAREDLOSS” ARE SUPPORTED WHICH FIND THE ABSOLUTE LOSS AND SQUARED LOSS PER SAMPLE RE
SPECTIVELY
IFLOSS IS A CALLABLE THEN IT SHOULD BE A FUNCTION THAT TAKES TWO ARRAYS AS INPUTS THE TRUE
AND PREDICTED VALUE AND RETURNS A 1D ARRAY WITH THE ITH VALUE OF THE ARRAY CORRESPONDING TO
THE LOSS ON XI
IF THE LOSS ON A SAMPLE IS GREATER THAN THE RESIDUALTHRESHOLD THEN THIS SAMPLE IS
CLASSIFIED AS AN OUTLIER
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE GENERATOR USED
TO INITIALIZE THE CENTERS IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENER
ATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE
RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES
ESTIMATOR OBJECT BEST FITTED MODEL COPY OF THE BASEESTIMATOR OBJECT
NTRIALS INT NUMBER OF RANDOM SELECTION TRIALS UNTIL ONE OF THE STOP CRITERIA IS MET IT IS
ALWAYS MAXTRIALS
INLIERMASK BOOL ARRAY OF SHAPE NSAMPLES BOOLEAN MASK OF INLIERS CLASSIFIED AS TRUE
NSKIPSNOINLIERS INT NUMBER OF ITERATIONS SKIPPED DUE TO FINDING ZERO INLIERS
NEW IN VERSION 019
NSKIPSINVALIDDATA INT NUMBER OF ITERATIONS SKIPPED DUE TO INVALID DATA DEFINED BY
ISDATAVALID
NEW IN VERSION 019
NSKIPSINVALIDMODEL INT NUMBER OF ITERATIONS SKIPPED DUE TO AN INVALID MODEL DEFINED BY
ISMODELVALID
NEW IN VERSION 019
REFERENCES
R80CE5B25CF9D1 R80CE5B25CF9D2 R80CE5B25CF9D3
EXAMPLES
 FROM SKLEARNLINEARMODEL IMPORT RANSACREGRESSOR
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y MAKEREGRESSION
 NSAMPLES200 NFEATURES2 NOISE40 RANDOMSTATE0
REG RANSACREGRESSORRANDOMSTATE0FITX Y
REGSCOREX Y
09885
REGPREDICTX1
ARRAY319417

METHODS
FITSELF X Y SAMPLEWEIGHT FIT ESTIMATOR USING RANSAC ALGORITHM
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE ESTIMATED MODEL
SCORE SELF X Y RETURNS THE SCORE OF THE PREDICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELF BASEESTIMATORNONE MINSAMPLESNONE RESIDUALTHRESHOLDNONE
ISDATAVALIDNONE ISMODELVALIDNONE MAXTRIALS100 MAXSKIPSINF
STOPNINLIERSINF STOPSCOREINF STOPPROBABILITY099 LOSS'ABSOLUTELOSS' RAN
DOMSTATENONE
FITSELFXYSAMPLEWEIGHTNONE
FIT ESTIMATOR USING RANSAC ALGORITHM
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES INDIVIDUAL WEIGHTS FOR EACH SAMPLE RAISES
ERROR IF SAMPLEWEIGHT IS PASSED AND BASEESTIMATOR FIT METHOD DOES NOT SUPPORT IT
RAISES
VALUEERROR IF NO VALID CONSENSUS SET COULD BE FOUND THIS OCCURS IF ISDATAVALID AND
ISMODELVALID RETURN FALSE FOR ALL MAXTRIALS RANDOMLY CHOSEN SUBSAMPLES
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE ESTIMATED MODEL
THIS IS A WRAPPER FOR ESTIMATORPREDICTX
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES
RETURNS
YARRAY SHAPE NSAMPLES OR NSAMPLES NTARGETS RETURNS PREDICTED VALUES
SCORESELFXY
RETURNS THE SCORE OF THE PREDICTION
THIS IS A WRAPPER FOR ESTIMATORSCOREX Y
PARAMETERS
XNUMPY ARRAY OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES TRAINING DATA

YARRAY SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
RETURNS
ZFLOAT SCORE OF THE PREDICTION
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELRANSACREGRESSOR
•ROBUST LINEAR MODEL ESTIMATION USING RANSAC
•THEILSEN REGRESSION
•ROBUST LINEAR ESTIMATOR FITTING
62217SKLEARNLINEARMODEL RIDGE
CLASSSKLEARNLINEARMODEL RIDGEALPHA10 FITINTERCEPTTRUE NORMALIZEFALSE
COPYXTRUE MAXITERNONE TOL0001 SOLVER'AUTO'
RANDOMSTATENONE
LINEAR LEAST SQUARES WITH L2 REGULARIZATION
MINIMIZES THE OBJECTIVE FUNCTION
Y XW22 ALPHA W22
THIS MODEL SOLVES A REGRESSION MODEL WHERE THE LOSS FUNCTION IS THE LINEAR LEAST SQUARES FUNCTION AND REGULARIZA
TION IS GIVEN BY THE L2NORM ALSO KNOWN AS RIDGE REGRESSION OR TIKHONOV REGULARIZATION THIS ESTIMATOR HAS
BUILTIN SUPPORT FOR MULTIVARIATE REGRESSION IE WHEN Y IS A 2DARRAY OF SHAPE NSAMPLES NTARGETS
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA FLOAT ARRAYLIKE SHAPE NTARGETS REGULARIZATION STRENGTH MUST BE A POSITIVE FLOAT
REGULARIZATION IMPROVES THE CONDITIONING OF THE PROBLEM AND REDUCES THE VARIANCE OF THE ES
TIMATES LARGER VALUES SPECIFY STRONGER REGULARIZATION ALPHA CORRESPONDS TO C1 IN OTHER
LINEAR MODELS SUCH AS LOGISTICREGRESSION OR LINEARSVC IF AN ARRAY IS PASSED PENALTIES ARE
ASSUMED TO BE SPECIFIC TO THE TARGETS HENCE THEY MUST CORRESPOND IN NUMBER
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN

MAXITER INT OPTIONAL MAXIMUM NUMBER OF ITERATIONS FOR CONJUGATE GRADIENT SOLVER FOR ‘SPARSECG’ AND ‘LSQR’ SOLVERS THE DEFAULT VALUE IS DETERMINED BY SCIPYSPARSELINALG FOR ‘SAG’ SOLVER THE DEFAULT VALUE IS 1000
TOLFLOAT PRECISION OF THE SOLUTION
SOLVER ‘AUTO’ ‘SVD’ ‘CHOLESKY’ ‘LSQR’ ‘SPARSECG’ ‘SAG’ ‘SAGA’ SOLVER TO USE IN THE COM PUTATIONAL ROUTINES
• ‘AUTO’ CHOOSES THE SOLVER AUTOMATICALLY BASED ON THE TYPE OF DATA
• ‘SVD’ USES A SINGULAR VALUE DECOMPOSITION OF X TO COMPUTE THE RIDGE COEFFICIENTS MORE STABLE FOR SINGULAR MATRICES THAN ‘CHOLESKY’
• ‘CHOLESKY’ USES THE STANDARD SCIPYLINALGSOLVE FUNCTION TO OBTAIN A CLOSEDFORM SOLUTION
• ‘SPARSECG’ USES THE CONJUGATE GRADIENT SOLVER AS FOUND IN SCIPYSPARSELINALGCG AS AN ITERATIVE ALGORITHM THIS SOLVER IS MORE APPROPRIATE THAN ‘CHOLESKY’ FOR LARGESCALE DATA POSSIBILITY TO SET TOL ANDMAXITER
• ‘LSQR’ USES THE DEDICATED REGULARIZED LEASTSQUARES ROUTINE SCIPYSPARSELINALGLSQR IT IS THE FASTEST AND USES AN ITERATIVE PROCEDURE
• ‘SAG’ USES A STOCHASTIC AVERAGE GRADIENT DESCENT AND ‘SAGA’ USES ITS IMPROVED UNBIASED VERSION NAMED SAGA BOTH METHODS ALSO USE AN ITERATIVE PROCEDURE AND ARE OFTEN FASTER THAN OTHER SOLVERS WHEN BOTH NSAMPLES AND NFEATURES ARE LARGE NOTE THAT ‘SAG’ AND ‘SAGA’ FAST CONVERGENCE IS ONLY GUARANTEED ON FEATURES WITH APPROXIMATELY THE SAME SCALE YOU CAN PREPROCESS THE DATA WITH A SCALER FROM SKLEARNPREPROCESSING
ALL LAST FIVE SOLVERS SUPPORT BOTH DENSE AND SPARSE DATA HOWEVER ONLY ‘SAG’ AND ‘SPARSECG’ SUPPORTS SPARSE INPUT WHEN FITINTERCEPT IS TRUE
NEW IN VERSION 017 STOCHASTIC AVERAGE GRADIENT DESCENT SOLVER
NEW IN VERSION 019 SAGA SOLVER
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SOLVER ‘SAG’
NEW IN VERSION 017 RANDOMSTATE TO SUPPORT STOCHASTIC AVERAGE GRADIENT
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES OR NTARGETS NFEATURES WEIGHT VECTORS
INTERCEPT FLOAT ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION SET TO 00 IFFITINTERCEPT FALSE
NITER ARRAY OR NONE SHAPE NTARGETS ACTUAL NUMBER OF ITERATIONS FOR EACH TARGET AVAIL ABLE ONLY FOR SAG AND LSQR SOLVERS OTHER SOLVERS WILL RETURN NONE
NEW IN VERSION 017
SEE ALSO
RIDGECLASSIFIER RIDGE CLASSIFIER
RIDGECV RIDGE REGRESSION WITH BUILTIN CROSS VALIDATION
SKLEARNKERNELRIDGEKERNELRIDGE KERNEL RIDGE REGRESSION COMBINES RIDGE REGRESSION WITH THE KERNEL TRICK

EXAMPLES
```
 FROM SKLEARNLINEARMODEL IMPORT RIDGE
 IMPORT NUMPY AS NP
NSAMPLES NFEATURES  10 5
RNG  NPRANDOMRANDOMSTATE0
Y  RNGRANDNNSAMPLES
X  RNGRANDNNSAMPLES NFEATURES
CLF  RIDGEALPHA10
CLFFITX Y
```
RIDGEALPHA10 COPYXTRUE FITINTERCEPTTRUE MAXITERNONE
NORMALIZEFALSE RANDOMSTATENONE SOLVERAUTO TOL0001
METHODS
FITSELF X Y SAMPLEWEIGHT FIT RIDGE REGRESSION MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHA10 FITINTERCEPTTRUE NORMALIZEFALSE COPYXTRUE MAXITERNONE
TOL0001 SOLVER'AUTO' RANDOMSTATENONE
FITSELFXYSAMPLEWEIGHTNONE
FIT RIDGE REGRESSION MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
SAMPLEWEIGHT FLOAT OR NUMPY ARRAY OF SHAPE NSAMPLES INDIVIDUAL WEIGHTS FOR EACH
SAMPLE
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES

RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELRIDGE
•COMPRESSIVE SENSING TOMOGRAPHY RECONSTRUCTION WITH L1 PRIOR LASSO
•PREDICTION LATENCY
•PLOT RIDGE COEFFICIENTS AS A FUNCTION OF THE REGULARIZATION
•ORDINARY LEAST SQUARES AND RIDGE REGRESSION VARIANCE
•PLOT RIDGE COEFFICIENTS AS A FUNCTION OF THE L2 REGULARIZATION
•POLYNOMIAL INTERPOLATION
•HUBERREGRESSOR VS RIDGE ON DATASET WITH STRONG OUTLIERS

62218SKLEARNLINEARMODEL RIDGECLASSIFIER
CLASSSKLEARNLINEARMODEL RIDGECLASSIFIER ALPHA10 FITINTERCEPTTRUE NORMALIZEFALSE
COPYXTRUE MAXITERNONE TOL0001
CLASSWEIGHTNONE SOLVER'AUTO' RAN
DOMSTATENONE
CLASSIFIER USING RIDGE REGRESSION
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA FLOAT REGULARIZATION STRENGTH MUST BE A POSITIVE FLOAT REGULARIZATION IMPROVES THE CON
DITIONING OF THE PROBLEM AND REDUCES THE VARIANCE OF THE ESTIMATES LARGER VALUES SPECIFY
STRONGER REGULARIZATION ALPHA CORRESPONDS TO C1 IN OTHER LINEAR MODELS SUCH AS LOGISTI
CREGRESSION OR LINEARSVC
FITINTERCEPT BOOLEAN WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO
INTERCEPT WILL BE USED IN CALCULATIONS EG DATA IS EXPECTED TO BE ALREADY CENTERED
NORMALIZE BOOLEAN OPTIONAL DEFAULT FALSE THIS PARAMETER IS IGNORED WHEN
FITINTERCEPT IS SET TO FALSE IF TRUE THE REGRESSORS X WILL BE NORMALIZED BE
FORE REGRESSION BY SUBTRACTING THE MEAN AND DIVIDING BY THE L2NORM IF YOU WISH TO
STANDARDIZE PLEASE USE SKLEARNPREPROCESSINGSTANDARDSCALER BEFORE
CALLINGFIT ON AN ESTIMATOR WITH NORMALIZEFALSE
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
MAXITER INT OPTIONAL MAXIMUM NUMBER OF ITERATIONS FOR CONJUGATE GRADIENT SOLVER THE
DEFAULT VALUE IS DETERMINED BY SCIPYSPARSELINALG
TOLFLOAT PRECISION OF THE SOLUTION
CLASSWEIGHT DICT OR 'BALANCED' OPTIONAL WEIGHTS ASSOCIATED WITH CLASSES IN THE FORM
CLASSLABEL WEIGHT IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT ONE
THE "BALANCED" MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP
BINCOUNTY
SOLVER 'AUTO' 'SVD' 'CHOLESKY' 'LSQR' 'SPARSECG' 'SAG' 'SAGA' SOLVER TO USE IN THE COM
PUTATIONAL ROUTINES
• 'AUTO' CHOOSES THE SOLVER AUTOMATICALLY BASED ON THE TYPE OF DATA
• 'SVD' USES A SINGULAR VALUE DECOMPOSITION OF X TO COMPUTE THE RIDGE COEFFICIENTS MORE
STABLE FOR SINGULAR MATRICES THAN 'CHOLESKY'
• 'CHOLESKY' USES THE STANDARD SCIPYLINALGSOLVE FUNCTION TO OBTAIN A CLOSEDFORM SOLUTION
• 'SPARSECG' USES THE CONJUGATE GRADIENT SOLVER AS FOUND IN SCIPYSPARSELINALGCG AS AN
ITERATIVE ALGORITHM THIS SOLVER IS MORE APPROPRIATE THAN 'CHOLESKY' FOR LARGESCALE DATA
POSSIBILITY TO SET TOL ANDMAXITER
• 'LSQR' USES THE DEDICATED REGULARIZED LEASTSQUARES ROUTINE SCIPYSPARSELINALGLSQR IT IS THE
FASTEST AND USES AN ITERATIVE PROCEDURE
• 'SAG' USES A STOCHASTIC AVERAGE GRADIENT DESCENT AND 'SAGA' USES ITS UNBIASED AND MORE
FLEXIBLE VERSION NAMED SAGA BOTH METHODS USE AN ITERATIVE PROCEDURE AND ARE OFTEN
FASTER THAN OTHER SOLVERS WHEN BOTH NSAMPLES AND NFEATURES ARE LARGE NOTE THAT 'SAG'
AND 'SAGA' FAST CONVERGENCE IS ONLY GUARANTEED ON FEATURES WITH APPROXIMATELY THE SAME
SCALE YOU CAN PREPROCESS THE DATA WITH A SCALER FROM SKLEARNPREPROCESSING

NEW IN VERSION 017 STOCHASTIC AVERAGE GRADIENT DESCENT SOLVER
NEW IN VERSION 019 SAGA SOLVER
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM USED WHEN SOLVER 'SAG'
ATTRIBUTES
COEF ARRAY SHAPE 1 NFEATURES OR NCLASSES NFEATURES COEFFICIENT OF THE FEATURES IN THE
DECISION FUNCTION
COEF IS OF SHAPE 1 NFEATURES WHEN THE GIVEN PROBLEM IS BINARY
INTERCEPT FLOAT ARRAY SHAPE NTARGETS INDEPENDENT TERM IN DECISION FUNCTION SET TO 00
IFFITINTERCEPT FALSE
NITER ARRAY OR NONE SHAPE NTARGETS ACTUAL NUMBER OF ITERATIONS FOR EACH TARGET AVAIL
ABLE ONLY FOR SAG AND LSQR SOLVERS OTHER SOLVERS WILL RETURN NONE
SEE ALSO
RIDGE RIDGE REGRESSION
RIDGECLASSIFIERCV RIDGE CLASSIFIER WITH BUILTIN CROSS VALIDATION
NOTES
FOR MULTICLASS CLASSIFICATION NCLASS CLASSIFIERS ARE TRAINED IN A ONEVERSUSALL APPROACH CONCRETELY THIS IS
IMPLEMENTED BY TAKING ADVANTAGE OF THE MULTIVARIATE RESPONSE SUPPORT IN RIDGE
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADBREASTCANCER
 FROM SKLEARNLINEARMODEL IMPORT RIDGECLASSIFIER
X Y  LOADBREASTCANCERRETURNXY TRUE
CLF  RIDGECLASSIFIERFITX Y
CLFSCOREX Y
09595
```
METHODS
DECISIONFUNCTION SELF X PREDICT CONFIDENCE SCORES FOR SAMPLES
FITSELF X Y SAMPLEWEIGHT FIT RIDGE REGRESSION MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASS LABELS FOR SAMPLES IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

INIT SELFALPHA10 FITINTERCEPTTRUE NORMALIZEFALSE COPYXTRUE MAXITERNONE
TOL0001 CLASSWEIGHTNONE SOLVER’AUTO’ RANDOMSTATENONE
DECISIONFUNCTION SELFX
PREDICT CONFIDENCE SCORES FOR SAMPLES
THE CONFIDENCE SCORE FOR A SAMPLE IS THE SIGNED DISTANCE OF THAT SAMPLE TO THE HYPERPLANE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
ARRAY SHAPENSAMPLES IF NCLASSES 2 ELSE NSAMPLES NCLASSES CONFIDENCE
SCORES PER SAMPLE CLASS COMBINATION IN THE BINARY CASE CONFIDENCE SCORE FOR
SELFCLASSES1 WHERE 0 MEANS THIS CLASS WOULD BE PREDICTED
FITSELFXYSAMPLEWEIGHTNONE
FIT RIDGE REGRESSION MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLESNFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES
SAMPLEWEIGHT FLOAT OR NUMPY ARRAY OF SHAPE NSAMPLES SAMPLE WEIGHT
NEW IN VERSION 017 SAMPLEWEIGHT SUPPORT TO CLASSIFIER
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT CLASS LABELS FOR SAMPLES IN X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES PREDICTED CLASS LABEL PER SAMPLE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X

SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELRIDGECLASSIFIER
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
62219SKLEARNLINEARMODEL SGDCLASSIFIER
CLASSSKLEARNLINEARMODEL SGDCLASSIFIER LOSS'HINGE' PENALTY'L2' ALPHA00001
L1RATIO015 FITINTERCEPTTRUE MAXITER1000
TOL0001 SHUFFLETRUE VERBOSE0 EPSILON01
NJOBSNONE RANDOMSTATENONE LEARN
INGRATE'OPTIMAL' ETA000 POWERT05
EARLYSTOPPINGFALSE VALIDATIONFRACTION01
NITERNOCHANGE5 CLASSWEIGHTNONE
WARMSTARTFALSE AVERAGEFALSE
LINEAR CLASSIFIERS SVM LOGISTIC REGRESSION AO WITH SGD TRAINING
THIS ESTIMATOR IMPLEMENTS REGULARIZED LINEAR MODELS WITH STOCHASTIC GRADIENT DESCENT SGD LEARNING THE GRA
DIENT OF THE LOSS IS ESTIMATED EACH SAMPLE AT A TIME AND THE MODEL IS UPDATED ALONG THE WAY WITH A DECREASING
STRENGTH SCHEDULE AKA LEARNING RATE SGD ALLOWS MINIBATCH ONLINEOUTOFCORE LEARNING SEE THE PARTIALFIT
METHOD FOR BEST RESULTS USING THE DEFAULT LEARNING RATE SCHEDULE THE DATA SHOULD HAVE ZERO MEAN AND UNIT
VARIANCE
THIS IMPLEMENTATION WORKS WITH DATA REPRESENTED AS DENSE OR SPARSE ARRAYS OF FLOATING POINT VALUES FOR THE
FEATURES THE MODEL IT FITS CAN BE CONTROLLED WITH THE LOSS PARAMETER BY DEFAULT IT FITS A LINEAR SUPPORT VECTOR
MACHINE SVM
THE REGULARIZER IS A PENALTY ADDED TO THE LOSS FUNCTION THAT SHRINKS MODEL PARAMETERS TOWARDS THE ZERO VECTOR
USING EITHER THE SQUARED EUCLIDEAN NORM L2 OR THE ABSOLUTE NORM L1 OR A COMBINATION OF BOTH ELASTIC NET IF
THE PARAMETER UPDATE CROSSES THE 00 VALUE BECAUSE OF THE REGULARIZER THE UPDATE IS TRUNCATED TO 00 TO ALLOW FOR
LEARNING SPARSE MODELS AND ACHIEVE ONLINE FEATURE SELECTION
READ MORE IN THE USER GUIDE
PARAMETERS
LOSS STR DEFAULT 'HINGE' THE LOSS FUNCTION TO BE USED DEFAULTS TO 'HINGE' WHICH GIVES A LINEAR
SVM
THE POSSIBLE OPTIONS ARE 'HINGE' 'LOG' 'MODIFIEDHUBER' 'SQUAREDHINGE' 'PER
CEPTRON' OR A REGRESSION LOSS 'SQUAREDLOSS' 'HUBER' 'EPSILONINSENSITIVE' OR
'SQUAREDEPSILONINSENSITIVE'

THE ‘LOG’ LOSS GIVES LOGISTIC REGRESSION A PROBABILISTIC CLASSIFIER ‘MODIFIEDHUBER’ IS
ANOTHER SMOOTH LOSS THAT BRINGS TOLERANCE TO OUTLIERS AS WELL AS PROBABILITY ESTIMATES
‘SQUAREDHINGE’ IS LIKE HINGE BUT IS QUADRATICALLY PENALIZED ‘PERCEPTRON’ IS THE LINEAR LOSS
USED BY THE PERCEPTRON ALGORITHM THE OTHER LOSSES ARE DESIGNED FOR REGRESSION BUT CAN BE
USEFUL IN CLASSIFICATION AS WELL SEE SGDREGRESSOR FOR A DESCRIPTION
PENALTY STR ‘NONE’ ‘L2’ ‘L1’ OR ‘ELASTICNET’ THE PENALTY AKA REGULARIZATION TERM TO BE USED
DEFAULTS TO ‘L2’ WHICH IS THE STANDARD REGULARIZER FOR LINEAR SVM MODELS ‘L1’ AND ‘ELASTICNET’
MIGHT BRING SPARSITY TO THE MODEL FEATURE SELECTION NOT ACHIEVABLE WITH ‘L2’
ALPHA FLOAT CONSTANT THAT MULTIPLIES THE REGULARIZATION TERM DEFAULTS TO 00001 ALSO USED TO
COMPUTE LEARNINGRATE WHEN SET TO ‘OPTIMAL’
L1RATIO FLOAT THE ELASTIC NET MIXING PARAMETER WITH 0 L1RATIO 1 L1RATIO0 CORRE
SPONDS TO L2 PENALTY L1RATIO1 TO L1 DEFAULTS TO 015
FITINTERCEPT BOOL WHETHER THE INTERCEPT SHOULD BE ESTIMATED OR NOT IF FALSE THE DATA IS
ASSUMED TO BE ALREADY CENTERED DEFAULTS TO TRUE
MAXITER INT OPTIONAL DEFAULT1000 THE MAXIMUM NUMBER OF PASSES OVER THE TRAINING DATA
AKA EPOCHS IT ONLY IMPACTS THE BEHAVIOR IN THE FIT METHOD AND NOT THE PARTIALFIT
NEW IN VERSION 019
TOLFLOAT OR NONE OPTIONAL DEFAULT1E3 THE STOPPING CRITERION IF IT IS NOT NONE THE ITERA
TIONS WILL STOP WHEN LOSS BESTLOSS TOL FOR NITERNOCHANGE CONSECUTIVE EPOCHS
NEW IN VERSION 019
SHUFFLE BOOL OPTIONAL WHETHER OR NOT THE TRAINING DATA SHOULD BE SHUFFLED AFTER EACH EPOCH
DEFAULTS TO TRUE
VERBOSE INTEGER OPTIONAL THE VERBOSITY LEVEL
EPSILON FLOAT EPSILON IN THE EPSILONINSENSITIVE LOSS FUNCTIONS ONLY IF LOSS IS ‘HUBER’ ‘EP
SILONINSENSITIVE’ OR ‘SQUAREDEPSILONINSENSITIVE’ FOR ‘HUBER’ DETERMINES THE THRESH
OLD AT WHICH IT BECOMES LESS IMPORTANT TO GET THE PREDICTION EXACTLY RIGHT FOR EPSILON
INSENSITIVE ANY DIFFERENCES BETWEEN THE CURRENT PREDICTION AND THE CORRECT LABEL ARE IGNORED
IF THEY ARE LESS THAN THIS THRESHOLD
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF CPUS TO USE TO DO THE OV A ONE
VERSUS ALL FOR MULTICLASS PROBLEMS COMPUTATION NONE MEANS 1 UNLESS IN A JOBLIB
PARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE
DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
LEARNINGRATE STRING OPTIONAL THE LEARNING RATE SCHEDULE
‘CONSTANT’ ETA ETA0
‘OPTIMAL’ DEFAULT ETA 10 ALPHA T T0 WHERE T0 IS CHOSEN BY A HEURISTIC PROPOSED
BY LEON BOTTOU
‘INVSCALING’ ETA ETA0 POWT POWERT
‘ADAPTIVE’ ETA ETA0 AS LONG AS THE TRAINING KEEPS DECREASING EACH TIME
NITERNOCHANGE CONSECUTIVE EPOCHS FAIL TO DECREASE THE TRAINING LOSS BY TOL OR FAIL TO

INCREASE VALIDATION SCORE BY TOL IF EARLYSTOPPING IS TRUE THE CURRENT LEARNING RATE IS DI
VIDED BY 5
ETA0 DOUBLE THE INITIAL LEARNING RATE FOR THE ‘CONSTANT’ ‘INVSCALING’ OR ‘ADAPTIVE’ SCHEDULES
THE DEFAULT VALUE IS 00 AS ETA0 IS NOT USED BY THE DEFAULT SCHEDULE ‘OPTIMAL’
POWERT DOUBLE THE EXPONENT FOR INVERSE SCALING LEARNING RATE DEFAULT 05
EARLYSTOPPING BOOL DEFAULTFALSE WHETHER TO USE EARLY STOPPING TO TERMINATE TRAINING WHEN
VALIDATION SCORE IS NOT IMPROVING IF SET TO TRUE IT WILL AUTOMATICALLY SET ASIDE A STRATIFIED
FRACTION OF TRAINING DATA AS VALIDATION AND TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT
IMPROVING BY AT LEAST TOL FOR NITERNOCHANGE CONSECUTIVE EPOCHS
NEW IN VERSION 020
VALIDATIONFRACTION FLOAT DEFAULT01 THE PROPORTION OF TRAINING DATA TO SET ASIDE AS VALIDATION
SET FOR EARLY STOPPING MUST BE BETWEEN 0 AND 1 ONLY USED IF EARLYSTOPPING IS TRUE
NEW IN VERSION 020
NITERNOCHANGE INT DEFAULT5 NUMBER OF ITERATIONS WITH NO IMPROVEMENT TO WAIT BEFORE
EARLY STOPPING
NEW IN VERSION 020
CLASSWEIGHT DICT CLASSLABEL WEIGHT OR “BALANCED” OR NONE OPTIONAL PRESET FOR THE
CLASSWEIGHT FIT PARAMETER
WEIGHTS ASSOCIATED WITH CLASSES IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT ONE
THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP
BINCOUNTY
WARMSTART BOOL OPTIONAL WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS
INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
REPEATEDLY CALLING FIT OR PARTIALFIT WHEN WARMSTART IS TRUE CAN RESULT IN A DIFFERENT SOLUTION
THAN WHEN CALLING FIT A SINGLE TIME BECAUSE OF THE WAY THE DATA IS SHUFFLED IF A DYNAMIC
LEARNING RATE IS USED THE LEARNING RATE IS ADAPTED DEPENDING ON THE NUMBER OF SAMPLES AL
READY SEEN CALLING FIT RESETS THIS COUNTER WHILE PARTIALFIT WILL RESULT IN INCREASING
THE EXISTING COUNTER
AVERAGE BOOL OR INT OPTIONAL WHEN SET TO TRUE COMPUTES THE AVERAGED SGD WEIGHTS AND
STORES THE RESULT IN THE COEF ATTRIBUTE IF SET TO AN INT GREATER THAN 1 AVERAGING WILL BE
GIN ONCE THE TOTAL NUMBER OF SAMPLES SEEN REACHES AVERAGE SO AVERAGE10 WILL BEGIN
AVERAGING AFTER SEEING 10 SAMPLES
ATTRIBUTES
COEF ARRAY SHAPE 1 NFEATURES IF NCLASSES 2 ELSE NCLASSES NFEATURES WEIGHTS AS
SIGNED TO THE FEATURES
INTERCEPT ARRAY SHAPE 1 IF NCLASSES 2 ELSE NCLASSES CONSTANTS IN DECISION FUNCTION
NITER INT THE ACTUAL NUMBER OF ITERATIONS TO REACH THE STOPPING CRITERION FOR MULTICLASS FITS
IT IS THE MAXIMUM OVER EVERY BINARY FIT
LOSSFUNCTION CONCRETELOSSFUNCTION
SEE ALSO
SKLEARNSVMLINEARSVC LOGISTICREGRESSION PERCEPTRON

SCIKITLEARN USER GUIDE RELEASE 0213
EXAMPLES
IMPORT NUMPY AS NP
FROM SKLEARN IMPORT LINEARMODEL
X NPARRAY1 1 2 1 1 1 2 1
Y NPARRAY1 1 2 2
CLF LINEARMODELSGDCLASSIFIERMAXITER1000 TOL1E3
CLFFITX Y

SGDCLASSIFIERALPHA00001 AVERAGEFALSE CLASSWEIGHTNONE
EARLYSTOPPINGFALSE EPSILON01 ETA000 FITINTERCEPTTRUE
L1RATIO015 LEARNINGRATEOPTIMAL LOSSHINGE MAXITER1000
NITERNOCHANGE5 NJOBSNONE PENALTYL2 POWERT05
RANDOMSTATENONE SHUFFLETRUE TOL0001 VALIDATIONFRACTION01
VERBOSE0 WARMSTARTFALSE
PRINTCLFPREDICT08 1
1
METHODS
DECISIONFUNCTION SELF X PREDICT CONFIDENCE SCORES FOR SAMPLES
DENSIFY SELF CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
FITSELF X Y COEFINIT INTERCEPTINIT FIT LINEAR MODEL WITH STOCHASTIC GRADIENT DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y CLASSES SAMPLEWEIGHT PERFORM ONE EPOCH OF STOCHASTIC GRADIENT DESCENT ON
GIVEN SAMPLES
PREDICT SELF X PREDICT CLASS LABELS FOR SAMPLES IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF ARGS KWARGS
SPARSIFY SELF CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
INIT SELFLOSS'HINGE' PENALTY'L2' ALPHA00001 L1RATIO015 FITINTERCEPTTRUE
MAXITER1000 TOL0001 SHUFFLETRUE VERBOSE0 EPSILON01 NJOBSNONE RAN
DOMSTATENONE LEARNINGRATE'OPTIMAL' ETA000 POWERT05 EARLYSTOPPINGFALSE
VALIDATIONFRACTION01 NITERNOCHANGE5 CLASSWEIGHTNONE WARMSTARTFALSE AV
ERAGEFALSE
DECISIONFUNCTION SELFX
PREDICT CONFIDENCE SCORES FOR SAMPLES
THE CONFIDENCE SCORE FOR A SAMPLE IS THE SIGNED DISTANCE OF THAT SAMPLE TO THE HYPERPLANE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
ARRAY SHAPENSAMPLES IF NCLASSES 2 ELSE NSAMPLES NCLASSES CONFIDENCE
SCORES PER SAMPLE CLASS COMBINATION IN THE BINARY CASE CONFIDENCE SCORE FOR
SELFCLASSES1 WHERE 0 MEANS THIS CLASS WOULD BE PREDICTED

DENSIFYSELF
CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
CONVERTS THE COEF MEMBER BACK TO A NUMPYNDARRAY THIS IS THE DEFAULT FORMAT OF COEF AND IS
REQUIRED FOR FITTING SO CALLING THIS METHOD IS ONLY REQUIRED ON MODELS THAT HAVE PREVIOUSLY BEEN SPARSIFIED
OTHERWISE IT IS A NOOP
RETURNS
SELF ESTIMATOR
FITSELFXYCOEFINITNONE INTERCEPTINITNONE SAMPLEWEIGHTNONE
FIT LINEAR MODEL WITH STOCHASTIC GRADIENT DESCENT
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA
YNUMPY ARRAY SHAPE NSAMPLES TARGET VALUES
COEFINIT ARRAY SHAPE NCLASSES NFEATURES THE INITIAL COEFFICIENTS TO WARMSTART THE OP
TIMIZATION
INTERCEPTINIT ARRAY SHAPE NCLASSES THE INITIAL INTERCEPT TO WARMSTART THE OPTIMIZA
TION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL WEIGHTS APPLIED TO INDIVIDUAL
SAMPLES IF NOT PROVIDED UNIFORM WEIGHTS ARE ASSUMED THESE WEIGHTS WILL BE MULTIPLIED
WITH CLASSWEIGHT PASSED THROUGH THE CONSTRUCTOR IF CLASSWEIGHT IS SPECIFIED
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYCLASSESNONE SAMPLEWEIGHTNONE
PERFORM ONE EPOCH OF STOCHASTIC GRADIENT DESCENT ON GIVEN SAMPLES
INTERNALLY THIS METHOD USES MAXITER 1 THEREFORE IT IS NOT GUARANTEED THAT A MINIMUM OF THE COST
FUNCTION IS REACHED AFTER CALLING IT ONCE MATTERS SUCH AS OBJECTIVE CONVERGENCE AND EARLY STOPPING SHOULD
BE HANDLED BY THE USER
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SUBSET OF THE TRAINING DATA
YNUMPY ARRAY SHAPE NSAMPLES SUBSET OF THE TARGET VALUES
CLASSES ARRAY SHAPE NCLASSES CLASSES ACROSS ALL CALLS TO PARTIALFIT CAN BE OBTAINED BY
VIANPUNIQUEYALL WHERE YALL IS THE TARGET VECTOR OF THE ENTIRE DATASET THIS
ARGUMENT IS REQUIRED FOR THE FIRST CALL TO PARTIALFIT AND CAN BE OMITTED IN THE SUBSEQUENT
CALLS NOTE THAT Y DOESN’T NEED TO CONTAIN ALL LABELS IN CLASSES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL WEIGHTS APPLIED TO INDIVIDUAL
SAMPLES IF NOT PROVIDED UNIFORM WEIGHTS ARE ASSUMED

RETURNS
SELF RETURNS AN INSTANCE OF SELF
PREDICTSELFX
PREDICT CLASS LABELS FOR SAMPLES IN X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES PREDICTED CLASS LABEL PER SAMPLE
PREDICTLOGPROBA
LOG OF PROBABILITY ESTIMATES
THIS METHOD IS ONLY AVAILABLE FOR LOG LOSS AND MODIFIED HUBER LOSS
WHEN LOSS”MODIFIEDHUBER” PROBABILITY ESTIMATES MAY BE HARD ZEROS AND ONES SO TAKING THE LOGARITHM
IS NOT POSSIBLE
SEEPREDICTPROBA FOR DETAILS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
TARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE LOGPROBABILITY OF THE SAMPLE FOR
EACH CLASS IN THE MODEL WHERE CLASSES ARE ORDERED AS THEY ARE IN SELFCLASSES
PREDICTPROBA
PROBABILITY ESTIMATES
THIS METHOD IS ONLY AVAILABLE FOR LOG LOSS AND MODIFIED HUBER LOSS
MULTICLASS PROBABILITY ESTIMATES ARE DERIVED FROM BINARY ONEVSREST ESTIMATES BY SIMPLE NORMALIZATION
AS RECOMMENDED BY ZADROZNY AND ELKAN
BINARY PROBABILITY ESTIMATES FOR LOSS”MODIFIEDHUBER” ARE GIVEN BY CLIPDECISIONFUNCTIONX 1 1
1 2 FOR OTHER LOSS FUNCTIONS IT IS NECESSARY TO PERFORM PROPER PROBABILITY CALIBRATION BY WRAPPING THE
CLASSIFIER WITH SKLEARNCALIBRATIONCALIBRATEDCLASSIFIERCV INSTEAD
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES
RETURNS
ARRAY SHAPE NSAMPLES NCLASSES RETURNS THE PROBABILITY OF THE SAMPLE FOR EACH CLASS IN
THE MODEL WHERE CLASSES ARE ORDERED AS THEY ARE IN SELFCLASSES
REFERENCES
ZADROZNY AND ELKAN “TRANSFORMING CLASSIFIER SCORES INTO MULTICLASS PROBABILITY ESTIMATES” SIGKDD‘02
HTTPWWWRESEARCHIBMCOMPEOPLEZZADROZNYKDD2002TRANSFPDF
THE JUSTIFICATION FOR THE FORMULA IN THE LOSS”MODIFIEDHUBER” CASE IS IN THE APPENDIX B IN HTTPJMLR
CSAILMITEDUPAPERSVOLUME2ZHANG02CZHANG02CPDF

SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SPARSIFY SELF
CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
CONVERTS THE COEF MEMBER TO A SCIPYSPARSE MATRIX WHICH FOR L1REGULARIZED MODELS CAN BE MUCH MORE MEMORY AND STORAGEEFFICIENT THAN THE USUAL NUMPYNDARRAY REPRESENTATION
THEINTERCEPT MEMBER IS NOT CONVERTED
RETURNS
SELF ESTIMATOR
NOTES
FOR NONSPARSE MODELS IE WHEN THERE ARE NOT MANY ZEROS IN COEF THIS MAY ACTUALLY INCREASE MEMORY USAGE SO USE THIS METHOD WITH CARE A RULE OF THUMB IS THAT THE NUMBER OF ZERO ELEMENTS WHICH CAN BE COMPUTED WITH COEF 0SUM MUST BE MORE THAN 50 FOR THIS TO PROVIDE SIGNIFICANT BENEFITS
AFTER CALLING THIS METHOD FURTHER FITTING WITH THE PARTIALFIT METHOD IF ANY WILL NOT WORK UNTIL YOU CALL DENSIFY
EXAMPLES USING SKLEARNLINEARMODELSGDCLASSIFIER
•MODEL COMPLEXITY INFLUENCE
•OUTOFCORE CLASSIFICATION OF TEXT DOCUMENTS
•PIPELINING CHAINING A PCA AND A LOGISTIC REGRESSION
•SGD MAXIMUM MARGIN SEPARATING HYPERPLANE
•SGD WEIGHTED SAMPLES
•COMPARING VARIOUS ONLINE SOLVERS
•PLOT MULTICLASS SGD ON THE IRIS DATASET
•EARLY STOPPING OF STOCHASTIC GRADIENT DESCENT
•SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES

SCIKITLEARN USER GUIDE RELEASE 0213
62220SKLEARNLINEARMODEL SGDREGRESSOR
CLASSSKLEARNLINEARMODEL SGDREGRESSOR LOSS‘SQUAREDLOSS’ PENALTY’L2’ ALPHA00001
L1RATIO015 FITINTERCEPTTRUE MAXITER1000
TOL0001 SHUFFLETRUE VERBOSE0 EPSILON01
RANDOMSTATENONE LEARNINGRATE’INVSCALING’
ETA0001 POWERT025 EARLYSTOPPINGFALSE
VALIDATIONFRACTION01 NITERNOCHANGE5
WARMSTARTFALSE AVERAGEFALSE
LINEAR MODEL FITTED BY MINIMIZING A REGULARIZED EMPIRICAL LOSS WITH SGD
SGD STANDS FOR STOCHASTIC GRADIENT DESCENT THE GRADIENT OF THE LOSS IS ESTIMATED EACH SAMPLE AT A TIME AND THE MODEL IS UPDATED ALONG THE WAY WITH A DECREASING STRENGTH SCHEDULE AKA LEARNING RATE
THE REGULARIZER IS A PENALTY ADDED TO THE LOSS FUNCTION THAT SHRINKS MODEL PARAMETERS TOWARDS THE ZERO VECTOR USING EITHER THE SQUARED EUCLIDEAN NORM L2 OR THE ABSOLUTE NORM L1 OR A COMBINATION OF BOTH ELASTIC NET IF THE PARAMETER UPDATE CROSSES THE 00 VALUE BECAUSE OF THE REGULARIZER THE UPDATE IS TRUNCATED TO 00 TO ALLOW FOR LEARNING SPARSE MODELS AND ACHIEVE ONLINE FEATURE SELECTION
THIS IMPLEMENTATION WORKS WITH DATA REPRESENTED AS DENSE NUMPY ARRAYS OF FLOATING POINT VALUES FOR THE FEATURES
READ MORE IN THE USER GUIDE
PARAMETERS
LOSS STR DEFAULT ‘SQUAREDLOSS’ THE LOSS FUNCTION TO BE USED THE POSSIBLE VALUES ARE ‘SQUAREDLOSS’ ‘HUBER’ ‘EPSILONINSENSITIVE’ OR ‘SQUAREDEPSILONINSENSITIVE’
THE ‘SQUAREDLOSS’ REFERS TO THE ORDINARY LEAST SQUARES FIT ‘HUBER’ MODIFIES ‘SQUAREDLOSS’ TO FOCUS LESS ON GETTING OUTLIERS CORRECT BY SWITCHING FROM SQUARED TO LINEAR LOSS PAST A DISTANCE OF EPSILON ‘EPSILONINSENSITIVE’ IGNORES ERRORS LESS THAN EPSILON AND IS LINEAR PAST THAT THIS IS THE LOSS FUNCTION USED IN SVR ‘SQUAREDEPSILONINSENSITIVE’ IS THE SAME BUT BECOMES SQUARED LOSS PAST A TOLERANCE OF EPSILON
PENALTY STR ‘NONE’ ‘L2’ ‘L1’ OR ‘ELASTICNET’ THE PENALTY AKA REGULARIZATION TERM TO BE USED DEFAULTS TO ‘L2’ WHICH IS THE STANDARD REGULARIZER FOR LINEAR SVM MODELS ‘L1’ AND ‘ELASTICNET’ MIGHT BRING SPARSITY TO THE MODEL FEATURE SELECTION NOT ACHIEVABLE WITH ‘L2’
ALPHA FLOAT CONSTANT THAT MULTIPLIES THE REGULARIZATION TERM DEFAULTS TO 00001 ALSO USED TO COMPUTE LEARNINGRATE WHEN SET TO ‘OPTIMAL’
L1RATIO FLOAT THE ELASTIC NET MIXING PARAMETER WITH 0 L1RATIO 1 L1RATIO0 CORRE SPONDS TO L2 PENALTY L1RATIO1 TO L1 DEFAULTS TO 015
FITINTERCEPT BOOL WHETHER THE INTERCEPT SHOULD BE ESTIMATED OR NOT IF FALSE THE DATA IS ASSUMED TO BE ALREADY CENTERED DEFAULTS TO TRUE
MAXITER INT OPTIONAL DEFAULT1000 THE MAXIMUM NUMBER OF PASSES OVER THE TRAINING DATA AKA EPOCHS IT ONLY IMPACTS THE BEHAVIOR IN THE FIT METHOD AND NOT THE PARTIALFIT
NEW IN VERSION 019
TOLFLOAT OR NONE OPTIONAL DEFAULT1E3 THE STOPPING CRITERION IF IT IS NOT NONE THE ITERA TIONS WILL STOP WHEN LOSS BESTLOSS TOL FOR NITERNOCHANGE CONSECUTIVE EPOCHS
NEW IN VERSION 019
SHUFFLE BOOL OPTIONAL WHETHER OR NOT THE TRAINING DATA SHOULD BE SHUFFLED AFTER EACH EPOCH DEFAULTS TO TRUE
VERBOSE INTEGER OPTIONAL THE VERBOSITY LEVEL

EPSILON FLOAT EPSILON IN THE EPSILONINSENSITIVE LOSS FUNCTIONS ONLY IF LOSS IS ‘HUBER’ ‘EP
SILONINSENSITIVE’ OR ‘SQUAREDEPSILONINSENSITIVE’ FOR ‘HUBER’ DETERMINES THE THRESH
OLD AT WHICH IT BECOMES LESS IMPORTANT TO GET THE PREDICTION EXACTLY RIGHT FOR EPSILON
INSENSITIVE ANY DIFFERENCES BETWEEN THE CURRENT PREDICTION AND THE CORRECT LABEL ARE IGNORED
IF THEY ARE LESS THAN THIS THRESHOLD
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
LEARNINGRATE STRING OPTIONAL THE LEARNING RATE SCHEDULE
‘CONSTANT’ ETA ETA0
‘OPTIMAL’ ETA 10 ALPHA T T0 WHERE T0 IS CHOSEN BY A HEURISTIC PROPOSED BY LEON
BOTTOU
‘INVSCALING’ DEFAULT ETA ETA0 POWT POWERT
‘ADAPTIVE’ ETA ETA0 AS LONG AS THE TRAINING KEEPS DECREASING EACH TIME
NITERNOCHANGE CONSECUTIVE EPOCHS FAIL TO DECREASE THE TRAINING LOSS BY TOL OR FAIL TO
INCREASE VALIDATION SCORE BY TOL IF EARLYSTOPPING IS TRUE THE CURRENT LEARNING RATE IS DI
VIDED BY 5
ETA0 DOUBLE THE INITIAL LEARNING RATE FOR THE ‘CONSTANT’ ‘INVSCALING’ OR ‘ADAPTIVE’ SCHEDULES
THE DEFAULT VALUE IS 001
POWERT DOUBLE THE EXPONENT FOR INVERSE SCALING LEARNING RATE DEFAULT 05
EARLYSTOPPING BOOL DEFAULTFALSE WHETHER TO USE EARLY STOPPING TO TERMINATE TRAINING WHEN
VALIDATION SCORE IS NOT IMPROVING IF SET TO TRUE IT WILL AUTOMATICALLY SET ASIDE A FRACTION OF
TRAINING DATA AS VALIDATION AND TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT IMPROVING BY
AT LEAST TOL FOR NITERNOCHANGE CONSECUTIVE EPOCHS
NEW IN VERSION 020
VALIDATIONFRACTION FLOAT DEFAULT01 THE PROPORTION OF TRAINING DATA TO SET ASIDE AS VALIDATION
SET FOR EARLY STOPPING MUST BE BETWEEN 0 AND 1 ONLY USED IF EARLYSTOPPING IS TRUE
NEW IN VERSION 020
NITERNOCHANGE INT DEFAULT5 NUMBER OF ITERATIONS WITH NO IMPROVEMENT TO WAIT BEFORE
EARLY STOPPING
NEW IN VERSION 020
WARMSTART BOOL OPTIONAL WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS
INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
REPEATEDLY CALLING FIT OR PARTIALFIT WHEN WARMSTART IS TRUE CAN RESULT IN A DIFFERENT SOLUTION
THAN WHEN CALLING FIT A SINGLE TIME BECAUSE OF THE WAY THE DATA IS SHUFFLED IF A DYNAMIC
LEARNING RATE IS USED THE LEARNING RATE IS ADAPTED DEPENDING ON THE NUMBER OF SAMPLES AL
READY SEEN CALLING FIT RESETS THIS COUNTER WHILE PARTIALFIT WILL RESULT IN INCREASING
THE EXISTING COUNTER
AVERAGE BOOL OR INT OPTIONAL WHEN SET TO TRUE COMPUTES THE AVERAGED SGD WEIGHTS AND
STORES THE RESULT IN THE COEF ATTRIBUTE IF SET TO AN INT GREATER THAN 1 AVERAGING WILL BE
GIN ONCE THE TOTAL NUMBER OF SAMPLES SEEN REACHES AVERAGE SO AVERAGE10 WILL BEGIN
AVERAGING AFTER SEEING 10 SAMPLES
ATTRIBUTES

COEF ARRAY SHAPE NFEATURES WEIGHTS ASSIGNED TO THE FEATURES
INTERCEPT ARRAY SHAPE 1 THE INTERCEPT TERM
AVERAGECOEF ARRAY SHAPE NFEATURES AVERAGED WEIGHTS ASSIGNED TO THE FEATURES
AVERAGEINTERCEPT ARRAY SHAPE 1 THE AVERAGED INTERCEPT TERM
NITER INT THE ACTUAL NUMBER OF ITERATIONS TO REACH THE STOPPING CRITERION
SEE ALSO
RIDGE ELASTICNET LASSO SKLEARNSVMSVR
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT LINEARMODEL
NSAMPLES NFEATURES  10 5
RNG  NPRANDOMRANDOMSTATE0
Y  RNGRANDNNSAMPLES
X  RNGRANDNNSAMPLES NFEATURES
CLF  LINEARMODELSGDREGRESSORMAXITER1000 TOL1E3
CLFFITX Y

SGDREGRESSORALPHA00001 AVERAGEFALSE EARLYSTOPPINGFALSE
EPSILON01 ETA0001 FITINTERCEPTTRUE L1RATIO015
LEARNINGRATEINVSCALING LOSSSQUAREDLOSS MAXITER1000
NITERNOCHANGE5 PENALTYL2 POWERT025 RANDOMSTATENONE
SHUFFLETRUE TOL0001 VALIDATIONFRACTION01 VERBOSE0
WARMSTARTFALSE
```
METHODS
DENSIFY SELF CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
FITSELF X Y COEFINIT INTERCEPTINIT FIT LINEAR MODEL WITH STOCHASTIC GRADIENT DESCENT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y SAMPLEWEIGHT PERFORM ONE EPOCH OF STOCHASTIC GRADIENT DESCENT ON
GIVEN SAMPLES
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF ARGS KWARGS
SPARSIFY SELF CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
INIT SELFLOSS'SQUAREDLOSS' PENALTY'L2' ALPHA00001 L1RATIO015 FITINTERCEPTTRUE
MAXITER1000 TOL0001 SHUFFLETRUE VERBOSE0 EPSILON01 RANDOMSTATENONE
LEARNINGRATE'INVSCALING' ETA0001 POWERT025 EARLYSTOPPINGFALSE VALIDA
TIONFRACTION01 NITERNOCHANGE5 WARMSTARTFALSE AVERAGEFALSE
DENSIFYSELF
CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
CONVERTS THE COEF MEMBER BACK TO A NUMPYNDARRAY THIS IS THE DEFAULT FORMAT OF COEF AND IS
REQUIRED FOR FITTING SO CALLING THIS METHOD IS ONLY REQUIRED ON MODELS THAT HAVE PREVIOUSLY BEEN SPARSIFIED
```
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OTHERWISE IT IS A NOOP
RETURNS
SELF ESTIMATOR
FITSELFXYCOEFINITNONE INTERCEPTINITNONE SAMPLEWEIGHTNONE
FIT LINEAR MODEL WITH STOCHASTIC GRADIENT DESCENT
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA
YNUMPY ARRAY SHAPE NSAMPLES TARGET VALUES
COEFINIT ARRAY SHAPE NFEATURES THE INITIAL COEFFICIENTS TO WARMSTART THE OPTIMIZATION
INTERCEPTINIT ARRAY SHAPE 1 THE INITIAL INTERCEPT TO WARMSTART THE OPTIMIZATION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL WEIGHTS APPLIED TO INDIVIDUAL
SAMPLES 1 FOR UNWEIGHTED
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYSAMPLEWEIGHTNONE
PERFORM ONE EPOCH OF STOCHASTIC GRADIENT DESCENT ON GIVEN SAMPLES
INTERNALLY THIS METHOD USES MAXITER 1 THEREFORE IT IS NOT GUARANTEED THAT A MINIMUM OF THE COST
FUNCTION IS REACHED AFTER CALLING IT ONCE MATTERS SUCH AS OBJECTIVE CONVERGENCE AND EARLY STOPPING SHOULD
BE HANDLED BY THE USER
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SUBSET OF TRAINING DATA
YNUMPY ARRAY OF SHAPE NSAMPLES SUBSET OF TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL WEIGHTS APPLIED TO INDIVIDUAL
SAMPLES IF NOT PROVIDED UNIFORM WEIGHTS ARE ASSUMED
RETURNS
SELF RETURNS AN INSTANCE OF SELF
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES
RETURNS
ARRAY SHAPE NSAMPLES PREDICTED TARGET VALUES PER ELEMENT IN X

SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SPARSIFY SELF
CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
CONVERTS THE COEF MEMBER TO A SCIPYSPARSE MATRIX WHICH FOR L1REGULARIZED MODELS CAN BE MUCH MORE
MEMORY AND STORAGEEFFICIENT THAN THE USUAL NUMPYNDARRAY REPRESENTATION
THEINTERCEPT MEMBER IS NOT CONVERTED
RETURNS
SELF ESTIMATOR
NOTES
FOR NONSPARSE MODELS IE WHEN THERE ARE NOT MANY ZEROS IN COEF THIS MAY ACTUALLY INCREASE MEMORY
USAGE SO USE THIS METHOD WITH CARE A RULE OF THUMB IS THAT THE NUMBER OF ZERO ELEMENTS WHICH CAN BE
COMPUTED WITH COEF 0SUM MUST BE MORE THAN 50 FOR THIS TO PROVIDE SIGNIFICANT BENEFITS
AFTER CALLING THIS METHOD FURTHER FITTING WITH THE PARTIALFIT METHOD IF ANY WILL NOT WORK UNTIL YOU CALL
DENSIFY
EXAMPLES USING SKLEARNLINEARMODELSGDREGRESSOR
•PREDICTION LATENCY

62221SKLEARNLINEARMODEL THEILSENREGRESSOR
CLASSSKLEARNLINEARMODEL THEILSENREGRESSOR FITINTERCEPTTRUE COPYXTRUE
MAXSUBPOPULATION100000
NSUBSAMPLESNONE MAXITER300
TOL0001 RANDOMSTATENONE
NJOBSNONE VERBOSEFALSE
THEILSEN ESTIMATOR ROBUST MULTIVARIATE REGRESSION MODEL
THE ALGORITHM CALCULATES LEAST SQUARE SOLUTIONS ON SUBSETS WITH SIZE NSUBSAMPLES OF THE SAMPLES IN X ANY VALUE OF NSUBSAMPLES BETWEEN THE NUMBER OF FEATURES AND SAMPLES LEADS TO AN ESTIMATOR WITH A COMPROMISE BETWEEN ROBUSTNESS AND EFFICIENCY SINCE THE NUMBER OF LEAST SQUARE SOLUTIONS IS “NSAMPLES CHOOSE NSUBSAMPLES” IT CAN BE EXTREMELY LARGE AND CAN THEREFORE BE LIMITED WITH MAXSUBPOPULATION IF THIS LIMIT IS REACHED THE SUBSETS ARE CHOSEN RANDOMLY IN A FINAL STEP THE SPATIAL MEDIAN OR L1 MEDIAN IS CALCULATED OF ALL LEAST SQUARE SOLUTIONS
READ MORE IN THE USER GUIDE
PARAMETERS
FITINTERCEPT BOOLEAN OPTIONAL DEFAULT TRUE WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO INTERCEPT WILL BE USED IN CALCULATIONS
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
MAXSUBPOPULATION INT OPTIONAL DEFAULT 1E4 INSTEAD OF COMPUTING WITH A SET OF CARDINALITY ‘N CHOOSE K’ WHERE N IS THE NUMBER OF SAMPLES AND K IS THE NUMBER OF SUBSAMPLES AT LEAST NUMBER OF FEATURES CONSIDER ONLY A STOCHASTIC SUBPOPULATION OF A GIVEN MAXIMAL SIZE IF ‘N CHOOSE K’ IS LARGER THAN MAXSUBPOPULATION FOR OTHER THAN SMALL PROBLEM SIZES THIS PARAMETER WILL DETERMINE MEMORY USAGE AND RUNTIME IF NSUBSAMPLES IS NOT CHANGED
NSUBSAMPLES INT OPTIONAL DEFAULT NONE NUMBER OF SAMPLES TO CALCULATE THE PARAMETERS THIS IS AT LEAST THE NUMBER OF FEATURES PLUS 1 IF FITINTERCEPTTRUE AND THE NUMBER OF SAM PLES AS A MAXIMUM A LOWER NUMBER LEADS TO A HIGHER BREAKDOWN POINT AND A LOW EFFICIENCY WHILE A HIGH NUMBER LEADS TO A LOW BREAKDOWN POINT AND A HIGH EFFICIENCY IF NONE TAKE THE MINIMUM NUMBER OF SUBSAMPLES LEADING TO MAXIMAL ROBUSTNESS IF NSUBSAMPLES IS SET TO NSAMPLES THEILSEN IS IDENTICAL TO LEAST SQUARES
MAXITER INT OPTIONAL DEFAULT 300 MAXIMUM NUMBER OF ITERATIONS FOR THE CALCULATION OF SPA TIAL MEDIAN
TOLFLOAT OPTIONAL DEFAULT 1E3 TOLERANCE WHEN CALCULATING SPATIAL MEDIAN
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE A RANDOM NUMBER GENERATOR INSTANCE TO DEFINE THE STATE OF THE RANDOM PERMUTATIONS GENERATOR IF INT RAN DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RAN DOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF CPUS TO USE DURING THE CROSS VALIDA TIONNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
VERBOSE BOOLEAN OPTIONAL DEFAULT FALSE VERBOSE MODE WHEN FITTING THE MODEL
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES COEFFICIENTS OF THE REGRESSION MODEL MEDIAN OF DISTRIBUTION
INTERCEPT FLOAT ESTIMATED INTERCEPT OF REGRESSION MODEL
BREAKDOWN FLOAT APPROXIMATED BREAKDOWN POINT
NITER INT NUMBER OF ITERATIONS NEEDED FOR THE SPATIAL MEDIAN

SCIKITLEARN USER GUIDE RELEASE 0213
NSUBPOPULATION INT NUMBER OF COMBINATIONS TAKEN INTO ACCOUNT FROM ‘N CHOOSE K’ WHERE
N IS THE NUMBER OF SAMPLES AND K IS THE NUMBER OF SUBSAMPLES
REFERENCES
• THEILSEN ESTIMATORS IN A MULTIPLE LINEAR REGRESSION MODEL 2009 XIN DANG HANXIANG PENG XUEQIN
WANG AND HEPING ZHANG HTTPHOMEOLEMISSEDUXDANGPAPERSMTSEPDF
EXAMPLES
FROM SKLEARNLINEARMODEL IMPORT THEILSENREGRESSOR
FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y MAKEREGRESSION
NSAMPLES200 NFEATURES2 NOISE40 RANDOMSTATE0
REG THEILSENREGRESSORRANDOMSTATE0FITX Y
REGSCOREX Y
09884
REGPREDICTX1
ARRAY315871
METHODS
FITSELF X Y FIT LINEAR MODEL
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFFITINTERCEPTTRUE COPYXTRUE MAXSUBPOPULATION100000 NSUBSAMPLESNONE
MAXITER300 TOL0001 RANDOMSTATENONE NJOBSNONE VERBOSEFALSE
FITSELFXY
FIT LINEAR MODEL
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING DATA
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS

PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNLINEARMODELTHEILSENREGRESSOR
•THEILSEN REGRESSION
•ROBUST LINEAR ESTIMATOR FITTING

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LINEARMODELENETPATH X Y L1RATIO COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
LINEARMODELLARSPATH X Y XY GRAM COMPUTE LEAST ANGLE REGRESSION OR LASSO PATH USING
LARS ALGORITHM 1
LINEARMODELLARSPATHGRAM XY GRAM
NSAMPLESLARSPATH IN THE SUFFICIENT STATS MODE 1
LINEARMODELLASSOPATH X Y EPS COMPUTE LASSO PATH WITH COORDINATE DESCENT
LINEARMODELORTHOGONALMP X Y ORTHOGONAL MATCHING PURSUIT OMP
LINEARMODELORTHOGONALMPGRAM GRAM XY
  GRAM ORTHOGONAL MATCHING PURSUIT OMP
LINEARMODELRIDGEREGRESSION X Y ALPHA
  SOLVE THE RIDGE EQUATION BY THE METHOD OF NORMAL EQUA
TIONS
62222SKLEARNLINEARMODEL ENETPATH
SKLEARNLINEARMODEL ENETPATH XYL1RATIO05 EPS0001 NALPHAS100 ALPHASNONE
PRECOMPUTE’AUTO’ XYNONE COPYXTRUE COEFINITNONE
VERBOSEFALSE RETURNNITERFALSE POSITIVEFALSE
CHECKINPUTTRUE PARAMS
COMPUTE ELASTIC NET PATH WITH COORDINATE DESCENT
THE ELASTIC NET OPTIMIZATION FUNCTION VARIES FOR MONO AND MULTIOUTPUTS
FOR MONOOUTPUT TASKS IT IS
1 2NSAMPLES Y XW22
 ALPHA L1RATIO W1
 05ALPHA1 L1RATIO W22
FOR MULTIOUTPUT TASKS IT IS
1 2 NSAMPLES Y XWFRO2
 ALPHA L1RATIO W21
 05ALPHA1 L1RATIO WFRO2
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS FORTRAN
CONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF YIS MONOOUTPUT THEN XCAN
BE SPARSE
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
L1RATIO FLOAT OPTIONAL FLOAT BETWEEN 0 AND 1 PASSED TO ELASTIC NET SCALING BETWEEN L1 AND L2
PENALTIESL1RATIO1 CORRESPONDS TO THE LASSO
EPS FLOAT LENGTH OF THE PATH EPS1E3 MEANS THAT ALPHAMIN ALPHAMAX
1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH

ALPHAS NDARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE SET AUTOMATICALLY
PRECOMPUTE TRUE FALSE 'AUTO' ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE PASSED AS ARGUMENT
XYARRAYLIKE OPTIONAL XY NPDOTXT Y THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY WHEN THE GRAM MATRIX IS PRECOMPUTED
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
COEFINIT ARRAY SHAPE NFEATURES NONE THE INITIAL VALUES OF THE COEFFICIENTS
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
RETURNNITER BOOL WHETHER TO RETURN THE NUMBER OF ITERATIONS OR NOT
POSITIVE BOOL DEFAULT FALSE IF SET TO TRUE FORCES COEFFICIENTS TO BE POSITIVE ONLY ALLOWED WHENYNDIM 1
CHECKINPUT BOOL DEFAULT TRUE SKIP INPUT VALIDATION CHECKS INCLUDING THE GRAM MATRIX WHEN PROVIDED ASSUMING THERE ARE HANDLED BY THE CALLER WHEN CHECKINPUTFALSE
PARAMS KWARGS KEYWORD ARGUMENTS PASSED TO THE COORDINATE DESCENT SOLVER
RETURNS
ALPHAS ARRAY SHAPE NALPHAS THE ALPHAS ALONG THE PATH WHERE MODELS ARE COMPUTED
COEFS ARRAY SHAPE NFEATURES NALPHAS OR NOUTPUTS NFEATURES NALPHAS COEFFICIENTS ALONG THE PATH
DUALGAPS ARRAY SHAPE NALPHAS THE DUAL GAPS AT THE END OF THE OPTIMIZATION FOR EACH ALPHA
NITERS ARRAYLIKE SHAPE NALPHAS THE NUMBER OF ITERATIONS TAKEN BY THE COORDINATE DESCENT OPTIMIZER TO REACH THE SPECIFIED TOLERANCE FOR EACH ALPHA IS RETURNED WHEN RETURNNITER IS SET TO TRUE
SEE ALSO
MULTITASKELASTICNET
MULTITASKELASTICNETCV
ELASTICNET
ELASTICNETCV
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOCOORDINATEDESCENTPATHPY
EXAMPLES USING SKLEARNLINEARMODELENETPATH
•LASSO AND ELASTIC NET

SCIKITLEARN USER GUIDE RELEASE 0213
62223SKLEARNLINEARMODEL LARSPATH
SKLEARNLINEARMODEL LARSPATH XYXYNONE GRAMNONE MAXITER500 ALPHAMIN0
METHOD'LAR' COPYXTRUE EPS2220446049250313E
16COPYGRAMTRUE VERBOSE0 RETURNPATHTRUE RE
TURNNITERFALSE POSITIVEFALSE
COMPUTE LEAST ANGLE REGRESSION OR LASSO PATH USING LARS ALGORITHM 1
THE OPTIMIZATION OBJECTIVE FOR THE CASE METHOD'LASSO' IS
1 2 NSAMPLES Y XW22 ALPHA W1
IN THE CASE OF METHOD'LARS' THE OBJECTIVE FUNCTION IS ONLY KNOWN IN THE FORM OF AN IMPLICIT EQUATION SEE
DISCUSSION IN 1
READ MORE IN THE USER GUIDE
PARAMETERS
XNONE OR ARRAY SHAPE NSAMPLES NFEATURES INPUT DATA NOTE THAT IF X IS NONE THEN THE
GRAM MATRIX MUST BE SPECIFIED IE CANNOT BE NONE OR FALSE
DEPRECATED SINCE VERSION 021 THE USE OF XISNONE IN COMBINATION WITH GRAM IS NOT
NONE WILL BE REMOVED IN V023 USE LARSPATHGRAM INSTEAD
YNONE OR ARRAY SHAPE NSAMPLES INPUT TARGETS
XYARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS OPTIONAL XY NPDOTXT Y THAT
CAN BE PRECOMPUTED IT IS USEFUL ONLY WHEN THE GRAM MATRIX IS PRECOMPUTED
GRAM NONE 'AUTO' ARRAY SHAPE NFEATURES NFEATURES OPTIONAL PRECOMPUTED GRAM MATRIX
X' X IF AUTO THE GRAM MATRIX IS PRECOMPUTED FROM THE GIVEN X IF THERE ARE MORE
SAMPLES THAN FEATURES
DEPRECATED SINCE VERSION 021 THE USE OF XISNONE IN COMBINATION WITH GRAM IS NOT NONE
WILL BE REMOVED IN V023 USE LARSPATHGRAM INSTEAD
MAXITER INTEGER OPTIONAL DEFAULT500 MAXIMUM NUMBER OF ITERATIONS TO PERFORM SET TO
INFINITY FOR NO LIMIT
ALPHAMIN FLOAT OPTIONAL DEFAULT0 MINIMUM CORRELATION ALONG THE PATH IT CORRESPONDS TO
THE REGULARIZATION PARAMETER ALPHA PARAMETER IN THE LASSO
METHOD 'LAR' 'LASSO' OPTIONAL DEFAULT'LAR' SPECIFIES THE RETURNED MODEL SELECT LAR
FOR LEAST ANGLE REGRESSION LASSO FOR THE LASSO
COPYX BOOL OPTIONAL DEFAULTTRUE IF FALSE XIS OVERWRITTEN
EPS FLOAT OPTIONAL DEFAULT''NPFINFONPFLOATEPS'' THE MACHINEPRECISION REGULARIZATION IN
THE COMPUTATION OF THE CHOLESKY DIAGONAL FACTORS INCREASE THIS FOR VERY ILLCONDITIONED
SYSTEMS
COPYGRAM BOOL OPTIONAL DEFAULTTRUE IF FALSE GRAM IS OVERWRITTEN
VERBOSE INT DEFAULT0 CONTROLS OUTPUT VERBOSITY
RETURNPATH BOOL OPTIONAL DEFAULTTRUE IF RETURNPATHTRUE RETURNS THE ENTIRE PATH
ELSE RETURNS ONLY THE LAST POINT OF THE PATH
RETURNNITER BOOL OPTIONAL DEFAULTFALSE WHETHER TO RETURN THE NUMBER OF ITERATIONS
POSITIVE BOOLEAN DEFAULTFALSE RESTRICT COEFFICIENTS TO BE 0 THIS OPTION IS ONLY ALLOWED
WITH METHOD 'LASSO' NOTE THAT THE MODEL COEFFICIENTS WILL NOT CONVERGE TO THE ORDINARY
LEASTSQUARES SOLUTION FOR SMALL VALUES OF ALPHA ONLY COEFFICIENTS UP TO THE SMALLEST ALPHA

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VALUE ALPHASALPHAS 0MIN WHEN FITPATHTRUE REACHED BY THE STEP
WISE LARSLASSO ALGORITHM ARE TYPICALLY IN CONGRUENCE WITH THE SOLUTION OF THE COORDINATE
DESCENT LASSOPATH FUNCTION
RETURNS
ALPHAS ARRAY SHAPE NALPHAS 1 MAXIMUM OF COVARIANCES IN ABSOLUTE VALUE AT EACH ITER
ATIONNALPHAS IS EITHERMAXITER NFEATURES OR THE NUMBER OF NODES IN THE PATH
WITHALPHA ALPHAMIN WHICHEVER IS SMALLER
ACTIVE ARRAY SHAPE NALPHAS INDICES OF ACTIVE VARIABLES AT THE END OF THE PATH
COEFS ARRAY SHAPE NFEATURES NALPHAS 1 COEFFICIENTS ALONG THE PATH
NITER INT NUMBER OF ITERATIONS RUN RETURNED ONLY IF RETURNNITER IS SET TO TRUE
SEE ALSO
LARSPATHGRAM
LASSOPATH
LASSOPATHGRAM
LASSOLARS
LARS
LASSOLARSCV
LARSCV
SKLEARNDECOMPOSITIONSPARSEENCODE
REFERENCES
123
EXAMPLES USING SKLEARNLINEARMODELLARSPATH
•LASSO PATH USING LARS
62224SKLEARNLINEARMODEL LARSPATHGRAM
SKLEARNLINEARMODEL LARSPATHGRAM XY GRAM NSAMPLES MAXITER500 AL
PHAMIN0 METHOD'LAR' COPYXTRUE
EPS2220446049250313E16 COPYGRAMTRUE
VERBOSE0 RETURNPATHTRUE RETURNNITERFALSE
POSITIVEFALSE
LARSPATH IN THE SUFFICIENT STATS MODE 1
THE OPTIMIZATION OBJECTIVE FOR THE CASE METHOD'LASSO' IS
1 2 NSAMPLES Y XW22 ALPHA W1
IN THE CASE OF METHOD'LARS' THE OBJECTIVE FUNCTION IS ONLY KNOWN IN THE FORM OF AN IMPLICIT EQUATION SEE
DISCUSSION IN 1
READ MORE IN THE USER GUIDE
622SKLEARNLINEARMODEL GENERALIZED LINEAR MODELS 1957

SCIKITLEARN USER GUIDE RELEASE 0213
PARAMETERS
XYARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS XY NPDOTXT Y
GRAM ARRAY SHAPE NFEATURES NFEATURES GRAM NPDOTXT X
NSAMPLES INTEGER OR FLOAT EQUIVALENT SIZE OF SAMPLE
MAXITER INTEGER OPTIONAL DEFAULT500 MAXIMUM NUMBER OF ITERATIONS TO PERFORM SET TO INFINITY FOR NO LIMIT
ALPHAMIN FLOAT OPTIONAL DEFAULT0 MINIMUM CORRELATION ALONG THE PATH IT CORRESPONDS TO THE REGULARIZATION PARAMETER ALPHA PARAMETER IN THE LASSO
METHOD 'LAR' 'LASSO' OPTIONAL DEFAULT'LAR' SPECIFIES THE RETURNED MODEL SELECT LAR FOR LEAST ANGLE REGRESSION LASSO FOR THE LASSO
COPYX BOOL OPTIONAL DEFAULTTRUE IF FALSE XIS OVERWRITTEN
EPS FLOAT OPTIONAL DEFAULT''NPFINFONPFLOATEPS'' THE MACHINEPRECISION REGULARIZATION IN THE COMPUTATION OF THE CHOLESKY DIAGONAL FACTORS INCREASE THIS FOR VERY ILLCONDITIONED SYSTEMS
COPYGRAM BOOL OPTIONAL DEFAULTTRUE IF FALSE GRAM IS OVERWRITTEN
VERBOSE INT DEFAULT0 CONTROLS OUTPUT VERBOSITY
RETURNPATH BOOL OPTIONAL DEFAULTTRUE IF RETURNPATHTRUE RETURNS THE ENTIRE PATH ELSE RETURNS ONLY THE LAST POINT OF THE PATH
RETURNNITER BOOL OPTIONAL DEFAULTFALSE WHETHER TO RETURN THE NUMBER OF ITERATIONS
POSITIVE BOOLEAN DEFAULTFALSE RESTRICT COEFFICIENTS TO BE 0 THIS OPTION IS ONLY ALLOWED WITH METHOD 'LASSO' NOTE THAT THE MODEL COEFFICIENTS WILL NOT CONVERGE TO THE ORDINARY LEASTSQUARES SOLUTION FOR SMALL VALUES OF ALPHA ONLY COEFFICIENTS UP TO THE SMALLEST ALPHA VALUE ALPHASALPHAS 0MIN WHEN FITPATHTRUE REACHED BY THE STEP WISE LARSLASSO ALGORITHM ARE TYPICALLY IN CONGRUENCE WITH THE SOLUTION OF THE COORDINATE DESCENT LASSOPATH FUNCTION
RETURNS
ALPHAS ARRAY SHAPE NALPHAS 1 MAXIMUM OF COVARIANCES IN ABSOLUTE VALUE AT EACH ITERATIONNALPHAS IS EITHERMAXITER NFEATURES OR THE NUMBER OF NODES IN THE PATH WITHALPHA ALPHAMIN WHICHEVER IS SMALLER
ACTIVE ARRAY SHAPE NALPHAS INDICES OF ACTIVE VARIABLES AT THE END OF THE PATH
COEFS ARRAY SHAPE NFEATURES NALPHAS 1 COEFFICIENTS ALONG THE PATH
NITER INT NUMBER OF ITERATIONS RUN RETURNED ONLY IF RETURNNITER IS SET TO TRUE
SEE ALSO
LARSPATH
LASSOPATH
LASSOPATHGRAM
LASSOLARS
LARS
LASSOLARSCV
LARSCV

SKLEARNDECOMPOSITIONSPARSEENCODE
REFERENCES
123
62225SKLEARNLINEARMODEL LASSOPATH
SKLEARNLINEARMODEL LASSOPATH XYEPS0001 NALPHAS100 ALPHASNONE PRECOM
PUTE'AUTO' XYNONE COPYXTRUE COEFINITNONE VER
BOSEFALSE RETURNNITERFALSE POSITIVEFALSE PARAMS
COMPUTE LASSO PATH WITH COORDINATE DESCENT
THE LASSO OPTIMIZATION FUNCTION VARIES FOR MONO AND MULTIOUTPUTS
FOR MONOOUTPUT TASKS IT IS
1 2 NSAMPLES Y XW22 ALPHA W1
FOR MULTIOUTPUT TASKS IT IS
1 2 NSAMPLES Y XW2FRO ALPHA W21
WHERE
W21 SUMI SQRTSUMJ WIJ2
IE THE SUM OF NORM OF EACH ROW
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA PASS DIRECTLY AS
FORTRANCONTIGUOUS DATA TO AVOID UNNECESSARY MEMORY DUPLICATION IF YIS MONOOUTPUT THEN
XCAN BE SPARSE
YNDARRAY SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
EPS FLOAT OPTIONAL LENGTH OF THE PATH EPS1E3 MEANS THATALPHAMIN ALPHAMAX
 1E3
NALPHAS INT OPTIONAL NUMBER OF ALPHAS ALONG THE REGULARIZATION PATH
ALPHAS NDARRAY OPTIONAL LIST OF ALPHAS WHERE TO COMPUTE THE MODELS IF NONE ALPHAS ARE SET
AUTOMATICALLY
PRECOMPUTE TRUE FALSE 'AUTO' ARRAYLIKE WHETHER TO USE A PRECOMPUTED GRAM MATRIX TO
SPEED UP CALCULATIONS IF SET TO AUTO LET US DECIDE THE GRAM MATRIX CAN ALSO BE PASSED
AS ARGUMENT
XYARRAYLIKE OPTIONAL XY NPDOTXT Y THAT CAN BE PRECOMPUTED IT IS USEFUL ONLY WHEN
THE GRAM MATRIX IS PRECOMPUTED
COPYX BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE X WILL BE COPIED ELSE IT MAY BE OVERWRITTEN
COEFINIT ARRAY SHAPE NFEATURES   NONE THE INITIAL VALUES OF THE COEFFICIENTS
VERBOSE BOOL OR INTEGER AMOUNT OF VERBOSITY
RETURNNITER BOOL WHETHER TO RETURN THE NUMBER OF ITERATIONS OR NOT

POSITIVE BOOL DEFAULT FALSE IF SET TO TRUE FORCES COEFFICIENTS TO BE POSITIVE ONLY ALLOWED
WHENYNDIM 1
PARAMS KWARGS KEYWORD ARGUMENTS PASSED TO THE COORDINATE DESCENT SOLVER
RETURNS
ALPHAS ARRAY SHAPE NALPHAS THE ALPHAS ALONG THE PATH WHERE MODELS ARE COMPUTED
COEFS ARRAY SHAPE NFEATURES NALPHAS OR NOUTPUTS NFEATURES NALPHAS COEFFICIENTS
ALONG THE PATH
DUALGAPS ARRAY SHAPE NALPHAS THE DUAL GAPS AT THE END OF THE OPTIMIZATION FOR EACH
ALPHA
NITERS ARRAYLIKE SHAPE NALPHAS THE NUMBER OF ITERATIONS TAKEN BY THE COORDINATE DESCENT
OPTIMIZER TO REACH THE SPECIFIED TOLERANCE FOR EACH ALPHA
SEE ALSO
LARSPATH
LASSO
LASSOLARS
LASSOCV
LASSOLARSCV
SKLEARNDECOMPOSITIONSPARSEENCODE
NOTES
FOR AN EXAMPLE SEE EXAMPLESLINEARMODELPLOTLASSOCOORDINATEDESCENTPATHPY
TO AVOID UNNECESSARY MEMORY DUPLICATION THE X ARGUMENT OF THE FIT METHOD SHOULD BE DIRECTLY PASSED AS A
FORTRANCONTIGUOUS NUMPY ARRAY
NOTE THAT IN CERTAIN CASES THE LARS SOLVER MAY BE SIGNIFICANTLY FASTER TO IMPLEMENT THIS FUNCTIONALITY IN PARTICU
LAR LINEAR INTERPOLATION CAN BE USED TO RETRIEVE MODEL COEFFICIENTS BETWEEN THE VALUES OUTPUT BY LARSPATH
EXAMPLES
COMPARING LASSOPATH AND LARSPATH WITH INTERPOLATION
X NPARRAY1 2 31 23 54 43T
Y NPARRAY1 2 31
 USE LASSOPATH TO COMPUTE A COEFFICIENT PATH
 COEFPATH   LASSOPATHX Y ALPHAS5 1 5
PRINTCOEFPATH
0 0 046874778
02159048 04425765 023689075
 NOW USE LARSPATH AND 1D LINEAR INTERPOLATION TO COMPUTE THE
 SAME PATH
 FROM SKLEARNLINEARMODEL IMPORT LARSPATH
ALPHAS ACTIVE COEFPATHLARS LARSPATHX Y METHODLASSO
 FROM SCIPY IMPORT INTERPOLATE
COEFPATHCONTINUOUS INTERPOLATEINTERP1DALPHAS1

COEFPATHLARS 1
PRINTCOEFPATHCONTINUOUS5 1 5
0 0 046915237
02159048 04425765 023668876
EXAMPLES USING SKLEARNLINEARMODELLASSOPATH
•LASSO AND ELASTIC NET
62226SKLEARNLINEARMODEL ORTHOGONALMP
SKLEARNLINEARMODEL ORTHOGONALMP XYNNONZEROCOEFSNONE TOLNONE PRECOM
PUTEFALSE COPYXTRUE RETURNPATHFALSE RE
TURNNITERFALSE
ORTHOGONAL MATCHING PURSUIT OMP
SOLVES NTARGETS ORTHOGONAL MATCHING PURSUIT PROBLEMS AN INSTANCE OF THE PROBLEM HAS THE FORM
WHEN PARAMETRIZED BY THE NUMBER OF NONZERO COEFFICIENTS USING NNONZEROCOEFS ARGMIN Y
XGAMMA2 SUBJECT TO GAMMA0 NNONZERO COEFS
WHEN PARAMETRIZED BY ERROR USING THE PARAMETER TOL ARGMIN GAMMA0 SUBJECT TO Y XGAMMA2 TOL
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY SHAPE NSAMPLES NFEATURES INPUT DATA COLUMNS ARE ASSUMED TO HAVE UNIT NORM
YARRAY SHAPE NSAMPLES OR NSAMPLES NTARGETS INPUT TARGETS
NNONZEROCOEFS INT DESIRED NUMBER OF NONZERO ENTRIES IN THE SOLUTION IF NONE BY DEFAULT
THIS VALUE IS SET TO 10 OF NFEATURES
TOLFLOAT MAXIMUM NORM OF THE RESIDUAL IF NOT NONE OVERRIDES NNONZEROCOEFS
PRECOMPUTE TRUE FALSE ‘AUTO’ WHETHER TO PERFORM PRECOMPUTATIONS IMPROVES PERFOR
MANCE WHEN NTARGETS OR NSAMPLES IS VERY LARGE
COPYX BOOL OPTIONAL WHETHER THE DESIGN MATRIX X MUST BE COPIED BY THE ALGORITHM A FALSE
VALUE IS ONLY HELPFUL IF X IS ALREADY FORTRANORDERED OTHERWISE A COPY IS MADE ANYWAY
RETURNPATH BOOL OPTIONAL DEFAULT FALSE WHETHER TO RETURN EVERY VALUE OF THE NONZERO
COEFFICIENTS ALONG THE FORWARD PATH USEFUL FOR CROSSVALIDATION
RETURNNITER BOOL OPTIONAL DEFAULT FALSE WHETHER OR NOT TO RETURN THE NUMBER OF ITERATIONS
RETURNS
COEF ARRAY SHAPE NFEATURES OR NFEATURES NTARGETS COEFFICIENTS OF THE OMP SOLUTION IF
RETURNPATHTRUE THIS CONTAINS THE WHOLE COEFFICIENT PATH IN THIS CASE ITS SHAPE IS
NFEATURES NFEATURES OR NFEATURES NTARGETS NFEATURES AND ITERATING OVER THE LAST AXIS
YIELDS COEFFICIENTS IN INCREASING ORDER OF ACTIVE FEATURES
NITERS ARRAYLIKE OR INT NUMBER OF ACTIVE FEATURES ACROSS EVERY TARGET RETURNED ONLY IF
RETURNNITER IS SET TO TRUE
SEE ALSO
ORTHOGONALMATCHINGPURSUIT
622SKLEARNLINEARMODEL GENERALIZED LINEAR MODELS 1961

ORTHOGONALMPGRAM
LARSPATH
DECOMPOSITIONSPARSEENCODE
NOTES
ORTHOGONAL MATCHING PURSUIT WAS INTRODUCED IN S MALLAT Z ZHANG MATCHING PURSUITS WITH TIMEFREQUENCY
DICTIONARIES IEEE TRANSACTIONS ON SIGNAL PROCESSING V OL 41 NO 12 DECEMBER 1993 PP 33973415
HTTPBLANCHEPOLYTECHNIQUEFRMALLATPAPIERSMALLATPURSUIT93PDF
THIS IMPLEMENTATION IS BASED ON RUBINSTEIN R ZIBULEVSKY M AND ELAD M EFFICIENT IMPLEMENTATION OF
THE KSVD ALGORITHM USING BATCH ORTHOGONAL MATCHING PURSUIT TECHNICAL REPORT CS TECHNION APRIL 2008
HTTPSWWWCSTECHNIONACILRONRUBINPUBLICATIONSKSVDOMPV2PDF
62227SKLEARNLINEARMODEL ORTHOGONALMPGRAM
SKLEARNLINEARMODEL ORTHOGONALMPGRAM GRAM XYNNONZEROCOEFSNONE TOLNONE
NORMSSQUAREDNONE COPYGRAMTRUE
COPYXYTRUE RETURNPATHFALSE RE
TURNNITERFALSE
GRAM ORTHOGONAL MATCHING PURSUIT OMP
SOLVES NTARGETS ORTHOGONAL MATCHING PURSUIT PROBLEMS USING ONLY THE GRAM MATRIX XT X AND THE PRODUCT
XT Y
READ MORE IN THE USER GUIDE
PARAMETERS
GRAM ARRAY SHAPE NFEATURES NFEATURES GRAM MATRIX OF THE INPUT DATA XT X
XYARRAY SHAPE NFEATURES OR NFEATURES NTARGETS INPUT TARGETS MULTIPLIED BY X XT Y
NNONZEROCOEFS INT DESIRED NUMBER OF NONZERO ENTRIES IN THE SOLUTION IF NONE BY DEFAULT
THIS VALUE IS SET TO 10 OF NFEATURES
TOLFLOAT MAXIMUM NORM OF THE RESIDUAL IF NOT NONE OVERRIDES NNONZEROCOEFS
NORMSSQUARED ARRAYLIKE SHAPE NTARGETS SQUARED L2 NORMS OF THE LINES OF Y REQUIRED
IF TOL IS NOT NONE
COPYGRAM BOOL OPTIONAL WHETHER THE GRAM MATRIX MUST BE COPIED BY THE ALGORITHM A FALSE
VALUE IS ONLY HELPFUL IF IT IS ALREADY FORTRANORDERED OTHERWISE A COPY IS MADE ANYWAY
COPYXY BOOL OPTIONAL WHETHER THE COVARIANCE VECTOR XY MUST BE COPIED BY THE ALGORITHM
IF FALSE IT MAY BE OVERWRITTEN
RETURNPATH BOOL OPTIONAL DEFAULT FALSE WHETHER TO RETURN EVERY VALUE OF THE NONZERO
COEFFICIENTS ALONG THE FORWARD PATH USEFUL FOR CROSSVALIDATION
RETURNNITER BOOL OPTIONAL DEFAULT FALSE WHETHER OR NOT TO RETURN THE NUMBER OF ITERATIONS
RETURNS
COEF ARRAY SHAPE NFEATURES OR NFEATURES NTARGETS COEFFICIENTS OF THE OMP SOLUTION IF
RETURNPATHTRUE THIS CONTAINS THE WHOLE COEFFICIENT PATH IN THIS CASE ITS SHAPE IS
NFEATURES NFEATURES OR NFEATURES NTARGETS NFEATURES AND ITERATING OVER THE LAST AXIS
YIELDS COEFFICIENTS IN INCREASING ORDER OF ACTIVE FEATURES

NITERS ARRAYLIKE OR INT NUMBER OF ACTIVE FEATURES ACROSS EVERY TARGET RETURNED ONLY IF
RETURNNITER IS SET TO TRUE
SEE ALSO
ORTHOGONALMATCHINGPURSUIT
ORTHOGONALMP
LARSPATH
DECOMPOSITIONSPARSEENCODE
NOTES
ORTHOGONAL MATCHING PURSUIT WAS INTRODUCED IN G MALLAT Z ZHANG MATCHING PURSUITS WITH TIMEFREQUENCY
DICTIONARIES IEEE TRANSACTIONS ON SIGNAL PROCESSING V OL 41 NO 12 DECEMBER 1993 PP 33973415
HTTPBLANCHEPOLYTECHNIQUEFRMALLATPAPIERSMALLATPURSUIT93PDF
THIS IMPLEMENTATION IS BASED ON RUBINSTEIN R ZIBULEVSKY M AND ELAD M EFFICIENT IMPLEMENTATION OF
THE KSVD ALGORITHM USING BATCH ORTHOGONAL MATCHING PURSUIT TECHNICAL REPORT CS TECHNION APRIL 2008
HTTPSWWWCSTECHNIONACILRONRUBINPUBLICATIONSKSVDOMPV2PDF
62228SKLEARNLINEARMODEL RIDGEREGRESSION
SKLEARNLINEARMODEL RIDGEREGRESSION XYALPHA SAMPLEWEIGHTNONE SOLVER'AUTO'
MAXITERNONE TOL0001 VERBOSE0 RAN
DOMSTATENONE RETURNNITERFALSE RE
TURNINTERCEPTFALSE CHECKINPUTTRUE
SOLVE THE RIDGE EQUATION BY THE METHOD OF NORMAL EQUATIONS
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX LINEAROPERATOR SHAPE NSAMPLES NFEATURES TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS TARGET VALUES
ALPHA FLOAT ARRAYLIKE SHAPE NTARGETS IF ARRAYLIKE REGULARIZATION STRENGTH MUST BE
A POSITIVE FLOAT REGULARIZATION IMPROVES THE CONDITIONING OF THE PROBLEM AND REDUCES THE
VARIANCE OF THE ESTIMATES LARGER VALUES SPECIFY STRONGER REGULARIZATION ALPHA CORRESPONDS
TOC1 IN OTHER LINEAR MODELS SUCH AS LOGISTICREGRESSION OR LINEARSVC IF AN ARRAY IS
PASSED PENALTIES ARE ASSUMED TO BE SPECIFIC TO THE TARGETS HENCE THEY MUST CORRESPOND IN
NUMBER
SAMPLEWEIGHT FLOAT OR NUMPY ARRAY OF SHAPE NSAMPLES INDIVIDUAL WEIGHTS FOR EACH SAM
PLE IF SAMPLEWEIGHT IS NOT NONE AND SOLVER'AUTO' THE SOLVER WILL BE SET TO 'CHOLESKY'
NEW IN VERSION 017
SOLVER 'AUTO' 'SVD' 'CHOLESKY' 'LSQR' 'SPARSECG' 'SAG' 'SAGA' SOLVER TO USE IN THE COM
PUTATIONAL ROUTINES
• 'AUTO' CHOOSES THE SOLVER AUTOMATICALLY BASED ON THE TYPE OF DATA
• 'SVD' USES A SINGULAR VALUE DECOMPOSITION OF X TO COMPUTE THE RIDGE COEFFICIENTS MORE
STABLE FOR SINGULAR MATRICES THAN 'CHOLESKY'

• ‘CHOLESKY’ USES THE STANDARD SCIPYLINALGSOLVE FUNCTION TO OBTAIN A CLOSEDFORM SOLUTION VIA A CHOLESKY DECOMPOSITION OF DOTXT X
• ‘SPARSECG’ USES THE CONJUGATE GRADIENT SOLVER AS FOUND IN SCIPYSPARSELINALGCG AS AN ITERATIVE ALGORITHM THIS SOLVER IS MORE APPROPRIATE THAN ‘CHOLESKY’ FOR LARGESCALE DATA POSSIBILITY TO SET TOL ANDMAXITER
• ‘LSQR’ USES THE DEDICATED REGULARIZED LEASTSQUARES ROUTINE SCIPYSPARSELINALGLSQR IT IS THE FASTEST AND USES AN ITERATIVE PROCEDURE
• ‘SAG’ USES A STOCHASTIC AVERAGE GRADIENT DESCENT AND ‘SAGA’ USES ITS IMPROVED UNBIASED VERSION NAMED SAGA BOTH METHODS ALSO USE AN ITERATIVE PROCEDURE AND ARE OFTEN FASTER THAN OTHER SOLVERS WHEN BOTH NSAMPLES AND NFEATURES ARE LARGE NOTE THAT ‘SAG’ AND ‘SAGA’ FAST CONVERGENCE IS ONLY GUARANTEED ON FEATURES WITH APPROXIMATELY THE SAME SCALE YOU CAN PREPROCESS THE DATA WITH A SCALER FROM SKLEARNPREPROCESSING
ALL LAST FIVE SOLVERS SUPPORT BOTH DENSE AND SPARSE DATA HOWEVER ONLY ‘SAG’ AND ‘SPARSECG’ SUPPORTS SPARSE INPUT WHEN‘FITINTERCEPT‘ IS TRUE
NEW IN VERSION 017 STOCHASTIC AVERAGE GRADIENT DESCENT SOLVER
NEW IN VERSION 019 SAGA SOLVER
MAXITER INT OPTIONAL MAXIMUM NUMBER OF ITERATIONS FOR CONJUGATE GRADIENT SOLVER FOR THE ‘SPARSECG’ AND ‘LSQR’ SOLVERS THE DEFAULT VALUE IS DETERMINED BY SCIPYSPARSELINALG FOR ‘SAG’ AND SAGA SOLVER THE DEFAULT VALUE IS 1000
TOLFLOAT PRECISION OF THE SOLUTION
VERBOSE INT VERBOSITY LEVEL SETTING VERBOSE 0 WILL DISPLAY ADDITIONAL INFORMATION DEPENDING ON THE SOLVER USED
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SOLVER ‘SAG’
RETURNNITER BOOLEAN DEFAULT FALSE IF TRUE THE METHOD ALSO RETURNS NITER THE ACTUAL NUMBER OF ITERATION PERFORMED BY THE SOLVER
NEW IN VERSION 017
RETURNINTERCEPT BOOLEAN DEFAULT FALSE IF TRUE AND IF X IS SPARSE THE METHOD ALSO RE TURNS THE INTERCEPT AND THE SOLVER IS AUTOMATICALLY CHANGED TO ‘SAG’ THIS IS ONLY A TEMPORARY FIX FOR FITTING THE INTERCEPT WITH SPARSE DATA FOR DENSE DATA USE SKLEARNLINEARMODELPREPROCESSDATA BEFORE YOUR REGRESSION
NEW IN VERSION 017
CHECKINPUT BOOLEAN DEFAULT TRUE IF FALSE THE INPUT ARRAYS X AND Y WILL NOT BE CHECKED
NEW IN VERSION 021
RETURNS
COEF ARRAY SHAPE NFEATURES OR NTARGETS NFEATURES WEIGHT VECTORS
NITER INT OPTIONAL THE ACTUAL NUMBER OF ITERATION PERFORMED BY THE SOLVER ONLY RETURNED IF RETURNNITER IS TRUE
INTERCEPT FLOAT OR ARRAY SHAPE NTARGETS THE INTERCEPT OF THE MODEL ONLY RETURNED IF RETURNINTERCEPT IS TRUE AND IF X IS A SCIPY SPARSE ARRAY

NOTES
THIS FUNCTION WON’T COMPUTE THE INTERCEPT
623SKLEARNMANIFOLD MANIFOLD LEARNING
THESKLEARNMANIFOLD MODULE IMPLEMENTS DATA EMBEDDING TECHNIQUES
USER GUIDE SEE THE MANIFOLD LEARNING SECTION FOR FURTHER DETAILS
MANIFOLDISOMAP NNEIGHBORS NCOMPONENTS ISOMAP EMBEDDING
MANIFOLDLOCALLYLINEAREMBEDDING LOCALLY LINEAR EMBEDDING
MANIFOLDMDS NCOMPONENTS METRIC NINIT MULTIDIMENSIONAL SCALING
MANIFOLDSPECTRALEMBEDDING NCOMPONENTS
  SPECTRAL EMBEDDING FOR NONLINEAR DIMENSIONALITY REDUC
TION
MANIFOLDTSNE NCOMPONENTS PERPLEXITY TDISTRIBUTED STOCHASTIC NEIGHBOR EMBEDDING
6231SKLEARNMANIFOLD ISOMAP
CLASSSKLEARNMANIFOLD ISOMAPNNEIGHBORS5 NCOMPONENTS2 EIGENSOLVER’AUTO’ TOL0
MAXITERNONE PATHMETHOD’AUTO’ NEIGHBORSALGORITHM’AUTO’
NJOBSNONE
ISOMAP EMBEDDING
NONLINEAR DIMENSIONALITY REDUCTION THROUGH ISOMETRIC MAPPING
READ MORE IN THE USER GUIDE
PARAMETERS
NNEIGHBORS INTEGER NUMBER OF NEIGHBORS TO CONSIDER FOR EACH POINT
NCOMPONENTS INTEGER NUMBER OF COORDINATES FOR THE MANIFOLD
EIGENSOLVER ‘AUTO’’ARPACK’’DENSE’ ‘AUTO’ ATTEMPT TO CHOOSE THE MOST EFFICIENT SOLVER FOR
THE GIVEN PROBLEM
‘ARPACK’ USE ARNOLDI DECOMPOSITION TO FIND THE EIGENVALUES AND EIGENVECTORS
‘DENSE’ USE A DIRECT SOLVER IE LAPACK FOR THE EIGENVALUE DECOMPOSITION
TOLFLOAT CONVERGENCE TOLERANCE PASSED TO ARPACK OR LOBPCG NOT USED IF EIGENSOLVER
‘DENSE’
MAXITER INTEGER MAXIMUM NUMBER OF ITERATIONS FOR THE ARPACK SOLVER NOT USED IF
EIGENSOLVER ‘DENSE’
PATHMETHOD STRING ‘AUTO’’FW’’D’ METHOD TO USE IN FINDING SHORTEST PATH
‘AUTO’ ATTEMPT TO CHOOSE THE BEST ALGORITHM AUTOMATICALLY
‘FW’ FLOYDWARSHALL ALGORITHM
‘D’ DIJKSTRA’S ALGORITHM
NEIGHBORSALGORITHM STRING ‘AUTO’’BRUTE’’KDTREE’’BALLTREE’ ALGORITHM TO USE FOR NEAREST
NEIGHBORS SEARCH PASSED TO NEIGHBORSNEARESTNEIGHBORS INSTANCE

NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS
1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
ATTRIBUTES
EMBEDDING ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS STORES THE EMBEDDING VECTORS
KERNELPCA OBJECTKERNELPCA OBJECT USED TO IMPLEMENT THE EMBEDDING
TRAININGDATA ARRAYLIKE SHAPE NSAMPLES NFEATURES STORES THE TRAINING DATA
NBRS SKLEARNNEIGHBORSNEARESTNEIGHBORS INSTANCE STORES NEAREST NEIGHBORS INSTANCE IN
CLUDING BALLTREE OR KDTREE IF APPLICABLE
DISTMATRIX ARRAYLIKE SHAPE NSAMPLES NSAMPLES STORES THE GEODESIC DISTANCE MATRIX
OF TRAINING DATA
REFERENCES
R7F4D308F50541
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADDIGITS
 FROM SKLEARNMANIFOLD IMPORT ISOMAP
X   LOADDIGITSRETURNXY TRUE
XSHAPE
1797 64
EMBEDDING  ISOMAPNCOMPONENTS2
XTRANSFORMED  EMBEDDINGFITTRANSFORMX100
XTRANSFORMEDSHAPE
100 2
```
METHODS
FITSELF X Y COMPUTE THE EMBEDDING VECTORS FOR DATA X
FITTRANSFORM SELF X Y FIT THE MODEL FROM DATA IN X AND TRANSFORM X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
RECONSTRUCTIONERROR SELF COMPUTE THE RECONSTRUCTION ERROR FOR THE EMBEDDING
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM X
INIT SELFNNEIGHBORS5 NCOMPONENTS2 EIGENSOLVER’AUTO’ TOL0 MAXITERNONE
PATHMETHOD’AUTO’ NEIGHBORSALGORITHM’AUTO’ NJOBSNONE
FITSELFXYNONE
COMPUTE THE EMBEDDING VECTORS FOR DATA X
PARAMETERS
XARRAYLIKE SPARSE MATRIX BALLTREE KDTREE NEARESTNEIGHBORS SAMPLE DATA SHAPE
 NSAMPLES NFEATURES IN THE FORM OF A NUMPY ARRAY PRECOMPUTED TREE OR NEAREST
NEIGHBORS OBJECT

YIGNORED
RETURNS
SELF RETURNS AN INSTANCE OF SELF
FITTRANSFORM SELFXYNONE
FIT THE MODEL FROM DATA IN X AND TRANSFORM X
PARAMETERS
XARRAYLIKE SPARSE MATRIX BALLTREE KDTREE TRAINING VECTOR WHERE NSAMPLES IN THE
NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YIGNORED
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
RECONSTRUCTIONERROR SELF
COMPUTE THE RECONSTRUCTION ERROR FOR THE EMBEDDING
RETURNS
RECONSTRUCTIONERROR FLOAT
NOTES
THE COST FUNCTION OF AN ISOMAP EMBEDDING IS
E FROBENIUSNORMKD KDFIT NSAMPLES
WHERE D IS THE MATRIX OF DISTANCES FOR THE INPUT DATA X DFIT IS THE MATRIX OF DISTANCES FOR THE OUTPUT
EMBEDDING XFIT AND K IS THE ISOMAP KERNEL
KD 05 I 1NSAMPLES D2I 1NSAMPLES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM X

THIS IS IMPLEMENTED BY LINKING THE POINTS X INTO THE GRAPH OF GEODESIC DISTANCES OF THE TRAINING DATA
FIRST THENNEIGHBORS NEAREST NEIGHBORS OF X ARE FOUND IN THE TRAINING DATA AND FROM THESE THE SHORTEST
GEODESIC DISTANCES FROM EACH POINT IN X TO EACH POINT IN THE TRAINING DATA ARE COMPUTED IN ORDER TO CONSTRUCT
THE KERNEL THE EMBEDDING OF X IS THE PROJECTION OF THIS KERNEL ONTO THE EMBEDDING VECTORS OF THE TRAINING
SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
EXAMPLES USING SKLEARNMANIFOLDISOMAP
•COMPARISON OF MANIFOLD LEARNING METHODS
•MANIFOLD LEARNING METHODS ON A SEVERED SPHERE
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
6232SKLEARNMANIFOLD LOCALLYLINEAREMBEDDING
CLASSSKLEARNMANIFOLD LOCALLYLINEAREMBEDDING NNEIGHBORS5 NCOMPONENTS2
REG0001 EIGENSOLVER'AUTO' TOL1E
06MAXITER100 METHOD'STANDARD'
HESSIANTOL00001 MODIFIEDTOL1E
12 NEIGHBORSALGORITHM'AUTO' RAN
DOMSTATENONE NJOBSNONE
LOCALLY LINEAR EMBEDDING
READ MORE IN THE USER GUIDE
PARAMETERS
NNEIGHBORS INTEGER NUMBER OF NEIGHBORS TO CONSIDER FOR EACH POINT
NCOMPONENTS INTEGER NUMBER OF COORDINATES FOR THE MANIFOLD
REGFLOAT REGULARIZATION CONSTANT MULTIPLIES THE TRACE OF THE LOCAL COVARIANCE MATRIX OF THE
DISTANCES
EIGENSOLVER STRING 'AUTO' 'ARPACK' 'DENSE' AUTO ALGORITHM WILL ATTEMPT TO CHOOSE THE
BEST METHOD FOR INPUT DATA
ARPACK USE ARNOLDI ITERATION IN SHIFTINVERT MODE FOR THIS METHOD M MAY BE A DENSE
MATRIX SPARSE MATRIX OR GENERAL LINEAR OPERATOR WARNING ARPACK CAN BE UNSTABLE FOR
SOME PROBLEMS IT IS BEST TO TRY SEVERAL RANDOM SEEDS IN ORDER TO CHECK RESULTS
DENSE USE STANDARD DENSE MATRIX OPERATIONS FOR THE EIGENVALUE DECOMPOSITION FOR THIS
METHOD M MUST BE AN ARRAY OR MATRIX TYPE THIS METHOD SHOULD BE AVOIDED FOR LARGE
PROBLEMS
TOLFLOAT OPTIONAL TOLERANCE FOR 'ARPACK' METHOD NOT USED IF EIGENSOLVER'DENSE'
MAXITER INTEGER MAXIMUM NUMBER OF ITERATIONS FOR THE ARPACK SOLVER NOT USED IF
EIGENSOLVER'DENSE'
METHOD STRING 'STANDARD' 'HESSIAN' 'MODIFIED' OR 'LTSA'
STANDARD USE THE STANDARD LOCALLY LINEAR EMBEDDING ALGORITHM SEE REFERENCE 1

HESSIAN USE THE HESSIAN EIGENMAP METHOD THIS METHOD REQUIRES NNEIGHBORS
NCOMPONENTS 1 NCOMPONENTS 1 2 SEE REFERENCE 2
MODIFIED USE THE MODIFIED LOCALLY LINEAR EMBEDDING ALGORITHM SEE REFERENCE 3
LTSA USE LOCAL TANGENT SPACE ALIGNMENT ALGORITHM SEE REFERENCE 4
HESSIANTOL FLOAT OPTIONAL TOLERANCE FOR HESSIAN EIGENMAPPING METHOD ONLY USED IF
METHOD HESSIAN
MODIFIEDTOL FLOAT OPTIONAL TOLERANCE FOR MODIFIED LLE METHOD ONLY USED IF METHOD
MODIFIED
NEIGHBORSALGORITHM STRING ‘AUTO’’BRUTE’’KDTREE’’BALLTREE’ ALGORITHM TO USE FOR NEAREST
NEIGHBORS SEARCH PASSED TO NEIGHBORSNEARESTNEIGHBORS INSTANCE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RAN
DOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE
RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN EIGENSOLVER ‘ARPACK’
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS
1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
ATTRIBUTES
EMBEDDING ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS STORES THE EMBEDDING VECTORS
RECONSTRUCTIONERROR FLOAT RECONSTRUCTION ERROR ASSOCIATED WITH EMBEDDING
NBRS NEARESTNEIGHBORS OBJECT STORES NEAREST NEIGHBORS INSTANCE INCLUDING BALLTREE OR
KDTREE IF APPLICABLE
REFERENCES
R62E36DD1B0561 R62E36DD1B0562 R62E36DD1B0563 R62E36DD1B0564
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADDIGITS
 FROM SKLEARNMANIFOLD IMPORT LOCALLYLINEAREMBEDDING
X   LOADDIGITSRETURNXY TRUE
XSHAPE
1797 64
EMBEDDING  LOCALLYLINEAREMBEDDINGNCOMPONENTS2
XTRANSFORMED  EMBEDDINGFITTRANSFORMX100
XTRANSFORMEDSHAPE
100 2
```
METHODS
FITSELF X Y COMPUTE THE EMBEDDING VECTORS FOR DATA X
FITTRANSFORM SELF X Y COMPUTE THE EMBEDDING VECTORS FOR DATA X AND TRANS
FORM X
CONTINUED ON NEXT PAGE

TABLE 6173 – CONTINUED FROM PREVIOUS PAGE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM NEW POINTS INTO EMBEDDING SPACE
INIT SELFNNEIGHBORS5 NCOMPONENTS2 REG0001 EIGENSOLVER'AUTO' TOL1E06
MAXITER100 METHOD'STANDARD' HESSIANTOL00001 MODIFIEDTOL1E12 NEIGH
BORSALGORITHM'AUTO' RANDOMSTATENONE NJOBSNONE
FITSELFXYNONE
COMPUTE THE EMBEDDING VECTORS FOR DATA X
PARAMETERS
XARRAYLIKE OF SHAPE NSAMPLES NFEATURES TRAINING SET
YIGNORED
RETURNS
SELF RETURNS AN INSTANCE OF SELF
FITTRANSFORM SELFXYNONE
COMPUTE THE EMBEDDING VECTORS FOR DATA X AND TRANSFORM X
PARAMETERS
XARRAYLIKE OF SHAPE NSAMPLES NFEATURES TRAINING SET
YIGNORED
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM NEW POINTS INTO EMBEDDING SPACE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS

XNEW ARRAY SHAPE NSAMPLES NCOMPONENTS
NOTES
BECAUSE OF SCALING PERFORMED BY THIS METHOD IT IS DISCOURAGED TO USE IT TOGETHER WITH METHODS THAT ARE NOT SCALEINVARIANT LIKE SVMS
EXAMPLES USING SKLEARNMANIFOLDLOCALLYLINEAREMBEDDING
•VISUALIZING THE STOCK MARKET STRUCTURE
•COMPARISON OF MANIFOLD LEARNING METHODS
•MANIFOLD LEARNING METHODS ON A SEVERED SPHERE
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
6233SKLEARNMANIFOLD MDS
CLASSSKLEARNMANIFOLD MDSNCOMPONENTS2 METRICTRUE NINIT4 MAXITER300 VER BOSE0 EPS0001 NJOBSNONE RANDOMSTATENONE DISSIMILAR ITY'EUCLIDEAN'
MULTIDIMENSIONAL SCALING
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT OPTIONAL DEFAULT 2 NUMBER OF DIMENSIONS IN WHICH TO IMMERSE THE DIS SIMILARITIES
METRIC BOOLEAN OPTIONAL DEFAULT TRUE IF TRUE PERFORM METRIC MDS OTHERWISE PERFORM NONMETRIC MDS
NINIT INT OPTIONAL DEFAULT 4 NUMBER OF TIMES THE SMACOF ALGORITHM WILL BE RUN WITH DIFFERENT INITIALIZATIONS THE FINAL RESULTS WILL BE THE BEST OUTPUT OF THE RUNS DETERMINED BY THE RUN WITH THE SMALLEST FINAL STRESS
MAXITER INT OPTIONAL DEFAULT 300 MAXIMUM NUMBER OF ITERATIONS OF THE SMACOF ALGO RITHM FOR A SINGLE RUN
VERBOSE INT OPTIONAL DEFAULT 0 LEVEL OF VERBOSITY
EPS FLOAT OPTIONAL DEFAULT 1E3 RELATIVE TOLERANCE WITH RESPECT TO STRESS AT WHICH TO DECLARE CONVERGENCE
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION IF MULTIPLE INITIALIZATIONS ARE USED NINIT EACH RUN OF THE ALGORITHM IS COMPUTED IN PARALLEL
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE GENERATOR USED TO INITIALIZE THE CENTERS IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM

DISSIMILARITY ‘EUCLIDEAN’ ‘PRECOMPUTED’ OPTIONAL DEFAULT ‘EUCLIDEAN’ DISSIMILARITY MEA
SURE TO USE
•‘EUCLIDEAN’ PAIRWISE EUCLIDEAN DISTANCES BETWEEN POINTS IN THE DATASET
•‘PRECOMPUTED’ PRECOMPUTED DISSIMILARITIES ARE PASSED DIRECTLY TO FIT AND
FITTRANSFORM
ATTRIBUTES
EMBEDDING ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS STORES THE POSITION OF THE DATASET
IN THE EMBEDDING SPACE
STRESS FLOAT THE FINAL VALUE OF THE STRESS SUM OF SQUARED DISTANCE OF THE DISPARITIES AND THE
DISTANCES FOR ALL CONSTRAINED POINTS
REFERENCES
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“NONMETRIC MULTIDIMENSIONAL SCALING A NUMERICAL METHOD” KRUSKAL J PSYCHOMETRIKA 29 1964
“MULTIDIMENSIONAL SCALING BY OPTIMIZING GOODNESS OF FIT TO A NONMETRIC HYPOTHESIS” KRUSKAL J PSYCHOMETRIKA
29 1964
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADDIGITS
 FROM SKLEARNMANIFOLD IMPORT MDS
X   LOADDIGITSRETURNXY TRUE
XSHAPE
1797 64
EMBEDDING  MDSNCOMPONENTS2
XTRANSFORMED  EMBEDDINGFITTRANSFORMX100
XTRANSFORMEDSHAPE
100 2
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METHODS
FITSELF X Y INIT COMPUTES THE POSITION OF THE POINTS IN THE EMBEDDING
SPACE
FITTRANSFORM SELF X Y INIT FIT THE DATA FROM X AND RETURNS THE EMBEDDED COORDI
NATES
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNCOMPONENTS2 METRICTRUE NINIT4 MAXITER300 VERBOSE0 EPS0001
NJOBSNONE RANDOMSTATENONE DISSIMILARITY’EUCLIDEAN’
FITSELFXYNONE INITNONE
COMPUTES THE POSITION OF THE POINTS IN THE EMBEDDING SPACE
PARAMETERS

SCIKITLEARN USER GUIDE RELEASE 0213
XARRAY SHAPE NSAMPLES NFEATURES OR NSAMPLES NSAMPLES INPUT DATA IF
DISSIMILARITYPRECOMPUTED THE INPUT SHOULD BE THE DISSIMILARITY MATRIX
YIGNORED
INIT NDARRAY SHAPE NSAMPLES OPTIONAL DEFAULT NONE STARTING CONFIGURATION OF THE EM
BEDDING TO INITIALIZE THE SMACOF ALGORITHM BY DEFAULT THE ALGORITHM IS INITIALIZED WITH
A RANDOMLY CHOSEN ARRAY
FITTRANSFORM SELFXYNONE INITNONE
FIT THE DATA FROM X AND RETURNS THE EMBEDDED COORDINATES
PARAMETERS
XARRAY SHAPE NSAMPLES NFEATURES OR NSAMPLES NSAMPLES INPUT DATA IF
DISSIMILARITYPRECOMPUTED THE INPUT SHOULD BE THE DISSIMILARITY MATRIX
YIGNORED
INIT NDARRAY SHAPE NSAMPLES OPTIONAL DEFAULT NONE STARTING CONFIGURATION OF THE EM
BEDDING TO INITIALIZE THE SMACOF ALGORITHM BY DEFAULT THE ALGORITHM IS INITIALIZED WITH
A RANDOMLY CHOSEN ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNMANIFOLDMDS
•MULTIDIMENSIONAL SCALING
•COMPARISON OF MANIFOLD LEARNING METHODS
•MANIFOLD LEARNING METHODS ON A SEVERED SPHERE
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
623SKLEARNMANIFOLD MANIFOLD LEARNING 1973

6234SKLEARNMANIFOLD SPECTRALEMBEDDING
CLASSSKLEARNMANIFOLD SPECTRALEMBEDDING NCOMPONENTS2 AFFINITY'NEARESTNEIGHBORS'
GAMMANONE RANDOMSTATENONE
EIGENSOLVERNONE NNEIGHBORSNONE
NJOBSNONE
SPECTRAL EMBEDDING FOR NONLINEAR DIMENSIONALITY REDUCTION
FORMS AN AFFINITY MATRIX GIVEN BY THE SPECIFIED FUNCTION AND APPLIES SPECTRAL DECOMPOSITION TO THE CORRESPONDING
GRAPH LAPLACIAN THE RESULTING TRANSFORMATION IS GIVEN BY THE VALUE OF THE EIGENVECTORS FOR EACH DATA POINT
NOTE LAPLACIAN EIGENMAPS IS THE ACTUAL ALGORITHM IMPLEMENTED HERE
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INTEGER DEFAULT 2 THE DIMENSION OF THE PROJECTED SUBSPACE
AFFINITY STRING OR CALLABLE DEFAULT
HOW TO CONSTRUCT THE AFFINITY MATRIX
• 'NEARESTNEIGHBORS' CONSTRUCT AFFINITY MATRIX BY KNN GRAPH
• 'RBF' CONSTRUCT AFFINITY MATRIX BY RBF KERNEL
• 'PRECOMPUTED' INTERPRET X AS PRECOMPUTED AFFINITY MATRIX
• CALLABLE USE PASSED IN FUNCTION AS AFFINITY THE FUNCTION TAKES IN DATA MATRIX NSAMPLES
NFEATURES AND RETURN AFFINITY MATRIX NSAMPLES NSAMPLES
GAMMA FLOAT OPTIONAL DEFAULT KERNEL COEFFICIENT FOR RBF KERNEL
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE A PSEUDO RANDOM
NUMBER GENERATOR USED FOR THE INITIALIZATION OF THE LOBPCG EIGENVECTORS IF INT RANDOMSTATE
IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM USED WHEN SOLVER 'AMG'
EIGENSOLVER NONE 'ARPACK' 'LOBPCG' OR 'AMG' THE EIGENVALUE DECOMPOSITION STRATEGY TO
USE AMG REQUIRES PYAMG TO BE INSTALLED IT CAN BE FASTER ON VERY LARGE SPARSE PROBLEMS
BUT MAY ALSO LEAD TO INSTABILITIES
NNEIGHBORS INT DEFAULT NUMBER OF NEAREST NEIGHBORS FOR NEARESTNEIGHBORS GRAPH BUILDING
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS
1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
ATTRIBUTES
EMBEDDING ARRAY SHAPE NSAMPLES NCOMPONENTS SPECTRAL EMBEDDING OF THE TRAINING
MATRIX
AFFINITYMATRIX ARRAY SHAPE NSAMPLES NSAMPLES AFFINITYMATRIX CONSTRUCTED FROM
SAMPLES OR PRECOMPUTED
REFERENCES
• A TUTORIAL ON SPECTRAL CLUSTERING 2007 ULRIKE VON LUXBURG HTTPCITESEERXISTPSUEDUVIEWDOC
SUMMARYDOI10111659323

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• ON SPECTRAL CLUSTERING ANALYSIS AND AN ALGORITHM 2001 ANDREW Y NG MICHAEL I JORDAN YAIR WEISS
HTTPCITESEERXISTPSUEDUVIEWDOCSUMMARYDOI1011198100
• NORMALIZED CUTS AND IMAGE SEGMENTATION 2000 JIANBO SHI JITENDRA MALIK HTTPCITESEERISTPSUEDU
VIEWDOCSUMMARYDOI10111602324
EXAMPLES
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 FROM SKLEARNDATASETS IMPORT LOADDIGITS
 FROM SKLEARNMANIFOLD IMPORT SPECTRALEMBEDDING
X   LOADDIGITSRETURNXY TRUE
XSHAPE
1797 64
EMBEDDING  SPECTRALEMBEDDINGNCOMPONENTS2
XTRANSFORMED  EMBEDDINGFITTRANSFORMX100
XTRANSFORMEDSHAPE
100 2
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METHODS
FITSELF X Y FIT THE MODEL FROM DATA IN X
FITTRANSFORM SELF X Y FIT THE MODEL FROM DATA IN X AND TRANSFORM X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNCOMPONENTS2 AFFINITY’NEARESTNEIGHBORS’ GAMMANONE RANDOMSTATENONE
EIGENSOLVERNONE NNEIGHBORSNONE NJOBSNONE
FITSELFXYNONE
FIT THE MODEL FROM DATA IN X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
IF AFFINITY IS “PRECOMPUTED” X ARRAYLIKE SHAPE NSAMPLES NSAMPLES INTERPRET X AS
PRECOMPUTED ADJACENCY GRAPH COMPUTED FROM SAMPLES
RETURNS
SELF OBJECT RETURNS THE INSTANCE ITSELF
FITTRANSFORM SELFXYNONE
FIT THE MODEL FROM DATA IN X AND TRANSFORM X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IS THE NUM
BER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
IF AFFINITY IS “PRECOMPUTED” X ARRAYLIKE SHAPE NSAMPLES NSAMPLES INTERPRET X AS
PRECOMPUTED ADJACENCY GRAPH COMPUTED FROM SAMPLES
RETURNS
XNEW ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS

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GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNMANIFOLDSPECTRALEMBEDDING
•VARIOUS AGGLOMERATIVE CLUSTERING ON A 2D EMBEDDING OF DIGITS
•COMPARISON OF MANIFOLD LEARNING METHODS
•MANIFOLD LEARNING METHODS ON A SEVERED SPHERE
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
6235SKLEARNMANIFOLD TSNE
CLASSSKLEARNMANIFOLD TSNENCOMPONENTS2 PERPLEXITY300 EARLYEXAGGERATION120
LEARNINGRATE2000 NITER1000 NITERWITHOUTPROGRESS300
MINGRADNORM1E07 METRIC'EUCLIDEAN' INIT'RANDOM' VERBOSE0
RANDOMSTATENONE METHOD'BARNESHUT' ANGLE05
TDISTRIBUTED STOCHASTIC NEIGHBOR EMBEDDING
TSNE 1 IS A TOOL TO VISUALIZE HIGHDIMENSIONAL DATA IT CONVERTS SIMILARITIES BETWEEN DATA POINTS TO JOINT
PROBABILITIES AND TRIES TO MINIMIZE THE KULLBACKLEIBLER DIVERGENCE BETWEEN THE JOINT PROBABILITIES OF THE LOW
DIMENSIONAL EMBEDDING AND THE HIGHDIMENSIONAL DATA TSNE HAS A COST FUNCTION THAT IS NOT CONVEX IE WITH
DIFFERENT INITIALIZATIONS WE CAN GET DIFFERENT RESULTS
IT IS HIGHLY RECOMMENDED TO USE ANOTHER DIMENSIONALITY REDUCTION METHOD EG PCA FOR DENSE DATA OR TRUNCAT
EDSVD FOR SPARSE DATA TO REDUCE THE NUMBER OF DIMENSIONS TO A REASONABLE AMOUNT EG 50 IF THE NUMBER OF
FEATURES IS VERY HIGH THIS WILL SUPPRESS SOME NOISE AND SPEED UP THE COMPUTATION OF PAIRWISE DISTANCES BETWEEN
SAMPLES FOR MORE TIPS SEE LAURENS VAN DER MAATEN'S FAQ 2
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT OPTIONAL DEFAULT 2 DIMENSION OF THE EMBEDDED SPACE
PERPLEXITY FLOAT OPTIONAL DEFAULT 30 THE PERPLEXITY IS RELATED TO THE NUMBER OF NEAREST
NEIGHBORS THAT IS USED IN OTHER MANIFOLD LEARNING ALGORITHMS LARGER DATASETS USUALLY REQUIRE
A LARGER PERPLEXITY CONSIDER SELECTING A VALUE BETWEEN 5 AND 50 DIFFERENT VALUES CAN RESULT
IN SIGNIFICANLTY DIFFERENT RESULTS

EARLYEXAGGERATION FLOAT OPTIONAL DEFAULT 120 CONTROLS HOW TIGHT NATURAL CLUSTERS IN THE ORIGINAL SPACE ARE IN THE EMBEDDED SPACE AND HOW MUCH SPACE WILL BE BETWEEN THEM FOR LARGER VALUES THE SPACE BETWEEN NATURAL CLUSTERS WILL BE LARGER IN THE EMBEDDED SPACE AGAIN THE CHOICE OF THIS PARAMETER IS NOT VERY CRITICAL IF THE COST FUNCTION INCREASES DURING INITIAL OPTIMIZATION THE EARLY EXAGGERATION FACTOR OR THE LEARNING RATE MIGHT BE TOO HIGH
LEARNINGRATE FLOAT OPTIONAL DEFAULT 2000 THE LEARNING RATE FOR TSNE IS USUALLY IN THE RANGE 100 10000 IF THE LEARNING RATE IS TOO HIGH THE DATA MAY LOOK LIKE A ‘BALL’ WITH ANY POINT APPROXIMATELY EQUIDISTANT FROM ITS NEAREST NEIGHBOURS IF THE LEARNING RATE IS TOO LOW MOST POINTS MAY LOOK COMPRESSED IN A DENSE CLOUD WITH FEW OUTLIERS IF THE COST FUNCTION GETS STUCK IN A BAD LOCAL MINIMUM INCREASING THE LEARNING RATE MAY HELP
NITER INT OPTIONAL DEFAULT 1000 MAXIMUM NUMBER OF ITERATIONS FOR THE OPTIMIZATION SHOULD BE AT LEAST 250
NITERWITHOUTPROGRESS INT OPTIONAL DEFAULT 300 MAXIMUM NUMBER OF ITERATIONS WITHOUT PROGRESS BEFORE WE ABORT THE OPTIMIZATION USED AFTER 250 INITIAL ITERATIONS WITH EARLY EXAG GERATION NOTE THAT PROGRESS IS ONLY CHECKED EVERY 50 ITERATIONS SO THIS VALUE IS ROUNDED TO THE NEXT MULTIPLE OF 50
NEW IN VERSION 017 PARAMETER NITERWITHOUTPROGRESS TO CONTROL STOPPING CRITERIA
MINGRADNORM FLOAT OPTIONAL DEFAULT 1E7 IF THE GRADIENT NORM IS BELOW THIS THRESHOLD THE OPTIMIZATION WILL BE STOPPED
METRIC STRING OR CALLABLE OPTIONAL THE METRIC TO USE WHEN CALCULATING DISTANCE BETWEEN INSTANCES IN A FEATURE ARRAY IF METRIC IS A STRING IT MUST BE ONE OF THE OPTIONS AL LOWED BY SCIPYSPATIALDISTANCEPDIST FOR ITS METRIC PARAMETER OR A METRIC LISTED IN PAIR WISEPAIRWISEDISTANCEFUNCTIONS IF METRIC IS “PRECOMPUTED” X IS ASSUMED TO BE A DISTANCE MATRIX ALTERNATIVELY IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF INSTANCES ROWS AND THE RESULTING VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS FROM X AS INPUT AND RETURN A VALUE INDICATING THE DISTANCE BETWEEN THEM THE DEFAULT IS “EUCLIDEAN” WHICH IS INTERPRETED AS SQUARED EUCLIDEAN DISTANCE
INIT STRING OR NUMPY ARRAY OPTIONAL DEFAULT “RANDOM” INITIALIZATION OF EMBEDDING POSSIBLE OPTIONS ARE ‘RANDOM’ ‘PCA’ AND A NUMPY ARRAY OF SHAPE NSAMPLES NCOMPONENTS PCA INITIALIZATION CANNOT BE USED WITH PRECOMPUTED DISTANCES AND IS USUALLY MORE GLOBALLY STABLE THAN RANDOM INITIALIZATION
VERBOSE INT OPTIONAL DEFAULT 0 VERBOSITY LEVEL
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE IF INT RAN DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM NOTE THAT DIFFERENT INITIALIZATIONS MIGHT RESULT IN DIFFERENT LOCAL MINIMA OF THE COST FUNCTION
METHOD STRING DEFAULT ‘BARNESHUT’ BY DEFAULT THE GRADIENT CALCULATION ALGORITHM USES BARNESHUT APPROXIMATION RUNNING IN ONLOGN TIME METHOD’EXACT’ WILL RUN ON THE SLOWER BUT EXACT ALGORITHM IN ON2 TIME THE EXACT ALGORITHM SHOULD BE USED WHEN NEARESTNEIGHBOR ERRORS NEED TO BE BETTER THAN 3 HOWEVER THE EXACT METHOD CANNOT SCALE TO MILLIONS OF EXAMPLES
NEW IN VERSION 017 APPROXIMATE OPTIMIZATION METHOD VIA THE BARNESHUT
ANGLE FLOAT DEFAULT 05 ONLY USED IF METHOD’BARNESHUT’ THIS IS THE TRADEOFF BETWEEN SPEED AND ACCURACY FOR BARNESHUT TSNE ‘ANGLE’ IS THE ANGULAR SIZE REFERRED TO AS THETA IN 3 OF A DISTANT NODE AS MEASURED FROM A POINT IF THIS SIZE IS BELOW ‘ANGLE’ THEN IT IS USED AS A SUMMARY NODE OF ALL POINTS CONTAINED WITHIN IT THIS METHOD IS NOT VERY SENSITIVE TO

CHANGES IN THIS PARAMETER IN THE RANGE OF 02 08 ANGLE LESS THAN 02 HAS QUICKLY INCREASING
COMPUTATION TIME AND ANGLE GREATER 08 HAS QUICKLY INCREASING ERROR
ATTRIBUTES
EMBEDDING ARRAYLIKE SHAPE NSAMPLES NCOMPONENTS STORES THE EMBEDDING VECTORS
KLDIVERGENCE FLOAT KULLBACKLEIBLER DIVERGENCE AFTER OPTIMIZATION
NITER INT NUMBER OF ITERATIONS RUN
REFERENCES
1 VAN DER MAATEN LJP HINTON GE VISUALIZING HIGHDIMENSIONAL DATA USING TSNE JOURNAL OF MA
CHINE LEARNING RESEARCH 925792605 2008
2 VAN DER MAATEN LJP TDISTRIBUTED STOCHASTIC NEIGHBOR EMBEDDING HTTPSLVDMAATENGITHUBIOTSNE
3 LJP VAN DER MAATEN ACCELERATING TSNE USING TREEBASED ALGORITHMS JOURNAL OF MACHINE LEARN
ING RESEARCH 15OCT32213245 2014 HTTPSLVDMAATENGITHUBIOPUBLICATIONSPAPERSJMLR2014PDF
EXAMPLES
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 IMPORT NUMPY AS NP
 FROM SKLEARNMANIFOLD IMPORT TSNE
X  NPARRAY0 0 0 0 1 1 1 0 1 1 1 1
XEMBEDDED  TSNENCOMPONENTS2FITTRANSFORMX
XEMBEDDEDSHAPE
4 2
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METHODS
FITSELF X Y FIT X INTO AN EMBEDDED SPACE
FITTRANSFORM SELF X Y FIT X INTO AN EMBEDDED SPACE AND RETURN THAT TRANS
FORMED OUTPUT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNCOMPONENTS2 PERPLEXITY300 EARLYEXAGGERATION120 LEARNINGRATE2000
NITER1000 NITERWITHOUTPROGRESS300 MINGRADNORM1E07 METRIC’EUCLIDEAN’
INIT’RANDOM’ VERBOSE0 RANDOMSTATENONE METHOD’BARNESHUT’ ANGLE05
FITSELFXYNONE
FIT X INTO AN EMBEDDED SPACE
PARAMETERS
XARRAY SHAPE NSAMPLES NFEATURES OR NSAMPLES NSAMPLES IF THE METRIC IS ‘PRE
COMPUTED’ X MUST BE A SQUARE DISTANCE MATRIX OTHERWISE IT CONTAINS A SAMPLE PER ROW IF
THE METHOD IS ‘EXACT’ X MAY BE A SPARSE MATRIX OF TYPE ‘CSR’ ‘CSC’ OR ‘COO’
YIGNORED
FITTRANSFORM SELFXYNONE
FIT X INTO AN EMBEDDED SPACE AND RETURN THAT TRANSFORMED OUTPUT

PARAMETERS
XARRAY SHAPE NSAMPLES NFEATURES OR NSAMPLES NSAMPLES IF THE METRIC IS ‘PRE
COMPUTED’ X MUST BE A SQUARE DISTANCE MATRIX OTHERWISE IT CONTAINS A SAMPLE PER ROW
YIGNORED
RETURNS
XNEW ARRAY SHAPE NSAMPLES NCOMPONENTS EMBEDDING OF THE TRAINING DATA IN LOW
DIMENSIONAL SPACE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNMANIFOLDTSNE
•TSNE THE EFFECT OF VARIOUS PERPLEXITY VALUES ON THE SHAPE
•COMPARISON OF MANIFOLD LEARNING METHODS
•MANIFOLD LEARNING METHODS ON A SEVERED SPHERE
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
MANIFOLDLOCALLYLINEAREMBEDDING X
PERFORM A LOCALLY LINEAR EMBEDDING ANALYSIS ON THE DATA
MANIFOLDSMACOF DISSIMILARITIES METRIC COMPUTES MULTIDIMENSIONAL SCALING USING THE SMACOF
ALGORITHM
MANIFOLDSPECTRALEMBEDDING ADJACENCY PROJECT THE SAMPLE ON THE FIRST EIGENVECTORS OF THE GRAPH
LAPLACIAN
6236SKLEARNMANIFOLD LOCALLYLINEAREMBEDDING
SKLEARNMANIFOLD LOCALLYLINEAREMBEDDING XNNEIGHBORS NCOMPONENTS REG0001
EIGENSOLVER’AUTO’ TOL1E06 MAXITER100
METHOD’STANDARD’ HESSIANTOL00001
MODIFIEDTOL1E12 RANDOMSTATENONE
NJOBSNONE
PERFORM A LOCALLY LINEAR EMBEDDING ANALYSIS ON THE DATA
623SKLEARNMANIFOLD MANIFOLD LEARNING 1979

READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE NEARESTNEIGHBORS SAMPLE DATA SHAPE NSAMPLES NFEATURES IN THE FORM
OF A NUMPY ARRAY OR A NEARESTNEIGHBORS OBJECT
NNEIGHBORS INTEGER NUMBER OF NEIGHBORS TO CONSIDER FOR EACH POINT
NCOMPONENTS INTEGER NUMBER OF COORDINATES FOR THE MANIFOLD
REGFLOAT REGULARIZATION CONSTANT MULTIPLIES THE TRACE OF THE LOCAL COVARIANCE MATRIX OF THE
DISTANCES
EIGENSOLVER STRING ‘AUTO’ ‘ARPACK’ ‘DENSE’ AUTO ALGORITHM WILL ATTEMPT TO CHOOSE THE
BEST METHOD FOR INPUT DATA
ARPACK USE ARNOLDI ITERATION IN SHIFTINVERT MODE FOR THIS METHOD M MAY BE A DENSE
MATRIX SPARSE MATRIX OR GENERAL LINEAR OPERATOR WARNING ARPACK CAN BE UNSTABLE FOR
SOME PROBLEMS IT IS BEST TO TRY SEVERAL RANDOM SEEDS IN ORDER TO CHECK RESULTS
DENSE USE STANDARD DENSE MATRIX OPERATIONS FOR THE EIGENVALUE DECOMPOSITION FOR THIS
METHOD M MUST BE AN ARRAY OR MATRIX TYPE THIS METHOD SHOULD BE AVOIDED FOR LARGE
PROBLEMS
TOLFLOAT OPTIONAL TOLERANCE FOR ‘ARPACK’ METHOD NOT USED IF EIGENSOLVER’DENSE’
MAXITER INTEGER MAXIMUM NUMBER OF ITERATIONS FOR THE ARPACK SOLVER
METHOD ‘STANDARD’ ‘HESSIAN’ ‘MODIFIED’ ‘LTSA’
STANDARD USE THE STANDARD LOCALLY LINEAR EMBEDDING ALGORITHM SEE REFERENCE 1
HESSIAN USE THE HESSIAN EIGENMAP METHOD THIS METHOD REQUIRES NNEIGHBORS
NCOMPONENTS 1 NCOMPONENTS 1 2 SEE REFERENCE 2
MODIFIED USE THE MODIFIED LOCALLY LINEAR EMBEDDING ALGORITHM SEE REFERENCE 3
LTSA USE LOCAL TANGENT SPACE ALIGNMENT ALGORITHM SEE REFERENCE 4
HESSIANTOL FLOAT OPTIONAL TOLERANCE FOR HESSIAN EIGENMAPPING METHOD ONLY USED IF METHOD
 ‘HESSIAN’
MODIFIEDTOL FLOAT OPTIONAL TOLERANCE FOR MODIFIED LLE METHOD ONLY USED IF METHOD
‘MODIFIED’
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SOLVER ‘ARPACK’
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS
SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RETURNS
YARRAYLIKE SHAPE NSAMPLES NCOMPONENTS EMBEDDING VECTORS
SQUAREDERROR FLOAT RECONSTRUCTION ERROR FOR THE EMBEDDING VECTORS EQUIVALENT TO NORMY
 W Y FRO 2 WHERE W ARE THE RECONSTRUCTION WEIGHTS

REFERENCES
1234
EXAMPLES USING SKLEARNMANIFOLDLOCALLYLINEAREMBEDDING
•SWISS ROLL REDUCTION WITH LLE
6237SKLEARNMANIFOLD SMACOF
SKLEARNMANIFOLD SMACOFDISSIMILARITIES METRICTRUE NCOMPONENTS2 INITNONE NINIT8
NJOBSNONE MAXITER300 VERBOSE0 EPS0001 RANDOMSTATENONE
RETURNNITERFALSE
COMPUTES MULTIDIMENSIONAL SCALING USING THE SMACOF ALGORITHM
THE SMACOF SCALING BY MAJORIZING A COMPLICATED FUNCTION ALGORITHM IS A MULTIDIMENSIONAL SCALING ALGO
RITHM WHICH MINIMIZES AN OBJECTIVE FUNCTION THE STRESS USING A MAJORIZATION TECHNIQUE STRESS MAJORIZATION
ALSO KNOWN AS THE GUTTMAN TRANSFORM GUARANTEES A MONOTONE CONVERGENCE OF STRESS AND IS MORE POWERFUL THAN
TRADITIONAL TECHNIQUES SUCH AS GRADIENT DESCENT
THE SMACOF ALGORITHM FOR METRIC MDS CAN SUMMARIZED BY THE FOLLOWING STEPS
1 SET AN INITIAL START CONFIGURATION RANDOMLY OR NOT
2 COMPUTE THE STRESS
3 COMPUTE THE GUTTMAN TRANSFORM
4 ITERATE 2 AND 3 UNTIL CONVERGENCE
THE NONMETRIC ALGORITHM ADDS A MONOTONIC REGRESSION STEP BEFORE COMPUTING THE STRESS
PARAMETERS
DISSIMILARITIES NDARRAY SHAPE NSAMPLES NSAMPLES PAIRWISE DISSIMILARITIES BETWEEN THE
POINTS MUST BE SYMMETRIC
METRIC BOOLEAN OPTIONAL DEFAULT TRUE COMPUTE METRIC OR NONMETRIC SMACOF ALGORITHM
NCOMPONENTS INT OPTIONAL DEFAULT 2 NUMBER OF DIMENSIONS IN WHICH TO IMMERSE THE DIS
SIMILARITIES IF AN INIT ARRAY IS PROVIDED THIS OPTION IS OVERRIDDEN AND THE SHAPE OF INIT
IS USED TO DETERMINE THE DIMENSIONALITY OF THE EMBEDDING SPACE
INIT NDARRAY SHAPE NSAMPLES NCOMPONENTS OPTIONAL DEFAULT NONE STARTING CONFIGURA
TION OF THE EMBEDDING TO INITIALIZE THE ALGORITHM BY DEFAULT THE ALGORITHM IS INITIALIZED
WITH A RANDOMLY CHOSEN ARRAY
NINIT INT OPTIONAL DEFAULT 8 NUMBER OF TIMES THE SMACOF ALGORITHM WILL BE RUN WITH
DIFFERENT INITIALIZATIONS THE FINAL RESULTS WILL BE THE BEST OUTPUT OF THE RUNS DETERMINED BY
THE RUN WITH THE SMALLEST FINAL STRESS IF INIT IS PROVIDED THIS OPTION IS OVERRIDDEN AND A
SINGLE RUN IS PERFORMED
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION
IF MULTIPLE INITIALIZATIONS ARE USED NINIT EACH RUN OF THE ALGORITHM IS COMPUTED IN
PARALLEL
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL
PROCESSORS SEE GLOSSARY FOR MORE DETAILS
623SKLEARNMANIFOLD MANIFOLD LEARNING 1981

MAXITER INT OPTIONAL DEFAULT 300 MAXIMUM NUMBER OF ITERATIONS OF THE SMACOF ALGO
RITHM FOR A SINGLE RUN
VERBOSE INT OPTIONAL DEFAULT 0 LEVEL OF VERBOSITY
EPS FLOAT OPTIONAL DEFAULT 1E3 RELATIVE TOLERANCE WITH RESPECT TO STRESS AT WHICH TO DECLARE
CONVERGENCE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE GENERATOR
USED TO INITIALIZE THE CENTERS IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER
GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE
THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
RETURNNITER BOOL OPTIONAL DEFAULT FALSE WHETHER OR NOT TO RETURN THE NUMBER OF ITERATIONS
RETURNS
XNDARRAY SHAPE NSAMPLES NCOMPONENTS COORDINATES OF THE POINTS IN A
NCOMPONENTS SPACE
STRESS FLOAT THE FINAL VALUE OF THE STRESS SUM OF SQUARED DISTANCE OF THE DISPARITIES AND THE
DISTANCES FOR ALL CONSTRAINED POINTS
NITER INT THE NUMBER OF ITERATIONS CORRESPONDING TO THE BEST STRESS RETURNED ONLY IF
RETURNNITER IS SET TOTRUE
NOTES
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6238SKLEARNMANIFOLD SPECTRALEMBEDDING
SKLEARNMANIFOLD SPECTRALEMBEDDING ADJACENCY NCOMPONENTS8 EIGENSOLVERNONE RAN
DOMSTATENONE EIGENTOL00 NORMLAPLACIANTRUE
DROPFIRSTTRUE
PROJECT THE SAMPLE ON THE FIRST EIGENVECTORS OF THE GRAPH LAPLACIAN
THE ADJACENCY MATRIX IS USED TO COMPUTE A NORMALIZED GRAPH LAPLACIAN WHOSE SPECTRUM ESPECIALLY THE EIGEN
VECTORS ASSOCIATED TO THE SMALLEST EIGENVALUES HAS AN INTERPRETATION IN TERMS OF MINIMAL NUMBER OF CUTS NECES
SARY TO SPLIT THE GRAPH INTO COMPARABLY SIZED COMPONENTS
THIS EMBEDDING CAN ALSO ‘WORK’ EVEN IF THE ADJACENCY VARIABLE IS NOT STRICTLY THE ADJACENCY MATRIX OF A GRAPH
BUT MORE GENERALLY AN AFFINITY OR SIMILARITY MATRIX BETWEEN SAMPLES FOR INSTANCE THE HEAT KERNEL OF A EUCLIDEAN
DISTANCE MATRIX OR A KNN MATRIX
HOWEVER CARE MUST TAKEN TO ALWAYS MAKE THE AFFINITY MATRIX SYMMETRIC SO THAT THE EIGENVECTOR DECOMPOSITION
WORKS AS EXPECTED
NOTE LAPLACIAN EIGENMAPS IS THE ACTUAL ALGORITHM IMPLEMENTED HERE
READ MORE IN THE USER GUIDE
PARAMETERS

ADJACENCY ARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NSAMPLES THE ADJACENCY MATRIX
OF THE GRAPH TO EMBED
NCOMPONENTS INTEGER OPTIONAL DEFAULT 8 THE DIMENSION OF THE PROJECTION SUBSPACE
EIGENSOLVER NONE 'ARPACK' 'LOBPCG' OR 'AMG' DEFAULT NONE THE EIGENVALUE DECOMPO
SITION STRATEGY TO USE AMG REQUIRES PYAMG TO BE INSTALLED IT CAN BE FASTER ON VERY LARGE
SPARSE PROBLEMS BUT MAY ALSO LEAD TO INSTABILITIES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE A PSEUDO RANDOM
NUMBER GENERATOR USED FOR THE INITIALIZATION OF THE LOBPCG EIGENVECTORS DECOMPOSITION IF INT
RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE
RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SOLVER 'AMG'
EIGENTOL FLOAT OPTIONAL DEFAULT00 STOPPING CRITERION FOR EIGENDECOMPOSITION OF THE LAPLA
CIAN MATRIX WHEN USING ARPACK EIGENSOLVER
NORMLAPLACIAN BOOL OPTIONAL DEFAULTTRUE IF TRUE THEN COMPUTE NORMALIZED LAPLACIAN
DROPFIRST BOOL OPTIONAL DEFAULTTRUE WHETHER TO DROP THE FIRST EIGENVECTOR FOR SPECTRAL EM
BEDDING THIS SHOULD BE TRUE AS THE FIRST EIGENVECTOR SHOULD BE CONSTANT VECTOR FOR CONNECTED
GRAPH BUT FOR SPECTRAL CLUSTERING THIS SHOULD BE KEPT AS FALSE TO RETAIN THE FIRST EIGENVECTOR
RETURNS
EMBEDDING ARRAY SHAPENSAMPLES NCOMPONENTS THE REDUCED SAMPLES
NOTES
SPECTRAL EMBEDDING LAPLACIAN EIGENMAPS IS MOST USEFUL WHEN THE GRAPH HAS ONE CONNECTED COMPONENT IF
THERE GRAPH HAS MANY COMPONENTS THE FIRST FEW EIGENVECTORS WILL SIMPLY UNCOVER THE CONNECTED COMPONENTS OF
THE GRAPH
REFERENCES
• HTTPSENWIKIPEDIAORGWIKILOBPCG
• TOWARD THE OPTIMAL PRECONDITIONED EIGENSOLVER LOCALLY OPTIMAL BLOCK PRECONDITIONED CONJUGATE GRA
DIENT METHOD ANDREW V KNYAZEV HTTPSDOIORG1011372FS1064827500366124
624SKLEARNMETRICS METRICS
SEE THE MODEL EVALUATION QUANTIFYING THE QUALITY OF PREDICTIONS SECTION AND THE PAIRWISE METRICS AFFINITIES AND
KERNELS SECTION OF THE USER GUIDE FOR FURTHER DETAILS THE SKLEARNMETRICS MODULE INCLUDES SCORE FUNCTIONS
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6241 MODEL SELECTION INTERFACE
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METRICSCHECKSCORING ESTIMATOR SCORING DETERMINE SCORER FROM USER OPTIONS
METRICSGETSCORER SCORING GET A SCORER FROM STRING
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TABLE 6178 – CONTINUED FROM PREVIOUS PAGE
METRICSMAKESCORER SCOREFUNC MAKE A SCORER FROM A PERFORMANCE METRIC OR LOSS FUNCTION
SKLEARNMETRICS CHECKSCORING
SKLEARNMETRICS CHECKSCORING ESTIMATOR SCORINGNONE ALLOWNONEFALSE
DETERMINE SCORER FROM USER OPTIONS
A TYPEERROR WILL BE THROWN IF THE ESTIMATOR CANNOT BE SCORED
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT IMPLEMENTING ‘FIT’ THE OBJECT TO USE TO FIT THE DATA
SCORING STRING CALLABLE OR NONE OPTIONAL DEFAULT NONE A STRING SEE MODEL EVALUATION DOC
UMENTATION OR A SCORER CALLABLE OBJECT FUNCTION WITH SIGNATURE SCORERESTIMATOR
X Y
ALLOWNONE BOOLEAN OPTIONAL DEFAULT FALSE IF NO SCORING IS SPECIFIED AND THE ESTIMATOR HAS
NO SCORE FUNCTION WE CAN EITHER RETURN NONE OR RAISE AN EXCEPTION
RETURNS
SCORING CALLABLE A SCORER CALLABLE OBJECT FUNCTION WITH SIGNATURE SCORERESTIMATOR
X Y
SKLEARNMETRICS GETSCORER
SKLEARNMETRICS GETSCORER SCORING
GET A SCORER FROM STRING
PARAMETERS
SCORING STR CALLABLE SCORING METHOD AS STRING IF CALLABLE IT IS RETURNED AS IS
RETURNS
SCORER CALLABLE THE SCORER
SKLEARNMETRICS MAKESCORER
SKLEARNMETRICS MAKESCORER SCOREFUNC GREATERISBETTERTRUE NEEDSPROBAFALSE
NEEDSTHRESHOLDFALSE KWARGS
MAKE A SCORER FROM A PERFORMANCE METRIC OR LOSS FUNCTION
THIS FACTORY FUNCTION WRAPS SCORING FUNCTIONS FOR USE IN GRIDSEARCHCV AND CROSSVALSCORE IT TAKES
A SCORE FUNCTION SUCH AS ACCURACYSCORE MEANSQUAREDERROR ADJUSTEDRANDINDEX OR
AVERAGEPRECISION AND RETURNS A CALLABLE THAT SCORES AN ESTIMATOR’S OUTPUT
READ MORE IN THE USER GUIDE
PARAMETERS
SCOREFUNC CALLABLE SCORE FUNCTION OR LOSS FUNCTION WITH SIGNATURE SCOREFUNCY
YPRED KWARGS
GREATERISBETTER BOOLEAN DEFAULTTRUE WHETHER SCOREFUNC IS A SCORE FUNCTION DEFAULT
MEANING HIGH IS GOOD OR A LOSS FUNCTION MEANING LOW IS GOOD IN THE LATTER CASE THE SCORER
OBJECT WILL SIGNFLIP THE OUTCOME OF THE SCOREFUNC

NEEDSPROBA BOOLEAN DEFAULTFALSE WHETHER SCOREFUNC REQUIRES PREDICTPROBA TO GET PROB
ABILITY ESTIMATES OUT OF A CLASSIFIER
IF TRUE FOR BINARY YTRUE THE SCORE FUNCTION IS SUPPOSED TO ACCEPT A 1D YPRED IE
PROBABILITY OF THE POSITIVE CLASS SHAPE NSAMPLES
NEEDSTHRESHOLD BOOLEAN DEFAULTFALSE WHETHER SCOREFUNC TAKES A CONTINUOUS DECISION CER
TAINTY THIS ONLY WORKS FOR BINARY CLASSIFICATION USING ESTIMATORS THAT HAVE EITHER A DECI
SIONFUNCTION OR PREDICTPROBA METHOD
IF TRUE FOR BINARY YTRUE THE SCORE FUNCTION IS SUPPOSED TO ACCEPT A 1D YPRED IE
PROBABILITY OF THE POSITIVE CLASS OR THE DECISION FUNCTION SHAPE NSAMPLES
FOR EXAMPLE AVERAGEPRECISION OR THE AREA UNDER THE ROC CURVE CAN NOT BE COMPUTED
USING DISCRETE PREDICTIONS ALONE
KWARGS ADDITIONAL ARGUMENTS ADDITIONAL PARAMETERS TO BE PASSED TO SCOREFUNC
RETURNS
SCORER CALLABLE CALLABLE OBJECT THAT RETURNS A SCALAR SCORE GREATER IS BETTER
EXAMPLES
 FROM SKLEARNMETRICS IMPORT FBETASCORE MAKESCORER
FTWOSCORER MAKESCORERFBETASCORE BETA2
FTWOSCORER
MAKESCORERFBETASCORE BETA2
 FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
 FROM SKLEARNSVM IMPORT LINEARSVC
GRID GRIDSEARCHCVLINEARSVC PARAMGRIDC 1 10
 SCORINGFTWOSCORER
EXAMPLES USING SKLEARNMETRICSMAKESCORER
•DEMONSTRATION OF MULTIMETRIC EVALUATION ON CROSSVALSCORE AND GRIDSEARCHCV
6242 CLASSIFICATION METRICS
SEE THE CLASSIFICATION METRICS SECTION OF THE USER GUIDE FOR FURTHER DETAILS
METRICSACCURACYSCORE YTRUE YPRED ACCURACY CLASSIFICATION SCORE
METRICSAUC X Y REORDER COMPUTE AREA UNDER THE CURVE AUC USING THE TRAPE
ZOIDAL RULE
METRICSAVERAGEPRECISIONSCORE YTRUE
YSCORECOMPUTE AVERAGE PRECISION AP FROM PREDICTION SCORES
METRICSBALANCEDACCURACYSCORE YTRUE
YPREDCOMPUTE THE BALANCED ACCURACY
METRICSBRIERSCORELOSS YTRUE YPROB COMPUTE THE BRIER SCORE
METRICSCLASSIFICATIONREPORT YTRUE
YPREDBUILD A TEXT REPORT SHOWING THE MAIN CLASSIFICATION METRICS
METRICSCOHENKAPPASCORE Y1 Y2 LABELS COHEN'S KAPPA A STATISTIC THAT MEASURES INTERANNOTATOR
AGREEMENT
CONTINUED ON NEXT PAGE

TABLE 6179 – CONTINUED FROM PREVIOUS PAGE
METRICSCONFUSIONMATRIX YTRUE YPRED COMPUTE CONFUSION MATRIX TO EVALUATE THE ACCURACY OF A CLASSIFICATION
METRICSF1SCORE YTRUE YPRED LABELS COMPUTE THE F1 SCORE ALSO KNOWN AS BALANCED FSCORE OR FMEASURE
METRICSFBETASCORE YTRUE YPRED BETA COMPUTE THE FBETA SCORE
METRICSHAMMINGLOSS YTRUE YPRED COMPUTE THE AVERAGE HAMMING LOSS
METRICSHINGELOSS YTRUE PREDDECISION AVERAGE HINGE LOSS NONREGULARIZED
METRICSJACCARDSCORE YTRUE YPRED JACCARD SIMILARITY COEFFICIENT SCORE
METRICSLOGLOSS YTRUE YPRED EPS LOG LOSS AKA LOGISTIC LOSS OR CROSSENTROPY LOSS
METRICSMATTHEWSCORRCOEF YTRUE YPRED
COMPUTE THE MATTHEWS CORRELATION COEFFICIENT MCC
METRICSMULTILABELCONFUSIONMATRIX YTRUE
COMPUTE A CONFUSION MATRIX FOR EACH CLASS OR SAMPLE
METRICSPRECISIONRECALLCURVE YTRUE COMPUTE PRECISIONRECALL PAIRS FOR DIFFERENT PROBABILITY THRESHOLDS
METRICSPRECISIONRECALLFSCORESUPPORT COMPUTE PRECISION RECALL FMEASURE AND SUPPORT FOR EACH CLASS
METRICSPRECISIONSCORE YTRUE YPRED COMPUTE THE PRECISION
METRICSRECALLSCORE YTRUE YPRED COMPUTE THE RECALL
METRICSROCAUCSCORE YTRUE YSCORE COMPUTE AREA UNDER THE RECEIVER OPERATING CHARACTERIS TIC CURVE ROC AUC FROM PREDICTION SCORES
METRICSROCCURVE YTRUE YSCORE COMPUTE RECEIVER OPERATING CHARACTERISTIC ROC
METRICSZEROONELOSS YTRUE YPRED ZEROONE CLASSIFICATION LOSS
SKLEARNMETRICS ACCURACYSCORE
SKLEARNMETRICS ACCURACYSCORE YTRUE YPRED NORMALIZETRUE SAMPLEWEIGHTNONE
ACCURACY CLASSIFICATION SCORE
IN MULTILABEL CLASSIFICATION THIS FUNCTION COMPUTES SUBSET ACCURACY THE SET OF LABELS PREDICTED FOR A SAMPLE MUST EXACTLY MATCH THE CORRESPONDING SET OF LABELS IN YTRUE
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX GROUND TRUTH CORRECT LABELS
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX PREDICTED LABELS AS RETURNED BY A CLASSIFIER
NORMALIZE BOOL OPTIONAL DEFAULTTRUE IF FALSE RETURN THE NUMBER OF CORRECTLY CLASSIFIED SAMPLES OTHERWISE RETURN THE FRACTION OF CORRECTLY CLASSIFIED SAMPLES
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT IFNORMALIZE TRUE RETURN THE FRACTION OF CORRECTLY CLASSIFIED SAMPLES FLOAT ELSE RETURNS THE NUMBER OF CORRECTLY CLASSIFIED SAMPLES INT
THE BEST PERFORMANCE IS 1 WITH NORMALIZE TRUE AND THE NUMBER OF SAMPLES WITH NORMALIZE FALSE
SEE ALSO
JACCARDSCORE HAMMINGLOSS ZEROONELOSS

NOTES
IN BINARY AND MULTICLASS CLASSIFICATION THIS FUNCTION IS EQUAL TO THE JACCARDSCORE FUNCTION
EXAMPLES
```
 FROM SKLEARNMETRICS IMPORT ACCURACYSCORE
YPRED  0 2 1 3
YTRUE  0 1 2 3
ACCURACYSCOREYTRUE YPRED
05
ACCURACYSCOREYTRUE YPRED NORMALIZE FALSE
2
```
IN THE MULTILABEL CASE WITH BINARY LABEL INDICATORS
```
 IMPORT NUMPY AS NP
ACCURACYSCORENPARRAY0 1 1 1 NPONES2 2
05
```
EXAMPLES USING SKLEARNMETRICSACCURACYSCORE
•PLOT CLASSIFICATION PROBABILITY
•MULTICLASS ADABOOSTED DECISION TREES
•PROBABILISTIC PREDICTIONS WITH GAUSSIAN PROCESS CLASSIFICATION GPC
•DEMONSTRATION OF MULTIMETRIC EVALUATION ON CROSSVALSCORE AND GRIDSEARCHCV
•IMPORTANCE OF FEATURE SCALING
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
SKLEARNMETRICS AUC
SKLEARNMETRICS AUCXYREORDER’DEPRECATED’
COMPUTE AREA UNDER THE CURVE AUC USING THE TRAPEZOIDAL RULE
THIS IS A GENERAL FUNCTION GIVEN POINTS ON A CURVE FOR COMPUTING THE AREA UNDER THE ROC CURVE SEE ROCAUCSCORE FOR AN ALTERNATIVE WAY TO SUMMARIZE A PRECISIONRECALL CURVE SEE AVERAGEPRECISIONSCORE
PARAMETERS
XARRAY SHAPE N X COORDINATES THESE MUST BE EITHER MONOTONIC INCREASING OR MONOTONIC DECREASING
YARRAY SHAPE N Y COORDINATES
REORDER BOOLEAN OPTIONAL DEFAULT’DEPRECATED’ WHETHER TO SORT X BEFORE COMPUTING IF FALSE ASSUME THAT X MUST BE EITHER MONOTONIC INCREASING OR MONOTONIC DECREASING IF TRUE Y IS USED TO BREAK TIES WHEN SORTING X MAKE SURE THAT Y HAS A MONOTONIC RELATION TO X WHEN SETTING REORDER TO TRUE
DEPRECATED SINCE VERSION 020 PARAMETER REORDER HAS BEEN DEPRECATED IN VERSION 020 AND WILL BE REMOVED IN 022 IT’S INTRODUCED FOR ROCAUCSCORE NOT FOR GENERAL USE AND IS

NO LONGER USED THERE WHAT'S MORE THE RESULT FROM AUC WILL BE SIGNIFICANTLY INFLUENCED IF
X IS SORTED UNEXPECTEDLY DUE TO SLIGHT FLOATING POINT ERROR SEE ISSUE 9786 FUTURE AND
DEFAULT BEHAVIOR IS EQUIVALENT TO REORDERFALSE
RETURNS
AUC FLOAT
SEE ALSO
ROCAUCSCORE COMPUTE THE AREA UNDER THE ROC CURVE
AVERAGEPRECISIONSCORE COMPUTE AVERAGE PRECISION FROM PREDICTION SCORES
PRECISIONRECALLCURVE COMPUTE PRECISIONRECALL PAIRS FOR DIFFERENT PROBABILITY THRESHOLDS
EXAMPLES
IMPORT NUMPY AS NP
FROM SKLEARN IMPORT METRICS
Y NPARRAY1 1 2 2
PRED NPARRAY01 04 035 08
FPR TPR THRESHOLDS METRICSROCCURVEY PRED POSLABEL2
METRICSAUCFPR TPR
075
EXAMPLES USING SKLEARNMETRICSAUC
•SPECIES DISTRIBUTION MODELING
•RECEIVER OPERATING CHARACTERISTIC ROC WITH CROSS VALIDATION
•RECEIVER OPERATING CHARACTERISTIC ROC
SKLEARNMETRICS AVERAGEPRECISIONSCORE
SKLEARNMETRICS AVERAGEPRECISIONSCORE YTRUE YSCORE AVERAGE'MACRO' POSLABEL1
SAMPLEWEIGHTNONE
COMPUTE AVERAGE PRECISION AP FROM PREDICTION SCORES
AP SUMMARIZES A PRECISIONRECALL CURVE AS THE WEIGHTED MEAN OF PRECISIONS ACHIEVED AT EACH THRESHOLD WITH THE
INCREASE IN RECALL FROM THE PREVIOUS THRESHOLD USED AS THE WEIGHT
AP∑
□□□−□□−1□□
WHERE □□AND□□ARE THE PRECISION AND RECALL AT THE NTH THRESHOLD 1 THIS IMPLEMENTATION IS NOT INTERPOLATED
AND IS DIFFERENT FROM COMPUTING THE AREA UNDER THE PRECISIONRECALL CURVE WITH THE TRAPEZOIDAL RULE WHICH USES
LINEAR INTERPOLATION AND CAN BE TOO OPTIMISTIC
NOTE THIS IMPLEMENTATION IS RESTRICTED TO THE BINARY CLASSIFICATION TASK OR MULTILABEL CLASSIFICATION TASK
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAY SHAPE NSAMPLES OR NSAMPLES NCLASSES TRUE BINARY LABELS OR BINARY LABEL
INDICATORS

YSCORE ARRAY SHAPE NSAMPLES OR NSAMPLES NCLASSES TARGET SCORES CAN EITHER BE
PROBABILITY ESTIMATES OF THE POSITIVE CLASS CONFIDENCE VALUES OR NONTHRESHOLDED MEASURE
OF DECISIONS AS RETURNED BY “DECISIONFUNCTION” ON SOME CLASSIFIERS
AVERAGE STRING NONE ‘MICRO’ ‘MACRO’ DEFAULT ‘SAMPLES’ ‘WEIGHTED’ IF NONE THE SCORES
FOR EACH CLASS ARE RETURNED OTHERWISE THIS DETERMINES THE TYPE OF AVERAGING PERFORMED ON
THE DATA
MICRO CALCULATE METRICS GLOBALLY BY CONSIDERING EACH ELEMENT OF THE LABEL INDICATOR
MATRIX AS A LABEL
MACRO CALCULATE METRICS FOR EACH LABEL AND FIND THEIR UNWEIGHTED MEAN THIS DOES NOT
TAKE LABEL IMBALANCE INTO ACCOUNT
WEIGHTED CALCULATE METRICS FOR EACH LABEL AND FIND THEIR AVERAGE WEIGHTED BY SUP
PORT THE NUMBER OF TRUE INSTANCES FOR EACH LABEL
SAMPLES CALCULATE METRICS FOR EACH INSTANCE AND FIND THEIR AVERAGE
WILL BE IGNORED WHEN YTRUE IS BINARY
POSLABEL INT OR STR DEFAULT1 THE LABEL OF THE POSITIVE CLASS ONLY APPLIED TO BINARY
YTRUE FOR MULTILABELINDICATOR YTRUE POSLABEL IS FIXED TO 1
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
AVERAGEPRECISION FLOAT
SEE ALSO
ROCAUCSCORE COMPUTE THE AREA UNDER THE ROC CURVE
PRECISIONRECALLCURVE COMPUTE PRECISIONRECALL PAIRS FOR DIFFERENT PROBABILITY THRESHOLDS
NOTES
CHANGED IN VERSION 019 INSTEAD OF LINEARLY INTERPOLATING BETWEEN OPERATING POINTS PRECISIONS ARE WEIGHTED BY
THE CHANGE IN RECALL SINCE THE LAST OPERATING POINT
REFERENCES
1
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT AVERAGEPRECISIONSCORE
YTRUE  NPARRAY0 0 1 1
YSCORES  NPARRAY01 04 035 08
AVERAGEPRECISIONSCOREYTRUE YSCORES
083
```

EXAMPLES USING SKLEARNMETRICSAVERAGEPRECISIONSCORE
•PRECISIONRECALL
SKLEARNMETRICS BALANCEDACCURACYSCORE
SKLEARNMETRICS BALANCEDACCURACYSCORE YTRUE YPRED SAMPLEWEIGHTNONE AD
JUSTEDFALSE
COMPUTE THE BALANCED ACCURACY
THE BALANCED ACCURACY IN BINARY AND MULTICLASS CLASSIFICATION PROBLEMS TO DEAL WITH IMBALANCED DATASETS IT IS
DEFINED AS THE AVERAGE OF RECALL OBTAINED ON EACH CLASS
THE BEST VALUE IS 1 AND THE WORST VALUE IS 0 WHEN ADJUSTEDFALSE
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE GROUND TRUTH CORRECT TARGET VALUES
YPRED 1D ARRAYLIKE ESTIMATED TARGETS AS RETURNED BY A CLASSIFIER
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
ADJUSTED BOOL DEFAULTFALSE WHEN TRUE THE RESULT IS ADJUSTED FOR CHANCE SO THAT RANDOM
PERFORMANCE WOULD SCORE 0 AND PERFECT PERFORMANCE SCORES 1
RETURNS
BALANCEDACCURACY FLOAT
SEE ALSO
RECALLSCORE ROCAUCSCORE
NOTES
SOME LITERATURE PROMOTES ALTERNATIVE DEFINITIONS OF BALANCED ACCURACY OUR DEFINITION IS EQUIVALENT TO
ACCURACYSCORE WITH CLASSBALANCED SAMPLE WEIGHTS AND SHARES DESIRABLE PROPERTIES WITH THE BINARY CASE
SEE THE USER GUIDE
REFERENCES
12
EXAMPLES
 FROM SKLEARNMETRICS IMPORT BALANCEDACCURACYSCORE
YTRUE 0 1 0 0 1 0
YPRED 0 1 0 0 0 1
BALANCEDACCURACYSCOREYTRUE YPRED
0625

SKLEARNMETRICS BRIERSCORELOSS
SKLEARNMETRICS BRIERSCORELOSS YTRUE YPROB SAMPLEWEIGHTNONE POSLABELNONE
COMPUTE THE BRIER SCORE THE SMALLER THE BRIER SCORE THE BETTER HENCE THE NAMING WITH “LOSS” ACROSS ALL ITEMS IN A SET N PREDICTIONS THE BRIER SCORE MEASURES THE MEAN SQUARED DIFFERENCE BETWEEN 1 THE PREDICTED PROBABILITY ASSIGNED TO THE POSSIBLE OUTCOMES FOR ITEM I AND 2 THE ACTUAL OUTCOME THEREFORE THE LOWER THE BRIER SCORE IS FOR A SET OF PREDICTIONS THE BETTER THE PREDICTIONS ARE CALIBRATED NOTE THAT THE BRIER SCORE ALWAYS TAKES ON A VALUE BETWEEN ZERO AND ONE SINCE THIS IS THE LARGEST POSSIBLE DIFFERENCE BETWEEN A PREDICTED PROBABILITY WHICH MUST BE BETWEEN ZERO AND ONE AND THE ACTUAL OUTCOME WHICH CAN TAKE ON VALUES OF ONLY 0 AND 1 THE BRIER LOSS IS COMPOSED OF REFINEMENT LOSS AND CALIBRATION LOSS THE BRIER SCORE IS APPROPRIATE FOR BINARY AND CATEGORICAL OUTCOMES THAT CAN BE STRUCTURED AS TRUE OR FALSE BUT IS INAPPROPRIATE FOR ORDINAL VARIABLES WHICH CAN TAKE ON THREE OR MORE VALUES THIS IS BECAUSE THE BRIER SCORE ASSUMES THAT ALL POSSIBLE OUTCOMES ARE EQUIVALENTLY “DISTANT” FROM ONE ANOTHER WHICH LABEL IS CONSIDERED TO BE THE POSITIVE LABEL IS CONTROLLED VIA THE PARAMETER POSLABEL WHICH DEFAULTS TO 1 READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAY SHAPE NSAMPLES TRUE TARGETS
YPROB ARRAY SHAPE NSAMPLES PROBABILITIES OF THE POSITIVE CLASS
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
POSLABEL INT OR STR DEFAULTNONE LABEL OF THE POSITIVE CLASS DEFAULTS TO THE GREATER LABEL UNLESS YTRUE IS ALL 0 OR ALL 1 IN WHICH CASE POSLABEL DEFAULTS TO 1
RETURNS
SCORE FLOAT BRIER SCORE
REFERENCES
1
EXAMPLES
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT BRIERSCORELOSS
YTRUE NPARRAY0 1 1 0
YTRUECATEGORICAL NPARRAYSPAM HAM HAM SPAM
YPROB NPARRAY01 09 08 03
BRIERSCORELOSSYTRUE YPROB
0037
BRIERSCORELOSSYTRUE 1YPROB POSLABEL0
0037
BRIERSCORELOSSYTRUECATEGORICAL YPROB POS
‹→LABELHAM
0037
BRIERSCORELOSSYTRUE NPARRAYYPROB 05
00
EXAMPLES USING SKLEARNMETRICSBRIERSCORELOSS
•PROBABILITY CALIBRATION CURVES
624SKLEARNMETRICS METRICS 1991

•PROBABILITY CALIBRATION OF CLASSIFIERS
SKLEARNMETRICS CLASSIFICATIONREPORT
SKLEARNMETRICS CLASSIFICATIONREPORT YTRUE YPRED LABELSNONE TARGETNAMESNONE
SAMPLEWEIGHTNONE DIGITS2 OUTPUTDICTFALSE
BUILD A TEXT REPORT SHOWING THE MAIN CLASSIFICATION METRICS
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX GROUND TRUTH CORRECT TARGET VALUES
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX ESTIMATED TARGETS AS RETURNED BY A CLASSIFIER
LABELS ARRAY SHAPE NLABELS OPTIONAL LIST OF LABEL INDICES TO INCLUDE IN THE REPORT
TARGETNAMES LIST OF STRINGS OPTIONAL DISPLAY NAMES MATCHING THE LABELS SAME ORDER
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
DIGITS INT NUMBER OF DIGITS FOR FORMATTING OUTPUT FLOATING POINT VALUES WHEN OUTPUTDICT ISTRUE THIS WILL BE IGNORED AND THE RETURNED VALUES WILL NOT BE ROUNDED
OUTPUTDICT BOOL DEFAULT FALSE IF TRUE RETURN OUTPUT AS DICT
RETURNS
REPORT STRING DICT TEXT SUMMARY OF THE PRECISION RECALL F1 SCORE FOR EACH CLASS DICTIONARY RETURNED IF OUTPUTDICT IS TRUE DICTIONARY HAS THE FOLLOWING STRUCTURE
LABEL 1 PRECISION05
RECALL10
F1SCORE067
SUPPORT1
LABEL 2

THE REPORTED AVERAGES INCLUDE MACRO AVERAGE AVERAGING THE UNWEIGHTED MEAN PER LABEL WEIGHTED AVERAGE AVERAGING THE SUPPORTWEIGHTED MEAN PER LABEL SAMPLE AVERAGE ONLY FOR MULTILABEL CLASSIFICATION AND MICRO AVERAGE AVERAGING THE TO TAL TRUE POSITIVES FALSE NEGATIVES AND FALSE POSITIVES IT IS ONLY SHOWN FOR MULTI LABEL OR MULTICLASS WITH A SUBSET OF CLASSES BECAUSE IT IS ACCURACY OTHERWISE SEE ALSOFUNCPRECISIONRECALLFSCORESUPPORT FOR MORE DETAILS ON AVERAGES
NOTE THAT IN BINARY CLASSIFICATION RECALL OF THE POSITIVE CLASS IS ALSO KNOWN AS “SENSITIVITY” RECALL OF THE NEGATIVE CLASS IS “SPECIFICITY”
SEE ALSO
PRECISIONRECALLFSCORESUPPORT CONFUSIONMATRIX
MULTILABELCONFUSIONMATRIX

SCIKITLEARN USER GUIDE RELEASE 0213
EXAMPLES
FROM SKLEARNMETRICS IMPORT CLASSIFICATIONREPORT
YTRUE 0 1 2 2 2
YPRED 0 0 2 2 1
TARGETNAMES CLASS 0 CLASS 1 CLASS 2
PRINTCLASSIFICATIONREPORTYTRUE YPRED TARGETNAMESTARGETNAMES
PRECISION RECALL F1SCORE SUPPORT
CLASS 0 050 100 067 1
CLASS 1 000 000 000 1
CLASS 2 100 067 080 3
ACCURACY 060 5
MACRO AVG 050 056 049 5
WEIGHTED AVG 070 060 061 5
YPRED 1 1 0
YTRUE 1 1 1
PRINTCLASSIFICATIONREPORTYTRUE YPRED LABELS1 2 3
PRECISION RECALL F1SCORE SUPPORT
1 100 067 080 3
2 000 000 000 0
3 000 000 000 0
MICRO AVG 100 067 080 3
MACRO AVG 033 022 027 3
WEIGHTED AVG 100 067 080 3
EXAMPLES USING SKLEARNMETRICSCLASSIFICATIONREPORT
•FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
•RECOGNIZING HANDWRITTEN DIGITS
•COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
•PIPELINE ANOVA SVM
•PARAMETER ESTIMATION USING GRID SEARCH WITH CROSSVALIDATION
•RESTRICTED BOLTZMANN MACHINE FEATURES FOR DIGIT CLASSIFICATION
•LABEL PROPAGATION DIGITS DEMONSTRATING PERFORMANCE
•LABEL PROPAGATION DIGITS ACTIVE LEARNING
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
SKLEARNMETRICS COHENKAPPASCORE
SKLEARNMETRICS COHENKAPPASCORE Y1 Y2 LABELSNONE WEIGHTSNONE SAM
PLEWEIGHTNONE
COHEN’S KAPPA A STATISTIC THAT MEASURES INTERANNOTATOR AGREEMENT
624SKLEARNMETRICS METRICS 1993

THIS FUNCTION COMPUTES COHEN'S KAPPA 1 A SCORE THAT EXPRESSES THE LEVEL OF AGREEMENT BETWEEN TWO ANNOTATORS ON A CLASSIFICATION PROBLEM IT IS DEFINED AS
□ □□−□□1−□□
WHERE □□IS THE EMPIRICAL PROBABILITY OF AGREEMENT ON THE LABEL ASSIGNED TO ANY SAMPLE THE OBSERVED AGREEMENT RATIO AND □□IS THE EXPECTED AGREEMENT WHEN BOTH ANNOTATORS ASSIGN LABELS RANDOMLY □□IS ESTIMATED USING A PERANNOTATOR EMPIRICAL PRIOR OVER THE CLASS LABELS 2
READ MORE IN THE USER GUIDE
PARAMETERS
Y1ARRAY SHAPE NSAMPLES LABELS ASSIGNED BY THE FIRST ANNOTATOR
Y2ARRAY SHAPE NSAMPLES LABELS ASSIGNED BY THE SECOND ANNOTATOR THE KAPPA STATISTIC IS SYMMETRIC SO SWAPPING Y1ANDY2DOESN'T CHANGE THE VALUE
LABELS ARRAY SHAPE NCLASSES OPTIONAL LIST OF LABELS TO INDEX THE MATRIX THIS MAY BE USED TO SELECT A SUBSET OF LABELS IF NONE ALL LABELS THAT APPEAR AT LEAST ONCE IN Y1ORY2ARE USED
WEIGHTS STR OPTIONAL LIST OF WEIGHTING TYPE TO CALCULATE THE SCORE NONE MEANS NO WEIGHTED "LINEAR" MEANS LINEAR WEIGHTED "QUADRATIC" MEANS QUADRATIC WEIGHTED
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
KAPPA FLOAT THE KAPPA STATISTIC WHICH IS A NUMBER BETWEEN 1 AND 1 THE MAXIMUM VALUE MEANS COMPLETE AGREEMENT ZERO OR LOWER MEANS CHANCE AGREEMENT
REFERENCES
123
SKLEARNMETRICS CONFUSIONMATRIX
SKLEARNMETRICS CONFUSIONMATRIX YTRUE YPRED LABELSNONE SAMPLEWEIGHTNONE
COMPUTE CONFUSION MATRIX TO EVALUATE THE ACCURACY OF A CLASSIFICATION
BY DEFINITION A CONFUSION MATRIX □IS SUCH THAT □□□IS EQUAL TO THE NUMBER OF OBSERVATIONS KNOWN TO BE IN GROUP □BUT PREDICTED TO BE IN GROUP □
THUS IN BINARY CLASSIFICATION THE COUNT OF TRUE NEGATIVES IS □00 FALSE NEGATIVES IS □10 TRUE POSITIVES IS □11 AND FALSE POSITIVES IS □01
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAY SHAPE NSAMPLES GROUND TRUTH CORRECT TARGET VALUES
YPRED ARRAY SHAPE NSAMPLES ESTIMATED TARGETS AS RETURNED BY A CLASSIFIER
LABELS ARRAY SHAPE NCLASSES OPTIONAL LIST OF LABELS TO INDEX THE MATRIX THIS MAY BE USED TO REORDER OR SELECT A SUBSET OF LABELS IF NONE IS GIVEN THOSE THAT APPEAR AT LEAST ONCE IN YTRUE ORYPRED ARE USED IN SORTED ORDER
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
CARRAY SHAPE NCLASSES NCLASSES CONFUSION MATRIX

SCIKITLEARN USER GUIDE RELEASE 0213
REFERENCES
1
EXAMPLES
FROM SKLEARNMETRICS IMPORT CONFUSIONMATRIX
YTRUE 2 0 2 2 0 1
YPRED 0 0 2 2 0 2
CONFUSIONMATRIXYTRUE YPRED
ARRAY2 0 0
0 0 1
1 0 2
YTRUE CAT ANT CAT CAT ANT BIRD
YPRED ANT ANT CAT CAT ANT CAT
CONFUSIONMATRIXYTRUE YPRED LABELSANT BIRD CAT
ARRAY2 0 0
0 0 1
1 0 2
IN THE BINARY CASE WE CAN EXTRACT TRUE POSITIVES ETC AS FOLLOWS
TN FP FN TP CONFUSIONMATRIX0 1 0 1 1 1 1 0RAVEL
TN FP FN TP
0 2 1 1
EXAMPLES USING SKLEARNMETRICSCONFUSIONMATRIX
•FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
•RECOGNIZING HANDWRITTEN DIGITS
•CONFUSION MATRIX
•LABEL PROPAGATION DIGITS DEMONSTRATING PERFORMANCE
•LABEL PROPAGATION DIGITS ACTIVE LEARNING
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
SKLEARNMETRICS F1SCORE
SKLEARNMETRICS F1SCORE YTRUE YPRED LABELSNONE POSLABEL1 AVERAGE’BINARY’ SAM
PLEWEIGHTNONE
COMPUTE THE F1 SCORE ALSO KNOWN AS BALANCED FSCORE OR FMEASURE
THE F1 SCORE CAN BE INTERPRETED AS A WEIGHTED AVERAGE OF THE PRECISION AND RECALL WHERE AN F1 SCORE REACHES ITS
BEST VALUE AT 1 AND WORST SCORE AT 0 THE RELATIVE CONTRIBUTION OF PRECISION AND RECALL TO THE F1 SCORE ARE EQUAL
THE FORMULA FOR THE F1 SCORE IS
F1 2PRECISION RECALL PRECISION RECALL
624SKLEARNMETRICS METRICS 1995

IN THE MULTICLASS AND MULTILABEL CASE THIS IS THE AVERAGE OF THE F1 SCORE OF EACH CLASS WITH WEIGHTING DEPENDING ON THEAVERAGE PARAMETER
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX GROUND TRUTH CORRECT TARGET VALUES
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX ESTIMATED TARGETS AS RETURNED BY A CLASSIFIER
LABELS LIST OPTIONAL THE SET OF LABELS TO INCLUDE WHEN AVERAGE BINARY AND THEIR ORDER IFAVERAGE IS NONE LABELS PRESENT IN THE DATA CAN BE EXCLUDED FOR EXAMPLE TO CALCULATE A MULTICLASS AVERAGE IGNORING A MAJORITY NEGATIVE CLASS WHILE LABELS NOT PRESENT IN THE DATA WILL RESULT IN 0 COMPONENTS IN A MACRO AVERAGE FOR MULTILABEL TARGETS LABELS ARE COLUMN INDICES BY DEFAULT ALL LABELS IN YTRUE ANDYPRED ARE USED IN SORTED ORDER
CHANGED IN VERSION 017 PARAMETER LABELS IMPROVED FOR MULTICLASS PROBLEM
POSLABEL STR OR INT 1 BY DEFAULT THE CLASS TO REPORT IF AVERAGEBINARY AND THE DATA IS BINARY IF THE DATA ARE MULTICLASS OR MULTILABEL THIS WILL BE IGNORED SETTING LABELSPOSLABEL ANDAVERAGE BINARY WILL REPORT SCORES FOR THAT LA
BEL ONLY
AVERAGE STRING NONE ‘BINARY’ DEFAULT ‘MICRO’ ‘MACRO’ ‘SAMPLES’ ‘WEIGHTED’ THIS PA
RAMETER IS REQUIRED FOR MULTICLASSMULTILABEL TARGETS IF NONE THE SCORES FOR EACH CLASS ARE RETURNED OTHERWISE THIS DETERMINES THE TYPE OF AVERAGING PERFORMED ON THE DATA
BINARY ONLY REPORT RESULTS FOR THE CLASS SPECIFIED BY POSLABEL THIS IS APPLICABLE ONLY IF TARGETS YTRUEPRED ARE BINARY
MICRO CALCULATE METRICS GLOBALLY BY COUNTING THE TOTAL TRUE POSITIVES FALSE NEGATIVES AND FALSE POSITIVES
MACRO CALCULATE METRICS FOR EACH LABEL AND FIND THEIR UNWEIGHTED MEAN THIS DOES NOT TAKE LABEL IMBALANCE INTO ACCOUNT
WEIGHTED CALCULATE METRICS FOR EACH LABEL AND FIND THEIR AVERAGE WEIGHTED BY SUPPORT THE NUMBER OF TRUE INSTANCES FOR EACH LABEL THIS ALTERS ‘MACRO’ TO ACCOUNT FOR LABEL IMBALANCE IT CAN RESULT IN AN FSCORE THAT IS NOT BETWEEN PRECISION AND RECALL
SAMPLES CALCULATE METRICS FOR EACH INSTANCE AND FIND THEIR AVERAGE ONLY MEANINGFUL FOR MULTILABEL CLASSIFICATION WHERE THIS DIFFERS FROM ACCURACYSCORE
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
F1SCORE FLOAT OR ARRAY OF FLOAT SHAPE NUNIQUELABELS F1 SCORE OF THE POSITIVE CLASS IN BINARY CLASSIFICATION OR WEIGHTED AVERAGE OF THE F1 SCORES OF EACH CLASS FOR THE MULTICLASS TASK
SEE ALSO
FBETASCORE PRECISIONRECALLFSCORESUPPORT JACCARDSCORE MULTILABELCONFUSIONMATRIX

NOTES
WHENTRUE POSITIVE FALSE POSITIVE 0 ORTRUE POSITIVE FALSE NEGATIVE
 0 FSCORE RETURNS 0 AND RAISES UNDEFINEDMETRICWARNING
REFERENCES
1
EXAMPLES
 FROM SKLEARNMETRICS IMPORT F1SCORE
YTRUE 0 1 2 0 1 2
YPRED 0 2 1 0 0 1
F1SCOREYTRUE YPRED AVERAGEMACRO
026
F1SCOREYTRUE YPRED AVERAGEMICRO
033
F1SCOREYTRUE YPRED AVERAGEWEIGHTED
026
F1SCOREYTRUE YPRED AVERAGE NONE
ARRAY08 0 0
EXAMPLES USING SKLEARNMETRICSF1SCORE
•PROBABILITY CALIBRATION CURVES
SKLEARNMETRICS FBETASCORE
SKLEARNMETRICS FBETASCORE YTRUE YPRED BETALABELSNONE POSLABEL1 AVERAGE’BINARY’
SAMPLEWEIGHTNONE
COMPUTE THE FBETA SCORE
THE FBETA SCORE IS THE WEIGHTED HARMONIC MEAN OF PRECISION AND RECALL REACHING ITS OPTIMAL VALUE AT 1 AND ITS
WORST VALUE AT 0
THEBETA PARAMETER DETERMINES THE WEIGHT OF RECALL IN THE COMBINED SCORE BETA 1 LENDS MORE WEIGHT TO
PRECISION WHILE BETA 1 FAVORS RECALL BETA 0 CONSIDERS ONLY PRECISION BETA INF ONLY RECALL
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX GROUND TRUTH CORRECT TARGET
VALUES
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX ESTIMATED TARGETS AS RETURNED BY
A CLASSIFIER
BETA FLOAT WEIGHT OF PRECISION IN HARMONIC MEAN
LABELS LIST OPTIONAL THE SET OF LABELS TO INCLUDE WHEN AVERAGE BINARY AND THEIR
ORDER IFAVERAGE IS NONE LABELS PRESENT IN THE DATA CAN BE EXCLUDED FOR EXAMPLE TO
CALCULATE A MULTICLASS AVERAGE IGNORING A MAJORITY NEGATIVE CLASS WHILE LABELS NOT PRESENT IN

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THE DATA WILL RESULT IN 0 COMPONENTS IN A MACRO AVERAGE FOR MULTILABEL TARGETS LABELS ARE
COLUMN INDICES BY DEFAULT ALL LABELS IN YTRUE ANDYPRED ARE USED IN SORTED ORDER
CHANGED IN VERSION 017 PARAMETER LABELS IMPROVED FOR MULTICLASS PROBLEM
POSLABEL STR OR INT 1 BY DEFAULT THE CLASS TO REPORT IF AVERAGEBINARY AND THE
DATA IS BINARY IF THE DATA ARE MULTICLASS OR MULTILABEL THIS WILL BE IGNORED SETTING
LABELSPOSLABEL ANDAVERAGE BINARY WILL REPORT SCORES FOR THAT LA
BEL ONLY
AVERAGE STRING NONE ‘BINARY’ DEFAULT ‘MICRO’ ‘MACRO’ ‘SAMPLES’ ‘WEIGHTED’ THIS PA
RAMETER IS REQUIRED FOR MULTICLASSMULTILABEL TARGETS IF NONE THE SCORES FOR EACH CLASS ARE
RETURNED OTHERWISE THIS DETERMINES THE TYPE OF AVERAGING PERFORMED ON THE DATA
BINARY ONLY REPORT RESULTS FOR THE CLASS SPECIFIED BY POSLABEL THIS IS APPLICABLE
ONLY IF TARGETS YTRUEPRED ARE BINARY
MICRO CALCULATE METRICS GLOBALLY BY COUNTING THE TOTAL TRUE POSITIVES FALSE NEGATIVES
AND FALSE POSITIVES
MACRO CALCULATE METRICS FOR EACH LABEL AND FIND THEIR UNWEIGHTED MEAN THIS DOES NOT
TAKE LABEL IMBALANCE INTO ACCOUNT
WEIGHTED CALCULATE METRICS FOR EACH LABEL AND FIND THEIR AVERAGE WEIGHTED BY SUPPORT
THE NUMBER OF TRUE INSTANCES FOR EACH LABEL THIS ALTERS ‘MACRO’ TO ACCOUNT FOR LABEL
IMBALANCE IT CAN RESULT IN AN FSCORE THAT IS NOT BETWEEN PRECISION AND RECALL
SAMPLES CALCULATE METRICS FOR EACH INSTANCE AND FIND THEIR AVERAGE ONLY MEANINGFUL
FOR MULTILABEL CLASSIFICATION WHERE THIS DIFFERS FROM ACCURACYSCORE
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
FBETASCORE FLOAT IF AVERAGE IS NOT NONE OR ARRAY OF FLOAT SHAPE NUNIQUELABELS FBETA
SCORE OF THE POSITIVE CLASS IN BINARY CLASSIFICATION OR WEIGHTED AVERAGE OF THE FBETA SCORE OF
EACH CLASS FOR THE MULTICLASS TASK
SEE ALSO
PRECISIONRECALLFSCORESUPPORT MULTILABELCONFUSIONMATRIX
NOTES
WHENTRUE POSITIVE FALSE POSITIVE 0 ORTRUE POSITIVE FALSE NEGATIVE
 0 FSCORE RETURNS 0 AND RAISES UNDEFINEDMETRICWARNING
REFERENCES
12
EXAMPLES
 FROM SKLEARNMETRICS IMPORT FBETASCORE
YTRUE 0 1 2 0 1 2
YPRED 0 2 1 0 0 1
FBETASCOREYTRUE YPRED AVERAGEMACRO BETA05

023
FBETASCOREYTRUE YPRED AVERAGEMICRO BETA05

033
FBETASCOREYTRUE YPRED AVERAGEWEIGHTED BETA05

023
FBETASCOREYTRUE YPRED AVERAGE NONE BETA05

ARRAY071 0 0
SKLEARNMETRICS HAMMINGLOSS
SKLEARNMETRICS HAMMINGLOSS YTRUE YPRED LABELSNONE SAMPLEWEIGHTNONE
COMPUTE THE AVERAGE HAMMING LOSS
THE HAMMING LOSS IS THE FRACTION OF LABELS THAT ARE INCORRECTLY PREDICTED
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX GROUND TRUTH CORRECT LABELS
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX PREDICTED LABELS AS RETURNED BY
A CLASSIFIER
LABELS ARRAY SHAPE NLABELS OPTIONAL DEFAULT'DEPRECATED' INTEGER ARRAY OF LABELS IF NOT
PROVIDED LABELS WILL BE INFERRED FROM YTRUE AND YPRED
NEW IN VERSION 018
DEPRECATED SINCE VERSION 021 THIS PARAMETER LABELS IS DEPRECATED IN VERSION 021 AND
WILL BE REMOVED IN VERSION 023 HAMMING LOSS USES YTRUESHAPE1 FOR THE NUMBER
OF LABELS WHEN YTRUE IS BINARY LABEL INDICATORS SO IT IS UNNECESSARY FOR THE USER TO SPECIFY
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
NEW IN VERSION 018
RETURNS
LOSS FLOAT OR INT RETURN THE AVERAGE HAMMING LOSS BETWEEN ELEMENT OF YTRUE ANDYPRED
SEE ALSO
ACCURACYSCORE JACCARDSCORE ZEROONELOSS
NOTES
IN MULTICLASS CLASSIFICATION THE HAMMING LOSS CORRESPONDS TO THE HAMMING DISTANCE BETWEEN YTRUE AND
YPRED WHICH IS EQUIVALENT TO THE SUBSET ZEROONELOSS FUNCTION WHEN NORMALIZE PARAMETER IS SET TO
TRUE
IN MULTILABEL CLASSIFICATION THE HAMMING LOSS IS DIFFERENT FROM THE SUBSET ZEROONE LOSS THE ZEROONE LOSS
CONSIDERS THE ENTIRE SET OF LABELS FOR A GIVEN SAMPLE INCORRECT IF IT DOES NOT ENTIRELY MATCH THE TRUE SET OF LABELS
HAMMING LOSS IS MORE FORGIVING IN THAT IT PENALIZES ONLY THE INDIVIDUAL LABELS
624SKLEARNMETRICS METRICS 1999

THE HAMMING LOSS IS UPPERBOUNDED BY THE SUBSET ZEROONE LOSS WHEN NORMALIZE PARAMETER IS SET TO TRUE IT IS ALWAYS BETWEEN 0 AND 1 LOWER BEING BETTER
REFERENCES
12
EXAMPLES
FROM SKLEARNMETRICS IMPORT HAMMINGLOSS
YPRED 1 2 3 4
YTRUE 2 2 3 4
HAMMINGLOSSYTRUE YPRED
025
IN THE MULTILABEL CASE WITH BINARY LABEL INDICATORS
IMPORT NUMPY AS NP
HAMMINGLOSSNPARRAY0 1 1 1 NPZEROS2 2
075
EXAMPLES USING SKLEARNMETRICSHAMMINGLOSS
•MODEL COMPLEXITY INFLUENCE
SKLEARNMETRICS HINGELOSS
SKLEARNMETRICS HINGELOSS YTRUE PREDDECISION LABELSNONE SAMPLEWEIGHTNONE
AVERAGE HINGE LOSS NONREGULARIZED
IN BINARY CLASS CASE ASSUMING LABELS IN YTRUE ARE ENCODED WITH 1 AND 1 WHEN A PREDICTION MISTAKE IS MADEMARGIN YTRUE PREDDECISION IS ALWAYS NEGATIVE SINCE THE SIGNS DISAGREE IMPLYING
1 MARGIN IS ALWAYS GREATER THAN 1 THE CUMULATED HINGE LOSS IS THEREFORE AN UPPER BOUND OF THE NUMBER OF MISTAKES MADE BY THE CLASSIFIER
IN MULTICLASS CASE THE FUNCTION EXPECTS THAT EITHER ALL THE LABELS ARE INCLUDED IN YTRUE OR AN OPTIONAL LABELS ARGUMENT IS PROVIDED WHICH CONTAINS ALL THE LABELS THE MULTILABEL MARGIN IS CALCULATED ACCORDING TO CRAMMER SINGER'S METHOD AS IN THE BINARY CASE THE CUMULATED HINGE LOSS IS AN UPPER BOUND OF THE NUMBER OF MISTAKES MADE BY THE CLASSIFIER
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAY SHAPE NSAMPLES TRUE TARGET CONSISTING OF INTEGERS OF TWO VALUES THE POSITIVE LABEL MUST BE GREATER THAN THE NEGATIVE LABEL
PREDDECISION ARRAY SHAPE NSAMPLES OR NSAMPLES NCLASSES PREDICTED DECISIONS AS OUTPUT BY DECISIONFUNCTION FLOATS
LABELS ARRAY OPTIONAL DEFAULT NONE CONTAINS ALL THE LABELS FOR THE PROBLEM USED IN MULTICLASS HINGE LOSS
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS

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RETURNS
LOSS FLOAT
REFERENCES
123
EXAMPLES
FROM SKLEARN IMPORT SVM
FROM SKLEARNMETRICS IMPORT HINGELOSS
X 0 1
Y 1 1
EST SVMLINEARSVCRANDOMSTATE0
ESTFITX Y
LINEARSVCC10 CLASSWEIGHTNONE DUALTRUE FITINTERCEPTTRUE
INTERCEPTSCALING1 LOSSSQUAREDHINGE MAXITER1000
MULTICLASSOVR PENALTYL2 RANDOMSTATE0 TOL00001
VERBOSE0
PREDDECISION ESTDECISIONFUNCTION2 3 05
PREDDECISION
ARRAY218 236 009
HINGELOSS1 1 1 PREDDECISION
030
IN THE MULTICLASS CASE
IMPORT NUMPY AS NP
X NPARRAY0 1 2 3
Y NPARRAY0 1 2 3
LABELS NPARRAY0 1 2 3
EST SVMLINEARSVC
ESTFITX Y
LINEARSVCC10 CLASSWEIGHTNONE DUALTRUE FITINTERCEPTTRUE
INTERCEPTSCALING1 LOSSSQUAREDHINGE MAXITER1000
MULTICLASSOVR PENALTYL2 RANDOMSTATENONE TOL00001
VERBOSE0
PREDDECISION ESTDECISIONFUNCTION1 2 3
YTRUE 0 2 3
HINGELOSSYTRUE PREDDECISION LABELS
056
SKLEARNMETRICS JACCARDSCORE
SKLEARNMETRICS JACCARDSCORE YTRUE YPRED LABELSNONE POSLABEL1 AVERAGE’BINARY’
SAMPLEWEIGHTNONE
JACCARD SIMILARITY COEFFICIENT SCORE
THE JACCARD INDEX 1 OR JACCARD SIMILARITY COEFFICIENT DEFINED AS THE SIZE OF THE INTERSECTION DIVIDED BY THE SIZE OF THE UNION OF TWO LABEL SETS IS USED TO COMPARE SET OF PREDICTED LABELS FOR A SAMPLE TO THE CORRESPONDING SET OF LABELS INYTRUE
READ MORE IN THE USER GUIDE
624SKLEARNMETRICS METRICS 2001

PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX GROUND TRUTH CORRECT LABELS
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX PREDICTED LABELS AS RETURNED BY
A CLASSIFIER
LABELS LIST OPTIONAL THE SET OF LABELS TO INCLUDE WHEN AVERAGE BINARY AND THEIR
ORDER IFAVERAGE IS NONE LABELS PRESENT IN THE DATA CAN BE EXCLUDED FOR EXAMPLE TO
CALCULATE A MULTICLASS AVERAGE IGNORING A MAJORITY NEGATIVE CLASS WHILE LABELS NOT PRESENT IN
THE DATA WILL RESULT IN 0 COMPONENTS IN A MACRO AVERAGE FOR MULTILABEL TARGETS LABELS ARE
COLUMN INDICES BY DEFAULT ALL LABELS IN YTRUE ANDYPRED ARE USED IN SORTED ORDER
POSLABEL STR OR INT 1 BY DEFAULT THE CLASS TO REPORT IF AVERAGEBINARY AND THE
DATA IS BINARY IF THE DATA ARE MULTICLASS OR MULTILABEL THIS WILL BE IGNORED SETTING
LABELSPOSLABEL ANDAVERAGE BINARY WILL REPORT SCORES FOR THAT LA
BEL ONLY
AVERAGE STRING NONE ‘BINARY’ DEFAULT ‘MICRO’ ‘MACRO’ ‘SAMPLES’ ‘WEIGHTED’ IF NONE
THE SCORES FOR EACH CLASS ARE RETURNED OTHERWISE THIS DETERMINES THE TYPE OF AVERAGING
PERFORMED ON THE DATA
BINARY ONLY REPORT RESULTS FOR THE CLASS SPECIFIED BY POSLABEL THIS IS APPLICABLE
ONLY IF TARGETS YTRUEPRED ARE BINARY
MICRO CALCULATE METRICS GLOBALLY BY COUNTING THE TOTAL TRUE POSITIVES FALSE NEGATIVES
AND FALSE POSITIVES
MACRO CALCULATE METRICS FOR EACH LABEL AND FIND THEIR UNWEIGHTED MEAN THIS DOES NOT
TAKE LABEL IMBALANCE INTO ACCOUNT
WEIGHTED CALCULATE METRICS FOR EACH LABEL AND FIND THEIR AVERAGE WEIGHTED BY SUP
PORT THE NUMBER OF TRUE INSTANCES FOR EACH LABEL THIS ALTERS ‘MACRO’ TO ACCOUNT FOR LABEL
IMBALANCE
SAMPLES CALCULATE METRICS FOR EACH INSTANCE AND FIND THEIR AVERAGE ONLY MEANINGFUL
FOR MULTILABEL CLASSIFICATION
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT IF AVERAGE IS NOT NONE OR ARRAY OF FLOATS SHAPE NUNIQUELABELS
SEE ALSO
ACCURACYSCORE FSCORE MULTILABELCONFUSIONMATRIX
NOTES
JACCARDSCORE MAY BE A POOR METRIC IF THERE ARE NO POSITIVES FOR SOME SAMPLES OR CLASSES JACCARD IS
UNDEFINED IF THERE ARE NO TRUE OR PREDICTED LABELS AND OUR IMPLEMENTATION WILL RETURN A SCORE OF 0 WITH A WARNING
REFERENCES
1

EXAMPLES
IMPORT NUMPY AS NP
FROM SKLEARNMETRICS IMPORT JACCARDSCORE
YTRUE NPARRAY0 1 1
1 1 0
YPRED NPARRAY1 1 1
1 0 0
IN THE BINARY CASE
JACCARDSCOREYTRUE0 YPRED0
06666
IN THE MULTILABEL CASE
JACCARDSCOREYTRUE YPRED AVERAGESAMPLES
05833
JACCARDSCOREYTRUE YPRED AVERAGEMACRO
06666
JACCARDSCOREYTRUE YPRED AVERAGE NONE
ARRAY05 05 1
IN THE MULTICLASS CASE
YPRED 0 2 1 2
YTRUE 0 1 2 2
JACCARDSCOREYTRUE YPRED AVERAGE NONE

ARRAY1 0 033
EXAMPLES USING SKLEARNMETRICSJACCARDSCORE
•CLASSIFIER CHAIN
SKLEARNMETRICS LOGLOSS
SKLEARNMETRICS LOGLOSS YTRUE YPRED EPS1E15 NORMALIZETRUE SAMPLEWEIGHTNONE LA
BELSNONE
LOG LOSS AKA LOGISTIC LOSS OR CROSSENTROPY LOSS
THIS IS THE LOSS FUNCTION USED IN MULTINOMIAL LOGISTIC REGRESSION AND EXTENSIONS OF IT SUCH AS NEURAL NETWORKS
DEFINED AS THE NEGATIVE LOGLIKELIHOOD OF THE TRUE LABELS GIVEN A PROBABILISTIC CLASSIFIER'S PREDICTIONS THE LOG LOSS
IS ONLY DEFINED FOR TWO OR MORE LABELS FOR A SINGLE SAMPLE WITH TRUE LABEL YT IN 01 AND ESTIMATED PROBABILITY
YP THAT YT 1 THE LOG LOSS IS
LOG PYTYP YT LOGYP 1 YT LOG1 YP
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAYLIKE OR LABEL INDICATOR MATRIX GROUND TRUTH CORRECT LABELS FOR NSAMPLES SAM
PLES

YPRED ARRAYLIKE OF FLOAT SHAPE NSAMPLES NCLASSES OR NSAMPLES PREDICTED PROB
ABILITIES AS RETURNED BY A CLASSIFIER’S PREDICTPROBA METHOD IF YPREDSHAPE
NSAMPLES THE PROBABILITIES PROVIDED ARE ASSUMED TO BE THAT OF THE POSITIVE CLASS THE
LABELS INYPRED ARE ASSUMED TO BE ORDERED ALPHABETICALLY AS DONE BY PREPROCESSING
LABELBINARIZER
EPS FLOAT LOG LOSS IS UNDEFINED FOR P0 OR P1 SO PROBABILITIES ARE CLIPPED TO MAXEPS MIN1
 EPS P
NORMALIZE BOOL OPTIONAL DEFAULTTRUE IF TRUE RETURN THE MEAN LOSS PER SAMPLE OTHERWISE
RETURN THE SUM OF THE PERSAMPLE LOSSES
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
LABELS ARRAYLIKE OPTIONAL DEFAULTNONE IF NOT PROVIDED LABELS WILL BE INFERRED FROM YTRUE
IFLABELS ISNONE ANDYPRED HAS SHAPE NSAMPLES THE LABELS ARE ASSUMED TO BE
BINARY AND ARE INFERRED FROM YTRUE   VERSIONADDED 018
RETURNS
LOSS FLOAT
NOTES
THE LOGARITHM USED IS THE NATURAL LOGARITHM BASEE
REFERENCES
CM BISHOP 2006 PATTERN RECOGNITION AND MACHINE LEARNING SPRINGER P 209
EXAMPLES
 FROM SKLEARNMETRICS IMPORT LOGLOSS
LOGLOSSSPAM HAM HAM SPAM
 1 9 9 1 8 2 35 65
021616
EXAMPLES USING SKLEARNMETRICSLOGLOSS
•PROBABILITY CALIBRATION FOR 3CLASS CLASSIFICATION
•PROBABILISTIC PREDICTIONS WITH GAUSSIAN PROCESS CLASSIFICATION GPC
SKLEARNMETRICS MATTHEWSCORRCOEF
SKLEARNMETRICS MATTHEWSCORRCOEF YTRUE YPRED SAMPLEWEIGHTNONE
COMPUTE THE MATTHEWS CORRELATION COEFFICIENT MCC
THE MATTHEWS CORRELATION COEFFICIENT IS USED IN MACHINE LEARNING AS A MEASURE OF THE QUALITY OF BINARY AND
MULTICLASS CLASSIFICATIONS IT TAKES INTO ACCOUNT TRUE AND FALSE POSITIVES AND NEGATIVES AND IS GENERALLY REGARDED
AS A BALANCED MEASURE WHICH CAN BE USED EVEN IF THE CLASSES ARE OF VERY DIFFERENT SIZES THE MCC IS IN ESSENCE A
CORRELATION COEFFICIENT VALUE BETWEEN 1 AND 1 A COEFFICIENT OF 1 REPRESENTS A PERFECT PREDICTION 0 AN AVERAGE

RANDOM PREDICTION AND 1 AN INVERSE PREDICTION THE STATISTIC IS ALSO KNOWN AS THE PHI COEFFICIENT SOURCE WIKIPEDIA
BINARY AND MULTICLASS LABELS ARE SUPPORTED ONLY IN THE BINARY CASE DOES THIS RELATE TO INFORMATION ABOUT TRUE AND FALSE POSITIVES AND NEGATIVES SEE REFERENCES BELOW
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAY SHAPE NSAMPLES GROUND TRUTH CORRECT TARGET VALUES
YPRED ARRAY SHAPE NSAMPLES ESTIMATED TARGETS AS RETURNED BY A CLASSIFIER
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES DEFAULT NONE SAMPLE WEIGHTS
RETURNS
MCC FLOAT THE MATTHEWS CORRELATION COEFFICIENT 1 REPRESENTS A PERFECT PREDICTION 0 AN AVER AGE RANDOM PREDICTION AND 1 AND INVERSE PREDICTION
REFERENCES
1234
EXAMPLES
 FROM SKLEARNMETRICS IMPORT MATTHEWSCORRCOEF
YTRUE 1 1 1 1
YPRED 1 1 1 1
MATTHEWSCORRCOEFYTRUE YPRED
033
SKLEARNMETRICS MULTILABELCONFUSIONMATRIX
SKLEARNMETRICS MULTILABELCONFUSIONMATRIX YTRUE YPRED SAMPLEWEIGHTNONE LA BELSNONE SAMPLEWISEFALSE
COMPUTE A CONFUSION MATRIX FOR EACH CLASS OR SAMPLE
NEW IN VERSION 021
COMPUTE CLASSWISE DEFAULT OR SAMPLEWISE SAMPLEWISETRUE MULTILABEL CONFUSION MATRIX TO EVALUATE THE ACCURACY OF A CLASSIFICATION AND OUTPUT CONFUSION MATRICES FOR EACH CLASS OR SAMPLE
IN MULTILABEL CONFUSION MATRIX □□□ THE COUNT OF TRUE NEGATIVES IS □□□ 00 FALSE NEGATIVES IS □□□ 10 TRUE POSITIVES IS □□□ 11AND FALSE POSITIVES IS □□□ 01
MULTICLASS DATA WILL BE TREATED AS IF BINARIZED UNDER A ONEVSREST TRANSFORMATION RETURNED CONFUSION MATRICES WILL BE IN THE ORDER OF SORTED UNIQUE LABELS IN THE UNION OF YTRUE YPRED
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX OF SHAPE NSAMPLES NOUTPUTS OR NSAMPLES GROUND TRUTH CORRECT TARGET VALUES
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX OF SHAPE NSAMPLES NOUTPUTS OR NSAMPLES ESTIMATED TARGETS AS RETURNED BY A CLASSIFIER

SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
LABELS ARRAYLIKE A LIST OF CLASSES OR COLUMN INDICES TO SELECT SOME OR TO FORCE INCLUSION OF
CLASSES ABSENT FROM THE DATA
SAMPLEWISE BOOL DEFAULTFALSE IN THE MULTILABEL CASE THIS CALCULATES A CONFUSION MATRIX PER
SAMPLE
RETURNS
MULTICONFUSION ARRAY SHAPE NOUTPUTS 2 2 A 2X2 CONFUSION MATRIX CORRESPONDING TO EACH
OUTPUT IN THE INPUT WHEN CALCULATING CLASSWISE MULTICONFUSION DEFAULT THEN NOUTPUTS
 NLABELS WHEN CALCULATING SAMPLEWISE MULTICONFUSION SAMPLEWISETRUE NOUTPUTS
 NSAMPLES IF LABELS IS DEFINED THE RESULTS WILL BE RETURNED IN THE ORDER SPECIFIED IN
LABELS OTHERWISE THE RESULTS WILL BE RETURNED IN SORTED ORDER BY DEFAULT
SEE ALSO
CONFUSIONMATRIX
NOTES
THE MULTILABELCONFUSIONMATRIX CALCULATES CLASSWISE OR SAMPLEWISE MULTILABEL CONFUSION MATRICES AND IN
MULTICLASS TASKS LABELS ARE BINARIZED UNDER A ONEVSREST WAY WHILE CONFUSIONMATRIX CALCULATES ONE CONFUSION
MATRIX FOR CONFUSION BETWEEN EVERY TWO CLASSES
EXAMPLES
MULTILABELINDICATOR CASE
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT MULTILABELCONFUSIONMATRIX
YTRUE NPARRAY1 0 1
 0 1 0
YPRED NPARRAY1 0 0
 0 1 1
MULTILABELCONFUSIONMATRIXYTRUE YPRED
ARRAY1 0
0 1
1 0
0 1
0 1
1 0
MULTICLASS CASE
YTRUE CAT ANT CAT CAT ANT BIRD
YPRED ANT ANT CAT CAT ANT CAT
MULTILABELCONFUSIONMATRIXYTRUE YPRED
 LABELSANT BIRD CAT
ARRAY3 1
0 2
5 0
1 0

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2 1
1 2
SKLEARNMETRICS PRECISIONRECALLCURVE
SKLEARNMETRICS PRECISIONRECALLCURVE YTRUE PROBASPRED POSLABELNONE SAM
PLEWEIGHTNONE
COMPUTE PRECISIONRECALL PAIRS FOR DIFFERENT PROBABILITY THRESHOLDS
NOTE THIS IMPLEMENTATION IS RESTRICTED TO THE BINARY CLASSIFICATION TASK
THE PRECISION IS THE RATIO TP TP FP WHERETPIS THE NUMBER OF TRUE POSITIVES AND FPTHE NUMBER OF
FALSE POSITIVES THE PRECISION IS INTUITIVELY THE ABILITY OF THE CLASSIFIER NOT TO LABEL AS POSITIVE A SAMPLE THAT IS
NEGATIVE
THE RECALL IS THE RATIO TP TP FN WHERETPIS THE NUMBER OF TRUE POSITIVES AND FNTHE NUMBER OF FALSE
NEGATIVES THE RECALL IS INTUITIVELY THE ABILITY OF THE CLASSIFIER TO FIND ALL THE POSITIVE SAMPLES
THE LAST PRECISION AND RECALL VALUES ARE 1 AND 0 RESPECTIVELY AND DO NOT HAVE A CORRESPONDING THRESHOLD THIS
ENSURES THAT THE GRAPH STARTS ON THE Y AXIS
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAY SHAPE NSAMPLES TRUE BINARY LABELS IF LABELS ARE NOT EITHER 1 1 OR 0 1
THEN POSLABEL SHOULD BE EXPLICITLY GIVEN
PROBASPRED ARRAY SHAPE NSAMPLES ESTIMATED PROBABILITIES OR DECISION FUNCTION
POSLABEL INT OR STR DEFAULTNONE THE LABEL OF THE POSITIVE CLASS WHEN POSLABELNONE
IF YTRUE IS IN 1 1 OR 0 1 POSLABEL IS SET TO 1 OTHERWISE AN ERROR WILL BE RAISED
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
PRECISION ARRAY SHAPE NTHRESHOLDS 1 PRECISION VALUES SUCH THAT ELEMENT I IS THE PRECI
SION OF PREDICTIONS WITH SCORE THRESHOLDSI AND THE LAST ELEMENT IS 1
RECALL ARRAY SHAPE NTHRESHOLDS 1 DECREASING RECALL VALUES SUCH THAT ELEMENT I IS THE
RECALL OF PREDICTIONS WITH SCORE THRESHOLDSI AND THE LAST ELEMENT IS 0
THRESHOLDS ARRAY SHAPE NTHRESHOLDS LENNPUNIQUEPROBASPRED INCREASING THRESH
OLDS ON THE DECISION FUNCTION USED TO COMPUTE PRECISION AND RECALL
SEE ALSO
AVERAGEPRECISIONSCORE COMPUTE AVERAGE PRECISION FROM PREDICTION SCORES
ROCCURVE COMPUTE RECEIVER OPERATING CHARACTERISTIC ROC CURVE
EXAMPLES
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT PRECISIONRECALLCURVE
YTRUE NPARRAY0 0 1 1
YSCORES NPARRAY01 04 035 08
624SKLEARNMETRICS METRICS 2007

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PRECISION RECALL THRESHOLDS PRECISIONRECALLCURVE
 YTRUE YSCORES
PRECISION
ARRAY066666667 05 1 1
RECALL
ARRAY1 05 05 0
THRESHOLDS
ARRAY035 04 08
EXAMPLES USING SKLEARNMETRICSPRECISIONRECALLCURVE
•PRECISIONRECALL
SKLEARNMETRICS PRECISIONRECALLFSCORESUPPORT
SKLEARNMETRICS PRECISIONRECALLFSCORESUPPORT YTRUE YPRED BETA10 LA
BELSNONE POSLABEL1 AVER
AGENONE WARNFOR‘PRECISION’
’RECALL’ ’FSCORE’ SAM
PLEWEIGHTNONE
COMPUTE PRECISION RECALL FMEASURE AND SUPPORT FOR EACH CLASS
THE PRECISION IS THE RATIO TP TP FP WHERETPIS THE NUMBER OF TRUE POSITIVES AND FPTHE NUMBER OF
FALSE POSITIVES THE PRECISION IS INTUITIVELY THE ABILITY OF THE CLASSIFIER NOT TO LABEL AS POSITIVE A SAMPLE THAT IS
NEGATIVE
THE RECALL IS THE RATIO TP TP FN WHERETPIS THE NUMBER OF TRUE POSITIVES AND FNTHE NUMBER OF FALSE
NEGATIVES THE RECALL IS INTUITIVELY THE ABILITY OF THE CLASSIFIER TO FIND ALL THE POSITIVE SAMPLES
THE FBETA SCORE CAN BE INTERPRETED AS A WEIGHTED HARMONIC MEAN OF THE PRECISION AND RECALL WHERE AN FBETA
SCORE REACHES ITS BEST VALUE AT 1 AND WORST SCORE AT 0
THE FBETA SCORE WEIGHTS RECALL MORE THAN PRECISION BY A FACTOR OF BETA BETA 10 MEANS RECALL AND
PRECISION ARE EQUALLY IMPORTANT
THE SUPPORT IS THE NUMBER OF OCCURRENCES OF EACH CLASS IN YTRUE
IFPOSLABEL IS NONE AND IN BINARY CLASSIFICATION THIS FUNCTION RETURNS THE AVERAGE PRECISION RECALL AND
FMEASURE IF AVERAGE IS ONE OFMICRO MACRO WEIGHTED ORSAMPLES
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX GROUND TRUTH CORRECT TARGET
VALUES
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX ESTIMATED TARGETS AS RETURNED BY
A CLASSIFIER
BETA FLOAT 10 BY DEFAULT THE STRENGTH OF RECALL VERSUS PRECISION IN THE FSCORE
LABELS LIST OPTIONAL THE SET OF LABELS TO INCLUDE WHEN AVERAGE BINARY AND THEIR
ORDER IFAVERAGE IS NONE LABELS PRESENT IN THE DATA CAN BE EXCLUDED FOR EXAMPLE TO
CALCULATE A MULTICLASS AVERAGE IGNORING A MAJORITY NEGATIVE CLASS WHILE LABELS NOT PRESENT IN
THE DATA WILL RESULT IN 0 COMPONENTS IN A MACRO AVERAGE FOR MULTILABEL TARGETS LABELS ARE
COLUMN INDICES BY DEFAULT ALL LABELS IN YTRUE ANDYPRED ARE USED IN SORTED ORDER

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POSLABEL STR OR INT 1 BY DEFAULT THE CLASS TO REPORT IF AVERAGEBINARY AND THE
DATA IS BINARY IF THE DATA ARE MULTICLASS OR MULTILABEL THIS WILL BE IGNORED SETTING
LABELSPOSLABEL ANDAVERAGE BINARY WILL REPORT SCORES FOR THAT LA
BEL ONLY
AVERAGE STRING NONE DEFAULT ‘BINARY’ ‘MICRO’ ‘MACRO’ ‘SAMPLES’ ‘WEIGHTED’ IF NONE
THE SCORES FOR EACH CLASS ARE RETURNED OTHERWISE THIS DETERMINES THE TYPE OF AVERAGING
PERFORMED ON THE DATA
BINARY ONLY REPORT RESULTS FOR THE CLASS SPECIFIED BY POSLABEL THIS IS APPLICABLE
ONLY IF TARGETS YTRUEPRED ARE BINARY
MICRO CALCULATE METRICS GLOBALLY BY COUNTING THE TOTAL TRUE POSITIVES FALSE NEGATIVES
AND FALSE POSITIVES
MACRO CALCULATE METRICS FOR EACH LABEL AND FIND THEIR UNWEIGHTED MEAN THIS DOES NOT
TAKE LABEL IMBALANCE INTO ACCOUNT
WEIGHTED CALCULATE METRICS FOR EACH LABEL AND FIND THEIR AVERAGE WEIGHTED BY SUPPORT
THE NUMBER OF TRUE INSTANCES FOR EACH LABEL THIS ALTERS ‘MACRO’ TO ACCOUNT FOR LABEL
IMBALANCE IT CAN RESULT IN AN FSCORE THAT IS NOT BETWEEN PRECISION AND RECALL
SAMPLES CALCULATE METRICS FOR EACH INSTANCE AND FIND THEIR AVERAGE ONLY MEANINGFUL
FOR MULTILABEL CLASSIFICATION WHERE THIS DIFFERS FROM ACCURACYSCORE
WARNFOR TUPLE OR SET FOR INTERNAL USE THIS DETERMINES WHICH WARNINGS WILL BE MADE IN THE
CASE THAT THIS FUNCTION IS BEING USED TO RETURN ONLY ONE OF ITS METRICS
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
PRECISION FLOAT IF AVERAGE IS NOT NONE OR ARRAY OF FLOAT SHAPE NUNIQUELABELS
RECALL FLOAT IF AVERAGE IS NOT NONE OR ARRAY OF FLOAT SHAPE NUNIQUELABELS
FBETASCORE FLOAT IF AVERAGE IS NOT NONE OR ARRAY OF FLOAT SHAPE NUNIQUELABELS
SUPPORT INT IF AVERAGE IS NOT NONE OR ARRAY OF INT SHAPE NUNIQUELABELS THE NUMBER OF
OCCURRENCES OF EACH LABEL IN YTRUE
NOTES
WHENTRUE POSITIVE FALSE POSITIVE 0 PRECISION IS UNDEFINED WHEN TRUE POSITIVE
 FALSE NEGATIVE 0 RECALL IS UNDEFINED IN SUCH CASES THE METRIC WILL BE SET TO 0 AS WILL FSCORE
ANDUNDEFINEDMETRICWARNING WILL BE RAISED
REFERENCES
123
EXAMPLES
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT PRECISIONRECALLFSCORESUPPORT
YTRUE NPARRAYCAT DOG PIG CAT DOG PIG
YPRED NPARRAYCAT PIG DOG CAT CAT DOG
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PRECISIONRECALLFSCORESUPPORTYTRUE YPRED AVERAGEMACRO

022 033 026 NONE
PRECISIONRECALLFSCORESUPPORTYTRUE YPRED AVERAGEMICRO

033 033 033 NONE
PRECISIONRECALLFSCORESUPPORTYTRUE YPRED AVERAGEWEIGHTED

022 033 026 NONE
IT IS POSSIBLE TO COMPUTE PERLABEL PRECISIONS RECALLS F1SCORES AND SUPPORTS INSTEAD OF AVERAGING
PRECISIONRECALLFSCORESUPPORTYTRUE YPRED AVERAGE NONE
LABELSPIG DOG CAT

ARRAY0 0 066
ARRAY0 0 1 ARRAY0 0 08
ARRAY2 2 2
SKLEARNMETRICS PRECISIONSCORE
SKLEARNMETRICS PRECISIONSCORE YTRUE YPRED LABELSNONE POSLABEL1 AVERAGE'BINARY'
SAMPLEWEIGHTNONE
COMPUTE THE PRECISION
THE PRECISION IS THE RATIO TP TP FP WHERETPIS THE NUMBER OF TRUE POSITIVES AND FPTHE NUMBER OF
FALSE POSITIVES THE PRECISION IS INTUITIVELY THE ABILITY OF THE CLASSIFIER NOT TO LABEL AS POSITIVE A SAMPLE THAT IS
NEGATIVE
THE BEST VALUE IS 1 AND THE WORST VALUE IS 0
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX GROUND TRUTH CORRECT TARGET
VALUES
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX ESTIMATED TARGETS AS RETURNED BY
A CLASSIFIER
LABELS LIST OPTIONAL THE SET OF LABELS TO INCLUDE WHEN AVERAGE BINARY AND THEIR
ORDER IFAVERAGE IS NONE LABELS PRESENT IN THE DATA CAN BE EXCLUDED FOR EXAMPLE TO
CALCULATE A MULTICLASS AVERAGE IGNORING A MAJORITY NEGATIVE CLASS WHILE LABELS NOT PRESENT IN
THE DATA WILL RESULT IN 0 COMPONENTS IN A MACRO AVERAGE FOR MULTILABEL TARGETS LABELS ARE
COLUMN INDICES BY DEFAULT ALL LABELS IN YTRUE ANDYPRED ARE USED IN SORTED ORDER
CHANGED IN VERSION 017 PARAMETER LABELS IMPROVED FOR MULTICLASS PROBLEM
POSLABEL STR OR INT 1 BY DEFAULT THE CLASS TO REPORT IF AVERAGEBINARY AND THE
DATA IS BINARY IF THE DATA ARE MULTICLASS OR MULTILABEL THIS WILL BE IGNORED SETTING
LABELSPOSLABEL ANDAVERAGE BINARY WILL REPORT SCORES FOR THAT LA
BEL ONLY
AVERAGE STRING NONE 'BINARY' DEFAULT 'MICRO' 'MACRO' 'SAMPLES' 'WEIGHTED' THIS PA
RAMETER IS REQUIRED FOR MULTICLASSMULTILABEL TARGETS IF NONE THE SCORES FOR EACH CLASS ARE
RETURNED OTHERWISE THIS DETERMINES THE TYPE OF AVERAGING PERFORMED ON THE DATA

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BINARY ONLY REPORT RESULTS FOR THE CLASS SPECIFIED BY POSLABEL THIS IS APPLICABLE
ONLY IF TARGETS YTRUEPRED ARE BINARY
MICRO CALCULATE METRICS GLOBALLY BY COUNTING THE TOTAL TRUE POSITIVES FALSE NEGATIVES
AND FALSE POSITIVES
MACRO CALCULATE METRICS FOR EACH LABEL AND FIND THEIR UNWEIGHTED MEAN THIS DOES NOT
TAKE LABEL IMBALANCE INTO ACCOUNT
WEIGHTED CALCULATE METRICS FOR EACH LABEL AND FIND THEIR AVERAGE WEIGHTED BY SUPPORT
THE NUMBER OF TRUE INSTANCES FOR EACH LABEL THIS ALTERS ‘MACRO’ TO ACCOUNT FOR LABEL
IMBALANCE IT CAN RESULT IN AN FSCORE THAT IS NOT BETWEEN PRECISION AND RECALL
SAMPLES CALCULATE METRICS FOR EACH INSTANCE AND FIND THEIR AVERAGE ONLY MEANINGFUL
FOR MULTILABEL CLASSIFICATION WHERE THIS DIFFERS FROM ACCURACYSCORE
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
PRECISION FLOAT IF AVERAGE IS NOT NONE OR ARRAY OF FLOAT SHAPE NUNIQUELABELS PRECISION
OF THE POSITIVE CLASS IN BINARY CLASSIFICATION OR WEIGHTED AVERAGE OF THE PRECISION OF EACH
CLASS FOR THE MULTICLASS TASK
SEE ALSO
PRECISIONRECALLFSCORESUPPORT MULTILABELCONFUSIONMATRIX
NOTES
WHENTRUE POSITIVE FALSE POSITIVE 0 PRECISION RETURNS 0 AND RAISES
UNDEFINEDMETRICWARNING
EXAMPLES
 FROM SKLEARNMETRICS IMPORT PRECISIONSCORE
YTRUE 0 1 2 0 1 2
YPRED 0 2 1 0 0 1
PRECISIONSCOREYTRUE YPRED AVERAGEMACRO
022
PRECISIONSCOREYTRUE YPRED AVERAGEMICRO
033
PRECISIONSCOREYTRUE YPRED AVERAGEWEIGHTED

022
PRECISIONSCOREYTRUE YPRED AVERAGE NONE
ARRAY066 0 0
EXAMPLES USING SKLEARNMETRICSPRECISIONSCORE
•PROBABILITY CALIBRATION CURVES
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SKLEARNMETRICS RECALLSCORE
SKLEARNMETRICS RECALLSCORE YTRUE YPRED LABELSNONE POSLABEL1 AVERAGE’BINARY’ SAM
PLEWEIGHTNONE
COMPUTE THE RECALL
THE RECALL IS THE RATIO TP TP FN WHERETPIS THE NUMBER OF TRUE POSITIVES AND FNTHE NUMBER OF FALSE
NEGATIVES THE RECALL IS INTUITIVELY THE ABILITY OF THE CLASSIFIER TO FIND ALL THE POSITIVE SAMPLES
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VALUES
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX ESTIMATED TARGETS AS RETURNED BY
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LABELS LIST OPTIONAL THE SET OF LABELS TO INCLUDE WHEN AVERAGE BINARY AND THEIR
ORDER IFAVERAGE IS NONE LABELS PRESENT IN THE DATA CAN BE EXCLUDED FOR EXAMPLE TO
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THE DATA WILL RESULT IN 0 COMPONENTS IN A MACRO AVERAGE FOR MULTILABEL TARGETS LABELS ARE
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CHANGED IN VERSION 017 PARAMETER LABELS IMPROVED FOR MULTICLASS PROBLEM
POSLABEL STR OR INT 1 BY DEFAULT THE CLASS TO REPORT IF AVERAGEBINARY AND THE
DATA IS BINARY IF THE DATA ARE MULTICLASS OR MULTILABEL THIS WILL BE IGNORED SETTING
LABELSPOSLABEL ANDAVERAGE BINARY WILL REPORT SCORES FOR THAT LA
BEL ONLY
AVERAGE STRING NONE ‘BINARY’ DEFAULT ‘MICRO’ ‘MACRO’ ‘SAMPLES’ ‘WEIGHTED’ THIS PA
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AND FALSE POSITIVES
MACRO CALCULATE METRICS FOR EACH LABEL AND FIND THEIR UNWEIGHTED MEAN THIS DOES NOT
TAKE LABEL IMBALANCE INTO ACCOUNT
WEIGHTED CALCULATE METRICS FOR EACH LABEL AND FIND THEIR AVERAGE WEIGHTED BY SUPPORT
THE NUMBER OF TRUE INSTANCES FOR EACH LABEL THIS ALTERS ‘MACRO’ TO ACCOUNT FOR LABEL
IMBALANCE IT CAN RESULT IN AN FSCORE THAT IS NOT BETWEEN PRECISION AND RECALL
SAMPLES CALCULATE METRICS FOR EACH INSTANCE AND FIND THEIR AVERAGE ONLY MEANINGFUL
FOR MULTILABEL CLASSIFICATION WHERE THIS DIFFERS FROM ACCURACYSCORE
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
RECALL FLOAT IF AVERAGE IS NOT NONE OR ARRAY OF FLOAT SHAPE NUNIQUELABELS RECALL OF THE
POSITIVE CLASS IN BINARY CLASSIFICATION OR WEIGHTED AVERAGE OF THE RECALL OF EACH CLASS FOR THE
MULTICLASS TASK
SEE ALSO

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PRECISIONRECALLFSCORESUPPORT BALANCEDACCURACYSCORE
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NOTES
WHENTRUE POSITIVE FALSE NEGATIVE 0 RECALL RETURNS 0 AND RAISES
UNDEFINEDMETRICWARNING
EXAMPLES
 FROM SKLEARNMETRICS IMPORT RECALLSCORE
YTRUE 0 1 2 0 1 2
YPRED 0 2 1 0 0 1
RECALLSCOREYTRUE YPRED AVERAGEMACRO
033
RECALLSCOREYTRUE YPRED AVERAGEMICRO
033
RECALLSCOREYTRUE YPRED AVERAGEWEIGHTED
033
RECALLSCOREYTRUE YPRED AVERAGE NONE
ARRAY1 0 0
EXAMPLES USING SKLEARNMETRICSRECALLSCORE
•PROBABILITY CALIBRATION CURVES
SKLEARNMETRICS ROCAUCSCORE
SKLEARNMETRICS ROCAUCSCORE YTRUE YSCORE AVERAGE’MACRO’ SAMPLEWEIGHTNONE
MAXFPRNONE
COMPUTE AREA UNDER THE RECEIVER OPERATING CHARACTERISTIC CURVE ROC AUC FROM PREDICTION SCORES
NOTE THIS IMPLEMENTATION IS RESTRICTED TO THE BINARY CLASSIFICATION TASK OR MULTILABEL CLASSIFICATION TASK IN LABEL
INDICATOR FORMAT
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAY SHAPE NSAMPLES OR NSAMPLES NCLASSES TRUE BINARY LABELS OR BINARY LABEL
INDICATORS
YSCORE ARRAY SHAPE NSAMPLES OR NSAMPLES NCLASSES TARGET SCORES CAN EITHER BE
PROBABILITY ESTIMATES OF THE POSITIVE CLASS CONFIDENCE VALUES OR NONTHRESHOLDED MEASURE
OF DECISIONS AS RETURNED BY “DECISIONFUNCTION” ON SOME CLASSIFIERS FOR BINARY YTRUE
YSCORE IS SUPPOSED TO BE THE SCORE OF THE CLASS WITH GREATER LABEL
AVERAGE STRING NONE ‘MICRO’ ‘MACRO’ DEFAULT ‘SAMPLES’ ‘WEIGHTED’ IF NONE THE SCORES
FOR EACH CLASS ARE RETURNED OTHERWISE THIS DETERMINES THE TYPE OF AVERAGING PERFORMED ON
THE DATA
MICRO CALCULATE METRICS GLOBALLY BY CONSIDERING EACH ELEMENT OF THE LABEL INDICATOR
MATRIX AS A LABEL
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MACRO CALCULATE METRICS FOR EACH LABEL AND FIND THEIR UNWEIGHTED MEAN THIS DOES NOT
TAKE LABEL IMBALANCE INTO ACCOUNT
WEIGHTED CALCULATE METRICS FOR EACH LABEL AND FIND THEIR AVERAGE WEIGHTED BY SUP
PORT THE NUMBER OF TRUE INSTANCES FOR EACH LABEL
SAMPLES CALCULATE METRICS FOR EACH INSTANCE AND FIND THEIR AVERAGE
WILL BE IGNORED WHEN YTRUE IS BINARY
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
MAXFPR FLOAT 0 AND 1 OPTIONAL IF NOT NONE THE STANDARDIZED PARTIAL AUC 3OVER THE
RANGE 0 MAXFPR IS RETURNED
RETURNS
AUC FLOAT
SEE ALSO
AVERAGEPRECISIONSCORE AREA UNDER THE PRECISIONRECALL CURVE
ROCCURVE COMPUTE RECEIVER OPERATING CHARACTERISTIC ROC CURVE
REFERENCES
123
EXAMPLES
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT ROCAUCSCORE
YTRUE NPARRAY0 0 1 1
YSCORES NPARRAY01 04 035 08
ROCAUCSCOREYTRUE YSCORES
075
SKLEARNMETRICS ROCCURVE
SKLEARNMETRICS ROCCURVE YTRUE YSCORE POSLABELNONE SAMPLEWEIGHTNONE
DROPINTERMEDIATETRUE
COMPUTE RECEIVER OPERATING CHARACTERISTIC ROC
NOTE THIS IMPLEMENTATION IS RESTRICTED TO THE BINARY CLASSIFICATION TASK
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAY SHAPE NSAMPLES TRUE BINARY LABELS IF LABELS ARE NOT EITHER 1 1 OR 0 1
THEN POSLABEL SHOULD BE EXPLICITLY GIVEN
YSCORE ARRAY SHAPE NSAMPLES TARGET SCORES CAN EITHER BE PROBABILITY ESTIMATES OF THE
POSITIVE CLASS CONFIDENCE VALUES OR NONTHRESHOLDED MEASURE OF DECISIONS AS RETURNED BY
“DECISIONFUNCTION” ON SOME CLASSIFIERS
POSLABEL INT OR STR DEFAULTNONE THE LABEL OF THE POSITIVE CLASS WHEN POSLABELNONE
IF YTRUE IS IN 1 1 OR 0 1 POSLABEL IS SET TO 1 OTHERWISE AN ERROR WILL BE RAISED

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SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
DROPINTERMEDIATE BOOLEAN OPTIONAL DEFAULTTRUE WHETHER TO DROP SOME SUBOPTIMAL
THRESHOLDS WHICH WOULD NOT APPEAR ON A PLOTTED ROC CURVE THIS IS USEFUL IN ORDER TO
CREATE LIGHTER ROC CURVES
NEW IN VERSION 017 PARAMETER DROPINTERMEDIATE
RETURNS
FPRARRAY SHAPE 2 INCREASING FALSE POSITIVE RATES SUCH THAT ELEMENT I IS THE FALSE POSITIVE
RATE OF PREDICTIONS WITH SCORE THRESHOLDSI
TPRARRAY SHAPE 2 INCREASING TRUE POSITIVE RATES SUCH THAT ELEMENT I IS THE TRUE POSITIVE
RATE OF PREDICTIONS WITH SCORE THRESHOLDSI
THRESHOLDS ARRAY SHAPE NTHRESHOLDS DECREASING THRESHOLDS ON THE DECISION FUNCTION USED
TO COMPUTE FPR AND TPR THRESHOLDS0 REPRESENTS NO INSTANCES BEING PREDICTED AND IS
ARBITRARILY SET TO MAXYSCORE 1
SEE ALSO
ROCAUCSCORE COMPUTE THE AREA UNDER THE ROC CURVE
NOTES
SINCE THE THRESHOLDS ARE SORTED FROM LOW TO HIGH VALUES THEY ARE REVERSED UPON RETURNING THEM TO ENSURE THEY
CORRESPOND TO BOTH FPR ANDTPR WHICH ARE SORTED IN REVERSED ORDER DURING THEIR CALCULATION
REFERENCES
12
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT METRICS
Y  NPARRAY1 1 2 2
SCORES  NPARRAY01 04 035 08
FPR TPR THRESHOLDS  METRICSROCCURVEY SCORES POSLABEL2
FPR
ARRAY0  0  05 05 1
TPR
ARRAY0  05 05 1  1
THRESHOLDS
ARRAY18  08  04  035 01
```
EXAMPLES USING SKLEARNMETRICSROCCURVE
•SPECIES DISTRIBUTION MODELING
•FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES
•RECEIVER OPERATING CHARACTERISTIC ROC WITH CROSS VALIDATION
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•RECEIVER OPERATING CHARACTERISTIC ROC
SKLEARNMETRICS ZEROONELOSS
SKLEARNMETRICS ZEROONELOSS YTRUE YPRED NORMALIZETRUE SAMPLEWEIGHTNONE
ZEROONE CLASSIFICATION LOSS
IF NORMALIZE IS TRUE RETURN THE FRACTION OF MISCLASSIFICATIONS FLOAT ELSE IT RETURNS THE NUMBER OF MISCLASSIFICA
TIONS INT THE BEST PERFORMANCE IS 0
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX GROUND TRUTH CORRECT LABELS
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX PREDICTED LABELS AS RETURNED BY
A CLASSIFIER
NORMALIZE BOOL OPTIONAL DEFAULTTRUE IF FALSE RETURN THE NUMBER OF MISCLASSIFICATIONS
OTHERWISE RETURN THE FRACTION OF MISCLASSIFICATIONS
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
LOSS FLOAT OR INT IF NORMALIZE TRUE RETURN THE FRACTION OF MISCLASSIFICATIONS FLOAT
ELSE IT RETURNS THE NUMBER OF MISCLASSIFICATIONS INT
SEE ALSO
ACCURACYSCORE HAMMINGLOSS JACCARDSCORE
NOTES
IN MULTILABEL CLASSIFICATION THE ZEROONELOSS FUNCTION CORRESPONDS TO THE SUBSET ZEROONE LOSS FOR EACH SAMPLE
THE ENTIRE SET OF LABELS MUST BE CORRECTLY PREDICTED OTHERWISE THE LOSS FOR THAT SAMPLE IS EQUAL TO ONE
EXAMPLES
 FROM SKLEARNMETRICS IMPORT ZEROONELOSS
YPRED 1 2 3 4
YTRUE 2 2 3 4
ZEROONELOSSYTRUE YPRED
025
ZEROONELOSSYTRUE YPRED NORMALIZE FALSE
1
IN THE MULTILABEL CASE WITH BINARY LABEL INDICATORS
 IMPORT NUMPY AS NP
ZEROONELOSSNPARRAY0 1 1 1 NPONES2 2
05

EXAMPLES USING SKLEARNMETRICSZEROONELOSS
•DISCRETE VERSUS REAL ADABOOST
6243 REGRESSION METRICS
SEE THE REGRESSION METRICS SECTION OF THE USER GUIDE FOR FURTHER DETAILS
METRICSEXPLAINEDVARIANCESCORE YTRUE
YPREDEXPLAINED VARIANCE REGRESSION SCORE FUNCTION
METRICSMAXERROR YTRUE YPRED MAXERROR METRIC CALCULATES THE MAXIMUM RESIDUAL ERROR
METRICSMEANABSOLUTEERROR YTRUE YPRED MEAN ABSOLUTE ERROR REGRESSION LOSS
METRICSMEANSQUAREDERROR YTRUE YPRED
MEAN SQUARED ERROR REGRESSION LOSS
METRICSMEANSQUAREDLOGERROR YTRUE
YPREDMEAN SQUARED LOGARITHMIC ERROR REGRESSION LOSS
METRICSMEDIANABSOLUTEERROR YTRUE
YPREDMEDIAN ABSOLUTE ERROR REGRESSION LOSS
METRICSR2SCORE YTRUE YPRED R2 COEFFICIENT OF DETERMINATION REGRESSION SCORE FUNC
TION
SKLEARNMETRICS EXPLAINEDVARIANCESCORE
SKLEARNMETRICS EXPLAINEDVARIANCESCORE YTRUE YPRED SAMPLEWEIGHTNONE MULTIOUT
PUT’UNIFORMAVERAGE’
EXPLAINED VARIANCE REGRESSION SCORE FUNCTION
BEST POSSIBLE SCORE IS 10 LOWER VALUES ARE WORSE
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAYLIKE OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS GROUND TRUTH CORRECT
TARGET VALUES
YPRED ARRAYLIKE OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS ESTIMATED TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
MULTIOUTPUT STRING IN ‘RAWVALUES’ ‘UNIFORMAVERAGE’ ‘VARIANCEWEIGHTED’ OR ARRAYLIKE OF
SHAPE NOUTPUTS DEFINES AGGREGATING OF MULTIPLE OUTPUT SCORES ARRAYLIKE VALUE DEFINES
WEIGHTS USED TO AVERAGE SCORES
‘RAWVALUES’ RETURNS A FULL SET OF SCORES IN CASE OF MULTIOUTPUT INPUT
‘UNIFORMAVERAGE’ SCORES OF ALL OUTPUTS ARE AVERAGED WITH UNIFORM WEIGHT
‘VARIANCEWEIGHTED’ SCORES OF ALL OUTPUTS ARE AVERAGED WEIGHTED BY THE VARIANCES OF
EACH INDIVIDUAL OUTPUT
RETURNS
SCORE FLOAT OR NDARRAY OF FLOATS THE EXPLAINED VARIANCE OR NDARRAY IF ‘MULTIOUTPUT’ IS
‘RAWVALUES’

NOTES
THIS IS NOT A SYMMETRIC FUNCTION
EXAMPLES
FROM SKLEARNMETRICS IMPORT EXPLAINEDVARIANCESCORE
YTRUE 3 05 2 7
YPRED 25 00 2 8
EXPLAINEDVARIANCESCOREYTRUE YPRED
0957
YTRUE 05 1 1 1 7 6
YPRED 0 2 1 2 8 5
EXPLAINEDVARIANCESCOREYTRUE YPRED MULTIOUTPUTUNIFORMAVERAGE

0983
SKLEARNMETRICS MAXERROR
SKLEARNMETRICS MAXERROR YTRUE YPRED
MAXERROR METRIC CALCULATES THE MAXIMUM RESIDUAL ERROR
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAYLIKE OF SHAPE NSAMPLES GROUND TRUTH CORRECT TARGET VALUES
YPRED ARRAYLIKE OF SHAPE NSAMPLES ESTIMATED TARGET VALUES
RETURNS
MAXERROR FLOAT A POSITIVE FLOATING POINT VALUE THE BEST VALUE IS 00
EXAMPLES
FROM SKLEARNMETRICS IMPORT MAXERROR
YTRUE 3 2 7 1
YPRED 4 2 7 1
MAXERRORYTRUE YPRED
1
SKLEARNMETRICS MEANABSOLUTEERROR
SKLEARNMETRICS MEANABSOLUTEERROR YTRUE YPRED SAMPLEWEIGHTNONE MULTIOUT
PUT’UNIFORMAVERAGE’
MEAN ABSOLUTE ERROR REGRESSION LOSS
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAYLIKE OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS GROUND TRUTH CORRECT
TARGET VALUES

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YPRED ARRAYLIKE OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS ESTIMATED TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
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DEFINES AGGREGATING OF MULTIPLE OUTPUT VALUES ARRAYLIKE VALUE DEFINES WEIGHTS USED TO
AVERAGE ERRORS
‘RAWVALUES’ RETURNS A FULL SET OF ERRORS IN CASE OF MULTIOUTPUT INPUT
‘UNIFORMAVERAGE’ ERRORS OF ALL OUTPUTS ARE AVERAGED WITH UNIFORM WEIGHT
RETURNS
LOSS FLOAT OR NDARRAY OF FLOATS IF MULTIOUTPUT IS ‘RAWVALUES’ THEN MEAN ABSOLUTE ERROR IS RE
TURNED FOR EACH OUTPUT SEPARATELY IF MULTIOUTPUT IS ‘UNIFORMAVERAGE’ OR AN NDARRAY OF
WEIGHTS THEN THE WEIGHTED AVERAGE OF ALL OUTPUT ERRORS IS RETURNED
MAE OUTPUT IS NONNEGATIVE FLOATING POINT THE BEST VALUE IS 00
EXAMPLES
 FROM SKLEARNMETRICS IMPORT MEANABSOLUTEERROR
YTRUE 3 05 2 7
YPRED 25 00 2 8
MEANABSOLUTEERRORYTRUE YPRED
05
YTRUE 05 1 1 1 7 6
YPRED 0 2 1 2 8 5
MEANABSOLUTEERRORYTRUE YPRED
075
MEANABSOLUTEERRORYTRUE YPRED MULTIOUTPUTRAWVALUES
ARRAY05 1
MEANABSOLUTEERRORYTRUE YPRED MULTIOUTPUT03 07

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SKLEARNMETRICS MEANSQUAREDERROR
SKLEARNMETRICS MEANSQUAREDERROR YTRUE YPRED SAMPLEWEIGHTNONE MULTIOUT
PUT’UNIFORMAVERAGE’
MEAN SQUARED ERROR REGRESSION LOSS
READ MORE IN THE USER GUIDE
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YTRUE ARRAYLIKE OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS GROUND TRUTH CORRECT
TARGET VALUES
YPRED ARRAYLIKE OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS ESTIMATED TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
MULTIOUTPUT STRING IN ‘RAWVALUES’ ‘UNIFORMAVERAGE’ OR ARRAYLIKE OF SHAPE NOUTPUTS
DEFINES AGGREGATING OF MULTIPLE OUTPUT VALUES ARRAYLIKE VALUE DEFINES WEIGHTS USED TO
AVERAGE ERRORS
‘RAWVALUES’ RETURNS A FULL SET OF ERRORS IN CASE OF MULTIOUTPUT INPUT
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‘UNIFORMAVERAGE’ ERRORS OF ALL OUTPUTS ARE AVERAGED WITH UNIFORM WEIGHT
RETURNS
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YTRUE 3 05 2 7
YPRED 25 00 2 8
MEANSQUAREDERRORYTRUE YPRED
0375
YTRUE 05 11 17 6
YPRED 0 21 28 5
MEANSQUAREDERRORYTRUE YPRED
0708
MEANSQUAREDERRORYTRUE YPRED MULTIOUTPUTRAWVALUES

ARRAY041666667 1
MEANSQUAREDERRORYTRUE YPRED MULTIOUTPUT03 07

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•ROBUST LINEAR ESTIMATOR FITTING
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YTRUE 3 5 25 7
YPRED 25 5 4 8
MEANSQUAREDLOGERRORYTRUE YPRED
0039
YTRUE 05 1 1 2 7 6
YPRED 05 2 1 25 8 8
MEANSQUAREDLOGERRORYTRUE YPRED
0044
MEANSQUAREDLOGERRORYTRUE YPRED MULTIOUTPUTRAWVALUES

ARRAY000462428 008377444
MEANSQUAREDLOGERRORYTRUE YPRED MULTIOUTPUT03 07

0060
SKLEARNMETRICS MEDIANABSOLUTEERROR
SKLEARNMETRICS MEDIANABSOLUTEERROR YTRUE YPRED
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YPRED ARRAYLIKE OF SHAPE NSAMPLES ESTIMATED TARGET VALUES
RETURNS
LOSS FLOAT A POSITIVE FLOATING POINT VALUE THE BEST VALUE IS 00
EXAMPLES
 FROM SKLEARNMETRICS IMPORT MEDIANABSOLUTEERROR
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YPRED 25 00 2 8
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SKLEARNMETRICS R2SCORE YTRUE YPRED SAMPLEWEIGHTNONE MULTIOUTPUT’UNIFORMAVERAGE’
R2 COEFFICIENT OF DETERMINATION REGRESSION SCORE FUNCTION
BEST POSSIBLE SCORE IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
READ MORE IN THE USER GUIDE
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YPRED ARRAYLIKE OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS ESTIMATED TARGET VALUES
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MULTIOUTPUT STRING IN ‘RAWVALUES’ ‘UNIFORMAVERAGE’ ‘VARIANCEWEIGHTED’ OR NONE OR ARRAYLIKE OF SHAPE NOUTPUTS DEFINES AGGREGATING OF MULTIPLE OUTPUT SCORES ARRAYLIKE VALUE DEFINES WEIGHTS USED TO AVERAGE SCORES DEFAULT IS “UNIFORMAVERAGE”
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CHANGED IN VERSION 019 DEFAULT VALUE OF MULTIOUTPUT IS ‘UNIFORMAVERAGE’
RETURNS
ZFLOAT OR NDARRAY OF FLOATS THE R2 SCORE OR NDARRAY OF SCORES IF ‘MULTIOUTPUT’ IS ‘RAWVALUES’
NOTES
THIS IS NOT A SYMMETRIC FUNCTION
UNLIKE MOST OTHER SCORES R2 SCORE MAY BE NEGATIVE IT NEED NOT ACTUALLY BE THE SQUARE OF A QUANTITY R
THIS METRIC IS NOT WELLDEFINED FOR SINGLE SAMPLES AND WILL RETURN A NAN VALUE IF NSAMPLES IS LESS THAN TWO
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1
EXAMPLES
 FROM SKLEARNMETRICS IMPORT R2SCORE
YTRUE 3 05 2 7
YPRED 25 00 2 8
R2SCOREYTRUE YPRED
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YTRUE 05 1 1 1 7 6
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 MULTIOUTPUTVARIANCEWEIGHTED

0938
YTRUE 1 2 3
YPRED 1 2 3
R2SCOREYTRUE YPRED
10
YTRUE 1 2 3
YPRED 2 2 2
R2SCOREYTRUE YPRED
00
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•EFFECT OF TRANSFORMING THE TARGETS IN REGRESSION MODEL
•LINEAR REGRESSION EXAMPLE
•LASSO AND ELASTIC NET FOR SPARSE SIGNALS
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SEE THE MULTILABEL RANKING METRICS SECTION OF THE USER GUIDE FOR FURTHER DETAILS
METRICSCOVERAGEERROR YTRUE YSCORE COVERAGE ERROR MEASURE
METRICSLABELRANKINGAVERAGEPRECISIONSCORE COMPUTE RANKINGBASED AVERAGE PRECISION
METRICSLABELRANKINGLOSS YTRUE YSCORE COMPUTE RANKING LOSS MEASURE
SKLEARNMETRICS COVERAGEERROR
SKLEARNMETRICS COVERAGEERROR YTRUE YSCORE SAMPLEWEIGHTNONE
COVERAGE ERROR MEASURE
COMPUTE HOW FAR WE NEED TO GO THROUGH THE RANKED SCORES TO COVER ALL TRUE LABELS THE BEST VALUE IS EQUAL TO THE AVERAGE NUMBER OF LABELS IN YTRUE PER SAMPLE
TIES INYSCORES ARE BROKEN BY GIVING MAXIMAL RANK THAT WOULD HAVE BEEN ASSIGNED TO ALL TIED VALUES
NOTE OUR IMPLEMENTATION’S SCORE IS 1 GREATER THAN THE ONE GIVEN IN TSOUMAKAS ET AL 2010 THIS EXTENDS IT TO HANDLE THE DEGENERATE CASE IN WHICH AN INSTANCE HAS 0 TRUE LABELS
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE ARRAY SHAPE NSAMPLES NLABELS TRUE BINARY LABELS IN BINARY INDICATOR FORMAT
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MATES OF THE POSITIVE CLASS CONFIDENCE VALUES OR NONTHRESHOLDED MEASURE OF DECISIONS AS RETURNED BY “DECISIONFUNCTION” ON SOME CLASSIFIERS
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1
SKLEARNMETRICS LABELRANKINGAVERAGEPRECISIONSCORE
SKLEARNMETRICS LABELRANKINGAVERAGEPRECISIONSCORE YTRUE YSCORE SAM
PLEWEIGHTNONE
COMPUTE RANKINGBASED AVERAGE PRECISION
LABEL RANKING AVERAGE PRECISION LRAP IS THE AVERAGE OVER EACH GROUND TRUTH LABEL ASSIGNED TO EACH SAMPLE OF THE RATIO OF TRUE VS TOTAL LABELS WITH LOWER SCORE
THIS METRIC IS USED IN MULTILABEL RANKING PROBLEM WHERE THE GOAL IS TO GIVE BETTER RANK TO THE LABELS ASSOCIATED TO EACH SAMPLE
THE OBTAINED SCORE IS ALWAYS STRICTLY GREATER THAN 0 AND THE BEST VALUE IS 1
READ MORE IN THE USER GUIDE
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YTRUE ARRAY OR SPARSE MATRIX SHAPE NSAMPLES NLABELS TRUE BINARY LABELS IN BINARY
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 FROM SKLEARNMETRICS IMPORT LABELRANKINGAVERAGEPRECISIONSCORE
YTRUE NPARRAY1 0 0 0 0 1
YSCORE NPARRAY075 05 1 1 02 01
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COMPUTE RANKING LOSS MEASURE
COMPUTE THE AVERAGE NUMBER OF LABEL PAIRS THAT ARE INCORRECTLY ORDERED GIVEN YSCORE WEIGHTED BY THE SIZE OF THE LABEL SET AND THE NUMBER OF LABELS NOT IN THE LABEL SET
THIS IS SIMILAR TO THE ERROR SET SIZE BUT WEIGHTED BY THE NUMBER OF RELEVANT AND IRRELEVANT LABELS THE BEST PERFORMANCE IS ACHIEVED WITH A RANKING LOSS OF ZERO

READ MORE IN THE USER GUIDE
NEW IN VERSION 017 A FUNCTION LABELRANKINGLOSS
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MATES OF THE POSITIVE CLASS CONFIDENCE VALUES OR NONTHRESHOLDED MEASURE OF DECISIONS AS
RETURNED BY “DECISIONFUNCTION” ON SOME CLASSIFIERS
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
LOSS FLOAT
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1
6245 CLUSTERING METRICS
SEE THE CLUSTERING PERFORMANCE EVALUATION SECTION OF THE USER GUIDE FOR FURTHER DETAILS THE SKLEARNMETRICS
CLUSTER SUBMODULE CONTAINS EVALUATION METRICS FOR CLUSTER ANALYSIS RESULTS THERE ARE TWO FORMS OF EVALUATION
• SUPERVISED WHICH USES A GROUND TRUTH CLASS VALUES FOR EACH SAMPLE
• UNSUPERVISED WHICH DOES NOT AND MEASURES THE ‘QUALITY’ OF THE MODEL ITSELF
METRICSADJUSTEDMUTUALINFOSCORE
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METRICSADJUSTEDRANDSCORE LABELSTRUE RAND INDEX ADJUSTED FOR CHANCE
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  BUILD A CONTINGENCY MATRIX DESCRIBING THE RELATIONSHIP BE
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MEASURE SCORES AT ONCE
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METRICSSILHOUETTESAMPLES X LABELS METRIC COMPUTE THE SILHOUETTE COEFFICIENT FOR EACH SAMPLE
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BELSPREDVMEASURE CLUSTER LABELING GIVEN A GROUND TRUTH

SKLEARNMETRICS ADJUSTEDMUTUALINFOSCORE
SKLEARNMETRICS ADJUSTEDMUTUALINFOSCORE LABELSTRUE LABELSPRED AVER
AGEMETHOD'WARN'
ADJUSTED MUTUAL INFORMATION BETWEEN TWO CLUSTERINGS
ADJUSTED MUTUAL INFORMATION AMI IS AN ADJUSTMENT OF THE MUTUAL INFORMATION MI SCORE TO ACCOUNT FOR
CHANCE IT ACCOUNTS FOR THE FACT THAT THE MI IS GENERALLY HIGHER FOR TWO CLUSTERINGS WITH A LARGER NUMBER OF
CLUSTERS REGARDLESS OF WHETHER THERE IS ACTUALLY MORE INFORMATION SHARED FOR TWO CLUSTERINGS □AND□ THE AMI
IS GIVEN AS
AMIU V MIU V EMIU V AVGHU HV EMIU V
THIS METRIC IS INDEPENDENT OF THE ABSOLUTE VALUES OF THE LABELS A PERMUTATION OF THE CLASS OR CLUSTER LABEL VALUES
WON'T CHANGE THE SCORE VALUE IN ANY WAY
THIS METRIC IS FURTHERMORE SYMMETRIC SWITCHING LABELTRUE WITHLABELPRED WILL RETURN THE SAME SCORE
VALUE THIS CAN BE USEFUL TO MEASURE THE AGREEMENT OF TWO INDEPENDENT LABEL ASSIGNMENTS STRATEGIES ON THE SAME
DATASET WHEN THE REAL GROUND TRUTH IS NOT KNOWN
BE MINDFUL THAT THIS FUNCTION IS AN ORDER OF MAGNITUDE SLOWER THAN OTHER METRICS SUCH AS THE ADJUSTED RAND
INDEX
READ MORE IN THE USER GUIDE
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LABELSPRED ARRAY SHAPE NSAMPLES A CLUSTERING OF THE DATA INTO DISJOINT SUBSETS
AVERAGEMETHOD STRING OPTIONAL DEFAULT 'WARN' HOW TO COMPUTE THE NORMALIZER IN THE
DENOMINATOR POSSIBLE OPTIONS ARE 'MIN' 'GEOMETRIC' 'ARITHMETIC' AND 'MAX' IF 'WARN'
'MAX' WILL BE USED THE DEFAULT WILL CHANGE TO 'ARITHMETIC' IN VERSION 022
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RETURNS
AMI FLOAT UPPERLIMITED BY 10 THE AMI RETURNS A VALUE OF 1 WHEN THE TWO PARTITIONS ARE
IDENTICAL IE PERFECTLY MATCHED RANDOM PARTITIONS INDEPENDENT LABELLINGS HAVE AN EX
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```
 FROM SKLEARNMETRICSCLUSTER IMPORT ADJUSTEDMUTUALINFOSCORE
ADJUSTEDMUTUALINFOSCORE0 0 1 1 0 0 1 1

10
ADJUSTEDMUTUALINFOSCORE0 0 1 1 1 1 0 0

10
```
IF CLASSES MEMBERS ARE COMPLETELY SPLIT ACROSS DIFFERENT CLUSTERS THE ASSIGNMENT IS TOTALLY INCOMPLETE HENCE THE AMI IS NULL
```
ADJUSTEDMUTUALINFOSCORE0 0 0 0 0 1 2 3

00
```
EXAMPLES USING SKLEARNMETRICSADJUSTEDMUTUALINFOSCORE

- DEMO OF AFFINITY PROPAGATION CLUSTERING ALGORITHM
- DEMO OF DBSCAN CLUSTERING ALGORITHM
- ADJUSTMENT FOR CHANCE IN CLUSTERING PERFORMANCE EVALUATION
- A DEMO OF KMEANS CLUSTERING ON THE HANDWRITTEN DIGITS DATA

SKLEARNMETRICS ADJUSTEDRANDSCORE
SKLEARNMETRICS ADJUSTEDRANDSCORE LABELSTRUE LABELSPRED
RAND INDEX ADJUSTED FOR CHANCE
THE RAND INDEX COMPUTES A SIMILARITY MEASURE BETWEEN TWO CLUSTERINGS BY CONSIDERING ALL PAIRS OF SAMPLES AND COUNTING PAIRS THAT ARE ASSIGNED IN THE SAME OR DIFFERENT CLUSTERS IN THE PREDICTED AND TRUE CLUSTERINGS
THE RAW RI SCORE IS THEN “ADJUSTED FOR CHANCE” INTO THE ARI SCORE USING THE FOLLOWING SCHEME
ARI RI EXPECTEDRI MAXRI EXPECTEDRI
THE ADJUSTED RAND INDEX IS THUS ENSURED TO HAVE A VALUE CLOSE TO 00 FOR RANDOM LABELING INDEPENDENTLY OF THE NUMBER OF CLUSTERS AND SAMPLES AND EXACTLY 10 WHEN THE CLUSTERINGS ARE IDENTICAL UP TO A PERMUTATION
ARI IS A SYMMETRIC MEASURE
ADJUSTEDRANDSCOREA B ADJUSTEDRANDSCOREB A
READ MORE IN THE USER GUIDE
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10 STANDS FOR PERFECT MATCH
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PERFECTLY MATCHING LABELINGS HAVE A SCORE OF 1 EVEN
```
 FROM SKLEARNMETRICSCLUSTER IMPORT ADJUSTEDRANDSCORE
ADJUSTEDRANDSCORE0 0 1 1 0 0 1 1
10
ADJUSTEDRANDSCORE0 0 1 1 1 1 0 0
10
```
LABELINGS THAT ASSIGN ALL CLASSES MEMBERS TO THE SAME CLUSTERS ARE COMPLETE BE NOT ALWAYS PURE HENCE PENALIZED
```
ADJUSTEDRANDSCORE0 0 1 2 0 0 1 1
057
```
ARI IS SYMMETRIC SO LABELINGS THAT HAVE PURE CLUSTERS WITH MEMBERS COMING FROM THE SAME CLASSES BUT UNNEC
ESSARY SPLITS ARE PENALIZED
```
ADJUSTEDRANDSCORE0 0 1 1 0 0 1 2
057
```
IF CLASSES MEMBERS ARE COMPLETELY SPLIT ACROSS DIFFERENT CLUSTERS THE ASSIGNMENT IS TOTALLY INCOMPLETE HENCE THE
ARI IS VERY LOW
```
ADJUSTEDRANDSCORE0 0 0 0 0 1 2 3
00
```
EXAMPLES USING SKLEARNMETRICSADJUSTEDRANDSCORE
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•DEMO OF DBSCAN CLUSTERING ALGORITHM
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SKLEARNMETRICS CALINSKIHARABASZSCORE
SKLEARNMETRICS CALINSKIHARABASZSCORE XLABELS
COMPUTE THE CALINSKI AND HARABASZ SCORE
IT IS ALSO KNOWN AS THE VARIANCE RATIO CRITERION
THE SCORE IS DEFINED AS RATIO BETWEEN THE WITHINCLUSTER DISPERSION AND THE BETWEENCLUSTER DISPERSION
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SKLEARNMETRICS DAVIESBOULDINSCORE XLABELS
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THE MINIMUM SCORE IS ZERO WITH LOWER VALUES INDICATING BETTER CLUSTERING
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A CLUSTERING RESULT SATISFIES COMPLETENESS IF ALL THE DATA POINTS THAT ARE MEMBERS OF A GIVEN CLASS ARE ELEMENTS OF THE SAME CLUSTER
THIS METRIC IS INDEPENDENT OF THE ABSOLUTE VALUES OF THE LABELS A PERMUTATION OF THE CLASS OR CLUSTER LABEL VALUES WON’T CHANGE THE SCORE VALUE IN ANY WAY
THIS METRIC IS NOT SYMMETRIC SWITCHING LABELTRUE WITHLABELPRED WILL RETURN THE HOMOGENEITYSCORE WHICH WILL BE DIFFERENT IN GENERAL
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EXAMPLES
PERFECT LABELINGS ARE COMPLETE
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COMPLETENESSSCORE0 0 1 1 1 1 0 0
10
NONPERFECT LABELINGS THAT ASSIGN ALL CLASSES MEMBERS TO THE SAME CLUSTERS ARE STILL COMPLETE
PRINTCOMPLETENESSSCORE0 0 1 1 0 0 0 0
10
PRINTCOMPLETENESSSCORE0 1 2 3 0 0 1 1
0999
IF CLASSES MEMBERS ARE SPLIT ACROSS DIFFERENT CLUSTERS THE ASSIGNMENT CANNOT BE COMPLETE
PRINTCOMPLETENESSSCORE0 0 1 1 0 1 0 1
00
PRINTCOMPLETENESSSCORE0 0 0 0 0 1 2 3
00
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EPS NONE OR FLOAT OPTIONAL IF A FLOAT THAT VALUE IS ADDED TO ALL VALUES IN THE CONTINGENCY
MATRIX THIS HELPS TO STOP NAN PROPAGATION IF NONE NOTHING IS ADJUSTED
SPARSE BOOLEAN OPTIONAL IF TRUE RETURN A SPARSE CSR CONTINENCY MATRIX IF EPS IS NOT
NONE ANDSPARSE IS TRUE WILL THROW VALUEERROR
NEW IN VERSION 018
RETURNS
CONTINGENCY ARRAYLIKE SPARSE SHAPENCLASSESTRUE NCLASSESPRED MATRIX □SUCH THAT
□□□IS THE NUMBER OF SAMPLES IN TRUE CLASS □AND IN PREDICTED CLASS □ IFEPS IS NONE
THE DTYPE OF THIS ARRAY WILL BE INTEGER IF EPS IS GIVEN THE DTYPE WILL BE FLOAT WILL BE A
SCIPYSPARSECSRMATRIX IFSPARSETRUE
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SKLEARNMETRICS FOWLKESMALLOWSSCORE LABELSTRUE LABELSPRED SPARSEFALSE
MEASURE THE SIMILARITY OF TWO CLUSTERINGS OF A SET OF POINTS
THE FOWLKESMALLOWS INDEX FMI IS DEFINED AS THE GEOMETRIC MEAN BETWEEN OF THE PRECISION AND RECALL
FMI TP SQRTTP FP TP FN
WHERETPIS THE NUMBER OF TRUE POSITIVE IE THE NUMBER OF PAIR OF POINTS THAT BELONGS IN THE SAME CLUSTERS
IN BOTHLABELSTRUE ANDLABELSPRED FPIS THE NUMBER OF FALSE POSITIVE IE THE NUMBER OF PAIR OF
POINTS THAT BELONGS IN THE SAME CLUSTERS IN LABELSTRUE AND NOT INLABELSPRED ANDFNIS THE NUMBER
OFFALSE NEGATIVE IE THE NUMBER OF PAIR OF POINTS THAT BELONGS IN THE SAME CLUSTERS IN LABELSPRED AND NOT
INLABELSTRUE
THE SCORE RANGES FROM 0 TO 1 A HIGH VALUE INDICATES A GOOD SIMILARITY BETWEEN TWO CLUSTERS
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 FROM SKLEARNMETRICSCLUSTER IMPORT FOWLKESMALLOWSSCORE
FOWLKESMALLOWSSCORE0 0 1 1 0 0 1 1
10
FOWLKESMALLOWSSCORE0 0 1 1 1 1 0 0
10
IF CLASSES MEMBERS ARE COMPLETELY SPLIT ACROSS DIFFERENT CLUSTERS THE ASSIGNMENT IS TOTALLY RANDOM HENCE THE FMI IS NULL
FOWLKESMALLOWSSCORE0 0 0 0 0 1 2 3
00
SKLEARNMETRICS HOMOGENEITYCOMPLETENESSVMEASURE
SKLEARNMETRICS HOMOGENEITYCOMPLETENESSVMEASURE LABELSTRUE LABELSPRED
BETA10
COMPUTE THE HOMOGENEITY AND COMPLETENESS AND VMEASURE SCORES AT ONCE
THOSE METRICS ARE BASED ON NORMALIZED CONDITIONAL ENTROPY MEASURES OF THE CLUSTERING LABELING TO EVALUATE GIVEN THE KNOWLEDGE OF A GROUND TRUTH CLASS LABELS OF THE SAME SAMPLES
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A CLUSTERING RESULT SATISFIES COMPLETENESS IF ALL THE DATA POINTS THAT ARE MEMBERS OF A GIVEN CLASS ARE ELEMENTS OF THE SAME CLUSTER
BOTH SCORES HAVE POSITIVE VALUES BETWEEN 00 AND 10 LARGER VALUES BEING DESIRABLE
THOSE 3 METRICS ARE INDEPENDENT OF THE ABSOLUTE VALUES OF THE LABELS A PERMUTATION OF THE CLASS OR CLUSTER LABEL VALUES WON’T CHANGE THE SCORE VALUES IN ANY WAY
VMEASURE IS FURTHERMORE SYMMETRIC SWAPPING LABELSTRUE ANDLABELPRED WILL GIVE THE SAME SCORE THIS DOES NOT HOLD FOR HOMOGENEITY AND COMPLETENESS VMEASURE IS IDENTICAL TO NORMALIZEDMUTUALINFOSCORE WITH THE ARITHMETIC AVERAGING METHOD
READ MORE IN THE USER GUIDE
PARAMETERS
LABELSTRUE INT ARRAY SHAPE NSAMPLES GROUND TRUTH CLASS LABELS TO BE USED AS A REFERENCE
LABELSPRED ARRAY SHAPE NSAMPLES CLUSTER LABELS TO EVALUATE
BETA FLOAT RATIO OF WEIGHT ATTRIBUTED TO HOMOGENEITY VSCOMPLETENESS IFBETA IS GREATER THAN 1 COMPLETENESS IS WEIGHTED MORE STRONGLY IN THE CALCULATION IF BETA IS LESS THAN 1 HOMOGENEITY IS WEIGHTED MORE STRONGLY
RETURNS
HOMOGENEITY FLOAT SCORE BETWEEN 00 AND 10 10 STANDS FOR PERFECTLY HOMOGENEOUS LABELING
COMPLETENESS FLOAT SCORE BETWEEN 00 AND 10 10 STANDS FOR PERFECTLY COMPLETE LABELING
VMEASURE FLOAT HARMONIC MEAN OF THE FIRST TWO
SEE ALSO

HOMOGENEITYSCORE
COMPLETENESSSCORE
VMEASURESCORE
SKLEARNMETRICS HOMOGENEITYSCORE
SKLEARNMETRICS HOMOGENEITYSCORE LABELSTRUE LABELSPRED
HOMOGENEITY METRIC OF A CLUSTER LABELING GIVEN A GROUND TRUTH
A CLUSTERING RESULT SATISFIES HOMOGENEITY IF ALL OF ITS CLUSTERS CONTAIN ONLY DATA POINTS WHICH ARE MEMBERS OF A SINGLE CLASS
THIS METRIC IS INDEPENDENT OF THE ABSOLUTE VALUES OF THE LABELS A PERMUTATION OF THE CLASS OR CLUSTER LABEL VALUES WON'T CHANGE THE SCORE VALUE IN ANY WAY
THIS METRIC IS NOT SYMMETRIC SWITCHING LABELTRUE WITHLABELPRED WILL RETURN THE COMPLETENESSSCORE WHICH WILL BE DIFFERENT IN GENERAL
READ MORE IN THE USER GUIDE
PARAMETERS
LABELSTRUE INT ARRAY SHAPE NSAMPLES GROUND TRUTH CLASS LABELS TO BE USED AS A REFERENCE
LABELSPRED ARRAY SHAPE NSAMPLES CLUSTER LABELS TO EVALUATE
RETURNS
HOMOGENEITY FLOAT SCORE BETWEEN 00 AND 10 10 STANDS FOR PERFECTLY HOMOGENEOUS LABELING
SEE ALSO
COMPLETENESSSCORE
VMEASURESCORE
REFERENCES
1
EXAMPLES
PERFECT LABELINGS ARE HOMOGENEOUS
 FROM SKLEARNMETRICSCLUSTER IMPORT HOMOGENEITYSCORE
HOMOGENEITYSCORE0 0 1 1 1 1 0 0
10
NONPERFECT LABELINGS THAT FURTHER SPLIT CLASSES INTO MORE CLUSTERS CAN BE PERFECTLY HOMOGENEOUS
PRINT6F HOMOGENEITYSCORE0 0 1 1 0 0 1 2

1000000
PRINT6F HOMOGENEITYSCORE0 0 1 1 0 1 2 3

1000000

CLUSTERS THAT INCLUDE SAMPLES FROM DIFFERENT CLASSES DO NOT MAKE FOR AN HOMOGENEOUS LABELING
PRINT6F HOMOGENEITYSCORE0 0 1 1 0 1 0 1

00
PRINT6F HOMOGENEITYSCORE0 0 1 1 0 0 0 0

00
EXAMPLES USING SKLEARNMETRICSHOMOGENEITYSCORE
•DEMO OF AFFINITY PROPAGATION CLUSTERING ALGORITHM
•DEMO OF DBSCAN CLUSTERING ALGORITHM
•A DEMO OF KMEANS CLUSTERING ON THE HANDWRITTEN DIGITS DATA
•CLUSTERING TEXT DOCUMENTS USING KMEANS
SKLEARNMETRICS MUTUALINFOSCORE
SKLEARNMETRICS MUTUALINFOSCORE LABELSTRUE LABELSPRED CONTINGENCYNONE
MUTUAL INFORMATION BETWEEN TWO CLUSTERINGS
THE MUTUAL INFORMATION IS A MEASURE OF THE SIMILARITY BETWEEN TWO LABELS OF THE SAME DATA WHERE □□IS THE NUMBER OF THE SAMPLES IN CLUSTER □□AND□□IS THE NUMBER OF THE SAMPLES IN CLUSTER □□ THE MUTUAL INFORMATION BETWEEN CLUSTERINGS □AND□IS GIVEN AS
□□□ □ □∑
□1□∑
□1□□∩□□
□LOG□□□∩□□
□□□□
THIS METRIC IS INDEPENDENT OF THE ABSOLUTE VALUES OF THE LABELS A PERMUTATION OF THE CLASS OR CLUSTER LABEL VALUES WON’T CHANGE THE SCORE VALUE IN ANY WAY
THIS METRIC IS FURTHERMORE SYMMETRIC SWITCHING LABELTRUE WITHLABELPRED WILL RETURN THE SAME SCORE VALUE THIS CAN BE USEFUL TO MEASURE THE AGREEMENT OF TWO INDEPENDENT LABEL ASSIGNMENTS STRATEGIES ON THE SAME DATASET WHEN THE REAL GROUND TRUTH IS NOT KNOWN
READ MORE IN THE USER GUIDE
PARAMETERS
LABELSTRUE INT ARRAY SHAPE NSAMPLES A CLUSTERING OF THE DATA INTO DISJOINT SUBSETS
LABELSPRED ARRAY SHAPE NSAMPLES A CLUSTERING OF THE DATA INTO DISJOINT SUBSETS
CONTINGENCY NONE ARRAY SPARSE MATRIX SHAPE NCLASSESTRUE NCLASSESPRED A CON TINGENCY MATRIX GIVEN BY THE CONTINGENCYMATRIX FUNCTION IF VALUE IS NONE IT WILL BE COMPUTED OTHERWISE THE GIVEN VALUE IS USED WITH LABELSTRUE ANDLABELSPRED IGNORED
RETURNS
MIFLOAT MUTUAL INFORMATION A NONNEGATIVE VALUE
SEE ALSO
ADJUSTEDMUTUALINFOSCORE ADJUSTED AGAINST CHANCE MUTUAL INFORMATION
NORMALIZEDMUTUALINFOSCORE NORMALIZED MUTUAL INFORMATION

EXAMPLES USING SKLEARNMETRICSMUTUALINFOSCORE
•ADJUSTMENT FOR CHANCE IN CLUSTERING PERFORMANCE EVALUATION
SKLEARNMETRICS NORMALIZEDMUTUALINFOSCORE
SKLEARNMETRICS NORMALIZEDMUTUALINFOSCORE LABELSTRUE LABELSPRED AVER
AGEMETHOD'WARN'
NORMALIZED MUTUAL INFORMATION BETWEEN TWO CLUSTERINGS
NORMALIZED MUTUAL INFORMATION NMI IS A NORMALIZATION OF THE MUTUAL INFORMATION MI SCORE TO SCALE THE
RESULTS BETWEEN 0 NO MUTUAL INFORMATION AND 1 PERFECT CORRELATION IN THIS FUNCTION MUTUAL INFORMATION
IS NORMALIZED BY SOME GENERALIZED MEAN OF HLABELSTRUE ANDHLABELSPRED DEFINED BY THE
AVERAGEMETHOD
THIS MEASURE IS NOT ADJUSTED FOR CHANCE THEREFORE ADJUSTEDMUTUALINFOSCORE MIGHT BE PREFERRED
THIS METRIC IS INDEPENDENT OF THE ABSOLUTE VALUES OF THE LABELS A PERMUTATION OF THE CLASS OR CLUSTER LABEL VALUES
WON'T CHANGE THE SCORE VALUE IN ANY WAY
THIS METRIC IS FURTHERMORE SYMMETRIC SWITCHING LABELTRUE WITHLABELPRED WILL RETURN THE SAME SCORE
VALUE THIS CAN BE USEFUL TO MEASURE THE AGREEMENT OF TWO INDEPENDENT LABEL ASSIGNMENTS STRATEGIES ON THE SAME
DATASET WHEN THE REAL GROUND TRUTH IS NOT KNOWN
READ MORE IN THE USER GUIDE
PARAMETERS
LABELSTRUE INT ARRAY SHAPE NSAMPLES A CLUSTERING OF THE DATA INTO DISJOINT SUBSETS
LABELSPRED ARRAY SHAPE NSAMPLES A CLUSTERING OF THE DATA INTO DISJOINT SUBSETS
AVERAGEMETHOD STRING OPTIONAL DEFAULT 'WARN' HOW TO COMPUTE THE NORMALIZER IN THE
DENOMINATOR POSSIBLE OPTIONS ARE 'MIN' 'GEOMETRIC' 'ARITHMETIC' AND 'MAX' IF 'WARN'
'GEOMETRIC' WILL BE USED THE DEFAULT WILL CHANGE TO 'ARITHMETIC' IN VERSION 022
NEW IN VERSION 020
RETURNS
NMI FLOAT SCORE BETWEEN 00 AND 10 10 STANDS FOR PERFECTLY COMPLETE LABELING
SEE ALSO
VMEASURESCORE VMEASURE NMI WITH ARITHMETIC MEAN OPTION
ADJUSTEDRANDSCORE ADJUSTED RAND INDEX
ADJUSTEDMUTUALINFOSCORE ADJUSTED MUTUAL INFORMATION ADJUSTED AGAINST CHANCE
EXAMPLES
PERFECT LABELINGS ARE BOTH HOMOGENEOUS AND COMPLETE HENCE HAVE SCORE 10
FROM SKLEARNMETRICSCLUSTER IMPORT NORMALIZEDMUTUALINFOSCORE
NORMALIZEDMUTUALINFOSCORE0 0 1 1 0 0 1 1

10
NORMALIZEDMUTUALINFOSCORE0 0 1 1 1 1 0 0

10
IF CLASSES MEMBERS ARE COMPLETELY SPLIT ACROSS DIFFERENT CLUSTERS THE ASSIGNMENT IS TOTALLY INCOMPLETE HENCE THE NMI IS NULL
NORMALIZEDMUTUALINFOSCORE0 0 0 0 0 1 2 3

00
SKLEARNMETRICS SILHOUETTESCORE
SKLEARNMETRICS SILHOUETTESCORE XLABELS METRIC'EUCLIDEAN' SAMPLESIZENONE RAN
DOMSTATENONE KWDS
COMPUTE THE MEAN SILHOUETTE COEFFICIENT OF ALL SAMPLES
THE SILHOUETTE COEFFICIENT IS CALCULATED USING THE MEAN INTRACLUSTER DISTANCE A AND THE MEAN NEARESTCLUSTER DISTANCE B FOR EACH SAMPLE THE SILHOUETTE COEFFICIENT FOR A SAMPLE IS B A MAXA B TO CLARIFY
BIS THE DISTANCE BETWEEN A SAMPLE AND THE NEAREST CLUSTER THAT THE SAMPLE IS NOT A PART OF NOTE THAT SILHOUETTE COEFFICIENT IS ONLY DEFINED IF NUMBER OF LABELS IS 2 NLABELS NSAMPLES 1
THIS FUNCTION RETURNS THE MEAN SILHOUETTE COEFFICIENT OVER ALL SAMPLES TO OBTAIN THE VALUES FOR EACH SAMPLE USESILHOUETTESAMPLES
THE BEST VALUE IS 1 AND THE WORST VALUE IS 1 VALUES NEAR 0 INDICATE OVERLAPPING CLUSTERS NEGATIVE VALUES GENERALLY INDICATE THAT A SAMPLE HAS BEEN ASSIGNED TO THE WRONG CLUSTER AS A DIFFERENT CLUSTER IS MORE SIMILAR
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY NSAMPLESA NSAMPLESA IF METRIC "PRECOMPUTED" OR NSAMPLESA
NFEATURES OTHERWISE ARRAY OF PAIRWISE DISTANCES BETWEEN SAMPLES OR A FEATURE ARRAY
LABELS ARRAY SHAPE NSAMPLES PREDICTED LABELS FOR EACH SAMPLE
METRIC STRING OR CALLABLE THE METRIC TO USE WHEN CALCULATING DISTANCE BETWEEN INSTANCES IN A FEATURE ARRAY IF METRIC IS A STRING IT MUST BE ONE OF THE OPTIONS ALLOWED BY METRICSPAIRWISEPAIRWISEDISTANCES IF X IS THE DISTANCE ARRAY ITSELF USE METRICPRECOMPUTED
SAMPLESIZE INT OR NONE THE SIZE OF THE SAMPLE TO USE WHEN COMPUTING THE SILHOUETTE CO EFFICIENT ON A RANDOM SUBSET OF THE DATA IF SAMPLESIZE IS NONE NO SAMPLING IS USED
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE GENERATOR USED TO RANDOMLY SELECT A SUBSET OF SAMPLES IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NP RANDOM USED WHEN SAMPLESIZE IS NOT NONE
KWDS OPTIONAL KEYWORD PARAMETERS ANY FURTHER PARAMETERS ARE PASSED DIRECTLY TO THE DIS TANCE FUNCTION IF USING A SCIPYSPATIALDISTANCE METRIC THE PARAMETERS ARE STILL METRIC DE PENDENT SEE THE SCIPY DOCS FOR USAGE EXAMPLES
RETURNS
SILHOUETTE FLOAT MEAN SILHOUETTE COEFFICIENT FOR ALL SAMPLES

REFERENCES
12
EXAMPLES USING SKLEARNMETRICSSILHOUETTESCORE
•DEMO OF AFFINITY PROPAGATION CLUSTERING ALGORITHM
•DEMO OF DBSCAN CLUSTERING ALGORITHM
•A DEMO OF KMEANS CLUSTERING ON THE HANDWRITTEN DIGITS DATA
•SELECTING THE NUMBER OF CLUSTERS WITH SILHOUETTE ANALYSIS ON KMEANS CLUSTERING
•CLUSTERING TEXT DOCUMENTS USING KMEANS
SKLEARNMETRICS SILHOUETTESAMPLES
SKLEARNMETRICS SILHOUETTESAMPLES XLABELS METRIC'EUCLIDEAN' KWDS
COMPUTE THE SILHOUETTE COEFFICIENT FOR EACH SAMPLE
THE SILHOUETTE COEFFICIENT IS A MEASURE OF HOW WELL SAMPLES ARE CLUSTERED WITH SAMPLES THAT ARE SIMILAR TO THEMSELVES CLUSTERING MODELS WITH A HIGH SILHOUETTE COEFFICIENT ARE SAID TO BE DENSE WHERE SAMPLES IN THE SAME CLUSTER ARE SIMILAR TO EACH OTHER AND WELL SEPARATED WHERE SAMPLES IN DIFFERENT CLUSTERS ARE NOT VERY SIMILAR TO EACH OTHER
THE SILHOUETTE COEFFICIENT IS CALCULATED USING THE MEAN INTRACLUSTER DISTANCE A AND THE MEAN NEARESTCLUSTER DISTANCE B FOR EACH SAMPLE THE SILHOUETTE COEFFICIENT FOR A SAMPLE IS B A MAXA B NOTE THAT SILHOUETTE COEFFICIENT IS ONLY DEFINED IF NUMBER OF LABELS IS 2 NLABELS NSAMPLES 1
THIS FUNCTION RETURNS THE SILHOUETTE COEFFICIENT FOR EACH SAMPLE
THE BEST VALUE IS 1 AND THE WORST VALUE IS 1 VALUES NEAR 0 INDICATE OVERLAPPING CLUSTERS
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY NSAMPLESA NSAMPLESA IF METRIC "PRECOMPUTED" OR NSAMPLESA NFEATURES OTHERWISE ARRAY OF PAIRWISE DISTANCES BETWEEN SAMPLES OR A FEATURE ARRAY
LABELS ARRAY SHAPE NSAMPLES LABEL VALUES FOR EACH SAMPLE
METRIC STRING OR CALLABLE THE METRIC TO USE WHEN CALCULATING DISTANCE BETWEEN INSTANCES IN A FEATURE ARRAY IF METRIC IS A STRING IT MUST BE ONE OF THE OPTIONS ALLOWED BY SKLEARN METRICSPAIRWISEPAIRWISEDISTANCES IF X IS THE DISTANCE ARRAY ITSELF USE "PRECOMPUTED" AS THE METRIC
'KWDS' OPTIONAL KEYWORD PARAMETERS ANY FURTHER PARAMETERS ARE PASSED DIRECTLY TO THE DIS TANCE FUNCTION IF USING A SCIPYSPATIALDISTANCE METRIC THE PARAMETERS ARE STILL METRIC DEPENDENT SEE THE SCIPY DOCS FOR USAGE EXAMPLES
RETURNS
SILHOUETTE ARRAY SHAPE NSAMPLES SILHOUETTE COEFFICIENT FOR EACH SAMPLES
REFERENCES
12
624SKLEARNMETRICS METRICS 2037

EXAMPLES USING SKLEARNMETRICSSILHOUETTESAMPLES
•SELECTING THE NUMBER OF CLUSTERS WITH SILHOUETTE ANALYSIS ON KMEANS CLUSTERING
SKLEARNMETRICS VMEASURESCORE
SKLEARNMETRICS VMEASURESCORE LABELSTRUE LABELSPRED BETA10
VMEASURE CLUSTER LABELING GIVEN A GROUND TRUTH
THIS SCORE IS IDENTICAL TO NORMALIZEDMUTUALINFOSCORE WITH THEARITHMETIC OPTION FOR AVER
AGING
THE VMEASURE IS THE HARMONIC MEAN BETWEEN HOMOGENEITY AND COMPLETENESS
V 1 BETA HOMOGENEITY COMPLETENESS
 BETA HOMOGENEITY COMPLETENESS
THIS METRIC IS INDEPENDENT OF THE ABSOLUTE VALUES OF THE LABELS A PERMUTATION OF THE CLASS OR CLUSTER LABEL VALUES
WON’T CHANGE THE SCORE VALUE IN ANY WAY
THIS METRIC IS FURTHERMORE SYMMETRIC SWITCHING LABELTRUE WITHLABELPRED WILL RETURN THE SAME SCORE
VALUE THIS CAN BE USEFUL TO MEASURE THE AGREEMENT OF TWO INDEPENDENT LABEL ASSIGNMENTS STRATEGIES ON THE SAME
DATASET WHEN THE REAL GROUND TRUTH IS NOT KNOWN
READ MORE IN THE USER GUIDE
PARAMETERS
LABELSTRUE INT ARRAY SHAPE NSAMPLES GROUND TRUTH CLASS LABELS TO BE USED AS A REFERENCE
LABELSPRED ARRAY SHAPE NSAMPLES CLUSTER LABELS TO EVALUATE
BETA FLOAT RATIO OF WEIGHT ATTRIBUTED TO HOMOGENEITY VSCOMPLETENESS IFBETA IS
GREATER THAN 1 COMPLETENESS IS WEIGHTED MORE STRONGLY IN THE CALCULATION IF BETA IS
LESS THAN 1 HOMOGENEITY IS WEIGHTED MORE STRONGLY
RETURNS
VMEASURE FLOAT SCORE BETWEEN 00 AND 10 10 STANDS FOR PERFECTLY COMPLETE LABELING
SEE ALSO
HOMOGENEITYSCORE
COMPLETENESSSCORE
NORMALIZEDMUTUALINFOSCORE
REFERENCES
1
EXAMPLES
PERFECT LABELINGS ARE BOTH HOMOGENEOUS AND COMPLETE HENCE HAVE SCORE 10

```
 FROM SKLEARNMETRICSCLUSTER IMPORT VMEASURESCORE
VMEASURESCORE0 0 1 1 0 0 1 1
10
VMEASURESCORE0 0 1 1 1 1 0 0
10
```
LABELINGS THAT ASSIGN ALL CLASSES MEMBERS TO THE SAME CLUSTERS ARE COMPLETE BE NOT HOMOGENEOUS HENCE PENAL IZED
```
PRINT6F  VMEASURESCORE0 0 1 2 0 0 1 1

08
PRINT6F  VMEASURESCORE0 1 2 3 0 0 1 1

066
```
LABELINGS THAT HAVE PURE CLUSTERS WITH MEMBERS COMING FROM THE SAME CLASSES ARE HOMOGENEOUS BUT UN NECESSARY SPLITS HARMS COMPLETENESS AND THUS PENALIZE VMEASURE AS WELL
```
PRINT6F  VMEASURESCORE0 0 1 1 0 0 1 2

08
PRINT6F  VMEASURESCORE0 0 1 1 0 1 2 3

066
```
IF CLASSES MEMBERS ARE COMPLETELY SPLIT ACROSS DIFFERENT CLUSTERS THE ASSIGNMENT IS TOTALLY INCOMPLETE HENCE THE VMEASURE IS NULL
```
PRINT6F  VMEASURESCORE0 0 0 0 0 1 2 3

00
```
CLUSTERS THAT INCLUDE SAMPLES FROM TOTALLY DIFFERENT CLASSES TOTALLY DESTROY THE HOMOGENEITY OF THE LABELING HENCE
```
PRINT6F  VMEASURESCORE0 0 1 1 0 0 0 0

00
```
EXAMPLES USING SKLEARNMETRICSVMEASURESCORE
•BICLUSTERING DOCUMENTS WITH THE SPECTRAL COCLUSTERING ALGORITHM
•DEMO OF AFFINITY PROPAGATION CLUSTERING ALGORITHM
•DEMO OF DBSCAN CLUSTERING ALGORITHM
•ADJUSTMENT FOR CHANCE IN CLUSTERING PERFORMANCE EVALUATION
•A DEMO OF KMEANS CLUSTERING ON THE HANDWRITTEN DIGITS DATA
•CLUSTERING TEXT DOCUMENTS USING KMEANS
6246 BICLUSTERING METRICS
SEE THE BICLUSTERING EVALUATION SECTION OF THE USER GUIDE FOR FURTHER DETAILS
624SKLEARNMETRICS METRICS 2039
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METRICSCONSENSUSSCORE A B SIMILARITY THE SIMILARITY OF TWO SETS OF BICLUSTERS
SKLEARNMETRICS CONSENSUSSCORE
SKLEARNMETRICS CONSENSUSSCORE ABSIMILARITY'JACCARD'
THE SIMILARITY OF TWO SETS OF BICLUSTERS
SIMILARITY BETWEEN INDIVIDUAL BICLUSTERS IS COMPUTED THEN THE BEST MATCHING BETWEEN SETS IS FOUND USING THE HUNGARIAN ALGORITHM THE FINAL SCORE IS THE SUM OF SIMILARITIES DIVIDED BY THE SIZE OF THE LARGER SET
READ MORE IN THE USER GUIDE
PARAMETERS
AROWS COLUMNS TUPLE OF ROW AND COLUMN INDICATORS FOR A SET OF BICLUSTERS
BROWS COLUMNS ANOTHER SET OF BICLUSTERS LIKE A
SIMILARITY STRING OR FUNCTION OPTIONAL DEFAULT "JACCARD" MAY BE THE STRING "JACCARD" TO USE THE JACCARD COEFFICIENT OR ANY FUNCTION THAT TAKES FOUR ARGUMENTS EACH OF WHICH IS A 1D INDICATOR VECTOR AROWS ACOLUMNS BROWS BCOLUMNS
REFERENCES
• HOCHREITER BODENHOFER ET AL 2010 FABIA FACTOR ANALYSIS FOR BICLUSTER ACQUISITION
EXAMPLES USING SKLEARNMETRICSCONSENSUSSCORE
•A DEMO OF THE SPECTRAL COCLUSTERING ALGORITHM
•A DEMO OF THE SPECTRAL BICLUSTERING ALGORITHM
6247 PAIRWISE METRICS
SEE THE PAIRWISE METRICS AFFINITIES AND KERNELS SECTION OF THE USER GUIDE FOR FURTHER DETAILS
METRICSPAIRWISEADDITIVECHI2KERNEL X
YCOMPUTES THE ADDITIVE CHISQUARED KERNEL BETWEEN OBSER
VATIONS IN X AND Y
METRICSPAIRWISECHI2KERNEL X Y GAMMA COMPUTES THE EXPONENTIAL CHISQUARED KERNEL X AND Y
METRICSPAIRWISECOSINESIMILARITY X Y
  COMPUTE COSINE SIMILARITY BETWEEN SAMPLES IN X AND Y
METRICSPAIRWISECOSINEDISTANCES X Y COMPUTE COSINE DISTANCE BETWEEN SAMPLES IN X AND Y
METRICSPAIRWISEDISTANCEMETRICS VALID METRICS FOR PAIRWISEDISTANCES
METRICSPAIRWISEEUCLIDEANDISTANCES X
Y CONSIDERING THE ROWS OF X AND YX AS VECTORS COMPUTE
THE DISTANCE MATRIX BETWEEN EACH PAIR OF VECTORS
METRICSPAIRWISEHAVERSINEDISTANCES X
YCOMPUTE THE HAVERSINE DISTANCE BETWEEN SAMPLES IN X AND
Y
METRICSPAIRWISEKERNELMETRICS VALID METRICS FOR PAIRWISEKERNELS
METRICSPAIRWISELAPLACIANKERNEL X Y
GAMMACOMPUTE THE LAPLACIAN KERNEL BETWEEN X AND Y
METRICSPAIRWISELINEARKERNEL X Y COMPUTE THE LINEAR KERNEL BETWEEN X AND Y
CONTINUED ON NEXT PAGE

TABLE 6184 – CONTINUED FROM PREVIOUS PAGE
METRICSPAIRWISEMANHATTANDISTANCES X
Y COMPUTE THE L1 DISTANCES BETWEEN THE VECTORS IN X AND Y
METRICSPAIRWISEPAIRWISEKERNELS X Y
  COMPUTE THE KERNEL BETWEEN ARRAYS X AND OPTIONAL ARRAY Y
METRICSPAIRWISEPOLYNOMIALKERNEL X Y
  COMPUTE THE POLYNOMIAL KERNEL BETWEEN X AND Y
METRICSPAIRWISERBFKERNEL X Y GAMMA COMPUTE THE RBF GAUSSIAN KERNEL BETWEEN X AND Y
METRICSPAIRWISESIGMOIDKERNEL X Y COMPUTE THE SIGMOID KERNEL BETWEEN X AND Y
METRICSPAIRWISEPAIREDEUCLIDEANDISTANCES X
YCOMPUTES THE PAIRED EUCLIDEAN DISTANCES BETWEEN X AND Y
METRICSPAIRWISEPAIREDMANHATTANDISTANCES X
YCOMPUTE THE L1 DISTANCES BETWEEN THE VECTORS IN X AND Y
METRICSPAIRWISEPAIREDCOSINEDISTANCES X
YCOMPUTES THE PAIRED COSINE DISTANCES BETWEEN X AND Y
METRICSPAIRWISEPAIREDDISTANCES X Y
METRICCOMPUTES THE PAIRED DISTANCES BETWEEN X AND Y
METRICSPAIRWISEDISTANCES X Y METRIC COMPUTE THE DISTANCE MATRIX FROM A VECTOR ARRAY X AND OP
TIONAL Y
METRICSPAIRWISEDISTANCESARGMIN X Y
  COMPUTE MINIMUM DISTANCES BETWEEN ONE POINT AND A SET
OF POINTS
METRICSPAIRWISEDISTANCESARGMINMIN X
YCOMPUTE MINIMUM DISTANCES BETWEEN ONE POINT AND A SET
OF POINTS
METRICSPAIRWISEDISTANCESCHUNKED X Y
  GENERATE A DISTANCE MATRIX CHUNK BY CHUNK WITH OPTIONAL
REDUCTION
SKLEARNMETRICSPAIRWISE ADDITIVECHI2KERNEL
SKLEARNMETRICSPAIRWISE ADDITIVECHI2KERNEL XYNONE
COMPUTES THE ADDITIVE CHISQUARED KERNEL BETWEEN OBSERVATIONS IN X AND Y
THE CHISQUARED KERNEL IS COMPUTED BETWEEN EACH PAIR OF ROWS IN X AND Y X AND Y HAVE TO BE NONNEGATIVE
THIS KERNEL IS MOST COMMONLY APPLIED TO HISTOGRAMS
THE CHISQUARED KERNEL IS GIVEN BY
KX Y SUM X Y2 X Y
IT CAN BE INTERPRETED AS A WEIGHTED DIFFERENCE PER ENTRY
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE OF SHAPE NSAMPLESX NFEATURES
YARRAY OF SHAPE NSAMPLESY NFEATURES
RETURNS
KERNELMATRIX ARRAY OF SHAPE NSAMPLESX NSAMPLESY
SEE ALSO
CHI2KERNEL THE EXPONENTIATED VERSION OF THE KERNEL WHICH IS USUALLY PREFERABLE
SKLEARNKERNELAPPROXIMATIONADDITIVECHI2SAMPLER A FOURIER APPROXIMATION TO THIS KER
NEL

NOTES
AS THE NEGATIVE OF A DISTANCE THIS KERNEL IS ONLY CONDITIONALLY POSITIVE DEFINITE
REFERENCES
• ZHANG J AND MARSZALEK M AND LAZEBNIK S AND SCHMID C LOCAL FEATURES AND KERNELS FOR CLASSIFICATION
OF TEXTURE AND OBJECT CATEGORIES A COMPREHENSIVE STUDY INTERNATIONAL JOURNAL OF COMPUTER VISION 2007
HTTPSRESEARCHMICROSOFTCOMENUSUMPEOPLEMANIKPROJECTSTRADEOFFPAPERSZHANGIJCV06PDF
SKLEARNMETRICSPAIRWISE CHI2KERNEL
SKLEARNMETRICSPAIRWISE CHI2KERNEL XYNONE GAMMA10
COMPUTES THE EXPONENTIAL CHISQUARED KERNEL X AND Y
THE CHISQUARED KERNEL IS COMPUTED BETWEEN EACH PAIR OF ROWS IN X AND Y X AND Y HAVE TO BE NONNEGATIVE
THIS KERNEL IS MOST COMMONLY APPLIED TO HISTOGRAMS
THE CHISQUARED KERNEL IS GIVEN BY
KX Y EXPGAMMA SUM X Y2 X Y
IT CAN BE INTERPRETED AS A WEIGHTED DIFFERENCE PER ENTRY
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE OF SHAPE NSAMPLESX NFEATURES
YARRAY OF SHAPE NSAMPLESY NFEATURES
GAMMA FLOAT DEFAULT1 SCALING PARAMETER OF THE CHI2 KERNEL
RETURNS
KERNELMATRIX ARRAY OF SHAPE NSAMPLESX NSAMPLESY
SEE ALSO
ADDITIVECHI2KERNEL THE ADDITIVE VERSION OF THIS KERNEL
SKLEARNKERNELAPPROXIMATIONADDITIVECHI2SAMPLER A FOURIER APPROXIMATION TO THE ADDI
TIVE VERSION OF THIS KERNEL
REFERENCES
• ZHANG J AND MARSZALEK M AND LAZEBNIK S AND SCHMID C LOCAL FEATURES AND KERNELS FOR CLASSIFICATION
OF TEXTURE AND OBJECT CATEGORIES A COMPREHENSIVE STUDY INTERNATIONAL JOURNAL OF COMPUTER VISION 2007
HTTPSRESEARCHMICROSOFTCOMENUSUMPEOPLEMANIKPROJECTSTRADEOFFPAPERSZHANGIJCV06PDF
SKLEARNMETRICSPAIRWISE COSINESIMILARITY
SKLEARNMETRICSPAIRWISE COSINESIMILARITY XYNONE DENSEOUTPUTTRUE
COMPUTE COSINE SIMILARITY BETWEEN SAMPLES IN X AND Y
COSINE SIMILARITY OR THE COSINE KERNEL COMPUTES SIMILARITY AS THE NORMALIZED DOT PRODUCT OF X AND Y

KX Y X Y XY
ON L2NORMALIZED DATA THIS FUNCTION IS EQUIVALENT TO LINEARKERNEL
READ MORE IN THE USER GUIDE
PARAMETERS
XNDARRAY OR SPARSE ARRAY SHAPE NSAMPLESX NFEATURES INPUT DATA
YNDARRAY OR SPARSE ARRAY SHAPE NSAMPLESY NFEATURES INPUT DATA IF NONE THE OUTPUT
WILL BE THE PAIRWISE SIMILARITIES BETWEEN ALL SAMPLES IN X
DENSEOUTPUT BOOLEAN OPTIONAL DEFAULT TRUE WHETHER TO RETURN DENSE OUTPUT EVEN WHEN THE
INPUT IS SPARSE IF FALSE THE OUTPUT IS SPARSE IF BOTH INPUT ARRAYS ARE SPARSE
NEW IN VERSION 017 PARAMETER DENSEOUTPUT FOR DENSE OUTPUT
RETURNS
KERNEL MATRIX ARRAY AN ARRAY WITH SHAPE NSAMPLESX NSAMPLESY
SKLEARNMETRICSPAIRWISE COSINEDISTANCES
SKLEARNMETRICSPAIRWISE COSINEDISTANCES XYNONE
COMPUTE COSINE DISTANCE BETWEEN SAMPLES IN X AND Y
COSINE DISTANCE IS DEFINED AS 10 MINUS THE COSINE SIMILARITY
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX WITH SHAPE NSAMPLESX NFEATURES
YARRAYLIKE SPARSE MATRIX OPTIONAL WITH SHAPE NSAMPLESY NFEATURES
RETURNS
DISTANCE MATRIX ARRAY AN ARRAY WITH SHAPE NSAMPLESX NSAMPLESY
SEE ALSO
SKLEARNMETRICSPAIRWISECOSINESIMILARITY
SCIPYSPATIALDISTANCECOSINE DENSE MATRICES ONLY
SKLEARNMETRICSPAIRWISE DISTANCEMETRICS
SKLEARNMETRICSPAIRWISE DISTANCEMETRICS
VALID METRICS FOR PAIRWISEDISTANCES
THIS FUNCTION SIMPLY RETURNS THE VALID PAIRWISE DISTANCE METRICS IT EXISTS TO ALLOW FOR A DESCRIPTION OF THE
MAPPING FOR EACH OF THE VALID STRINGS
THE VALID DISTANCE METRICS AND THE FUNCTION THEY MAP TO ARE

METRIC FUNCTION
‘CITYBLOCK’ METRICSPAIRWISEMANHATTANDISTANCES
‘COSINE’ METRICSPAIRWISECOSINEDISTANCES
‘EUCLIDEAN’ METRICSPAIRWISEEUCLIDEANDISTANCES
‘HAVERSINE’ METRICSPAIRWISEHAVERSINEDISTANCES
‘L1’ METRICSPAIRWISEMANHATTANDISTANCES
‘L2’ METRICSPAIRWISEEUCLIDEANDISTANCES
‘MANHATTAN’ METRICSPAIRWISEMANHATTANDISTANCES
READ MORE IN THE USER GUIDE
SKLEARNMETRICSPAIRWISE EUCLIDEANDISTANCES
SKLEARNMETRICSPAIRWISE EUCLIDEANDISTANCES XYNONE YNORMSQUAREDNONE
SQUAREDFALSE XNORMSQUAREDNONE
CONSIDERING THE ROWS OF X AND YX AS VECTORS COMPUTE THE DISTANCE MATRIX BETWEEN EACH PAIR OF VECTORS
FOR EFFICIENCY REASONS THE EUCLIDEAN DISTANCE BETWEEN A PAIR OF ROW VECTOR X AND Y IS COMPUTED AS
DISTX Y SQRTDOTX X 2 DOTX Y DOTY Y
THIS FORMULATION HAS TWO ADVANTAGES OVER OTHER WAYS OF COMPUTING DISTANCES FIRST IT IS COMPUTATIONALLY EF
FICIENT WHEN DEALING WITH SPARSE DATA SECOND IF ONE ARGUMENT VARIES BUT THE OTHER REMAINS UNCHANGED THEN
DOTX X ANDORDOTY Y CAN BE PRECOMPUTED
HOWEVER THIS IS NOT THE MOST PRECISE WAY OF DOING THIS COMPUTATION AND THE DISTANCE MATRIX RETURNED BY THIS
FUNCTION MAY NOT BE EXACTLY SYMMETRIC AS REQUIRED BY EG SCIPYSPATIALDISTANCE FUNCTIONS
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES1 NFEATURES
YARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES2 NFEATURES
YNORMSQUARED ARRAYLIKE SHAPE NSAMPLES2 OPTIONAL PRECOMPUTED DOTPRODUCTS OF
VECTORS IN Y EG Y2SUMAXIS1 MAY BE IGNORED IN SOME CASES SEE THE NOTE
BELOW
SQUARED BOOLEAN OPTIONAL RETURN SQUARED EUCLIDEAN DISTANCES
XNORMSQUARED ARRAYLIKE SHAPE NSAMPLES1 OPTIONAL PRECOMPUTED DOTPRODUCTS OF
VECTORS IN X EG X2SUMAXIS1 MAY BE IGNORED IN SOME CASES SEE THE NOTE
BELOW
RETURNS
DISTANCES ARRAY SHAPE NSAMPLES1 NSAMPLES2
SEE ALSO
PAIREDDISTANCES DISTANCES BETWEENS PAIRS OF ELEMENTS OF X AND Y
NOTES
TO ACHIEVE BETTER ACCURACY XNORMSQUARED ANDYNORMSQUARED MAY BE UNUSED IF THEY ARE PASSED AS
FLOAT32

EXAMPLES
```
 FROM SKLEARNMETRICSPAIRWISE IMPORT EUCLIDEANDISTANCES
X  0 1 1 1
 DISTANCE BETWEEN ROWS OF X
EUCLIDEANDISTANCESX X
ARRAY0 1
1 0
 GET DISTANCE TO ORIGIN
EUCLIDEANDISTANCESX 0 0
ARRAY1
141421356
```
SKLEARNMETRICSPAIRWISE HAVERSINEDISTANCES
SKLEARNMETRICSPAIRWISE HAVERSINEDISTANCES XYNONE
COMPUTE THE HAVERSINE DISTANCE BETWEEN SAMPLES IN X AND Y
THE HAVERSINE OR GREAT CIRCLE DISTANCE IS THE ANGULAR DISTANCE BETWEEN TWO POINTS ON THE SURFACE OF A SPHERE THE FIRST DISTANCE OF EACH POINT IS ASSUMED TO BE THE LATITUDE THE SECOND IS THE LONGITUDE GIVEN IN RADIANS THE DIMENSION OF THE DATA MUST BE 2
□□ □ 2 ARCSIN√
SIN2□1−□12 COS □1 COS □1 SIN2□2−□22
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES1 2
YARRAYLIKE SHAPE NSAMPLES2 2 OPTIONAL
RETURNS
DISTANCE ARRAY SHAPE NSAMPLES1 NSAMPLES2
NOTES
AS THE EARTH IS NEARLY SPHERICAL THE HAVERSINE FORMULA PROVIDES A GOOD APPROXIMATION OF THE DISTANCE BETWEEN TWO POINTS OF THE EARTH SURFACE WITH A LESS THAN 1 ERROR ON AVERAGE
EXAMPLES
WE WANT TO CALCULATE THE DISTANCE BETWEEN THE EZEIZA AIRPORT BUENOS AIRES ARGENTINA AND THE CHARLES DE GAULLE AIRPORT PARIS FRANCE
```
 FROM SKLEARNMETRICSPAIRWISE IMPORT HAVERSINEDISTANCES
BSAS  3483333 585166646
PARIS  490083899664 253844117956
RESULT  HAVERSINEDISTANCESBSAS PARIS
RESULT63710001000  MULTIPLY BY EARTH RADIUS TO GET KILOMETERS
ARRAY 0  1127945379464
1127945379464 0
```

SKLEARNMETRICSPAIRWISE KERNELMETRICS
SKLEARNMETRICSPAIRWISE KERNELMETRICS
VALID METRICS FOR PAIRWISEKERNELS
THIS FUNCTION SIMPLY RETURNS THE VALID PAIRWISE DISTANCE METRICS IT EXISTS HOWEVER TO ALLOW FOR A VERBOSE DESCRIPTION OF THE MAPPING FOR EACH OF THE VALID STRINGS
THE VALID DISTANCE METRICS AND THE FUNCTION THEY MAP TO ARE
METRIC FUNCTION
‘ADDITIVECHI2’ SKLEARNPAIRWISEADDITIVECHI2KERNEL
‘CHI2’ SKLEARNPAIRWISECHI2KERNEL
‘LINEAR’ SKLEARNPAIRWISELINEARKERNEL
‘POLY’ SKLEARNPAIRWISEPOLYNOMIALKERNEL
‘POLYNOMIAL’ SKLEARNPAIRWISEPOLYNOMIALKERNEL
‘RBF’ SKLEARNPAIRWISERBFKERNEL
‘LAPLACIAN’ SKLEARNPAIRWISELAPLACIANKERNEL
‘SIGMOID’ SKLEARNPAIRWISESIGMOIDKERNEL
‘COSINE’ SKLEARNPAIRWISECOSINESIMILARITY
READ MORE IN THE USER GUIDE
SKLEARNMETRICSPAIRWISE LAPLACIANKERNEL
SKLEARNMETRICSPAIRWISE LAPLACIANKERNEL XYNONE GAMMANONE
COMPUTE THE LAPLACIAN KERNEL BETWEEN X AND Y
THE LAPLACIAN KERNEL IS DEFINED AS
KX Y EXPGAMMA XY1
FOR EACH PAIR OF ROWS X IN X AND Y IN Y READ MORE IN THE USER GUIDE
NEW IN VERSION 017
PARAMETERS
XARRAY OF SHAPE NSAMPLESX NFEATURES
YARRAY OF SHAPE NSAMPLESY NFEATURES
GAMMA FLOAT DEFAULT NONE IF NONE DEFAULTS TO 10 NFEATURES
RETURNS
KERNELMATRIX ARRAY OF SHAPE NSAMPLESX NSAMPLESY
SKLEARNMETRICSPAIRWISE LINEARKERNEL
SKLEARNMETRICSPAIRWISE LINEARKERNEL XYNONE DENSEOUTPUTTRUE
COMPUTE THE LINEAR KERNEL BETWEEN X AND Y
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY OF SHAPE NSAMPLES1 NFEATURES

SCIKITLEARN USER GUIDE RELEASE 0213
YARRAY OF SHAPE NSAMPLES2 NFEATURES
DENSEOUTPUT BOOLEAN OPTIONAL DEFAULT TRUE WHETHER TO RETURN DENSE OUTPUT EVEN WHEN THE
INPUT IS SPARSE IF FALSE THE OUTPUT IS SPARSE IF BOTH INPUT ARRAYS ARE SPARSE
NEW IN VERSION 020
RETURNS
GRAM MATRIX ARRAY OF SHAPE NSAMPLES1 NSAMPLES2
SKLEARNMETRICSPAIRWISE MANHATTANDISTANCES
SKLEARNMETRICSPAIRWISE MANHATTANDISTANCES XYNONE SUMOVERFEATURESTRUE
COMPUTE THE L1 DISTANCES BETWEEN THE VECTORS IN X AND Y
WITH SUMOVERFEATURES EQUAL TO FALSE IT RETURNS THE COMPONENTWISE DISTANCES
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE AN ARRAY WITH SHAPE NSAMPLESX NFEATURES
YARRAYLIKE OPTIONAL AN ARRAY WITH SHAPE NSAMPLESY NFEATURES
SUMOVERFEATURES BOOL DEFAULTTRUE IF TRUE THE FUNCTION RETURNS THE PAIRWISE DISTANCE MA
TRIX ELSE IT RETURNS THE COMPONENTWISE L1 PAIRWISEDISTANCES NOT SUPPORTED FOR SPARSE MA
TRIX INPUTS
RETURNS
DARRAY IF SUMOVERFEATURES IS FALSE SHAPE IS NSAMPLESX NSAMPLESY NFEATURES AND
D CONTAINS THE COMPONENTWISE L1 PAIRWISEDISTANCES IE ABSOLUTE DIFFERENCE ELSE SHAPE IS
NSAMPLESX NSAMPLESY AND D CONTAINS THE PAIRWISE L1 DISTANCES
EXAMPLES
 FROM SKLEARNMETRICSPAIRWISE IMPORT MANHATTANDISTANCES
MANHATTANDISTANCES3 3
ARRAY0
MANHATTANDISTANCES3 2
ARRAY1
MANHATTANDISTANCES2 3
ARRAY1
MANHATTANDISTANCES1 2 3 4 1 2 0 3
ARRAY0 2
4 4
 IMPORT NUMPY AS NP
X NPONES1 2
Y NPFULL2 2 2
MANHATTANDISTANCESX Y SUMOVERFEATURES FALSE
ARRAY1 1
1 1
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SKLEARNMETRICSPAIRWISE PAIRWISEKERNELS
SKLEARNMETRICSPAIRWISE PAIRWISEKERNELS X YNONE METRIC'LINEAR' FIL
TERPARAMSFALSE NJOBSNONE KWDS
COMPUTE THE KERNEL BETWEEN ARRAYS X AND OPTIONAL ARRAY Y
THIS METHOD TAKES EITHER A VECTOR ARRAY OR A KERNEL MATRIX AND RETURNS A KERNEL MATRIX IF THE INPUT IS A VECTOR ARRAY THE KERNELS ARE COMPUTED IF THE INPUT IS A KERNEL MATRIX IT IS RETURNED INSTEAD
THIS METHOD PROVIDES A SAFE WAY TO TAKE A KERNEL MATRIX AS INPUT WHILE PRESERVING COMPATIBILITY WITH MANY OTHER ALGORITHMS THAT TAKE A VECTOR ARRAY
IF Y IS GIVEN DEFAULT IS NONE THEN THE RETURNED MATRIX IS THE PAIRWISE KERNEL BETWEEN THE ARRAYS FROM BOTH X AND Y
VALID VALUES FOR METRIC ARE
'ADDITIVECHI2' 'CHI2' 'LINEAR' 'POLY' 'POLYNOMIAL' 'RBF' 'LAPLACIAN' 'SIGMOID' 'COSINE'
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY NSAMPLESA NSAMPLESA IF METRIC "PRECOMPUTED" OR NSAMPLESA
NFEATURES OTHERWISE ARRAY OF PAIRWISE KERNELS BETWEEN SAMPLES OR A FEATURE ARRAY
YARRAY NSAMPLESB NFEATURES A SECOND FEATURE ARRAY ONLY IF X HAS SHAPE NSAMPLESA
NFEATURES
METRIC STRING OR CALLABLE THE METRIC TO USE WHEN CALCULATING KERNEL BETWEEN INSTANCES
IN A FEATURE ARRAY IF METRIC IS A STRING IT MUST BE ONE OF THE METRICS IN PAIR
WISEPAIRWISEKERNELFUNCTIONS IF METRIC IS "PRECOMPUTED" X IS ASSUMED TO
BE A KERNEL MATRIX ALTERNATIVELY IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF
INSTANCES ROWS AND THE RESULTING VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS FROM
X AS INPUT AND RETURN A VALUE INDICATING THE DISTANCE BETWEEN THEM
FILTERPARAMS BOOLEAN WHETHER TO FILTER INVALID PARAMETERS OR NOT
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION
THIS WORKS BY BREAKING DOWN THE PAIRWISE MATRIX INTO NJOBS EVEN SLICES AND COMPUTING
THEM IN PARALLEL
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL
PROCESSORS SEE GLOSSARY FOR MORE DETAILS
KWDS OPTIONAL KEYWORD PARAMETERS ANY FURTHER PARAMETERS ARE PASSED DIRECTLY TO THE KERNEL FUNCTION
RETURNS
KARRAY NSAMPLESA NSAMPLESA OR NSAMPLESA NSAMPLESB A KERNEL MATRIX K SUCH
THAT KI J IS THE KERNEL BETWEEN THE ITH AND JTH VECTORS OF THE GIVEN MATRIX X IF Y IS NONE
IF Y IS NOT NONE THEN KI J IS THE KERNEL BETWEEN THE ITH ARRAY FROM X AND THE JTH ARRAY FROM Y
NOTES
IF METRIC IS 'PRECOMPUTED' Y IS IGNORED AND X IS RETURNED

SCIKITLEARN USER GUIDE RELEASE 0213
SKLEARNMETRICSPAIRWISE POLYNOMIALKERNEL
SKLEARNMETRICSPAIRWISE POLYNOMIALKERNEL XYNONE DEGREE3 GAMMANONE
COEF01
COMPUTE THE POLYNOMIAL KERNEL BETWEEN X AND Y
KX Y GAMMA X Y COEF0DEGREE
READ MORE IN THE USER GUIDE
PARAMETERS
XNDARRAY OF SHAPE NSAMPLES1 NFEATURES
YNDARRAY OF SHAPE NSAMPLES2 NFEATURES
DEGREE INT DEFAULT 3
GAMMA FLOAT DEFAULT NONE IF NONE DEFAULTS TO 10 NFEATURES
COEF0 FLOAT DEFAULT 1
RETURNS
GRAM MATRIX ARRAY OF SHAPE NSAMPLES1 NSAMPLES2
SKLEARNMETRICSPAIRWISE RBFKERNEL
SKLEARNMETRICSPAIRWISE RBFKERNEL XYNONE GAMMANONE
COMPUTE THE RBF GAUSSIAN KERNEL BETWEEN X AND Y
KX Y EXPGAMMA XY2
FOR EACH PAIR OF ROWS X IN X AND Y IN Y
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY OF SHAPE NSAMPLESX NFEATURES
YARRAY OF SHAPE NSAMPLESY NFEATURES
GAMMA FLOAT DEFAULT NONE IF NONE DEFAULTS TO 10 NFEATURES
RETURNS
KERNELMATRIX ARRAY OF SHAPE NSAMPLESX NSAMPLESY
SKLEARNMETRICSPAIRWISE SIGMOIDKERNEL
SKLEARNMETRICSPAIRWISE SIGMOIDKERNEL XYNONE GAMMANONE COEF01
COMPUTE THE SIGMOID KERNEL BETWEEN X AND Y
KX Y TANHGAMMA X Y COEF0
READ MORE IN THE USER GUIDE
PARAMETERS
XNDARRAY OF SHAPE NSAMPLES1 NFEATURES
YNDARRAY OF SHAPE NSAMPLES2 NFEATURES
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GAMMA FLOAT DEFAULT NONE IF NONE DEFAULTS TO 10 NFEATURES
COEF0 FLOAT DEFAULT 1
RETURNS
GRAM MATRIX ARRAY OF SHAPE NSAMPLES1 NSAMPLES2
SKLEARNMETRICSPAIRWISE PAIREDEUCLIDEANDISTANCES
SKLEARNMETRICSPAIRWISE PAIREDEUCLIDEANDISTANCES XY
COMPUTES THE PAIRED EUCLIDEAN DISTANCES BETWEEN X AND Y
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
YARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
DISTANCES NDARRAY NSAMPLES
SKLEARNMETRICSPAIRWISE PAIREDMANHATTANDISTANCES
SKLEARNMETRICSPAIRWISE PAIREDMANHATTANDISTANCES XY
COMPUTE THE L1 DISTANCES BETWEEN THE VECTORS IN X AND Y
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
YARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
DISTANCES NDARRAY NSAMPLES
SKLEARNMETRICSPAIRWISE PAIREDCOSINEDISTANCES
SKLEARNMETRICSPAIRWISE PAIREDCOSINEDISTANCES XY
COMPUTES THE PAIRED COSINE DISTANCES BETWEEN X AND Y
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
YARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
DISTANCES NDARRAY SHAPE NSAMPLES

NOTES
THE COSINE DISTANCE IS EQUIVALENT TO THE HALF THE SQUARED EUCLIDEAN DISTANCE IF EACH SAMPLE IS NORMALIZED TO UNIT NORM
SKLEARNMETRICSPAIRWISE PAIREDDISTANCES
SKLEARNMETRICSPAIRWISE PAIREDDISTANCES XYMETRIC'EUCLIDEAN' KWDS
COMPUTES THE PAIRED DISTANCES BETWEEN X AND Y
COMPUTES THE DISTANCES BETWEEN X0 Y0 X1 Y1 ETC
READ MORE IN THE USER GUIDE
PARAMETERS
XNDARRAY NSAMPLES NFEATURES ARRAY 1 FOR DISTANCE COMPUTATION
YNDARRAY NSAMPLES NFEATURES ARRAY 2 FOR DISTANCE COMPUTATION
METRIC STRING OR CALLABLE THE METRIC TO USE WHEN CALCULATING DISTANCE BETWEEN INSTANCES IN A FEATURE ARRAY IF METRIC IS A STRING IT MUST BE ONE OF THE OPTIONS SPECIFIED IN PAIREDDISTANCES INCLUDING "EUCLIDEAN" "MANHATTAN" OR "COSINE" ALTERNATIVELY IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF INSTANCES ROWS AND THE RESULTING VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS FROM X AS INPUT AND RETURN A VALUE INDICATING THE DISTANCE BETWEEN THEM
RETURNS
DISTANCES NDARRAY NSAMPLES
SEE ALSO
PAIRWISEDISTANCES COMPUTES THE DISTANCE BETWEEN EVERY PAIR OF SAMPLES
EXAMPLES
```
 FROM SKLEARNMETRICSPAIRWISE IMPORT PAIREDDISTANCES
X  0 1 1 1
Y  0 1 2 1
PAIREDDISTANCESX Y
ARRAY0 1
```
SKLEARNMETRICS PAIRWISEDISTANCES
SKLEARNMETRICS PAIRWISEDISTANCES XYNONE METRIC'EUCLIDEAN' NJOBSNONE KWDS
COMPUTE THE DISTANCE MATRIX FROM A VECTOR ARRAY X AND OPTIONAL Y
THIS METHOD TAKES EITHER A VECTOR ARRAY OR A DISTANCE MATRIX AND RETURNS A DISTANCE MATRIX IF THE INPUT IS A VECTOR ARRAY THE DISTANCES ARE COMPUTED IF THE INPUT IS A DISTANCES MATRIX IT IS RETURNED INSTEAD
THIS METHOD PROVIDES A SAFE WAY TO TAKE A DISTANCE MATRIX AS INPUT WHILE PRESERVING COMPATIBILITY WITH MANY OTHER ALGORITHMS THAT TAKE A VECTOR ARRAY
IF Y IS GIVEN DEFAULT IS NONE THEN THE RETURNED MATRIX IS THE PAIRWISE DISTANCE BETWEEN THE ARRAYS FROM BOTH X AND Y

VALID VALUES FOR METRIC ARE
• FROM SCIKITLEARN ‘CITYBLOCK’ ‘COSINE’ ‘EUCLIDEAN’ ‘L1’ ‘L2’ ‘MANHATTAN’ THESE METRICS SUPPORT SPARSE MATRIX INPUTS
• FROM SCIPYSPATIALDISTANCE ‘BRAYCURTIS’ ‘CANBERRA’ ‘CHEBYSHEV’ ‘CORRELATION’ ‘DICE’ ‘HAMMING’ ‘JACCARD’ ‘KULSINSKI’ ‘MAHALANOBIS’ ‘MINKOWSKI’ ‘ROGERSTANIMOTO’ ‘RUSSELLRAO’ ‘SEUCLIDEAN’ ‘SOKALMICHENER’ ‘SOKALSNEATH’ ‘SQEUCLIDEAN’ ‘YULE’ SEE THE DOCUMENTATION FOR SCIPYSPATIALDISTANCE FOR DETAILS ON THESE METRICS THESE METRICS DO NOT SUPPORT SPARSE MATRIX INPUTS
NOTE THAT IN THE CASE OF ‘CITYBLOCK’ ‘COSINE’ AND ‘EUCLIDEAN’ WHICH ARE VALID SCIPYSPATIALDISTANCE METRICS THE SCIKITLEARN IMPLEMENTATION WILL BE USED WHICH IS FASTER AND HAS SUPPORT FOR SPARSE MATRICES EXCEPT FOR ‘CITYBLOCK’ FOR A VERBOSE DESCRIPTION OF THE METRICS FROM SCIKITLEARN SEE THE DOC OF THE SKLEARNPAIRWISEDISTANCEMETRICS FUNCTION
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAY NSAMPLESA NSAMPLESA IF METRIC “PRECOMPUTED” OR NSAMPLESA NFEATURES OTHERWISE ARRAY OF PAIRWISE DISTANCES BETWEEN SAMPLES OR A FEATURE ARRAY
YARRAY NSAMPLESB NFEATURES OPTIONAL AN OPTIONAL SECOND FEATURE ARRAY ONLY ALLOWED IF METRIC “PRECOMPUTED”
METRIC STRING OR CALLABLE THE METRIC TO USE WHEN CALCULATING DISTANCE BETWEEN INSTANCES IN A FEATURE ARRAY IF METRIC IS A STRING IT MUST BE ONE OF THE OPTIONS ALLOWED BY SCIPYSPATIALDISTANCEPDIST FOR ITS METRIC PARAMETER OR A METRIC LISTED IN PAIRWISEPAIRWISEDISTANCEFUNCTIONS IF METRIC IS “PRECOMPUTED” X IS ASSUMED TO BE A DISTANCE MATRIX ALTERNATIVELY IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF INSTANCES ROWS AND THE RESULTING VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS FROM X AS INPUT AND RETURN A VALUE INDICATING THE DISTANCE BETWEEN THEM
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION THIS WORKS BY BREAKING DOWN THE PAIRWISE MATRIX INTO NJOBS EVEN SLICES AND COMPUTING THEM IN PARALLEL
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
KWDS OPTIONAL KEYWORD PARAMETERS ANY FURTHER PARAMETERS ARE PASSED DIRECTLY TO THE DISTANCE FUNCTION IF USING A SCIPYSPATIALDISTANCE METRIC THE PARAMETERS ARE STILL METRIC DEPENDENT SEE THE SCIPY DOCS FOR USAGE EXAMPLES
RETURNS
DARRAY NSAMPLESA NSAMPLESA OR NSAMPLESA NSAMPLESB A DISTANCE MATRIX D SUCH THAT DI J IS THE DISTANCE BETWEEN THE ITH AND JTH VECTORS OF THE GIVEN MATRIX X IF Y IS NONE IF Y IS NOT NONE THEN DI J IS THE DISTANCE BETWEEN THE ITH ARRAY FROM X AND THE JTH ARRAY FROM Y
SEE ALSO
PAIRWISEDISTANCESCHUNKED PERFORMS THE SAME CALCULATION AS THIS FUNCTION BUT RETURNS A GENERATOR OF CHUNKS OF THE DISTANCE MATRIX IN ORDER TO LIMIT MEMORY USAGE
PAIREDDISTANCES COMPUTES THE DISTANCES BETWEEN CORRESPONDING ELEMENTS OF TWO ARRAYS

SCIKITLEARN USER GUIDE RELEASE 0213
EXAMPLES USING SKLEARNMETRICSPAIRWISEDISTANCES
•AGGLOMERATIVE CLUSTERING WITH DIFFERENT METRICS
SKLEARNMETRICS PAIRWISEDISTANCESARGMIN
SKLEARNMETRICS PAIRWISEDISTANCESARGMIN X Y AXIS1 METRIC'EUCLIDEAN'
BATCHSIZENONE METRICKWARGSNONE
COMPUTE MINIMUM DISTANCES BETWEEN ONE POINT AND A SET OF POINTS
THIS FUNCTION COMPUTES FOR EACH ROW IN X THE INDEX OF THE ROW OF Y WHICH IS CLOSEST ACCORDING TO THE SPECIFIED DISTANCE
THIS IS MOSTLY EQUIVALENT TO CALLING
PAIRWISEDISTANCESX YY METRICMETRICARGMINAXISAXIS
BUT USES MUCH LESS MEMORY AND IS FASTER FOR LARGE ARRAYS
THIS FUNCTION WORKS WITH DENSE 2D ARRAYS ONLY
PARAMETERS
XARRAYLIKE ARRAYS CONTAINING POINTS RESPECTIVE SHAPES NSAMPLES1 NFEATURES AND NSAMPLES2 NFEATURES
YARRAYLIKE ARRAYS CONTAINING POINTS RESPECTIVE SHAPES NSAMPLES1 NFEATURES AND NSAMPLES2 NFEATURES
AXIS INT OPTIONAL DEFAULT 1 AXIS ALONG WHICH THE ARGMIN AND DISTANCES ARE TO BE COMPUTED
METRIC STRING OR CALLABLE METRIC TO USE FOR DISTANCE COMPUTATION ANY METRIC FROM SCIKITLEARN OR SCIPYSPATIALDISTANCE CAN BE USED
IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF INSTANCES ROWS AND THE RESULTING VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS AS INPUT AND RETURN ONE VALUE INDICATING THE DISTANCE BETWEEN THEM THIS WORKS FOR SCIPY'S METRICS BUT IS LESS EFFICIENT THAN PASSING THE METRIC NAME AS A STRING
DISTANCE MATRICES ARE NOT SUPPORTED
VALID VALUES FOR METRIC ARE
• FROM SCIKITLEARN 'CITYBLOCK' 'COSINE' 'EUCLIDEAN' 'L1' 'L2' 'MANHATTAN'
• FROM SCIPYSPATIALDISTANCE 'BRAYCURTIS' 'CANBERRA' 'CHEBYSHEV' 'CORRELATION' 'DICE' 'HAMMING' 'JACCARD' 'KULSINSKI' 'MAHALANOBIS' 'MINKOWSKI' 'ROGERSTANIMOTO' 'RUSSELLRAO' 'SEUCLIDEAN' 'SOKALMICHENER' 'SOKALSNEATH' 'SQEUCLIDEAN' 'YULE'
SEE THE DOCUMENTATION FOR SCIPYSPATIALDISTANCE FOR DETAILS ON THESE METRICS
BATCHSIZE INTEGER DEPRECATED SINCE VERSION 020 DEPRECATED FOR REMOVAL IN 022 USE SKLEARNSETCONFIGWORKINGMEMORY INSTEAD
METRICKWARGS DICT KEYWORD ARGUMENTS TO PASS TO SPECIFIED METRIC FUNCTION
RETURNS
ARGMIN NUMPYNDARRAY YARGMINI IS THE ROW IN Y THAT IS CLOSEST TO XI
SEE ALSO
SKLEARNMETRICSPAIRWISEDISTANCES
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SKLEARNMETRICSPAIRWISEDISTANCESARGMINMIN
EXAMPLES USING SKLEARNMETRICSPAIRWISEDISTANCESARGMIN
•COLOR QUANTIZATION USING KMEANS
•COMPARISON OF THE KMEANS AND MINIBATCHKMEANS CLUSTERING ALGORITHMS
SKLEARNMETRICS PAIRWISEDISTANCESARGMINMIN
SKLEARNMETRICS PAIRWISEDISTANCESARGMINMIN XYAXIS1 METRIC'EUCLIDEAN'
BATCHSIZENONE METRICKWARGSNONE
COMPUTE MINIMUM DISTANCES BETWEEN ONE POINT AND A SET OF POINTS
THIS FUNCTION COMPUTES FOR EACH ROW IN X THE INDEX OF THE ROW OF Y WHICH IS CLOSEST ACCORDING TO THE SPECIFIED
DISTANCE THE MINIMAL DISTANCES ARE ALSO RETURNED
THIS IS MOSTLY EQUIVALENT TO CALLING
PAIRWISEDISTANCESX YY METRICMETRICARGMINAXISAXIS PAIRWISEDISTANCESX YY
METRICMETRICMINAXISAXIS
BUT USES MUCH LESS MEMORY AND IS FASTER FOR LARGE ARRAYS
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES1 NFEATURES ARRAY CONTAINING POINTS
YARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES2 NFEATURES ARRAYS CONTAINING POINTS
AXIS INT OPTIONAL DEFAULT 1 AXIS ALONG WHICH THE ARGMIN AND DISTANCES ARE TO BE COMPUTED
METRIC STRING OR CALLABLE DEFAULT 'EUCLIDEAN' METRIC TO USE FOR DISTANCE COMPUTATION ANY
METRIC FROM SCIKITLEARN OR SCIPYSPATIALDISTANCE CAN BE USED
IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF INSTANCES ROWS AND THE RESULTING
VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS AS INPUT AND RETURN ONE VALUE INDICATING
THE DISTANCE BETWEEN THEM THIS WORKS FOR SCIPY'S METRICS BUT IS LESS EFFICIENT THAN PASSING
THE METRIC NAME AS A STRING
DISTANCE MATRICES ARE NOT SUPPORTED
VALID VALUES FOR METRIC ARE
• FROM SCIKITLEARN 'CITYBLOCK' 'COSINE' 'EUCLIDEAN' 'L1' 'L2' 'MANHATTAN'
• FROM SCIPYSPATIALDISTANCE 'BRAYCURTIS' 'CANBERRA' 'CHEBYSHEV' 'CORRELATION' 'DICE'
'HAMMING' 'JACCARD' 'KULSINSKI' 'MAHALANOBIS' 'MINKOWSKI' 'ROGERSTANIMOTO' 'RUS
SELLRAO' 'SEUCLIDEAN' 'SOKALMICHENER' 'SOKALSNEATH' 'SQEUCLIDEAN' 'YULE'
SEE THE DOCUMENTATION FOR SCIPYSPATIALDISTANCE FOR DETAILS ON THESE METRICS
BATCHSIZE INTEGER DEPRECATED SINCE VERSION 020 DEPRECATED FOR REMOVAL IN 022 USE
SKLEARNSETCONFIGWORKINGMEMORY INSTEAD
METRICKWARGS DICT OPTIONAL KEYWORD ARGUMENTS TO PASS TO SPECIFIED METRIC FUNCTION
RETURNS
ARGMIN NUMPYNDARRAY YARGMINI IS THE ROW IN Y THAT IS CLOSEST TO XI
DISTANCES NUMPYNDARRAY DISTANCESI IS THE DISTANCE BETWEEN THE ITH ROW IN X AND THE
ARGMINITH ROW IN Y

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SEE ALSO
SKLEARNMETRICSPAIRWISEDISTANCES
SKLEARNMETRICSPAIRWISEDISTANCESARGMIN
SKLEARNMETRICS PAIRWISEDISTANCESCHUNKED
SKLEARNMETRICS PAIRWISEDISTANCESCHUNKED XYNONE REDUCEFUNCNONE MET
RIC'EUCLIDEAN' NJOBSNONE WORK
INGMEMORYNONE KWDS
GENERATE A DISTANCE MATRIX CHUNK BY CHUNK WITH OPTIONAL REDUCTION
IN CASES WHERE NOT ALL OF A PAIRWISE DISTANCE MATRIX NEEDS TO BE STORED AT ONCE THIS IS USED TO CALCULATE PAIRWISE
DISTANCES IN WORKINGMEMORY SIZED CHUNKS IF REDUCEFUNC IS GIVEN IT IS RUN ON EACH CHUNK AND ITS
RETURN VALUES ARE CONCATENATED INTO LISTS ARRAYS OR SPARSE MATRICES
PARAMETERS
XARRAY NSAMPLESA NSAMPLESA IF METRIC "PRECOMPUTED" OR NSAMPLESA
NFEATURES OTHERWISE ARRAY OF PAIRWISE DISTANCES BETWEEN SAMPLES OR A FEATURE ARRAY
YARRAY NSAMPLESB NFEATURES OPTIONAL AN OPTIONAL SECOND FEATURE ARRAY ONLY ALLOWED
IF METRIC "PRECOMPUTED"
REDUCEFUNC CALLABLE OPTIONAL THE FUNCTION WHICH IS APPLIED ON EACH CHUNK OF THE DISTANCE
MATRIX REDUCING IT TO NEEDED VALUES REDUCEFUNCDCHUNK START IS CALLED RE
PEATEDLY WHERE DCHUNK IS A CONTIGUOUS VERTICAL SLICE OF THE PAIRWISE DISTANCE MATRIX
STARTING AT ROW START IT SHOULD RETURN AN ARRAY A LIST OR A SPARSE MATRIX OF LENGTH
DCHUNKSHAPE0 OR A TUPLE OF SUCH OBJECTS
IF NONE PAIRWISEDISTANCESCHUNKED RETURNS A GENERATOR OF VERTICAL CHUNKS OF THE DISTANCE
MATRIX
METRIC STRING OR CALLABLE THE METRIC TO USE WHEN CALCULATING DISTANCE BETWEEN IN
STANCES IN A FEATURE ARRAY IF METRIC IS A STRING IT MUST BE ONE OF THE OPTIONS AL
LOWED BY SCIPYSPATIALDISTANCEPDIST FOR ITS METRIC PARAMETER OR A METRIC LISTED IN PAIR
WISEPAIRWISEDISTANCEFUNCTIONS IF METRIC IS "PRECOMPUTED" X IS ASSUMED TO
BE A DISTANCE MATRIX ALTERNATIVELY IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR
OF INSTANCES ROWS AND THE RESULTING VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS
FROM X AS INPUT AND RETURN A VALUE INDICATING THE DISTANCE BETWEEN THEM
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION
THIS WORKS BY BREAKING DOWN THE PAIRWISE MATRIX INTO NJOBS EVEN SLICES AND COMPUTING
THEM IN PARALLEL
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL
PROCESSORS SEE GLOSSARY FOR MORE DETAILS
WORKINGMEMORY INT OPTIONAL THE SOUGHT MAXIMUM MEMORY FOR TEMPORARY
DISTANCE MATRIX CHUNKS WHEN NONE DEFAULT THE VALUE OF SKLEARN
GETCONFIGWORKINGMEMORY IS USED
'KWDS' OPTIONAL KEYWORD PARAMETERS ANY FURTHER PARAMETERS ARE PASSED DIRECTLY TO THE DIS
TANCE FUNCTION IF USING A SCIPYSPATIALDISTANCE METRIC THE PARAMETERS ARE STILL METRIC DE
PENDENT SEE THE SCIPY DOCS FOR USAGE EXAMPLES
YIELDS
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DCHUNK ARRAY OR SPARSE MATRIX A CONTIGUOUS SLICE OF DISTANCE MATRIX OPTIONALLY PROCESSED
BYREDUCEFUNC
EXAMPLES
WITHOUT REDUCEFUNC
 IMPORT NUMPY AS NP
 FROM SKLEARNMETRICS IMPORT PAIRWISEDISTANCESCHUNKED
X NPRANDOMRANDOMSTATE0RAND5 3
DCHUNK NEXTPAIRWISEDISTANCESCHUNKEDX
DCHUNK
ARRAY0 029 041 019 057
029 0 057 041 076
041 057 0 044 090
019 041 044 0 051
057 076 090 051 0
RETRIEVE ALL NEIGHBORS AND AVERAGE DISTANCE WITHIN RADIUS R
R 2
 DEF REDUCEFUNCDCHUNK START
 NEIGH NPFLATNONZEROD R FORDINDCHUNK
 AVGDIST DCHUNK DCHUNK RMEANAXIS1
 RETURN NEIGH AVGDIST
GEN PAIRWISEDISTANCESCHUNKEDX REDUCEFUNCREDUCEFUNC
NEIGH AVGDIST NEXTGEN
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AVGDIST
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WHERE R IS DEFINED PER SAMPLE WE NEED TO MAKE USE OF START
R 2 4 4 3 1
 DEF REDUCEFUNCDCHUNK START
 NEIGH NPFLATNONZEROD RI
 FOR I DINENUMERATEDCHUNK START
 RETURN NEIGH
NEIGH NEXTPAIRWISEDISTANCESCHUNKEDX REDUCEFUNCREDUCEFUNC
NEIGH
ARRAY0 3 ARRAY0 1 ARRAY2 ARRAY0 3 ARRAY4
FORCE ROWBYROW GENERATION BY REDUCING WORKINGMEMORY
GEN PAIRWISEDISTANCESCHUNKEDX REDUCEFUNCREDUCEFUNC
 WORKINGMEMORY0
NEXTGEN
ARRAY0 3
NEXTGEN
ARRAY0 1
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CLASSSKLEARNMIXTURE BAYESIANGAUSSIANMIXTURE NCOMPONENTS1 COVARIANCETYPE'FULL'
TOL0001 REGCOVAR1E06 MAXITER100
NINIT1 INITPARAMS'KMEANS'
WEIGHTCONCENTRATIONPRIORTYPE'DIRICHLETPROCESS'
WEIGHTCONCENTRATIONPRIORNONE
MEANPRECISIONPRIORNONE
MEANPRIORNONE DE
GREESOFFREEDOMPRIORNONE COVARI
ANCEPRIORNONE RANDOMSTATENONE
WARMSTARTFALSE VERBOSE0 VER
BOSEINTERVAL10
VARIATIONAL BAYESIAN ESTIMATION OF A GAUSSIAN MIXTURE
THIS CLASS ALLOWS TO INFER AN APPROXIMATE POSTERIOR DISTRIBUTION OVER THE PARAMETERS OF A GAUSSIAN MIXTURE DISTRIBUTION THE EFFECTIVE NUMBER OF COMPONENTS CAN BE INFERRED FROM THE DATA
THIS CLASS IMPLEMENTS TWO TYPES OF PRIOR FOR THE WEIGHTS DISTRIBUTION A FINITE MIXTURE MODEL WITH DIRICHLET DISTRIBUTION AND AN INFINITE MIXTURE MODEL WITH THE DIRICHLET PROCESS IN PRACTICE DIRICHLET PROCESS INFERENCE ALGORITHM IS APPROXIMATED AND USES A TRUNCATED DISTRIBUTION WITH A FIXED MAXIMUM NUMBER OF COMPONENTS CALLED THE STICKBREAKING REPRESENTATION THE NUMBER OF COMPONENTS ACTUALLY USED ALMOST ALWAYS DEPENDS ON THE DATA
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READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT DEFAULTS TO 1 THE NUMBER OF MIXTURE COMPONENTS DEPENDING ON THE DATA AND THE VALUE OF THE WEIGHTCONCENTRATIONPRIOR THE MODEL CAN DECIDE TO NOT USE ALL THE COMPONENTS BY SETTING SOME COMPONENT WEIGHTS TO VALUES VERY CLOSE TO ZERO THE NUMBER OF EFFECTIVE COMPONENTS IS THEREFORE SMALLER THAN NCOMPONENTS
COVARIANCETYPE 'FULL' 'TIED' 'DIAG' 'SPHERICAL' DEFAULTS TO 'FULL' STRING DESCRIBING THE TYPE OF COVARIANCE PARAMETERS TO USE MUST BE ONE OF
FULL EACH COMPONENT HAS ITS OWN GENERAL COVARIANCE MATRIX
TIED ALL COMPONENTS SHARE THE SAME GENERAL COVARIANCE MATRIX
DIAG EACH COMPONENT HAS ITS OWN DIAGONAL COVARIANCE MATRIX
SPHERICAL EACH COMPONENT HAS ITS OWN SINGLE VARIANCE
TOLFLOAT DEFAULTS TO 1E3 THE CONVERGENCE THRESHOLD EM ITERATIONS WILL STOP WHEN THE LOWER BOUND AVERAGE GAIN ON THE LIKELIHOOD OF THE TRAINING DATA WITH RESPECT TO THE MODEL IS BELOW THIS THRESHOLD
REGCOVAR FLOAT DEFAULTS TO 1E6 NONNEGATIVE REGULARIZATION ADDED TO THE DIAGONAL OF CO VARIANCE ALLOWS TO ASSURE THAT THE COVARIANCE MATRICES ARE ALL POSITIVE
MAXITER INT DEFAULTS TO 100 THE NUMBER OF EM ITERATIONS TO PERFORM

NINIT INT DEFAULTS TO 1 THE NUMBER OF INITIALIZATIONS TO PERFORM THE RESULT WITH THE HIGHEST
LOWER BOUND VALUE ON THE LIKELIHOOD IS KEPT
INITPARAMS ‘KMEANS’ ‘RANDOM’ DEFAULTS TO ‘KMEANS’ THE METHOD USED TO INITIALIZE THE
WEIGHTS THE MEANS AND THE COVARIANCES MUST BE ONE OF
KMEANS RESPONSIBILITIES ARE INITIALIZED USING KMEANS
RANDOM RESPONSIBILITIES ARE INITIALIZED RANDOMLY
WEIGHTCONCENTRATIONPRIORTYPE STR DEFAULTS TO ‘DIRICHLETPROCESS’ STRING DESCRIBING THE
TYPE OF THE WEIGHT CONCENTRATION PRIOR MUST BE ONE OF
DIRICHLETPROCESS USING THE STICKBREAKING REPRESENTATION
DIRICHLETDISTRIBUTION CAN FAVOR MORE UNIFORM WEIGHTS
WEIGHTCONCENTRATIONPRIOR FLOAT NONE OPTIONAL THE DIRICHLET CONCENTRATION OF EACH COM
PONENT ON THE WEIGHT DISTRIBUTION DIRICHLET THIS IS COMMONLY CALLED GAMMA IN THE LITERA
TURE THE HIGHER CONCENTRATION PUTS MORE MASS IN THE CENTER AND WILL LEAD TO MORE COMPO
NENTS BEING ACTIVE WHILE A LOWER CONCENTRATION PARAMETER WILL LEAD TO MORE MASS AT THE EDGE
OF THE MIXTURE WEIGHTS SIMPLEX THE VALUE OF THE PARAMETER MUST BE GREATER THAN 0 IF IT IS
NONE IT’S SET TO 1 NCOMPONENTS
MEANPRECISIONPRIOR FLOAT NONE OPTIONAL THE PRECISION PRIOR ON THE MEAN DISTRIBUTION
GAUSSIAN CONTROLS THE EXTEND TO WHERE MEANS CAN BE PLACED LARGER VALUES CONCENTRATE
THE MEANS OF EACH CLUSTERS AROUND MEANPRIOR THE VALUE OF THE PARAMETER MUST BE
GREATER THAN 0 IF IT IS NONE IT’S SET TO 1
MEANPRIOR ARRAYLIKE SHAPE NFEATURES OPTIONAL THE PRIOR ON THE MEAN DISTRIBUTION
GAUSSIAN IF IT IS NONE IT’S SET TO THE MEAN OF X
DEGREESOFFREEDOMPRIOR FLOAT NONE OPTIONAL THE PRIOR OF THE NUMBER OF DEGREES OF
FREEDOM ON THE COVARIANCE DISTRIBUTIONS WISHART IF IT IS NONE IT’S SET TO NFEATURES
COVARIANCEPRIOR FLOAT OR ARRAYLIKE OPTIONAL THE PRIOR ON THE COVARIANCE DISTRIBUTION
WISHART IF IT IS NONE THE EMIPRICAL COVARIANCE PRIOR IS INITIALIZED USING THE COVARIANCE
OF X THE SHAPE DEPENDS ON COVARIANCETYPE
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NFEATURES NFEATURES IFTIED
NFEATURES IFDIAG
FLOAT IFSPHERICAL
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
WARMSTART BOOL DEFAULT TO FALSE IF ‘WARMSTART’ IS TRUE THE SOLUTION OF THE LAST FITTING IS
USED AS INITIALIZATION FOR THE NEXT CALL OF FIT THIS CAN SPEED UP CONVERGENCE WHEN FIT IS
CALLED SEVERAL TIMES ON SIMILAR PROBLEMS SEE THE GLOSSARY
VERBOSE INT DEFAULT TO 0 ENABLE VERBOSE OUTPUT IF 1 THEN IT PRINTS THE CURRENT INITIALIZATION
AND EACH ITERATION STEP IF GREATER THAN 1 THEN IT PRINTS ALSO THE LOG PROBABILITY AND THE TIME
NEEDED FOR EACH STEP
VERBOSEINTERVAL INT DEFAULT TO 10 NUMBER OF ITERATION DONE BEFORE THE NEXT PRINT
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PRECISIONS ARRAYLIKE THE PRECISION MATRICES FOR EACH COMPONENT IN THE MIXTURE A PRECI
SION MATRIX IS THE INVERSE OF A COVARIANCE MATRIX A COVARIANCE MATRIX IS SYMMETRIC POSI
TIVE DEFINITE SO THE MIXTURE OF GAUSSIAN CAN BE EQUIVALENTLY PARAMETERIZED BY THE PRECISION
MATRICES STORING THE PRECISION MATRICES INSTEAD OF THE COVARIANCE MATRICES MAKES IT MORE
EFFICIENT TO COMPUTE THE LOGLIKELIHOOD OF NEW SAMPLES AT TEST TIME THE SHAPE DEPENDS ON
COVARIANCETYPE
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PARAMETERIZED BY THE PRECISION MATRICES STORING THE PRECISION MATRICES INSTEAD OF THE CO
VARIANCE MATRICES MAKES IT MORE EFFICIENT TO COMPUTE THE LOGLIKELIHOOD OF NEW SAMPLES AT
TEST TIME THE SHAPE DEPENDS ON COVARIANCETYPE
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NFEATURES NFEATURES IFTIED
NCOMPONENTS NFEATURES IFDIAG
NCOMPONENTS NFEATURES NFEATURES IFFULL
CONVERGED BOOL TRUE WHEN CONVERGENCE WAS REACHED IN FIT FALSE OTHERWISE
NITER INT NUMBER OF STEP USED BY THE BEST FIT OF INFERENCE TO REACH THE CONVERGENCE
LOWERBOUND FLOAT LOWER BOUND VALUE ON THE LIKELIHOOD OF THE TRAINING DATA WITH RESPECT TO
THE MODEL OF THE BEST FIT OF INFERENCE
WEIGHTCONCENTRATIONPRIOR TUPLE OR FLOAT THE DIRICHLET CONCENTRATION OF EACH
COMPONENT ON THE WEIGHT DISTRIBUTION DIRICHLET THE TYPE DEPENDS ON
WEIGHTCONCENTRATIONPRIORTYPE
FLOAT FLOAT IFDIRICHLETPROCESS BETA PARAMETERS
FLOAT IFDIRICHLETDISTRIBUTION DIRICHLET PARAMETERS
THE HIGHER CONCENTRATION PUTS MORE MASS IN THE CENTER AND WILL LEAD TO MORE COMPONENTS
BEING ACTIVE WHILE A LOWER CONCENTRATION PARAMETER WILL LEAD TO MORE MASS AT THE EDGE OF
THE SIMPLEX
WEIGHTCONCENTRATION ARRAYLIKE SHAPE NCOMPONENTS THE DIRICHLET CONCENTRATION OF
EACH COMPONENT ON THE WEIGHT DISTRIBUTION DIRICHLET
MEANPRECISIONPRIOR FLOAT THE PRECISION PRIOR ON THE MEAN DISTRIBUTION GAUSSIAN CON
TROLS THE EXTEND TO WHERE MEANS CAN BE PLACED LARGER VALUES CONCENTRATE THE MEANS OF EACH
CLUSTERS AROUND MEANPRIOR

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VARIANCE DISTRIBUTIONS WISHART
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SCORE SELF X Y COMPUTE THE PERSAMPLE AVERAGE LOGLIKELIHOOD OF THE
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PLE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNCOMPONENTS1 COVARIANCETYPE’FULL’ TOL0001 REGCOVAR1E06 MAXITER100
NINIT1 INITPARAMS’KMEANS’ WEIGHTCONCENTRATIONPRIORTYPE’DIRICHLETPROCESS’
WEIGHTCONCENTRATIONPRIORNONE MEANPRECISIONPRIORNONE MEANPRIORNONE
DEGREESOFFREEDOMPRIORNONE COVARIANCEPRIORNONE RANDOMSTATENONE
WARMSTARTFALSE VERBOSE0 VERBOSEINTERVAL10
FITSELFXYNONE
ESTIMATE MODEL PARAMETERS WITH THE EM ALGORITHM

THE METHOD FITS THE MODEL NINIT TIMES AND SETS THE PARAMETERS WITH WHICH THE MODEL HAS THE
LARGEST LIKELIHOOD OR LOWER BOUND WITHIN EACH TRIAL THE METHOD ITERATES BETWEEN ESTEP AND MSTEP
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CONVERGENCEWARNING IS RAISED IF WARMSTART ISTRUE THENNINIT IS IGNORED AND A SINGLE
INITIALIZATION IS PERFORMED UPON THE FIRST CALL UPON CONSECUTIVE CALLS TRAINING STARTS WHERE IT LEFT OFF
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FITPREDICT SELFXYNONE
ESTIMATE MODEL PARAMETERS USING X AND PREDICT THE LABELS FOR X
THE METHOD FITS THE MODEL NINIT TIMES AND SETS THE PARAMETERS WITH WHICH THE MODEL HAS THE LARGEST LIKELI
HOOD OR LOWER BOUND WITHIN EACH TRIAL THE METHOD ITERATES BETWEEN ESTEP AND MSTEP FOR MAXITER TIMES
UNTIL THE CHANGE OF LIKELIHOOD OR LOWER BOUND IS LESS THAN TOL OTHERWISE A CONVERGENCEWARNING IS
RAISED AFTER FITTING IT PREDICTS THE MOST PROBABLE LABEL FOR THE INPUT DATA POINTS
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MEANSINITNONE PRECISIONSINITNONE RAN
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COVARIANCE PARAMETERS TO USE MUST BE ONE OF
‘FULL’ EACH COMPONENT HAS ITS OWN GENERAL COVARIANCE MATRIX
‘TIED’ ALL COMPONENTS SHARE THE SAME GENERAL COVARIANCE MATRIX
‘DIAG’ EACH COMPONENT HAS ITS OWN DIAGONAL COVARIANCE MATRIX
‘SPHERICAL’ EACH COMPONENT HAS ITS OWN SINGLE VARIANCE
TOLFLOAT DEFAULTS TO 1E3 THE CONVERGENCE THRESHOLD EM ITERATIONS WILL STOP WHEN THE LOWER
BOUND AVERAGE GAIN IS BELOW THIS THRESHOLD
REGCOVAR FLOAT DEFAULTS TO 1E6 NONNEGATIVE REGULARIZATION ADDED TO THE DIAGONAL OF CO
VARIANCE ALLOWS TO ASSURE THAT THE COVARIANCE MATRICES ARE ALL POSITIVE
MAXITER INT DEFAULTS TO 100 THE NUMBER OF EM ITERATIONS TO PERFORM
NINIT INT DEFAULTS TO 1 THE NUMBER OF INITIALIZATIONS TO PERFORM THE BEST RESULTS ARE KEPT
INITPARAMS ‘KMEANS’ ‘RANDOM’ DEFAULTS TO ‘KMEANS’ THE METHOD USED TO INITIALIZE THE
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KMEANS RESPONSIBILITIES ARE INITIALIZED USING KMEANS
RANDOM RESPONSIBILITIES ARE INITIALIZED RANDOMLY
WEIGHTSINIT ARRAYLIKE SHAPE NCOMPONENTS OPTIONAL THE USERPROVIDED INITIAL WEIGHTS
DEFAULTS TO NONE IF IT NONE WEIGHTS ARE INITIALIZED USING THE INITPARAMS METHOD
MEANSINIT ARRAYLIKE SHAPE NCOMPONENTS NFEATURES OPTIONAL THE USERPROVIDED INITIAL
MEANS DEFAULTS TO NONE IF IT NONE MEANS ARE INITIALIZED USING THE INITPARAMS METHOD
PRECISIONSINIT ARRAYLIKE OPTIONAL THE USERPROVIDED INITIAL PRECISIONS INVERSE OF THE CO
VARIANCE MATRICES DEFAULTS TO NONE IF IT NONE PRECISIONS ARE INITIALIZED USING THE
‘INITPARAMS’ METHOD THE SHAPE DEPENDS ON ‘COVARIANCETYPE’
NCOMPONENTS IFSPHERICAL
NFEATURES NFEATURES IFTIED
NCOMPONENTS NFEATURES IFDIAG
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RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
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RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
WARMSTART BOOL DEFAULT TO FALSE IF 'WARMSTART' IS TRUE THE SOLUTION OF THE LAST FITTING IS
USED AS INITIALIZATION FOR THE NEXT CALL OF FIT THIS CAN SPEED UP CONVERGENCE WHEN FIT IS
CALLED SEVERAL TIMES ON SIMILAR PROBLEMS IN THAT CASE 'NINIT' IS IGNORED AND ONLY A SINGLE
INITIALIZATION OCCURS UPON THE FIRST CALL SEE THE GLOSSARY
VERBOSE INT DEFAULT TO 0 ENABLE VERBOSE OUTPUT IF 1 THEN IT PRINTS THE CURRENT INITIALIZATION
AND EACH ITERATION STEP IF GREATER THAN 1 THEN IT PRINTS ALSO THE LOG PROBABILITY AND THE TIME
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VERBOSEINTERVAL INT DEFAULT TO 10 NUMBER OF ITERATION DONE BEFORE THE NEXT PRINT
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WEIGHTS ARRAYLIKE SHAPE NCOMPONENTS THE WEIGHTS OF EACH MIXTURE COMPONENTS
MEANS ARRAYLIKE SHAPE NCOMPONENTS NFEATURES THE MEAN OF EACH MIXTURE COMPONENT
COVARIANCES ARRAYLIKE THE COVARIANCE OF EACH MIXTURE COMPONENT THE SHAPE DEPENDS ON
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NCOMPONENTS IFSPHERICAL
NFEATURES NFEATURES IFTIED
NCOMPONENTS NFEATURES IFDIAG
NCOMPONENTS NFEATURES NFEATURES IFFULL
PRECISIONS ARRAYLIKE THE PRECISION MATRICES FOR EACH COMPONENT IN THE MIXTURE A PRECI
SION MATRIX IS THE INVERSE OF A COVARIANCE MATRIX A COVARIANCE MATRIX IS SYMMETRIC POSI
TIVE DEFINITE SO THE MIXTURE OF GAUSSIAN CAN BE EQUIVALENTLY PARAMETERIZED BY THE PRECISION
MATRICES STORING THE PRECISION MATRICES INSTEAD OF THE COVARIANCE MATRICES MAKES IT MORE
EFFICIENT TO COMPUTE THE LOGLIKELIHOOD OF NEW SAMPLES AT TEST TIME THE SHAPE DEPENDS ON
COVARIANCETYPE
NCOMPONENTS IFSPHERICAL
NFEATURES NFEATURES IFTIED
NCOMPONENTS NFEATURES IFDIAG
NCOMPONENTS NFEATURES NFEATURES IFFULL
PRECISIONSCHOLESKY ARRAYLIKE THE CHOLESKY DECOMPOSITION OF THE PRECISION MATRICES OF
EACH MIXTURE COMPONENT A PRECISION MATRIX IS THE INVERSE OF A COVARIANCE MATRIX A COVARI
ANCE MATRIX IS SYMMETRIC POSITIVE DEFINITE SO THE MIXTURE OF GAUSSIAN CAN BE EQUIVALENTLY
PARAMETERIZED BY THE PRECISION MATRICES STORING THE PRECISION MATRICES INSTEAD OF THE CO
VARIANCE MATRICES MAKES IT MORE EFFICIENT TO COMPUTE THE LOGLIKELIHOOD OF NEW SAMPLES AT
TEST TIME THE SHAPE DEPENDS ON COVARIANCETYPE
NCOMPONENTS IFSPHERICAL
NFEATURES NFEATURES IFTIED
NCOMPONENTS NFEATURES IFDIAG
NCOMPONENTS NFEATURES NFEATURES IFFULL
CONVERGED BOOL TRUE WHEN CONVERGENCE WAS REACHED IN FIT FALSE OTHERWISE
NITER INT NUMBER OF STEP USED BY THE BEST FIT OF EM TO REACH THE CONVERGENCE
LOWERBOUND FLOAT LOWER BOUND VALUE ON THE LOGLIKELIHOOD OF THE TRAINING DATA WITH RE
SPECT TO THE MODEL OF THE BEST FIT OF EM

SEE ALSO
BAYESIANGAUSSIANMIXTURE GAUSSIAN MIXTURE MODEL FIT WITH A VARIATIONAL INFERENCE
METHODS
AICSELF X AKAIKE INFORMATION CRITERION FOR THE CURRENT MODEL ON
THE INPUT X
BICSELF X BAYESIAN INFORMATION CRITERION FOR THE CURRENT MODEL ON
THE INPUT X
FITSELF X Y ESTIMATE MODEL PARAMETERS WITH THE EM ALGORITHM
FITPREDICT SELF X Y ESTIMATE MODEL PARAMETERS USING X AND PREDICT THE LA
BELS FOR X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT THE LABELS FOR THE DATA SAMPLES IN X USING TRAINED
MODEL
PREDICTPROBA SELF X PREDICT POSTERIOR PROBABILITY OF EACH COMPONENT GIVEN
THE DATA
SAMPLE SELF NSAMPLES GENERATE RANDOM SAMPLES FROM THE FITTED GAUSSIAN DIS
TRIBUTION
SCORE SELF X Y COMPUTE THE PERSAMPLE AVERAGE LOGLIKELIHOOD OF THE
GIVEN DATA X
SCORESAMPLES SELF X COMPUTE THE WEIGHTED LOG PROBABILITIES FOR EACH SAM
PLE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELF NCOMPONENTS1 COVARIANCETYPE’FULL’ TOL0001 REGCOVAR1E06
MAXITER100 NINIT1 INITPARAMS’KMEANS’ WEIGHTSINITNONE MEANSINITNONE
PRECISIONSINITNONE RANDOMSTATENONE WARMSTARTFALSE VERBOSE0 VER
BOSEINTERVAL10
AICSELFX
AKAIKE INFORMATION CRITERION FOR THE CURRENT MODEL ON THE INPUT X
PARAMETERS
XARRAY OF SHAPE NSAMPLES NDIMENSIONS
RETURNS
AICFLOAT THE LOWER THE BETTER
BICSELFX
BAYESIAN INFORMATION CRITERION FOR THE CURRENT MODEL ON THE INPUT X
PARAMETERS
XARRAY OF SHAPE NSAMPLES NDIMENSIONS
RETURNS
BICFLOAT THE LOWER THE BETTER
FITSELFXYNONE
ESTIMATE MODEL PARAMETERS WITH THE EM ALGORITHM
THE METHOD FITS THE MODEL NINIT TIMES AND SETS THE PARAMETERS WITH WHICH THE MODEL HAS THE
LARGEST LIKELIHOOD OR LOWER BOUND WITHIN EACH TRIAL THE METHOD ITERATES BETWEEN ESTEP AND MSTEP

FORMAXITER TIMES UNTIL THE CHANGE OF LIKELIHOOD OR LOWER BOUND IS LESS THAN TOL OTHERWISE A
CONVERGENCEWARNING IS RAISED IF WARMSTART ISTRUE THENNINIT IS IGNORED AND A SINGLE
INITIALIZATION IS PERFORMED UPON THE FIRST CALL UPON CONSECUTIVE CALLS TRAINING STARTS WHERE IT LEFT OFF
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES LIST OF NFEATURESDIMENSIONAL DATA POINTS
EACH ROW CORRESPONDS TO A SINGLE DATA POINT
RETURNS
SELF
FITPREDICT SELFXYNONE
ESTIMATE MODEL PARAMETERS USING X AND PREDICT THE LABELS FOR X
THE METHOD FITS THE MODEL NINIT TIMES AND SETS THE PARAMETERS WITH WHICH THE MODEL HAS THE LARGEST LIKELI
HOOD OR LOWER BOUND WITHIN EACH TRIAL THE METHOD ITERATES BETWEEN ESTEP AND MSTEP FOR MAXITER TIMES
UNTIL THE CHANGE OF LIKELIHOOD OR LOWER BOUND IS LESS THAN TOL OTHERWISE A CONVERGENCEWARNING IS
RAISED AFTER FITTING IT PREDICTS THE MOST PROBABLE LABEL FOR THE INPUT DATA POINTS
NEW IN VERSION 020
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES LIST OF NFEATURESDIMENSIONAL DATA POINTS
EACH ROW CORRESPONDS TO A SINGLE DATA POINT
RETURNS
LABELS ARRAY SHAPE NSAMPLES COMPONENT LABELS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT THE LABELS FOR THE DATA SAMPLES IN X USING TRAINED MODEL
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES LIST OF NFEATURESDIMENSIONAL DATA POINTS
EACH ROW CORRESPONDS TO A SINGLE DATA POINT
RETURNS
LABELS ARRAY SHAPE NSAMPLES COMPONENT LABELS
PREDICTPROBA SELFX
PREDICT POSTERIOR PROBABILITY OF EACH COMPONENT GIVEN THE DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES LIST OF NFEATURESDIMENSIONAL DATA POINTS
EACH ROW CORRESPONDS TO A SINGLE DATA POINT
RETURNS

RESP ARRAY SHAPE NSAMPLES NCOMPONENTS RETURNS THE PROBABILITY EACH GAUSSIAN
STATE IN THE MODEL GIVEN EACH SAMPLE
SAMPLESELFNSAMPLES1
GENERATE RANDOM SAMPLES FROM THE FITTED GAUSSIAN DISTRIBUTION
PARAMETERS
NSAMPLES INT OPTIONAL NUMBER OF SAMPLES TO GENERATE DEFAULTS TO 1
RETURNS
XARRAY SHAPE NSAMPLES NFEATURES RANDOMLY GENERATED SAMPLE
YARRAY SHAPE NSAMPLES COMPONENT LABELS
SCORESELFXYNONE
COMPUTE THE PERSAMPLE AVERAGE LOGLIKELIHOOD OF THE GIVEN DATA X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NDIMENSIONS LIST OF NFEATURESDIMENSIONAL DATA POINTS
EACH ROW CORRESPONDS TO A SINGLE DATA POINT
RETURNS
LOGLIKELIHOOD FLOAT LOG LIKELIHOOD OF THE GAUSSIAN MIXTURE GIVEN X
SCORESAMPLES SELFX
COMPUTE THE WEIGHTED LOG PROBABILITIES FOR EACH SAMPLE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES LIST OF NFEATURESDIMENSIONAL DATA POINTS
EACH ROW CORRESPONDS TO A SINGLE DATA POINT
RETURNS
LOGPROB ARRAY SHAPE NSAMPLES LOG PROBABILITIES OF EACH DATA POINT IN X
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNMIXTUREGAUSSIANMIXTURE
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
•DENSITY ESTIMATION FOR A GAUSSIAN MIXTURE
•GAUSSIAN MIXTURE MODEL ELLIPSOIDS
•GAUSSIAN MIXTURE MODEL SELECTION
•GMM COVARIANCES
•GAUSSIAN MIXTURE MODEL SINE CURVE

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USER GUIDE SEE THE CROSSVALIDATION EVALUATING ESTIMATOR PERFORMANCE TUNING THE HYPERPARAMETERS OF AN ESTIMA
TORANDLEARNING CURVE SECTIONS FOR FURTHER DETAILS
6261 SPLITTER CLASSES
MODELSELECTIONGROUPKFOLD NSPLITS KFOLD ITERATOR VARIANT WITH NONOVERLAPPING GROUPS
MODELSELECTIONGROUPSHUFFLESPLIT SHUFFLEGROUPSOUT CROSSVALIDATION ITERATOR
MODELSELECTIONKFOLD NSPLITS SHUFFLE KFOLDS CROSSVALIDATOR
MODELSELECTIONLEAVEONEGROUPOUT LEAVE ONE GROUP OUT CROSSVALIDATOR
MODELSELECTIONLEAVEPGROUPSOUT NGROUPS LEAVE P GROUPS OUT CROSSVALIDATOR
MODELSELECTIONLEAVEONEOUT LEAVEONEOUT CROSSVALIDATOR
MODELSELECTIONLEAVEPOUT P LEAVEPOUT CROSSVALIDATOR
MODELSELECTIONPREDEFINEDSPLIT TESTFOLD PREDEFINED SPLIT CROSSVALIDATOR
MODELSELECTIONREPEATEDKFOLD NSPLITS
  REPEATED KFOLD CROSS VALIDATOR
MODELSELECTIONREPEATEDSTRATIFIEDKFOLD REPEATED STRATIFIED KFOLD CROSS VALIDATOR
MODELSELECTIONSHUFFLESPLIT NSPLITS RANDOM PERMUTATION CROSSVALIDATOR
MODELSELECTIONSTRATIFIEDKFOLD NSPLITS
  STRATIFIED KFOLDS CROSSVALIDATOR
MODELSELECTIONSTRATIFIEDSHUFFLESPLIT STRATIFIED SHUFFLESPLIT CROSSVALIDATOR
MODELSELECTIONTIMESERIESSPLIT NSPLITS
  TIME SERIES CROSSVALIDATOR
SKLEARNMODELSELECTION GROUPKFOLD
CLASSSKLEARNMODELSELECTION GROUPKFOLD NSPLITS’WARN’
KFOLD ITERATOR VARIANT WITH NONOVERLAPPING GROUPS
THE SAME GROUP WILL NOT APPEAR IN TWO DIFFERENT FOLDS THE NUMBER OF DISTINCT GROUPS HAS TO BE AT LEAST EQUAL TO
THE NUMBER OF FOLDS
THE FOLDS ARE APPROXIMATELY BALANCED IN THE SENSE THAT THE NUMBER OF DISTINCT GROUPS IS APPROXIMATELY THE SAME
IN EACH FOLD
PARAMETERS
NSPLITS INT DEFAULT3 NUMBER OF FOLDS MUST BE AT LEAST 2
CHANGED IN VERSION 020 NSPLITS DEFAULT VALUE WILL CHANGE FROM 3 TO 5 IN V022
SEE ALSO
LEAVEONEGROUPOUT FOR SPLITTING THE DATA ACCORDING TO EXPLICIT DOMAINSPECIFIC STRATIFICATION OF THE DATASET
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT GROUPKFOLD
X  NPARRAY1 2 3 4 5 6 7 8
Y  NPARRAY1 2 3 4
GROUPS  NPARRAY0 0 2 2
```

GROUPKFOLD GROUPKFOLDNSPLITS2
GROUPKFOLDGETNSPLITSX Y GROUPS
2
PRINTGROUPKFOLD
GROUPKFOLDNSPLITS2
 FOR TRAININDEX TESTINDEX INGROUPKFOLDSPLITX Y GROUPS
 PRINTTRAIN TRAININDEX TEST TESTINDEX
 XTRAIN XTEST XTRAININDEX XTESTINDEX
 YTRAIN YTEST YTRAININDEX YTESTINDEX
 PRINTXTRAIN XTEST YTRAIN YTEST

TRAIN 0 1 TEST 2 3
1 2
3 4 5 6
7 8 1 2 3 4
TRAIN 2 3 TEST 0 1
5 6
7 8 1 2
3 4 3 4 1 2
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFNSPLITS'WARN'
GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYNONE GROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES OPTIONAL THE TARGET VARIABLE FOR SUPERVISED LEARNING PROB
LEMS
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES GROUP LABELS FOR THE SAMPLES USED WHILE SPLIT
TING THE DATASET INTO TRAINTEST SET
YIELDS

TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
EXAMPLES USING SKLEARNMODELSELECTIONGROUPKFOLD
•VISUALIZING CROSSVALIDATION BEHAVIOR IN SCIKITLEARN
SKLEARNMODELSELECTION GROUPSHUFFLESPLIT
CLASSSKLEARNMODELSELECTION GROUPSHUFFLESPLIT NSPLITS5 TESTSIZENONE
TRAINSIZENONE RANDOMSTATENONE
SHUFFLEGROUPSOUT CROSSVALIDATION ITERATOR
PROVIDES RANDOMIZED TRAINTEST INDICES TO SPLIT DATA ACCORDING TO A THIRDPARTY PROVIDED GROUP THIS GROUP INFOR
MATION CAN BE USED TO ENCODE ARBITRARY DOMAIN SPECIFIC STRATIFICATIONS OF THE SAMPLES AS INTEGERS
FOR INSTANCE THE GROUPS COULD BE THE YEAR OF COLLECTION OF THE SAMPLES AND THUS ALLOW FOR CROSSVALIDATION AGAINST
TIMEBASED SPLITS
THE DIFFERENCE BETWEEN LEAVEPGROUPSOUT AND GROUPSHUFFLESPLIT IS THAT THE FORMER GENERATES SPLITS USING ALL
SUBSETS OF SIZE PUNIQUE GROUPS WHEREAS GROUPSHUFFLESPLIT GENERATES A USERDETERMINED NUMBER OF RANDOM TEST
SPLITS EACH WITH A USERDETERMINED FRACTION OF UNIQUE GROUPS
FOR EXAMPLE A LESS COMPUTATIONALLY INTENSIVE ALTERNATIVE TO LEAVEPGROUPSOUTP10 WOULD BE
GROUPSHUFFLESPLITTESTSIZE10 NSPLITS100
NOTE THE PARAMETERS TESTSIZE ANDTRAINSIZE REFER TO GROUPS AND NOT TO SAMPLES AS IN SHUFFLESPLIT
PARAMETERS
NSPLITS INT DEFAULT 5 NUMBER OF RESHUFFLING SPLITTING ITERATIONS
TESTSIZE FLOAT INT NONE OPTIONAL DEFAULTNONE IF FLOAT SHOULD BE BETWEEN 00 AND 10
AND REPRESENT THE PROPORTION OF THE DATASET TO INCLUDE IN THE TEST SPLIT IF INT REPRESENTS THE
ABSOLUTE NUMBER OF TEST GROUPS IF NONE THE VALUE IS SET TO THE COMPLEMENT OF THE TRAIN SIZE
IFTRAINSIZE IS ALSO NONE IT WILL BE SET TO 02
TRAINSIZE FLOAT INT OR NONE DEFAULT IS NONE IF FLOAT SHOULD BE BETWEEN 00 AND 10 AND
REPRESENT THE PROPORTION OF THE GROUPS TO INCLUDE IN THE TRAIN SPLIT IF INT REPRESENTS THE
ABSOLUTE NUMBER OF TRAIN GROUPS IF NONE THE VALUE IS AUTOMATICALLY SET TO THE COMPLEMENT
OF THE TEST SIZE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFNSPLITS5 TESTSIZENONE TRAINSIZENONE RANDOMSTATENONE

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GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYNONE GROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES OPTIONAL THE TARGET VARIABLE FOR SUPERVISED LEARNING PROB
LEMS
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES GROUP LABELS FOR THE SAMPLES USED WHILE SPLIT
TING THE DATASET INTO TRAINTEST SET
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
NOTES
RANDOMIZED CV SPLITTERS MAY RETURN DIFFERENT RESULTS FOR EACH CALL OF SPLIT YOU CAN MAKE THE RESULTS
IDENTICAL BY SETTING RANDOMSTATE TO AN INTEGER
EXAMPLES USING SKLEARNMODELSELECTIONGROUPSHUFFLESPLIT
•VISUALIZING CROSSVALIDATION BEHAVIOR IN SCIKITLEARN
SKLEARNMODELSELECTION KFOLD
CLASSSKLEARNMODELSELECTION KFOLDNSPLITS'WARN' SHUFFLEFALSE RANDOMSTATENONE
KFOLDS CROSSVALIDATOR
PROVIDES TRAINTEST INDICES TO SPLIT DATA IN TRAINTEST SETS SPLIT DATASET INTO K CONSECUTIVE FOLDS WITHOUT SHUFFLING
BY DEFAULT
EACH FOLD IS THEN USED ONCE AS A VALIDATION WHILE THE K 1 REMAINING FOLDS FORM THE TRAINING SET
READ MORE IN THE USER GUIDE
PARAMETERS
NSPLITS INT DEFAULT3 NUMBER OF FOLDS MUST BE AT LEAST 2
CHANGED IN VERSION 020 NSPLITS DEFAULT VALUE WILL CHANGE FROM 3 TO 5 IN V022
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SHUFFLE BOOLEAN OPTIONAL WHETHER TO SHUFFLE THE DATA BEFORE SPLITTING INTO BATCHES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SHUFFLE TRUE
SEE ALSO
STRATIFIEDKFOLD TAKES GROUP INFORMATION INTO ACCOUNT TO AVOID BUILDING FOLDS WITH IMBALANCED CLASS
DISTRIBUTIONS FOR BINARY OR MULTICLASS CLASSIFICATION TASKS
GROUPKFOLD KFOLD ITERATOR VARIANT WITH NONOVERLAPPING GROUPS
REPEATEDKFOLD REPEATS KFOLD N TIMES
NOTES
THE FIRSTNSAMPLES NSPLITS FOLDS HAVE SIZE NSAMPLES NSPLITS 1 OTHER FOLDS HAVE
SIZENSAMPLES NSPLITS WHERENSAMPLES IS THE NUMBER OF SAMPLES
RANDOMIZED CV SPLITTERS MAY RETURN DIFFERENT RESULTS FOR EACH CALL OF SPLIT YOU CAN MAKE THE RESULTS IDENTICAL
BY SETTINGRANDOMSTATE TO AN INTEGER
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT KFOLD
X  NPARRAY1 2 3 4 1 2 3 4
Y  NPARRAY1 2 3 4
KF  KFOLDNSPLITS2
KFGETNSPLITSX
2
PRINTKF
KFOLDNSPLITS2 RANDOMSTATENONE SHUFFLEFALSE
 FOR TRAININDEX TESTINDEX INKFSPLITX
PRINTTRAIN TRAININDEX TEST TESTINDEX
XTRAIN XTEST  XTRAININDEX XTESTINDEX
YTRAIN YTEST  YTRAININDEX YTESTINDEX
TRAIN 2 3 TEST 0 1
TRAIN 0 1 TEST 2 3
```
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFNSPLITS’WARN’ SHUFFLEFALSE RANDOMSTATENONE
GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS

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XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYNONE GROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VARIABLE FOR SUPERVISED LEARNING PROBLEMS
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED
WHILE SPLITTING THE DATASET INTO TRAINTEST SET
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
EXAMPLES USING SKLEARNMODELSELECTIONKFOLD
•FEATURE AGGLOMERATION VS UNIVARIATE SELECTION
•GRADIENT BOOSTING OUTOFBAG ESTIMATES
•CROSSVALIDATION ON DIABETES DATASET EXERCISE
•NESTED VERSUS NONNESTED CROSSVALIDATION
•VISUALIZING CROSSVALIDATION BEHAVIOR IN SCIKITLEARN
SKLEARNMODELSELECTION LEAVEONEGROUPOUT
CLASSSKLEARNMODELSELECTION LEAVEONEGROUPOUT
LEAVE ONE GROUP OUT CROSSVALIDATOR
PROVIDES TRAINTEST INDICES TO SPLIT DATA ACCORDING TO A THIRDPARTY PROVIDED GROUP THIS GROUP INFORMATION CAN BE
USED TO ENCODE ARBITRARY DOMAIN SPECIFIC STRATIFICATIONS OF THE SAMPLES AS INTEGERS
FOR INSTANCE THE GROUPS COULD BE THE YEAR OF COLLECTION OF THE SAMPLES AND THUS ALLOW FOR CROSSVALIDATION AGAINST
TIMEBASED SPLITS
READ MORE IN THE USER GUIDE
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT LEAVEONEGROUPOUT
X  NPARRAY1 2 3 4 5 6 7 8
Y  NPARRAY1 2 1 2
GROUPS  NPARRAY1 1 2 2
```

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LOGO LEAVEONEGROUPOUT
LOGOGETNSPLITSX Y GROUPS
2
LOGOGETNSPLITSGROUPSGROUPS GROUPS IS ALWAYS REQUIRED
2
PRINTLOGO
LEAVEONEGROUPOUT
 FOR TRAININDEX TESTINDEX INLOGOSPLITX Y GROUPS
PRINTTRAIN TRAININDEX TEST TESTINDEX
XTRAIN XTEST XTRAININDEX XTESTINDEX
YTRAIN YTEST YTRAININDEX YTESTINDEX
PRINTXTRAIN XTEST YTRAIN YTEST
TRAIN 2 3 TEST 0 1
5 6
7 8 1 2
3 4 1 2 1 2
TRAIN 0 1 TEST 2 3
1 2
3 4 5 6
7 8 1 2 1 2
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES GROUP LABELS FOR THE SAMPLES USED WHILE SPLIT
TING THE DATASET INTO TRAINTEST SET THIS ‘GROUPS’ PARAMETER MUST ALWAYS BE SPECIFIED TO
CALCULATE THE NUMBER OF SPLITS THOUGH THE OTHER PARAMETERS CAN BE OMITTED
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYNONE GROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE OF LENGTH NSAMPLES OPTIONAL THE TARGET VARIABLE FOR SUPERVISED LEARNING
PROBLEMS

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GROUPS ARRAYLIKE WITH SHAPE NSAMPLES GROUP LABELS FOR THE SAMPLES USED WHILE SPLIT
TING THE DATASET INTO TRAINTEST SET
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
SKLEARNMODELSELECTION LEAVEPGROUPSOUT
CLASSSKLEARNMODELSELECTION LEAVEPGROUPSOUT NGROUPS
LEAVE P GROUPS OUT CROSSVALIDATOR
PROVIDES TRAINTEST INDICES TO SPLIT DATA ACCORDING TO A THIRDPARTY PROVIDED GROUP THIS GROUP INFORMATION CAN BE
USED TO ENCODE ARBITRARY DOMAIN SPECIFIC STRATIFICATIONS OF THE SAMPLES AS INTEGERS
FOR INSTANCE THE GROUPS COULD BE THE YEAR OF COLLECTION OF THE SAMPLES AND THUS ALLOW FOR CROSSVALIDATION AGAINST
TIMEBASED SPLITS
THE DIFFERENCE BETWEEN LEAVEPGROUPSOUT AND LEAVEONEGROUPOUT IS THAT THE FORMER BUILDS THE TEST SETS WITH
ALL THE SAMPLES ASSIGNED TO PDIFFERENT VALUES OF THE GROUPS WHILE THE LATTER USES SAMPLES ALL ASSIGNED THE SAME
GROUPS
READ MORE IN THE USER GUIDE
PARAMETERS
NGROUPS INT NUMBER OF GROUPS P TO LEAVE OUT IN THE TEST SPLIT
SEE ALSO
GROUPKFOLD KFOLD ITERATOR VARIANT WITH NONOVERLAPPING GROUPS
EXAMPLES
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT LEAVEPGROUPSOUT
X NPARRAY1 2 3 4 5 6
Y NPARRAY1 2 1
GROUPS NPARRAY1 2 3
LPGO LEAVEPGROUPSOUTNGROUPS2
LPGOGETNSPLITSX Y GROUPS
3
LPGOGETNSPLITSGROUPSGROUPS GROUPS IS ALWAYS REQUIRED
3
PRINTLPGO
LEAVEPGROUPSOUTNGROUPS2
 FOR TRAININDEX TESTINDEX INLPGOSPLITX Y GROUPS
PRINTTRAIN TRAININDEX TEST TESTINDEX
XTRAIN XTEST XTRAININDEX XTESTINDEX
YTRAIN YTEST YTRAININDEX YTESTINDEX
PRINTXTRAIN XTEST YTRAIN YTEST
TRAIN 2 TEST 0 1
5 6 1 2
3 4 1 1 2
TRAIN 1 TEST 0 2
3 4 1 2
5 6 2 1 1
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TRAIN 0 TEST 1 2
1 2 3 4
5 6 1 2 1
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFNGROUPS
GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES GROUP LABELS FOR THE SAMPLES USED WHILE SPLIT
TING THE DATASET INTO TRAINTEST SET THIS ‘GROUPS’ PARAMETER MUST ALWAYS BE SPECIFIED TO
CALCULATE THE NUMBER OF SPLITS THOUGH THE OTHER PARAMETERS CAN BE OMITTED
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYNONE GROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE OF LENGTH NSAMPLES OPTIONAL THE TARGET VARIABLE FOR SUPERVISED LEARNING
PROBLEMS
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES GROUP LABELS FOR THE SAMPLES USED WHILE SPLIT
TING THE DATASET INTO TRAINTEST SET
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
SKLEARNMODELSELECTION LEAVEONEOUT
CLASSSKLEARNMODELSELECTION LEAVEONEOUT
LEAVEONEOUT CROSSVALIDATOR
PROVIDES TRAINTEST INDICES TO SPLIT DATA IN TRAINTEST SETS EACH SAMPLE IS USED ONCE AS A TEST SET SINGLETON WHILE
THE REMAINING SAMPLES FORM THE TRAINING SET
NOTELEAVEONEOUT IS EQUIVALENT TO KFOLDNSPLITSN ANDLEAVEPOUTP1 WHERENIS THE
NUMBER OF SAMPLES

DUE TO THE HIGH NUMBER OF TEST SETS WHICH IS THE SAME AS THE NUMBER OF SAMPLES THIS CROSSVALIDATION METHOD
CAN BE VERY COSTLY FOR LARGE DATASETS ONE SHOULD FAVOR KFOLD SHUFFLESPLIT ORSTRATIFIEDKFOLD
READ MORE IN THE USER GUIDE
SEE ALSO
LEAVEONEGROUPOUT FOR SPLITTING THE DATA ACCORDING TO EXPLICIT DOMAINSPECIFIC STRATIFICATION OF THE DATASET
GROUPKFOLD KFOLD ITERATOR VARIANT WITH NONOVERLAPPING GROUPS
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT LEAVEONEOUT
X  NPARRAY1 2 3 4
Y  NPARRAY1 2
LOO  LEAVEONEOUT
LOOGETNSPLITSX
2
PRINTLOO
LEAVEONEOUT
 FOR TRAININDEX TESTINDEX INLOOSPLITX
PRINTTRAIN TRAININDEX TEST TESTINDEX
XTRAIN XTEST  XTRAININDEX XTESTINDEX
YTRAIN YTEST  YTRAININDEX YTESTINDEX
PRINTXTRAIN XTEST YTRAIN YTEST
TRAIN 1 TEST 0
3 4 1 2 2 1
TRAIN 0 TEST 1
1 2 3 4 1 2
```
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
GETNSPLITS SELFXYNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR

SPLITSELFXYNONE GROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE OF LENGTH NSAMPLES THE TARGET VARIABLE FOR SUPERVISED LEARNING PROBLEMS
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED
WHILE SPLITTING THE DATASET INTO TRAINTEST SET
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
SKLEARNMODELSELECTION LEAVEPOUT
CLASSSKLEARNMODELSELECTION LEAVEPOUT P
LEAVEPOUT CROSSVALIDATOR
PROVIDES TRAINTEST INDICES TO SPLIT DATA IN TRAINTEST SETS THIS RESULTS IN TESTING ON ALL DISTINCT SAMPLES OF SIZE P
WHILE THE REMAINING N P SAMPLES FORM THE TRAINING SET IN EACH ITERATION
NOTELEAVEPOUTP IS NOT EQUIVALENT TO KFOLDNSPLITSNSAMPLES P WHICH CREATES NON
OVERLAPPING TEST SETS
DUE TO THE HIGH NUMBER OF ITERATIONS WHICH GROWS COMBINATORICALLY WITH THE NUMBER OF SAMPLES THIS CROSS
VALIDATION METHOD CAN BE VERY COSTLY FOR LARGE DATASETS ONE SHOULD FAVOR KFOLD STRATIFIEDKFOLD OR
SHUFFLESPLIT
READ MORE IN THE USER GUIDE
PARAMETERS
PINT SIZE OF THE TEST SETS MUST BE STRICTLY GREATER THAN THE NUMBER OF SAMPLES
EXAMPLES
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT LEAVEPOUT
X NPARRAY1 2 3 4 5 6 7 8
Y NPARRAY1 2 3 4
LPO LEAVEPOUT2
LPOGETNSPLITSX
6
PRINTLPO
LEAVEPOUTP2
 FOR TRAININDEX TESTINDEX INLPOSPLITX
PRINTTRAIN TRAININDEX TEST TESTINDEX
XTRAIN XTEST XTRAININDEX XTESTINDEX
YTRAIN YTEST YTRAININDEX YTESTINDEX
TRAIN 2 3 TEST 0 1
TRAIN 1 3 TEST 0 2
TRAIN 1 2 TEST 0 3
TRAIN 0 3 TEST 1 2

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TRAIN 0 2 TEST 1 3
TRAIN 0 1 TEST 2 3
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFP
GETNSPLITS SELFXYNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
SPLITSELFXYNONE GROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE OF LENGTH NSAMPLES THE TARGET VARIABLE FOR SUPERVISED LEARNING PROBLEMS
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED
WHILE SPLITTING THE DATASET INTO TRAINTEST SET
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
SKLEARNMODELSELECTION PREDEFINEDSPLIT
CLASSSKLEARNMODELSELECTION PREDEFINEDSPLIT TESTFOLD
PREDEFINED SPLIT CROSSVALIDATOR
PROVIDES TRAINTEST INDICES TO SPLIT DATA INTO TRAINTEST SETS USING A PREDEFINED SCHEME SPECIFIED BY THE USER WITH
THETESTFOLD PARAMETER
READ MORE IN THE USER GUIDE
PARAMETERS
TESTFOLD ARRAYLIKE SHAPE NSAMPLES THE ENTRY TESTFOLDI REPRESENTS THE INDEX OF
THE TEST SET THAT SAMPLE IBELONGS TO IT IS POSSIBLE TO EXCLUDE SAMPLE IFROM ANY TEST SET IE
INCLUDE SAMPLE IIN EVERY TRAINING SET BY SETTING TESTFOLDI EQUAL TO 1
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EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT PREDEFINEDSPLIT
X  NPARRAY1 2 3 4 1 2 3 4
Y  NPARRAY0 0 1 1
TESTFOLD  0 1 1 1
PS  PREDEFINEDSPLITTESTFOLD
PSGETNSPLITS
2
PRINTPS
PREDEFINEDSPLITTESTFOLDARRAY 0 1 1 1
 FOR TRAININDEX TESTINDEX INPSSPLIT
PRINTTRAIN TRAININDEX TEST TESTINDEX
XTRAIN XTEST  XTRAININDEX XTESTINDEX
YTRAIN YTEST  YTRAININDEX YTESTINDEX
TRAIN 1 2 3 TEST 0
TRAIN 0 2 TEST 1 3
```
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFTESTFOLD
GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXNONE YNONE GROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT

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SKLEARNMODELSELECTION REPEATEDKFOLD
CLASSSKLEARNMODELSELECTION REPEATEDKFOLD NSPLITS5 NREPEATS10 RAN
DOMSTATENONE
REPEATED KFOLD CROSS VALIDATOR
REPEATS KFOLD N TIMES WITH DIFFERENT RANDOMIZATION IN EACH REPETITION
READ MORE IN THE USER GUIDE
PARAMETERS
NSPLITS INT DEFAULT5 NUMBER OF FOLDS MUST BE AT LEAST 2
NREPEATS INT DEFAULT10 NUMBER OF TIMES CROSSVALIDATOR NEEDS TO BE REPEATED
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
SEE ALSO
REPEATEDSTRATIFIEDKFOLD REPEATS STRATIFIED KFOLD N TIMES
NOTES
RANDOMIZED CV SPLITTERS MAY RETURN DIFFERENT RESULTS FOR EACH CALL OF SPLIT YOU CAN MAKE THE RESULTS IDENTICAL
BY SETTINGRANDOMSTATE TO AN INTEGER
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT REPEATEDKFOLD
X  NPARRAY1 2 3 4 1 2 3 4
Y  NPARRAY0 0 1 1
RKF  REPEATEDKFOLDNSPLITS2 NREPEATS2 RANDOMSTATE2652124
 FOR TRAININDEX TESTINDEX INRKFSPLITX
 PRINTTRAIN TRAININDEX TEST TESTINDEX
 XTRAIN XTEST  XTRAININDEX XTESTINDEX
 YTRAIN YTEST  YTRAININDEX YTESTINDEX

TRAIN 0 1 TEST 2 3
TRAIN 2 3 TEST 0 1
TRAIN 1 2 TEST 0 3
TRAIN 0 3 TEST 1 2
```
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATES INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFNSPLITS5 NREPEATS10 RANDOMSTATENONE

GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY NPZEROSNSAMPLES MAY BE
USED AS A PLACEHOLDER
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY NPZEROSNSAMPLES MAY BE
USED AS A PLACEHOLDER
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED
WHILE SPLITTING THE DATASET INTO TRAINTEST SET
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYNONE GROUPSNONE
GENERATES INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE OF LENGTH NSAMPLES THE TARGET VARIABLE FOR SUPERVISED LEARNING PROBLEMS
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED
WHILE SPLITTING THE DATASET INTO TRAINTEST SET
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
SKLEARNMODELSELECTION REPEATEDSTRATIFIEDKFOLD
CLASSSKLEARNMODELSELECTION REPEATEDSTRATIFIEDKFOLD NSPLITS5 NREPEATS10 RAN
DOMSTATENONE
REPEATED STRATIFIED KFOLD CROSS VALIDATOR
REPEATS STRATIFIED KFOLD N TIMES WITH DIFFERENT RANDOMIZATION IN EACH REPETITION
READ MORE IN THE USER GUIDE
PARAMETERS
NSPLITS INT DEFAULT5 NUMBER OF FOLDS MUST BE AT LEAST 2
NREPEATS INT DEFAULT10 NUMBER OF TIMES CROSSVALIDATOR NEEDS TO BE REPEATED
RANDOMSTATE NONE INT OR RANDOMSTATE DEFAULTNONE RANDOM STATE TO BE USED TO GENERATE
RANDOM STATE FOR EACH REPETITION
SEE ALSO
REPEATEDKFOLD REPEATS KFOLD N TIMES

NOTES
RANDOMIZED CV SPLITTERS MAY RETURN DIFFERENT RESULTS FOR EACH CALL OF SPLIT YOU CAN MAKE THE RESULTS IDENTICAL BY SETTINGRANDOMSTATE TO AN INTEGER
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT REPEATEDSTRATIFIEDKFOLD
X  NPARRAY1 2 3 4 1 2 3 4
Y  NPARRAY0 0 1 1
RSKF  REPEATEDSTRATIFIEDKFOLDNSPLITS2 NREPEATS2
 RANDOMSTATE36851234
 FOR TRAININDEX TESTINDEX INRSKFSPLITX Y
 PRINTTRAIN TRAININDEX TEST TESTINDEX
 XTRAIN XTEST  XTRAININDEX XTESTINDEX
 YTRAIN YTEST  YTRAININDEX YTESTINDEX

TRAIN 1 2 TEST 0 3
TRAIN 0 3 TEST 1 2
TRAIN 1 3 TEST 0 2
TRAIN 0 2 TEST 1 3
```
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS VALIDATOR
SPLIT SELF X Y GROUPS GENERATES INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFNSPLITS5 NREPEATS10 RANDOMSTATENONE
GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY NPZEROSNSAMPLES MAY BE USED AS A PLACEHOLDER
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY NPZEROSNSAMPLES MAY BE USED AS A PLACEHOLDER
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED WHILE SPLITTING THE DATASET INTO TRAINTEST SET
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYNONE GROUPSNONE
GENERATES INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES

YARRAYLIKE OF LENGTH NSAMPLES THE TARGET VARIABLE FOR SUPERVISED LEARNING PROBLEMS
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED
WHILE SPLITTING THE DATASET INTO TRAINTEST SET
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
SKLEARNMODELSELECTION SHUFFLESPLIT
CLASSSKLEARNMODELSELECTION SHUFFLESPLIT NSPLITS10 TESTSIZENONE TRAINSIZENONE
RANDOMSTATENONE
RANDOM PERMUTATION CROSSVALIDATOR
YIELDS INDICES TO SPLIT DATA INTO TRAINING AND TEST SETS
NOTE CONTRARY TO OTHER CROSSVALIDATION STRATEGIES RANDOM SPLITS DO NOT GUARANTEE THAT ALL FOLDS WILL BE DIFFERENT
ALTHOUGH THIS IS STILL VERY LIKELY FOR SIZEABLE DATASETS
READ MORE IN THE USER GUIDE
PARAMETERS
NSPLITS INT DEFAULT 10 NUMBER OF RESHUFFLING SPLITTING ITERATIONS
TESTSIZE FLOAT INT NONE DEFAULTNONE IF FLOAT SHOULD BE BETWEEN 00 AND 10 AND REPRE
SENT THE PROPORTION OF THE DATASET TO INCLUDE IN THE TEST SPLIT IF INT REPRESENTS THE ABSOLUTE
NUMBER OF TEST SAMPLES IF NONE THE VALUE IS SET TO THE COMPLEMENT OF THE TRAIN SIZE IF
TRAINSIZE IS ALSO NONE IT WILL BE SET TO 01
TRAINSIZE FLOAT INT OR NONE DEFAULTNONE IF FLOAT SHOULD BE BETWEEN 00 AND 10 AND REPRE
SENT THE PROPORTION OF THE DATASET TO INCLUDE IN THE TRAIN SPLIT IF INT REPRESENTS THE ABSOLUTE
NUMBER OF TRAIN SAMPLES IF NONE THE VALUE IS AUTOMATICALLY SET TO THE COMPLEMENT OF THE
TEST SIZE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT SHUFFLESPLIT
X  NPARRAY1 2 3 4 5 6 7 8 3 4 5 6
Y  NPARRAY1 2 1 2 1 2
RS  SHUFFLESPLITNSPLITS5 TESTSIZE25 RANDOMSTATE0
RSGETNSPLITSX
5
PRINTRS
SHUFFLESPLITNSPLITS5 RANDOMSTATE0 TESTSIZE025 TRAINSIZENONE
 FOR TRAININDEX TESTINDEX INRSSPLITX
PRINTTRAIN TRAININDEX TEST TESTINDEX

TRAIN 1 3 0 4 TEST 5 2
TRAIN 4 0 2 5 TEST 1 3
```

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TRAIN 1 2 4 0 TEST 3 5
TRAIN 3 4 1 0 TEST 5 2
TRAIN 3 5 1 0 TEST 2 4
RS SHUFFLESPLITNSPLITS5 TRAINSIZE05 TESTSIZE25
 RANDOMSTATE0
 FOR TRAININDEX TESTINDEX INRSSPLITX
PRINTTRAIN TRAININDEX TEST TESTINDEX

TRAIN 1 3 0 TEST 5 2
TRAIN 4 0 2 TEST 1 3
TRAIN 1 2 4 TEST 3 5
TRAIN 3 4 1 TEST 5 2
TRAIN 3 5 1 TEST 2 4
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFNSPLITS10 TESTSIZENONE TRAINSIZENONE RANDOMSTATENONE
GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYNONE GROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES THE TARGET VARIABLE FOR SUPERVISED LEARNING PROBLEMS
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED
WHILE SPLITTING THE DATASET INTO TRAINTEST SET
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
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NOTES
RANDOMIZED CV SPLITTERS MAY RETURN DIFFERENT RESULTS FOR EACH CALL OF SPLIT YOU CAN MAKE THE RESULTS
IDENTICAL BY SETTING RANDOMSTATE TO AN INTEGER
EXAMPLES USING SKLEARNMODELSELECTIONSHUFFLESPLIT
•VISUALIZING CROSSVALIDATION BEHAVIOR IN SCIKITLEARN
•PLOTTING LEARNING CURVES
•SCALING THE REGULARIZATION PARAMETER FOR SVCS
SKLEARNMODELSELECTION STRATIFIEDKFOLD
CLASSSKLEARNMODELSELECTION STRATIFIEDKFOLD NSPLITS'WARN' SHUFFLEFALSE RAN
DOMSTATENONE
STRATIFIED KFOLDS CROSSVALIDATOR
PROVIDES TRAINTEST INDICES TO SPLIT DATA IN TRAINTEST SETS
THIS CROSSVALIDATION OBJECT IS A VARIATION OF KFOLD THAT RETURNS STRATIFIED FOLDS THE FOLDS ARE MADE BY PRESERVING
THE PERCENTAGE OF SAMPLES FOR EACH CLASS
READ MORE IN THE USER GUIDE
PARAMETERS
NSPLITS INT DEFAULT3 NUMBER OF FOLDS MUST BE AT LEAST 2
CHANGED IN VERSION 020 NSPLITS DEFAULT VALUE WILL CHANGE FROM 3 TO 5 IN V022
SHUFFLE BOOLEAN OPTIONAL WHETHER TO SHUFFLE EACH CLASS'S SAMPLES BEFORE SPLITTING INTO BATCHES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SHUFFLE TRUE
SEE ALSO
REPEATEDSTRATIFIEDKFOLD REPEATS STRATIFIED KFOLD N TIMES
NOTES
TRAIN AND TEST SIZES MAY BE DIFFERENT IN EACH FOLD WITH A DIFFERENCE OF AT MOST NCLASSES
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT STRATIFIEDKFOLD
X  NPARRAY1 2 3 4 1 2 3 4
Y  NPARRAY0 0 1 1
SKF  STRATIFIEDKFOLDNSPLITS2
SKFGETNSPLITSX Y
2
```

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PRINTSKF
STRATIFIEDKFOLDNSPLITS2 RANDOMSTATENONE SHUFFLEFALSE
 FOR TRAININDEX TESTINDEX INSKFSPLITX Y
PRINTTRAIN TRAININDEX TEST TESTINDEX
XTRAIN XTEST XTRAININDEX XTESTINDEX
YTRAIN YTEST YTRAININDEX YTESTINDEX
TRAIN 1 3 TEST 0 2
TRAIN 0 2 TEST 1 3
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFNSPLITS'WARN' SHUFFLEFALSE RANDOMSTATENONE
GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYGROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
NOTE THAT PROVIDING YIS SUFFICIENT TO GENERATE THE SPLITS AND HENCE NP
ZEROSNSAMPLES MAY BE USED AS A PLACEHOLDER FOR XINSTEAD OF ACTUAL TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES THE TARGET VARIABLE FOR SUPERVISED LEARNING PROBLEMS
STRATIFICATION IS DONE BASED ON THE Y LABELS
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
NOTES
RANDOMIZED CV SPLITTERS MAY RETURN DIFFERENT RESULTS FOR EACH CALL OF SPLIT YOU CAN MAKE THE RESULTS
IDENTICAL BY SETTING RANDOMSTATE TO AN INTEGER
626SKLEARNMODELSELECTION MODEL SELECTION 2087

EXAMPLES USING SKLEARNMODELSELECTIONSTRATIFIEDKFOLD
•RECURSIVE FEATURE ELIMINATION WITH CROSSVALIDATION
•TEST WITH PERMUTATIONS THE SIGNIFICANCE OF A CLASSIFICATION SCORE
•GMM COVARIANCES
•RECEIVER OPERATING CHARACTERISTIC ROC WITH CROSS VALIDATION
•VISUALIZING CROSSVALIDATION BEHAVIOR IN SCIKITLEARN
SKLEARNMODELSELECTION STRATIFIEDSHUFFLESPLIT
CLASSSKLEARNMODELSELECTION STRATIFIEDSHUFFLESPLIT NSPLITS10 TESTSIZENONE
TRAINSIZENONE RAN
DOMSTATENONE
STRATIFIED SHUFFLESPLIT CROSSVALIDATOR
PROVIDES TRAINTEST INDICES TO SPLIT DATA IN TRAINTEST SETS
THIS CROSSVALIDATION OBJECT IS A MERGE OF STRATIFIEDKFOLD AND SHUFFLESPLIT WHICH RETURNS STRATIFIED RANDOMIZED
FOLDS THE FOLDS ARE MADE BY PRESERVING THE PERCENTAGE OF SAMPLES FOR EACH CLASS
NOTE LIKE THE SHUFFLESPLIT STRATEGY STRATIFIED RANDOM SPLITS DO NOT GUARANTEE THAT ALL FOLDS WILL BE DIFFERENT
ALTHOUGH THIS IS STILL VERY LIKELY FOR SIZEABLE DATASETS
READ MORE IN THE USER GUIDE
PARAMETERS
NSPLITS INT DEFAULT 10 NUMBER OF RESHUFFLING SPLITTING ITERATIONS
TESTSIZE FLOAT INT NONE OPTIONAL DEFAULTNONE IF FLOAT SHOULD BE BETWEEN 00 AND 10
AND REPRESENT THE PROPORTION OF THE DATASET TO INCLUDE IN THE TEST SPLIT IF INT REPRESENTS THE
ABSOLUTE NUMBER OF TEST SAMPLES IF NONE THE VALUE IS SET TO THE COMPLEMENT OF THE TRAIN
SIZE IFTRAINSIZE IS ALSO NONE IT WILL BE SET TO 01
TRAINSIZE FLOAT INT OR NONE DEFAULT IS NONE IF FLOAT SHOULD BE BETWEEN 00 AND 10 AND
REPRESENT THE PROPORTION OF THE DATASET TO INCLUDE IN THE TRAIN SPLIT IF INT REPRESENTS THE
ABSOLUTE NUMBER OF TRAIN SAMPLES IF NONE THE VALUE IS AUTOMATICALLY SET TO THE COMPLEMENT
OF THE TEST SIZE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT STRATIFIEDSHUFFLESPLIT
X  NPARRAY1 2 3 4 1 2 3 4 1 2 3 4
Y  NPARRAY0 0 0 1 1 1
SSS  STRATIFIEDSHUFFLESPLITNSPLITS5 TESTSIZE05 RANDOMSTATE0
SSSGETNSPLITSX Y
5
PRINTSSS
STRATIFIEDSHUFFLESPLITNSPLITS5 RANDOMSTATE0
```

FOR TRAININDEX TESTINDEX INSSSSPLITX Y
PRINTTRAIN TRAININDEX TEST TESTINDEX
XTRAIN XTEST XTRAININDEX XTESTINDEX
YTRAIN YTEST YTRAININDEX YTESTINDEX
TRAIN 5 2 3 TEST 4 1 0
TRAIN 5 1 4 TEST 0 2 3
TRAIN 5 0 2 TEST 4 3 1
TRAIN 4 1 0 TEST 2 3 5
TRAIN 0 5 1 TEST 3 4 2
METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFNSPLITS10 TESTSIZENONE TRAINSIZENONE RANDOMSTATENONE
GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYGROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
NOTE THAT PROVIDING YIS SUFFICIENT TO GENERATE THE SPLITS AND HENCE NP
ZEROSNSAMPLES MAY BE USED AS A PLACEHOLDER FOR XINSTEAD OF ACTUAL TRAINING DATA
YARRAYLIKE SHAPE NSAMPLES THE TARGET VARIABLE FOR SUPERVISED LEARNING PROBLEMS
STRATIFICATION IS DONE BASED ON THE Y LABELS
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
NOTES
RANDOMIZED CV SPLITTERS MAY RETURN DIFFERENT RESULTS FOR EACH CALL OF SPLIT YOU CAN MAKE THE RESULTS
IDENTICAL BY SETTING RANDOMSTATE TO AN INTEGER

EXAMPLES USING SKLEARNMODELSELECTIONSTRATIFIEDSHUFFLESPLIT
•VISUALIZING CROSSVALIDATION BEHAVIOR IN SCIKITLEARN
•RBF SVM PARAMETERS
SKLEARNMODELSELECTION TIMESERIESSPLIT
CLASSSKLEARNMODELSELECTION TIMESERIESSPLIT NSPLITS'WARN' MAXTRAINSIZENONE
TIME SERIES CROSSVALIDATOR
PROVIDES TRAINTEST INDICES TO SPLIT TIME SERIES DATA SAMPLES THAT ARE OBSERVED AT FIXED TIME INTERVALS IN TRAINTEST SETS IN EACH SPLIT TEST INDICES MUST BE HIGHER THAN BEFORE AND THUS SHUFFLING IN CROSS VALIDATOR IS INAPPROPRIATE
THIS CROSSVALIDATION OBJECT IS A VARIATION OF KFOLD IN THE KTH SPLIT IT RETURNS FIRST K FOLDS AS TRAIN SET AND THE K1TH FOLD AS TEST SET
NOTE THAT UNLIKE STANDARD CROSSVALIDATION METHODS SUCCESSIVE TRAINING SETS ARE SUPERSETS OF THOSE THAT COME BEFORE THEM
READ MORE IN THE USER GUIDE
PARAMETERS
NSPLITS INT DEFAULT3 NUMBER OF SPLITS MUST BE AT LEAST 2
CHANGED IN VERSION 020 NSPLITS DEFAULT VALUE WILL CHANGE FROM 3 TO 5 IN V022
MAXTRAINSIZE INT OPTIONAL MAXIMUM SIZE FOR A SINGLE TRAINING SET
NOTES
THE TRAINING SET HAS SIZE INSAMPLES NSPLITS 1 NSAMPLES NSPLITS
 1 IN THEITH SPLIT WITH A TEST SET OF SIZE NSAMPLESNSPLITS 1
WHERENSAMPLES IS THE NUMBER OF SAMPLES
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT TIMESERIESSPLIT
X  NPARRAY1 2 3 4 1 2 3 4 1 2 3 4
Y  NPARRAY1 2 3 4 5 6
TSCV  TIMESERIESSPLITNSPLITS5
PRINTTSCV
TIMESERIESSPLITMAXTRAINSIZENONE NSPLITS5
 FOR TRAININDEX TESTINDEX INTSCVSPLITX
PRINTTRAIN TRAININDEX TEST TESTINDEX
XTRAIN XTEST  XTRAININDEX XTESTINDEX
YTRAIN YTEST  YTRAININDEX YTESTINDEX
TRAIN 0 TEST 1
TRAIN 0 1 TEST 2
TRAIN 0 1 2 TEST 3
TRAIN 0 1 2 3 TEST 4
TRAIN 0 1 2 3 4 TEST 5
```

METHODS
GETNSPLITS SELF X Y GROUPS RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSS
VALIDATOR
SPLIT SELF X Y GROUPS GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
INIT SELFNSPLITS'WARN' MAXTRAINSIZENONE
GETNSPLITS SELFXNONE YNONE GROUPSNONE
RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
PARAMETERS
XOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YOBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS OBJECT ALWAYS IGNORED EXISTS FOR COMPATIBILITY
RETURNS
NSPLITS INT RETURNS THE NUMBER OF SPLITTING ITERATIONS IN THE CROSSVALIDATOR
SPLITSELFXYNONE GROUPSNONE
GENERATE INDICES TO SPLIT DATA INTO TRAINING AND TEST SET
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES ALWAYS IGNORED EXISTS FOR COMPATIBILITY
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES ALWAYS IGNORED EXISTS FOR COMPATIBILITY
YIELDS
TRAIN NDARRAY THE TRAINING SET INDICES FOR THAT SPLIT
TEST NDARRAY THE TESTING SET INDICES FOR THAT SPLIT
EXAMPLES USING SKLEARNMODELSELECTIONTIMESERIESSPLIT
•VISUALIZING CROSSVALIDATION BEHAVIOR IN SCIKITLEARN
6262 SPLITTER FUNCTIONS
MODELSELECTIONCHECKCV CV Y CLASSIFIER INPUT CHECKER UTILITY FOR BUILDING A CROSSVALIDATOR
MODELSELECTIONTRAINTESTSPLIT ARRAYS
SPLIT ARRAYS OR MATRICES INTO RANDOM TRAIN AND TEST SUBSETS
SKLEARNMODELSELECTION CHECKCV
SKLEARNMODELSELECTION CHECKCV CV'WARN' YNONE CLASSIFIERFALSE
INPUT CHECKER UTILITY FOR BUILDING A CROSSVALIDATOR
PARAMETERS
626SKLEARNMODELSELECTION MODEL SELECTION 2091

SCIKITLEARN USER GUIDE RELEASE 0213
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF CLASSIFIER IS TRUE AND YIS EITHER BINARY OR MULTICLASS
STRATIFIEDKFOLD IS USED IN ALL OTHER CASES KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE WILL CHANGE FROM 3FOLD TO 5FOLD IN V022
YARRAYLIKE OPTIONAL THE TARGET VARIABLE FOR SUPERVISED LEARNING PROBLEMS
CLASSIFIER BOOLEAN OPTIONAL DEFAULT FALSE WHETHER THE TASK IS A CLASSIFICATION TASK IN WHICH
CASE STRATIFIED KFOLD WILL BE USED
RETURNS
CHECKEDCV A CROSSVALIDATOR INSTANCE THE RETURN VALUE IS A CROSSVALIDATOR WHICH GENERATES
THE TRAINTEST SPLITS VIA THE SPLIT METHOD
SKLEARNMODELSELECTION TRAINTESTSPLIT
SKLEARNMODELSELECTION TRAINTESTSPLIT ARRAYS OPTIONS
SPLIT ARRAYS OR MATRICES INTO RANDOM TRAIN AND TEST SUBSETS
QUICK UTILITY THAT WRAPS INPUT VALIDATION AND NEXTSHUFFLESPLITSPLITX Y AND APPLICATION TO
INPUT DATA INTO A SINGLE CALL FOR SPLITTING AND OPTIONALLY SUBSAMPLING DATA IN A ONELINER
READ MORE IN THE USER GUIDE
PARAMETERS
ARRAYS SEQUENCE OF INDEXABLES WITH SAME LENGTH SHAPE0 ALLOWED INPUTS ARE LISTS NUMPY
ARRAYS SCIPYSPARSE MATRICES OR PANDAS DATAFRAMES
TESTSIZE FLOAT INT OR NONE OPTIONAL DEFAULTNONE IF FLOAT SHOULD BE BETWEEN 00 AND 10
AND REPRESENT THE PROPORTION OF THE DATASET TO INCLUDE IN THE TEST SPLIT IF INT REPRESENTS THE
ABSOLUTE NUMBER OF TEST SAMPLES IF NONE THE VALUE IS SET TO THE COMPLEMENT OF THE TRAIN
SIZE IFTRAINSIZE IS ALSO NONE IT WILL BE SET TO 025
TRAINSIZE FLOAT INT OR NONE DEFAULTNONE IF FLOAT SHOULD BE BETWEEN 00 AND 10 AND
REPRESENT THE PROPORTION OF THE DATASET TO INCLUDE IN THE TRAIN SPLIT IF INT REPRESENTS THE
ABSOLUTE NUMBER OF TRAIN SAMPLES IF NONE THE VALUE IS AUTOMATICALLY SET TO THE COMPLEMENT
OF THE TEST SIZE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
SHUFFLE BOOLEAN OPTIONAL DEFAULTTRUE WHETHER OR NOT TO SHUFFLE THE DATA BEFORE SPLITTING IF
SHUFFLEFALSE THEN STRATIFY MUST BE NONE
STRATIFY ARRAYLIKE OR NONE DEFAULTNONE IF NOT NONE DATA IS SPLIT IN A STRATIFIED FASHION
USING THIS AS THE CLASS LABELS

RETURNS
SPLITTING LIST LENGTH2 LENARRAYS LIST CONTAINING TRAINTEST SPLIT OF INPUTS
NEW IN VERSION 016 IF THE INPUT IS SPARSE THE OUTPUT WILL BE A SCIPYSPARSE
CSRMATRIX ELSE OUTPUT TYPE IS THE SAME AS THE INPUT TYPE
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
X Y  NPARANGE10RESHAPE5 2 RANGE5
X
ARRAY0 1
2 3
4 5
6 7
8 9
LISTY
0 1 2 3 4
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLIT
 X Y TESTSIZE033 RANDOMSTATE42

XTRAIN
ARRAY4 5
0 1
6 7
YTRAIN
2 0 3
XTEST
ARRAY2 3
8 9
YTEST
1 4
TRAINTESTSPLITY SHUFFLE FALSE
0 1 2 3 4
```
EXAMPLES USING SKLEARNMODELSELECTIONTRAINTESTSPLIT
•FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
•PREDICTION LATENCY
•PROBABILITY CALIBRATION CURVES
•PROBABILITY CALIBRATION OF CLASSIFIERS
•CLASSIFIER COMPARISON
•COLUMN TRANSFORMER WITH MIXED TYPES
•EFFECT OF TRANSFORMING THE TARGETS IN REGRESSION MODEL
•COMPARING RANDOM FORESTS AND THE MULTIOUTPUT META ESTIMATOR
•EARLY STOPPING OF GRADIENT BOOSTING

•FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES
•GRADIENT BOOSTING OUTOFBAG ESTIMATES
•PIPELINE ANOVA SVM
•COMPARING VARIOUS ONLINE SOLVERS
•MNIST CLASSFIFICATION USING MULTINOMIAL LOGISTIC L1
•MULTICLASS SPARSE LOGISITIC REGRESSION ON NEWGROUPS20
•EARLY STOPPING OF STOCHASTIC GRADIENT DESCENT
•PARAMETER ESTIMATION USING GRID SEARCH WITH CROSSVALIDATION
•CONFUSION MATRIX
•RECEIVER OPERATING CHARACTERISTIC ROC
•PRECISIONRECALL
•CLASSIFIER CHAIN
•COMPARING NEAREST NEIGHBORS WITH AND WITHOUT NEIGHBORHOOD COMPONENTS ANALYSIS
•DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
•RESTRICTED BOLTZMANN MACHINE FEATURES FOR DIGIT CLASSIFICATION
•VARYING REGULARIZATION IN MULTILAYER PERCEPTRON
•USING FUNCTIONTRANSFORMER TO SELECT COLUMNS
•IMPORTANCE OF FEATURE SCALING
•MAP DATA TO A NORMAL DISTRIBUTION
•FEATURE DISCRETIZATION
•UNDERSTANDING THE DECISION TREE STRUCTURE
6263 HYPERPARAMETER OPTIMIZERS
MODELSELECTIONGRIDSEARCHCV ESTIMATOR EXHAUSTIVE SEARCH OVER SPECIFIED PARAMETER VALUES FOR AN ESTIMATOR
MODELSELECTIONPARAMETERGRID PARAMGRID GRID OF PARAMETERS WITH A DISCRETE NUMBER OF VALUES FOR EACH
MODELSELECTIONPARAMETERSAMPLER GENERATOR ON PARAMETERS SAMPLED FROM GIVEN DISTRIBUTIONS
MODELSELECTIONRANDOMIZEDSEARCHCV
  RANDOMIZED SEARCH ON HYPER PARAMETERS
SKLEARNMODELSELECTION GRIDSEARCHCV
CLASSSKLEARNMODELSELECTION GRIDSEARCHCV ESTIMATOR PARAMGRID SCORINGNONE
NJOBSNONE IID'WARN' REFITTRUE
CV'WARN' VERBOSE0 PREDISPATCH'2NJOBS'
ERRORSCORE'RAISEDEPRECATING' RE
TURNTRAINSCOREFALSE
EXHAUSTIVE SEARCH OVER SPECIFIED PARAMETER VALUES FOR AN ESTIMATOR
IMPORTANT MEMBERS ARE FIT PREDICT

GRIDSEARCHCV IMPLEMENTS A “FIT” AND A “SCORE” METHOD IT ALSO IMPLEMENTS “PREDICT” “PREDICTPROBA” “DECI
SIONFUNCTION” “TRANSFORM” AND “INVERSETRANSFORM” IF THEY ARE IMPLEMENTED IN THE ESTIMATOR USED
THE PARAMETERS OF THE ESTIMATOR USED TO APPLY THESE METHODS ARE OPTIMIZED BY CROSSVALIDATED GRIDSEARCH OVER
A PARAMETER GRID
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT THIS IS ASSUMED TO IMPLEMENT THE SCIKITLEARN ESTIMATOR INTERFACE
EITHER ESTIMATOR NEEDS TO PROVIDE A SCORE FUNCTION OR SCORING MUST BE PASSED
PARAMGRID DICT OR LIST OF DICTIONARIES DICTIONARY WITH PARAMETERS NAMES STRING AS KEYS AND
LISTS OF PARAMETER SETTINGS TO TRY AS VALUES OR A LIST OF SUCH DICTIONARIES IN WHICH CASE THE
GRIDS SPANNED BY EACH DICTIONARY IN THE LIST ARE EXPLORED THIS ENABLES SEARCHING OVER ANY
SEQUENCE OF PARAMETER SETTINGS
SCORING STRING CALLABLE LISTTUPLE DICT OR NONE DEFAULT NONE A SINGLE STRING SEE THE SCORING
PARAMETER DEFINING MODEL EVALUATION RULES OR A CALLABLE SEE DEFINING YOUR SCORING STRATEGY
FROM METRIC FUNCTIONS TO EVALUATE THE PREDICTIONS ON THE TEST SET
FOR EVALUATING MULTIPLE METRICS EITHER GIVE A LIST OF UNIQUE STRINGS OR A DICT WITH NAMES AS
KEYS AND CALLABLES AS VALUES
NOTE THAT WHEN USING CUSTOM SCORERS EACH SCORER SHOULD RETURN A SINGLE VALUE METRIC
FUNCTIONS RETURNING A LISTARRAY OF VALUES CAN BE WRAPPED INTO MULTIPLE SCORERS THAT RETURN
ONE VALUE EACH
SEESPECIFYING MULTIPLE METRICS FOR EVALUATION FOR AN EXAMPLE
IF NONE THE ESTIMATOR’S SCORE METHOD IS USED
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF JOBS TO RUN IN PARALLEL NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
PREDISPATCH INT OR STRING OPTIONAL CONTROLS THE NUMBER OF JOBS THAT GET DISPATCHED DURING
PARALLEL EXECUTION REDUCING THIS NUMBER CAN BE USEFUL TO AVOID AN EXPLOSION OF MEMORY
CONSUMPTION WHEN MORE JOBS GET DISPATCHED THAN CPUS CAN PROCESS THIS PARAMETER CAN
BE
• NONE IN WHICH CASE ALL THE JOBS ARE IMMEDIATELY CREATED AND SPAWNED USE THIS FOR
LIGHTWEIGHT AND FASTRUNNING JOBS TO AVOID DELAYS DUE TO ONDEMAND SPAWNING OF THE JOBS
• AN INT GIVING THE EXACT NUMBER OF TOTAL JOBS THAT ARE SPAWNED
• A STRING GIVING AN EXPRESSION AS A FUNCTION OF NJOBS AS IN ‘2NJOBS’
IIDBOOLEAN DEFAULT’WARN’ IF TRUE RETURN THE AVERAGE SCORE ACROSS FOLDS WEIGHTED BY THE
NUMBER OF SAMPLES IN EACH TEST SET IN THIS CASE THE DATA IS ASSUMED TO BE IDENTICALLY DIS
TRIBUTED ACROSS THE FOLDS AND THE LOSS MINIMIZED IS THE TOTAL LOSS PER SAMPLE AND NOT THE
MEAN LOSS ACROSS THE FOLDS IF FALSE RETURN THE AVERAGE SCORE ACROSS FOLDS DEFAULT IS TRUE
BUT WILL CHANGE TO FALSE IN VERSION 022 TO CORRESPOND TO THE STANDARD DEFINITION OF CROSS
VALIDATION
CHANGED IN VERSION 020 PARAMETER IID WILL CHANGE FROM TRUE TO FALSE BY DEFAULT IN
VERSION 022 AND WILL BE REMOVED IN 024
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSS VALIDATION

• INTEGER TO SPECIFY THE NUMBER OF FOLDS IN A STRATIFIEDKFOLD
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF THE ESTIMATOR IS A CLASSIFIER AND YIS EITHER BINARY OR MULTICLASS
STRATIFIEDKFOLD IS USED IN ALL OTHER CASES KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
REFIT BOOLEAN STRING OR CALLABLE DEFAULTTRUE REFIT AN ESTIMATOR USING THE BEST FOUND PARAM
ETERS ON THE WHOLE DATASET
FOR MULTIPLE METRIC EVALUATION THIS NEEDS TO BE A STRING DENOTING THE SCORER THAT WOULD BE
USED TO FIND THE BEST PARAMETERS FOR REFITTING THE ESTIMATOR AT THE END
WHERE THERE ARE CONSIDERATIONS OTHER THAN MAXIMUM SCORE IN CHOOSING A BEST ESTIMA
TORREFIT CAN BE SET TO A FUNCTION WHICH RETURNS THE SELECTED BESTINDEX GIVEN
CVRESULTS
THE REFITTED ESTIMATOR IS MADE AVAILABLE AT THE BESTESTIMATOR ATTRIBUTE AND PERMITS
USINGPREDICT DIRECTLY ON THIS GRIDSEARCHCV INSTANCE
ALSO FOR MULTIPLE METRIC EVALUATION THE ATTRIBUTES BESTINDEX BESTSCORE AND
BESTPARAMS WILL ONLY BE AVAILABLE IF REFIT IS SET AND ALL OF THEM WILL BE DETERMINED
WRT THIS SPECIFIC SCORER BESTSCORE IS NOT RETURNED IF REFIT IS CALLABLE
SEESCORING PARAMETER TO KNOW MORE ABOUT MULTIPLE METRIC EVALUATION
CHANGED IN VERSION 020 SUPPORT FOR CALLABLE ADDED
VERBOSE INTEGER CONTROLS THE VERBOSITY THE HIGHER THE MORE MESSAGES
ERRORSCORE ‘RAISE’ OR NUMERIC VALUE TO ASSIGN TO THE SCORE IF AN ERROR OCCURS IN ESTIMATOR
FITTING IF SET TO ‘RAISE’ THE ERROR IS RAISED IF A NUMERIC VALUE IS GIVEN FITFAILEDWARNING
IS RAISED THIS PARAMETER DOES NOT AFFECT THE REFIT STEP WHICH WILL ALWAYS RAISE THE ERROR
DEFAULT IS ‘RAISE’ BUT FROM VERSION 022 IT WILL CHANGE TO NPNAN
RETURNTRAINSCORE BOOLEAN DEFAULTFALSE IF FALSE THECVRESULTS ATTRIBUTE WILL NOT
INCLUDE TRAINING SCORES COMPUTING TRAINING SCORES IS USED TO GET INSIGHTS ON HOW DIFFER
ENT PARAMETER SETTINGS IMPACT THE OVERFITTINGUNDERFITTING TRADEOFF HOWEVER COMPUTING THE
SCORES ON THE TRAINING SET CAN BE COMPUTATIONALLY EXPENSIVE AND IS NOT STRICTLY REQUIRED TO
SELECT THE PARAMETERS THAT YIELD THE BEST GENERALIZATION PERFORMANCE
ATTRIBUTES
CVRESULTS DICT OF NUMPY MASKED NDARRAYS A DICT WITH KEYS AS COLUMN HEADERS AND VALUES
AS COLUMNS THAT CAN BE IMPORTED INTO A PANDAS DATAFRAME
FOR INSTANCE THE BELOW GIVEN TABLE
PARAMKERNEL PARAMGAMMA PARAMDEGREE SPLIT0TESTSCORE RANKT
‘POLY’ – 2 080 2
‘POLY’ – 3 070 4
‘RBF’ 01 – 080 3
‘RBF’ 02 – 093 1
WILL BE REPRESENTED BY A CVRESULTS DICT OF

PARAMKERNEL MASKEDARRAYDATA POLY POLY RBF RBF
MASK   FALSE FALSE FALSE FALSE
PARAMGAMMA MASKEDARRAYDATA   01 02
MASK   TRUE TRUE FALSE FALSE
PARAMDEGREE MASKEDARRAYDATA 20 30
MASK   FALSE FALSE TRUE TRUE
SPLIT0TESTSCORE 080 070 080 093
SPLIT1TESTSCORE 082 050 070 078
MEANTESTSCORE 081 060 075 085
STDTESTSCORE 001 010 005 008
RANKTESTSCORE 2 4 3 1
SPLIT0TRAINSCORE 080 092 070 093
SPLIT1TRAINSCORE 082 055 070 087
MEANTRAINSCORE 081 074 070 090
STDTRAINSCORE 001 019 000 003
MEANFITTIME 073 063 043 049
STDFITTIME 001 002 001 001
MEANSCORETIME 001 006 004 004
STDSCORETIME 000 000 000 001
PARAMS KERNEL POLY DEGREE 2

NOTE
THE KEYPARAMS IS USED TO STORE A LIST OF PARAMETER SETTINGS DICTS FOR ALL THE PARAMETER
CANDIDATES
THEMEANFITTIME STDFITTIME MEANSCORETIME AND
STDSCORETIME ARE ALL IN SECONDS
FOR MULTIMETRIC EVALUATION THE SCORES FOR ALL THE SCORERS ARE AVAILABLE IN THE
CVRESULTS DICT AT THE KEYS ENDING WITH THAT SCORER'S NAME SCORERNAME
INSTEAD OFSCORE SHOWN ABOVE 'SPLIT0TESTPRECISION' 'MEANTRAINPRECISION' ETC
BESTESTIMATOR ESTIMATOR OR DICT ESTIMATOR THAT WAS CHOSEN BY THE SEARCH IE ESTIMATOR
WHICH GAVE HIGHEST SCORE OR SMALLEST LOSS IF SPECIFIED ON THE LEFT OUT DATA NOT AVAILABLE IF
REFITFALSE
SEEREFIT PARAMETER FOR MORE INFORMATION ON ALLOWED VALUES
BESTSCORE FLOAT MEAN CROSSVALIDATED SCORE OF THE BESTESTIMATOR
FOR MULTIMETRIC EVALUATION THIS IS PRESENT ONLY IF REFIT IS SPECIFIED
BESTPARAMS DICT PARAMETER SETTING THAT GAVE THE BEST RESULTS ON THE HOLD OUT DATA
FOR MULTIMETRIC EVALUATION THIS IS PRESENT ONLY IF REFIT IS SPECIFIED
BESTINDEX INT THE INDEX OF THE CVRESULTS ARRAYS WHICH CORRESPONDS TO THE BEST CAN
DIDATE PARAMETER SETTING
THE DICT AT SEARCHCVRESULTSPARAMSSEARCHBESTINDEX GIVES
THE PARAMETER SETTING FOR THE BEST MODEL THAT GIVES THE HIGHEST MEAN SCORE SEARCH
BESTSCORE
FOR MULTIMETRIC EVALUATION THIS IS PRESENT ONLY IF REFIT IS SPECIFIED
SCORER FUNCTION OR A DICT SCORER FUNCTION USED ON THE HELD OUT DATA TO CHOOSE THE BEST PARAM
ETERS FOR THE MODEL
626SKLEARNMODELSELECTION MODEL SELECTION 2097

FOR MULTIMETRIC EVALUATION THIS ATTRIBUTE HOLDS THE VALIDATED SCORING DICT WHICH MAPS
THE SCORER KEY TO THE SCORER CALLABLE
NSPLITS INT THE NUMBER OF CROSSVALIDATION SPLITS FOLDSITERATIONS
REFITTIME FLOAT SECONDS USED FOR REFITTING THE BEST MODEL ON THE WHOLE DATASET
THIS IS PRESENT ONLY IF REFIT IS NOT FALSE
SEE ALSO
PARAMETERGRID GENERATES ALL THE COMBINATIONS OF A HYPERPARAMETER GRID
SKLEARNMODELSELECTIONTRAINTESTSPLIT UTILITY FUNCTION TO SPLIT THE DATA INTO A DEVELOPMENT
SET USABLE FOR FITTING A GRIDSEARCHCV INSTANCE AND AN EVALUATION SET FOR ITS FINAL EVALUATION
SKLEARNMETRICSMAKESCORER MAKE A SCORER FROM A PERFORMANCE METRIC OR LOSS FUNCTION
NOTES
THE PARAMETERS SELECTED ARE THOSE THAT MAXIMIZE THE SCORE OF THE LEFT OUT DATA UNLESS AN EXPLICIT SCORE IS PASSED
IN WHICH CASE IT IS USED INSTEAD
IFNJOBS WAS SET TO A VALUE HIGHER THAN ONE THE DATA IS COPIED FOR EACH POINT IN THE GRID AND NOT NJOBS TIMES
THIS IS DONE FOR EFFICIENCY REASONS IF INDIVIDUAL JOBS TAKE VERY LITTLE TIME BUT MAY RAISE ERRORS IF THE DATASET
IS LARGE AND NOT ENOUGH MEMORY IS AVAILABLE A WORKAROUND IN THIS CASE IS TO SET PREDISPATCH THEN
THE MEMORY IS COPIED ONLY PREDISPATCH MANY TIMES A REASONABLE VALUE FOR PREDISPATCH IS2
NJOBS
EXAMPLES
 FROM SKLEARN IMPORT SVM DATASETS
 FROM SKLEARNMODELSELECTION IMPORT GRIDSEARCHCV
IRIS DATASETSLOADIRIS
PARAMETERS KERNELLINEAR RBF C1 10
SVC SVMSVCGAMMASCALE
CLF GRIDSEARCHCVSVC PARAMETERS CV5
CLFFITIRISDATA IRISTARGET

GRIDSEARCHCVCV5 ERRORSCORE
ESTIMATORSVCC10 CACHESIZE CLASSWEIGHT COEF0
DECISIONFUNCTIONSHAPEOVR DEGREE GAMMA
KERNELRBF MAXITER1 PROBABILITYFALSE
RANDOMSTATENONE SHRINKINGTRUE TOL
VERBOSEFALSE
IID NJOBSNONE
PARAMGRID PREDISPATCH REFIT RETURNTRAINSCORE
SCORING VERBOSE
SORTEDCLFCVRESULTSKEYS

MEANFITTIME MEANSCORETIME MEANTESTSCORE
PARAMC PARAMKERNEL PARAMS
RANKTESTSCORE SPLIT0TESTSCORE
SPLIT2TESTSCORE
STDFITTIME STDSCORETIME STDTESTSCORE

METHODS
DECISIONFUNCTION SELF X CALL DECISIONFUNCTION ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
FITSELF X Y GROUPS RUN FIT WITH ALL SETS OF PARAMETERS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF XT CALL INVERSETRANSFORM ON THE ESTIMATOR WITH THE BEST FOUND PARAMS
PREDICT SELF X CALL PREDICT ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
PREDICTLOGPROBA SELF X CALL PREDICTLOGPROBA ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
PREDICTPROBA SELF X CALL PREDICTPROBA ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
SCORE SELF X Y RETURNS THE SCORE ON THE GIVEN DATA IF THE ESTIMATOR HAS BEEN REFIT
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X CALL TRANSFORM ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
INIT SELFESTIMATOR PARAMGRID SCORINGNONE NJOBSNONE IID'WARN' REFITTRUE CV'WARN' VERBOSE0 PREDISPATCH'2NJOBS' ERRORSCORE'RAISEDEPRECATING' RETURNTRAINSCOREFALSE
DECISIONFUNCTION SELFX
CALL DECISIONFUNCTION ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
ONLY AVAILABLE IF REFITTRUE AND THE UNDERLYING ESTIMATOR SUPPORTS DECISIONFUNCTION
PARAMETERS
XINDEXABLE LENGTH NSAMPLES MUST FULFILL THE INPUT ASSUMPTIONS OF THE UNDERLYING ESTIMATOR
FITSELFXYNONE GROUPSNONE FITPARAMS
RUN FIT WITH ALL SETS OF PARAMETERS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUT OPTIONAL TARGET RELATIVE TO X FOR CLASSIFICATION OR REGRESSION NONE FOR UNSUPERVISED LEARNING
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED WHILE SPLITTING THE DATASET INTO TRAINTEST SET ONLY USED IN CONJUNCTION WITH A "GROUP" CV INSTANCE EG GROUPKFOLD
FITPARAMS DICT OF STRING OBJECT PARAMETERS PASSED TO THE FIT METHOD OF THE ESTIMATOR
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED SUBOBJECTS THAT ARE ESTIMATORS

RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFXT
CALL INVERSETRANSFORM ON THE ESTIMATOR WITH THE BEST FOUND PARAMS
ONLY AVAILABLE IF THE UNDERLYING ESTIMATOR IMPLEMENTS INVERSETRANSFORM ANDREFITTRUE
PARAMETERS
XTINDEXABLE LENGTH NSAMPLES MUST FULFILL THE INPUT ASSUMPTIONS OF THE UNDERLYING ESTI
MATOR
PREDICTSELFX
CALL PREDICT ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
ONLY AVAILABLE IF REFITTRUE AND THE UNDERLYING ESTIMATOR SUPPORTS PREDICT
PARAMETERS
XINDEXABLE LENGTH NSAMPLES MUST FULFILL THE INPUT ASSUMPTIONS OF THE UNDERLYING ESTI
MATOR
PREDICTLOGPROBA SELFX
CALL PREDICTLOGPROBA ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
ONLY AVAILABLE IF REFITTRUE AND THE UNDERLYING ESTIMATOR SUPPORTS PREDICTLOGPROBA
PARAMETERS
XINDEXABLE LENGTH NSAMPLES MUST FULFILL THE INPUT ASSUMPTIONS OF THE UNDERLYING ESTI
MATOR
PREDICTPROBA SELFX
CALL PREDICTPROBA ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
ONLY AVAILABLE IF REFITTRUE AND THE UNDERLYING ESTIMATOR SUPPORTS PREDICTPROBA
PARAMETERS
XINDEXABLE LENGTH NSAMPLES MUST FULFILL THE INPUT ASSUMPTIONS OF THE UNDERLYING ESTI
MATOR
SCORESELFXYNONE
RETURNS THE SCORE ON THE GIVEN DATA IF THE ESTIMATOR HAS BEEN REFIT
THIS USES THE SCORE DEFINED BY SCORING WHERE PROVIDED AND THE BESTESTIMATORSCORE METHOD
OTHERWISE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT DATA WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUT OPTIONAL TARGET RELATIVE TO X
FOR CLASSIFICATION OR REGRESSION NONE FOR UNSUPERVISED LEARNING
RETURNS
SCORE FLOAT
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR

THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
CALL TRANSFORM ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
ONLY AVAILABLE IF THE UNDERLYING ESTIMATOR SUPPORTS TRANSFORM ANDREFITTRUE
PARAMETERS
XINDEXABLE LENGTH NSAMPLES MUST FULFILL THE INPUT ASSUMPTIONS OF THE UNDERLYING ESTI
MATOR
EXAMPLES USING SKLEARNMODELSELECTIONGRIDSEARCHCV
•COMPARISON OF KERNEL RIDGE REGRESSION AND SVR
•FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
•FEATURE AGGLOMERATION VS UNIVARIATE SELECTION
•CONCATENATING MULTIPLE FEATURE EXTRACTION METHODS
•PIPELINING CHAINING A PCA AND A LOGISTIC REGRESSION
•COLUMN TRANSFORMER WITH MIXED TYPES
•SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV
•SHRINKAGE COVARIANCE ESTIMATION LEDOITWOLF VS OAS AND MAXLIKELIHOOD
•MODEL SELECTION WITH PROBABILISTIC PCA AND FACTOR ANALYSIS FA
•CROSSVALIDATION ON DIABETES DATASET EXERCISE
•COMPARISON OF KERNEL RIDGE AND GAUSSIAN PROCESS REGRESSION
•PARAMETER ESTIMATION USING GRID SEARCH WITH CROSSVALIDATION
•COMPARING RANDOMIZED SEARCH AND GRID SEARCH FOR HYPERPARAMETER ESTIMATION
•NESTED VERSUS NONNESTED CROSSVALIDATION
•DEMONSTRATION OF MULTIMETRIC EVALUATION ON CROSSVALSCORE AND GRIDSEARCHCV
•BALANCE MODEL COMPLEXITY AND CROSSVALIDATED SCORE
•SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
•KERNEL DENSITY ESTIMATION
•FEATURE DISCRETIZATION
•SCALING THE REGULARIZATION PARAMETER FOR SVCS
•RBF SVM PARAMETERS

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SKLEARNMODELSELECTION PARAMETERGRID
CLASSSKLEARNMODELSELECTION PARAMETERGRID PARAMGRID
GRID OF PARAMETERS WITH A DISCRETE NUMBER OF VALUES FOR EACH
CAN BE USED TO ITERATE OVER PARAMETER VALUE COMBINATIONS WITH THE PYTHON BUILTIN FUNCTION ITER
READ MORE IN THE USER GUIDE
PARAMETERS
PARAMGRID DICT OF STRING TO SEQUENCE OR SEQUENCE OF SUCH THE PARAMETER GRID TO EXPLORE AS
A DICTIONARY MAPPING ESTIMATOR PARAMETERS TO SEQUENCES OF ALLOWED VALUES
AN EMPTY DICT SIGNIFIES DEFAULT PARAMETERS
A SEQUENCE OF DICTS SIGNIFIES A SEQUENCE OF GRIDS TO SEARCH AND IS USEFUL TO AVOID EXPLORING
PARAMETER COMBINATIONS THAT MAKE NO SENSE OR HAVE NO EFFECT SEE THE EXAMPLES BELOW
SEE ALSO
GRIDSEARCHCV USESPARAMETERGRID TO PERFORM A FULL PARALLELIZED PARAMETER SEARCH
EXAMPLES
FROM SKLEARNMODELSELECTION IMPORT PARAMETERGRID
PARAMGRID A 1 2 B TRUEFALSE
LISTPARAMETERGRIDPARAMGRID
A 1 B TRUE A 1 B FALSE
A 2 B TRUE A 2 B FALSE
TRUE
GRID KERNEL LINEAR KERNEL RBF GAMMA 1 10
LISTPARAMETERGRIDGRID KERNEL LINEAR
KERNEL RBF GAMMA 1
KERNEL RBF GAMMA 10
TRUE
PARAMETERGRIDGRID1 KERNEL RBF GAMMA 1
TRUE
INIT SELFPARAMGRID
SKLEARNMODELSELECTION PARAMETERSAMPLER
CLASSSKLEARNMODELSELECTION PARAMETERSAMPLER PARAMDISTRIBUTIONS NITER RAN
DOMSTATENONE
GENERATOR ON PARAMETERS SAMPLED FROM GIVEN DISTRIBUTIONS
NONDETERMINISTIC ITERABLE OVER RANDOM CANDIDATE COMBINATIONS FOR HYPER PARAMETER SEARCH IF ALL PARAMETERS
ARE PRESENTED AS A LIST SAMPLING WITHOUT REPLACEMENT IS PERFORMED IF AT LEAST ONE PARAMETER IS GIVEN AS A
DISTRIBUTION SAMPLING WITH REPLACEMENT IS USED IT IS HIGHLY RECOMMENDED TO USE CONTINUOUS DISTRIBUTIONS FOR
CONTINUOUS PARAMETERS
NOTE THAT BEFORE SCIPY 016 THE SCIPYSTATSDISTRIBUTIONS DO NOT ACCEPT A CUSTOM RNG INSTANCE
AND ALWAYS USE THE SINGLETON RNG FROM NUMPYRANDOM HENCE SETTING RANDOMSTATE WILL NOT GUARANTEE
A DETERMINISTIC ITERATION WHENEVER SCIPYSTATS DISTRIBUTIONS ARE USED TO DEFINE THE PARAMETER SEARCH SPACE
DETERMINISTIC BEHAVIOR IS HOWEVER GUARANTEED FROM SCIPY 016 ONWARDS

SCIKITLEARN USER GUIDE RELEASE 0213
READ MORE IN THE USER GUIDE
PARAMETERS
PARAMDISTRIBUTIONS DICT DICTIONARY WHERE THE KEYS ARE PARAMETERS AND VALUES ARE DISTRIBU
TIONS FROM WHICH A PARAMETER IS TO BE SAMPLED DISTRIBUTIONS EITHER HAVE TO PROVIDE A RVS
FUNCTION TO SAMPLE FROM THEM OR CAN BE GIVEN AS A LIST OF VALUES WHERE A UNIFORM DISTRIBU
TION IS ASSUMED
NITER INTEGER NUMBER OF PARAMETER SETTINGS THAT ARE PRODUCED
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE PSEUDO RANDOM
NUMBER GENERATOR STATE USED FOR RANDOM UNIFORM SAMPLING FROM LISTS OF POSSIBLE VALUES
INSTEAD OF SCIPYSTATS DISTRIBUTIONS IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM
NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR
IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
RETURNS
PARAMS DICT OF STRING TO ANY YIELDS DICTIONARIES MAPPING EACH ESTIMATOR PARAMETER TO AS SAM
PLED VALUE
EXAMPLES
 FROM SKLEARNMODELSELECTION IMPORT PARAMETERSAMPLER
 FROM SCIPYSTATSDISTRIBUTIONS IMPORT EXPON
 IMPORT NUMPY AS NP
RNG NPRANDOMRANDOMSTATE0
PARAMGRID A1 2 B EXPON
PARAMLIST LISTPARAMETERSAMPLERPARAMGRID NITER4
 RANDOMSTATERNG
ROUNDEDLIST DICTK ROUNDV 6 FORK VINDITEMS
 FOR DINPARAMLIST
ROUNDEDLIST B 089856 A 1
 B 0923223 A 1
 B 1878964 A 2
 B 1038159 A 2
TRUE
INIT SELFPARAMDISTRIBUTIONS NITER RANDOMSTATENONE
SKLEARNMODELSELECTION RANDOMIZEDSEARCHCV
CLASSSKLEARNMODELSELECTION RANDOMIZEDSEARCHCV ESTIMATOR PARAMDISTRIBUTIONS
NITER10 SCORINGNONE
NJOBSNONE IID’WARN’ RE
FITTRUE CV’WARN’ VER
BOSE0 PREDISPATCH‘2NJOBS’
RANDOMSTATENONE
ERRORSCORE‘RAISEDEPRECATING’ RE
TURNTRAINSCOREFALSE
RANDOMIZED SEARCH ON HYPER PARAMETERS
RANDOMIZEDSEARCHCV IMPLEMENTS A “FIT” AND A “SCORE” METHOD IT ALSO IMPLEMENTS “PREDICT” “PREDICTPROBA”
“DECISIONFUNCTION” “TRANSFORM” AND “INVERSETRANSFORM” IF THEY ARE IMPLEMENTED IN THE ESTIMATOR USED
626SKLEARNMODELSELECTION MODEL SELECTION 2103

THE PARAMETERS OF THE ESTIMATOR USED TO APPLY THESE METHODS ARE OPTIMIZED BY CROSSVALIDATED SEARCH OVER PARAMETER SETTINGS
IN CONTRAST TO GRIDSEARCHCV NOT ALL PARAMETER VALUES ARE TRIED OUT BUT RATHER A FIXED NUMBER OF PARAMETER SETTINGS IS SAMPLED FROM THE SPECIFIED DISTRIBUTIONS THE NUMBER OF PARAMETER SETTINGS THAT ARE TRIED IS GIVEN BY NITER
IF ALL PARAMETERS ARE PRESENTED AS A LIST SAMPLING WITHOUT REPLACEMENT IS PERFORMED IF AT LEAST ONE PARAMETER IS GIVEN AS A DISTRIBUTION SAMPLING WITH REPLACEMENT IS USED IT IS HIGHLY RECOMMENDED TO USE CONTINUOUS DISTRIBUTIONS FOR CONTINUOUS PARAMETERS
NOTE THAT BEFORE SCIPY 016 THE SCIPYSTATSDISTRIBUTIONS DO NOT ACCEPT A CUSTOM RNG INSTANCE AND ALWAYS USE THE SINGLETON RNG FROM NUMPYRANDOM HENCE SETTING RANDOMSTATE WILL NOT GUARANTEE A DETERMINISTIC ITERATION WHENEVER SCIPYSTATS DISTRIBUTIONS ARE USED TO DEFINE THE PARAMETER SEARCH SPACE
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT A OBJECT OF THAT TYPE IS INSTANTIATED FOR EACH GRID POINT THIS IS ASSUMED TO IMPLEMENT THE SCIKITLEARN ESTIMATOR INTERFACE EITHER ESTIMATOR NEEDS TO PROVIDE ASCORE FUNCTION OR SCORING MUST BE PASSED
PARAMDISTRIBUTIONS DICT DICTIONARY WITH PARAMETERS NAMES STRING AS KEYS AND DISTRIBUTIONS OR LISTS OF PARAMETERS TO TRY DISTRIBUTIONS MUST PROVIDE A RVS METHOD FOR SAMPLING SUCH AS THOSE FROM SCIPYSTATSDISTRIBUTIONS IF A LIST IS GIVEN IT IS SAMPLED UNIFORMLY
NITER INT DEFAULT10 NUMBER OF PARAMETER SETTINGS THAT ARE SAMPLED NITER TRADES OFF RUNTIME VS QUALITY OF THE SOLUTION
SCORING STRING CALLABLE LISTTUPLE DICT OR NONE DEFAULT NONE A SINGLE STRING SEE THE SCORING PARAMETER DEFINING MODEL EVALUATION RULES OR A CALLABLE SEE DEFINING YOUR SCORING STRATEGY FROM METRIC FUNCTIONS TO EVALUATE THE PREDICTIONS ON THE TEST SET
FOR EVALUATING MULTIPLE METRICS EITHER GIVE A LIST OF UNIQUE STRINGS OR A DICT WITH NAMES AS KEYS AND CALLABLES AS VALUES
NOTE THAT WHEN USING CUSTOM SCORERS EACH SCORER SHOULD RETURN A SINGLE VALUE METRIC FUNCTIONS RETURNING A LISTARRAY OF VALUES CAN BE WRAPPED INTO MULTIPLE SCORERS THAT RETURN ONE VALUE EACH
SEESPECIFYING MULTIPLE METRICS FOR EVALUATION FOR AN EXAMPLE
IF NONE THE ESTIMATOR’S SCORE METHOD IS USED
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF JOBS TO RUN IN PARALLEL NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
PREDISPATCH INT OR STRING OPTIONAL CONTROLS THE NUMBER OF JOBS THAT GET DISPATCHED DURING PARALLEL EXECUTION REDUCING THIS NUMBER CAN BE USEFUL TO AVOID AN EXPLOSION OF MEMORY CONSUMPTION WHEN MORE JOBS GET DISPATCHED THAN CPUS CAN PROCESS THIS PARAMETER CAN BE
• NONE IN WHICH CASE ALL THE JOBS ARE IMMEDIATELY CREATED AND SPAWNED USE THIS FOR LIGHTWEIGHT AND FASTRUNNING JOBS TO AVOID DELAYS DUE TO ONDEMAND SPAWNING OF THE JOBS
• AN INT GIVING THE EXACT NUMBER OF TOTAL JOBS THAT ARE SPAWNED
• A STRING GIVING AN EXPRESSION AS A FUNCTION OF NJOBS AS IN ‘2NJOBS’

IIDBOOLEAN DEFAULT'WARN' IF TRUE RETURN THE AVERAGE SCORE ACROSS FOLDS WEIGHTED BY THE NUMBER OF SAMPLES IN EACH TEST SET IN THIS CASE THE DATA IS ASSUMED TO BE IDENTICALLY DIS TRIBUTED ACROSS THE FOLDS AND THE LOSS MINIMIZED IS THE TOTAL LOSS PER SAMPLE AND NOT THE MEAN LOSS ACROSS THE FOLDS IF FALSE RETURN THE AVERAGE SCORE ACROSS FOLDS DEFAULT IS TRUE BUT WILL CHANGE TO FALSE IN VERSION 022 TO CORRESPOND TO THE STANDARD DEFINITION OF CROSS VALIDATION
CHANGED IN VERSION 020 PARAMETER IID WILL CHANGE FROM TRUE TO FALSE BY DEFAULT IN VERSION 022 AND WILL BE REMOVED IN 024
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSS VALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS IN A STRATIFIEDKFOLD
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF THE ESTIMATOR IS A CLASSIFIER AND YIS EITHER BINARY OR MULTICLASS STRATIFIEDKFOLD IS USED IN ALL OTHER CASES KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN V022
REFIT BOOLEAN STRING OR CALLABLE DEFAULTTRUE REFIT AN ESTIMATOR USING THE BEST FOUND PARAM ETERS ON THE WHOLE DATASET
FOR MULTIPLE METRIC EVALUATION THIS NEEDS TO BE A STRING DENOTING THE SCORER THAT WOULD BE USED TO FIND THE BEST PARAMETERS FOR REFITTING THE ESTIMATOR AT THE END
WHERE THERE ARE CONSIDERATIONS OTHER THAN MAXIMUM SCORE IN CHOOSING A BEST ESTIMATOR REFIT CAN BE SET TO A FUNCTION WHICH RETURNS THE SELECTED BESTINDEX GIVEN THE CVRESULTS
THE REFITTED ESTIMATOR IS MADE AVAILABLE AT THE BESTESTIMATOR ATTRIBUTE AND PERMITS USINGPREDICT DIRECTLY ON THIS RANDOMIZEDSEARCHCV INSTANCE
ALSO FOR MULTIPLE METRIC EVALUATION THE ATTRIBUTES BESTINDEX BESTSCORE AND BESTPARAMS WILL ONLY BE AVAILABLE IF REFIT IS SET AND ALL OF THEM WILL BE DETERMINED WRT THIS SPECIFIC SCORER WHEN REFIT IS CALLABLE BESTSCORE IS DISABLED
SEESCORING PARAMETER TO KNOW MORE ABOUT MULTIPLE METRIC EVALUATION
CHANGED IN VERSION 020 SUPPORT FOR CALLABLE ADDED
VERBOSE INTEGER CONTROLS THE VERBOSITY THE HIGHER THE MORE MESSAGES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE PSEUDO RANDOM NUMBER GENERATOR STATE USED FOR RANDOM UNIFORM SAMPLING FROM LISTS OF POSSIBLE VALUES INSTEAD OF SCIPYSTATS DISTRIBUTIONS IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ERRORSCORE 'RAISE' OR NUMERIC VALUE TO ASSIGN TO THE SCORE IF AN ERROR OCCURS IN ESTIMATOR FITTING IF SET TO 'RAISE' THE ERROR IS RAISED IF A NUMERIC VALUE IS GIVEN FITFAILEDWARNING IS RAISED THIS PARAMETER DOES NOT AFFECT THE REFIT STEP WHICH WILL ALWAYS RAISE THE ERROR DEFAULT IS 'RAISE' BUT FROM VERSION 022 IT WILL CHANGE TO NPNAN

RETURNTRAINSCORE BOOLEAN DEFAULTFALSE IF FALSE THECVRESULTS ATTRIBUTE WILL NOT
INCLUDE TRAINING SCORES COMPUTING TRAINING SCORES IS USED TO GET INSIGHTS ON HOW DIFFER
ENT PARAMETER SETTINGS IMPACT THE OVERFITTINGUNDERFITTING TRADEOFF HOWEVER COMPUTING THE
SCORES ON THE TRAINING SET CAN BE COMPUTATIONALLY EXPENSIVE AND IS NOT STRICTLY REQUIRED TO
SELECT THE PARAMETERS THAT YIELD THE BEST GENERALIZATION PERFORMANCE
ATTRIBUTES
CVRESULTS DICT OF NUMPY MASKED NDARRAYS A DICT WITH KEYS AS COLUMN HEADERS AND VALUES
AS COLUMNS THAT CAN BE IMPORTED INTO A PANDAS DATAFRAME
FOR INSTANCE THE BELOW GIVEN TABLE
PARAMKERNEL PARAMGAMMA SPLIT0TESTSCORE RANKTESTSCORE
‘RBF’ 01 080 2
‘RBF’ 02 090 1
‘RBF’ 03 070 1
WILL BE REPRESENTED BY A CVRESULTS DICT OF

PARAMKERNEL MASKEDARRAYDATA RBF RBF RBF
MASK FALSE
PARAMGAMMA MASKEDARRAYDATA 01 02 03 MASK FALSE
SPLIT0TESTSCORE 080 090 070
SPLIT1TESTSCORE 082 050 070
MEANTESTSCORE 081 070 070
STDTESTSCORE 001 020 000
RANKTESTSCORE 3 1 1
SPLIT0TRAINSCORE 080 092 070
SPLIT1TRAINSCORE 082 055 070
MEANTRAINSCORE 081 074 070
STDTRAINSCORE 001 019 000
MEANFITTIME 073 063 043
STDFITTIME 001 002 001
MEANSCORETIME 001 006 004
STDSCORETIME 000 000 000
PARAMS KERNEL RBF GAMMA 01

NOTE
THE KEYPARAMS IS USED TO STORE A LIST OF PARAMETER SETTINGS DICTS FOR ALL THE PARAMETER
CANDIDATES
THEMEANFITTIME STDFITTIME MEANSCORETIME AND
STDSCORETIME ARE ALL IN SECONDS
FOR MULTIMETRIC EVALUATION THE SCORES FOR ALL THE SCORERS ARE AVAILABLE IN THE
CVRESULTS DICT AT THE KEYS ENDING WITH THAT SCORER’S NAME SCORERNAME
INSTEAD OFSCORE SHOWN ABOVE ‘SPLIT0TESTPRECISION’ ‘MEANTRAINPRECISION’ ETC
BESTESTIMATOR ESTIMATOR OR DICT ESTIMATOR THAT WAS CHOSEN BY THE SEARCH IE ESTIMATOR
WHICH GAVE HIGHEST SCORE OR SMALLEST LOSS IF SPECIFIED ON THE LEFT OUT DATA NOT AVAILABLE IF
REFITFALSE
FOR MULTIMETRIC EVALUATION THIS ATTRIBUTE IS PRESENT ONLY IF REFIT IS SPECIFIED
SEEREFIT PARAMETER FOR MORE INFORMATION ON ALLOWED VALUES

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BESTSCORE FLOAT MEAN CROSSVALIDATED SCORE OF THE BESTESTIMATOR
FOR MULTIMETRIC EVALUATION THIS IS NOT AVAILABLE IF REFIT ISFALSE SEEREFIT PARAMETER
FOR MORE INFORMATION
BESTPARAMS DICT PARAMETER SETTING THAT GAVE THE BEST RESULTS ON THE HOLD OUT DATA
FOR MULTIMETRIC EVALUATION THIS IS NOT AVAILABLE IF REFIT ISFALSE SEEREFIT PARAMETER
FOR MORE INFORMATION
BESTINDEX INT THE INDEX OF THE CVRESULTS ARRAYS WHICH CORRESPONDS TO THE BEST CAN
DIDATE PARAMETER SETTING
THE DICT AT SEARCHCVRESULTSPARAMSSEARCHBESTINDEX GIVES
THE PARAMETER SETTING FOR THE BEST MODEL THAT GIVES THE HIGHEST MEAN SCORE SEARCH
BESTSCORE
FOR MULTIMETRIC EVALUATION THIS IS NOT AVAILABLE IF REFIT ISFALSE SEEREFIT PARAMETER
FOR MORE INFORMATION
SCORER FUNCTION OR A DICT SCORER FUNCTION USED ON THE HELD OUT DATA TO CHOOSE THE BEST PARAM
ETERS FOR THE MODEL
FOR MULTIMETRIC EVALUATION THIS ATTRIBUTE HOLDS THE VALIDATED SCORING DICT WHICH MAPS
THE SCORER KEY TO THE SCORER CALLABLE
NSPLITS INT THE NUMBER OF CROSSVALIDATION SPLITS FOLDSITERATIONS
REFITTIME FLOAT SECONDS USED FOR REFITTING THE BEST MODEL ON THE WHOLE DATASET
THIS IS PRESENT ONLY IF REFIT IS NOT FALSE
SEE ALSO
GRIDSEARCHCV DOES EXHAUSTIVE SEARCH OVER A GRID OF PARAMETERS
PARAMETERSAMPLER A GENERATOR OVER PARAMETER SETTINGS CONSTRUCTED FROM PARAMDISTRIBUTIONS
NOTES
THE PARAMETERS SELECTED ARE THOSE THAT MAXIMIZE THE SCORE OF THE HELDOUT DATA ACCORDING TO THE SCORING PARAM
ETER
IFNJOBS WAS SET TO A VALUE HIGHER THAN ONE THE DATA IS COPIED FOR EACH PARAMETER SETTINGAND NOT NJOBS TIMES
THIS IS DONE FOR EFFICIENCY REASONS IF INDIVIDUAL JOBS TAKE VERY LITTLE TIME BUT MAY RAISE ERRORS IF THE DATASET
IS LARGE AND NOT ENOUGH MEMORY IS AVAILABLE A WORKAROUND IN THIS CASE IS TO SET PREDISPATCH THEN
THE MEMORY IS COPIED ONLY PREDISPATCH MANY TIMES A REASONABLE VALUE FOR PREDISPATCH IS2
NJOBS
METHODS
DECISIONFUNCTION SELF X CALL DECISIONFUNCTION ON THE ESTIMATOR WITH THE BEST
FOUND PARAMETERS
FITSELF X Y GROUPS RUN FIT WITH ALL SETS OF PARAMETERS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF XT CALL INVERSETRANSFORM ON THE ESTIMATOR WITH THE BEST
FOUND PARAMS
CONTINUED ON NEXT PAGE

TABLE 6206 – CONTINUED FROM PREVIOUS PAGE
PREDICT SELF X CALL PREDICT ON THE ESTIMATOR WITH THE BEST FOUND PARAM
ETERS
PREDICTLOGPROBA SELF X CALL PREDICTLOGPROBA ON THE ESTIMATOR WITH THE BEST
FOUND PARAMETERS
PREDICTPROBA SELF X CALL PREDICTPROBA ON THE ESTIMATOR WITH THE BEST FOUND
PARAMETERS
SCORE SELF X Y RETURNS THE SCORE ON THE GIVEN DATA IF THE ESTIMATOR HAS
BEEN REFIT
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X CALL TRANSFORM ON THE ESTIMATOR WITH THE BEST FOUND PA
RAMETERS
INIT SELFESTIMATOR PARAMDISTRIBUTIONS NITER10 SCORINGNONE NJOBSNONE IID'WARN'
REFITTRUE CV'WARN' VERBOSE0 PREDISPATCH'2NJOBS' RANDOMSTATENONE
ERRORSCORE'RAISEDEPRECATING' RETURNTRAINSCOREFALSE
DECISIONFUNCTION SELFX
CALL DECISIONFUNCTION ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
ONLY AVAILABLE IF REFITTRUE AND THE UNDERLYING ESTIMATOR SUPPORTS DECISIONFUNCTION
PARAMETERS
XINDEXABLE LENGTH NSAMPLES MUST FULFILL THE INPUT ASSUMPTIONS OF THE UNDERLYING ESTI
MATOR
FITSELFXYNONE GROUPSNONE FITPARAMS
RUN FIT WITH ALL SETS OF PARAMETERS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IS THE
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GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED
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TOR
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
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DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
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INVERSETRANSFORM SELFXT
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PARAMETERS

XTINDEXABLE LENGTH NSAMPLES MUST FULFILL THE INPUT ASSUMPTIONS OF THE UNDERLYING ESTI
MATOR
PREDICTSELFX
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PARAMETERS
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MATOR
PREDICTLOGPROBA SELFX
CALL PREDICTLOGPROBA ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
ONLY AVAILABLE IF REFITTRUE AND THE UNDERLYING ESTIMATOR SUPPORTS PREDICTLOGPROBA
PARAMETERS
XINDEXABLE LENGTH NSAMPLES MUST FULFILL THE INPUT ASSUMPTIONS OF THE UNDERLYING ESTI
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CALL PREDICTPROBA ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
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RETURNS
SCORE FLOAT
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
CALL TRANSFORM ON THE ESTIMATOR WITH THE BEST FOUND PARAMETERS
ONLY AVAILABLE IF THE UNDERLYING ESTIMATOR SUPPORTS TRANSFORM ANDREFITTRUE

PARAMETERS
XINDEXABLE LENGTH NSAMPLES MUST FULFILL THE INPUT ASSUMPTIONS OF THE UNDERLYING ESTI
MATOR
EXAMPLES USING SKLEARNMODELSELECTIONRANDOMIZEDSEARCHCV
•COMPARING RANDOMIZED SEARCH AND GRID SEARCH FOR HYPERPARAMETER ESTIMATION
MODELSELECTIONFITGRIDPOINT X Y
RUN FIT ON ONE SET OF PARAMETERS
SKLEARNMODELSELECTION FITGRIDPOINT
SKLEARNMODELSELECTION FITGRIDPOINT XYESTIMATOR PARAMETERS TRAIN TESTSCORER
VERBOSE ERRORSCORE'RAISEDEPRECATING'
FITPARAMS
RUN FIT ON ONE SET OF PARAMETERS
PARAMETERS
XARRAYLIKE SPARSE MATRIX OR LIST INPUT DATA
YARRAYLIKE OR NONE TARGETS FOR INPUT DATA
ESTIMATOR ESTIMATOR OBJECT A OBJECT OF THAT TYPE IS INSTANTIATED FOR EACH GRID POINT THIS IS
ASSUMED TO IMPLEMENT THE SCIKITLEARN ESTIMATOR INTERFACE EITHER ESTIMATOR NEEDS TO PROVIDE
ASCORE FUNCTION OR SCORING MUST BE PASSED
PARAMETERS DICT PARAMETERS TO BE SET ON ESTIMATOR FOR THIS GRID POINT
TRAIN NDARRAY DTYPE INT OR BOOL BOOLEAN MASK OR INDICES FOR TRAINING SET
TEST NDARRAY DTYPE INT OR BOOL BOOLEAN MASK OR INDICES FOR TEST SET
SCORER CALLABLE OR NONE THE SCORER CALLABLE OBJECT FUNCTION MUST HAVE ITS SIGNATURE AS
SCORERESTIMATOR X Y
IFNONE THE ESTIMATOR'S SCORE METHOD IS USED
VERBOSE INT VERBOSITY LEVEL
FITPARAMS KWARGS ADDITIONAL PARAMETER PASSED TO THE FIT FUNCTION OF THE ESTIMATOR
ERRORSCORE 'RAISE' OR NUMERIC VALUE TO ASSIGN TO THE SCORE IF AN ERROR OCCURS IN ESTIMATOR
FITTING IF SET TO 'RAISE' THE ERROR IS RAISED IF A NUMERIC VALUE IS GIVEN FITFAILEDWARNING
IS RAISED THIS PARAMETER DOES NOT AFFECT THE REFIT STEP WHICH WILL ALWAYS RAISE THE ERROR
DEFAULT IS 'RAISE' BUT FROM VERSION 022 IT WILL CHANGE TO NPNAN
RETURNS
SCORE FLOAT SCORE OF THIS PARAMETER SETTING ON GIVEN TEST SPLIT
PARAMETERS DICT THE PARAMETERS THAT HAVE BEEN EVALUATED
NSAMPLESTEST INT NUMBER OF TEST SAMPLES IN THIS SPLIT

MODELSELECTIONCROSSVALIDATE ESTIMATOR
XEVALUATE METRICS BY CROSSVALIDATION AND ALSO RECORD
FITSCORE TIMES
MODELSELECTIONCROSSVALPREDICT ESTIMATOR
XGENERATE CROSSVALIDATED ESTIMATES FOR EACH INPUT DATA POINT
MODELSELECTIONCROSSVALSCORE ESTIMATOR
XEVALUATE A SCORE BY CROSSVALIDATION
MODELSELECTIONLEARNINGCURVE ESTIMATOR X
YLEARNING CURVE
MODELSELECTIONPERMUTATIONTESTSCORE EVALUATE THE SIGNIFICANCE OF A CROSSVALIDATED SCORE WITH
PERMUTATIONS
MODELSELECTIONVALIDATIONCURVE ESTIMATOR
VALIDATION CURVE
SKLEARNMODELSELECTION CROSSVALIDATE
SKLEARNMODELSELECTION CROSSVALIDATE ESTIMATOR XYNONE GROUPSNONE SCOR
INGNONE CV'WARN' NJOBSNONE VERBOSE0
FITPARAMSNONE PREDISPATCH'2NJOBS' RE
TURNTRAINSCOREFALSE RETURNESTIMATORFALSE
ERRORSCORE'RAISEDEPRECATING'
EVALUATE METRICS BY CROSSVALIDATION AND ALSO RECORD FITSCORE TIMES
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT IMPLEMENTING 'FIT' THE OBJECT TO USE TO FIT THE DATA
XARRAYLIKE THE DATA TO FIT CAN BE FOR EXAMPLE A LIST OR AN ARRAY
YARRAYLIKE OPTIONAL DEFAULT NONE THE TARGET VARIABLE TO TRY TO PREDICT IN THE CASE OF SUPER
VISED LEARNING
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED WHILE
SPLITTING THE DATASET INTO TRAINTEST SET ONLY USED IN CONJUNCTION WITH A "GROUP" CVINSTANCE
EGGROUPKFOLD
SCORING STRING CALLABLE LISTTUPLE DICT OR NONE DEFAULT NONE A SINGLE STRING SEE THE SCORING
PARAMETER DEFINING MODEL EVALUATION RULES OR A CALLABLE SEE DEFINING YOUR SCORING STRATEGY
FROM METRIC FUNCTIONS TO EVALUATE THE PREDICTIONS ON THE TEST SET
FOR EVALUATING MULTIPLE METRICS EITHER GIVE A LIST OF UNIQUE STRINGS OR A DICT WITH NAMES AS
KEYS AND CALLABLES AS VALUES
NOTE THAT WHEN USING CUSTOM SCORERS EACH SCORER SHOULD RETURN A SINGLE VALUE METRIC
FUNCTIONS RETURNING A LISTARRAY OF VALUES CAN BE WRAPPED INTO MULTIPLE SCORERS THAT RETURN
ONE VALUE EACH
SEESPECIFYING MULTIPLE METRICS FOR EVALUATION FOR AN EXAMPLE
IF NONE THE ESTIMATOR'S SCORE METHOD IS USED
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSS VALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS IN A STRATIFIEDKFOLD
•CV SPLITTER
626SKLEARNMODELSELECTION MODEL SELECTION 2111

• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF THE ESTIMATOR IS A CLASSIFIER AND YIS EITHER BINARY OR MULTICLASS
STRATIFIEDKFOLD IS USED IN ALL OTHER CASES KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF CPUS TO USE TO DO THE COMPUTA
TIONNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING
ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
VERBOSE INTEGER OPTIONAL THE VERBOSITY LEVEL
FITPARAMS DICT OPTIONAL PARAMETERS TO PASS TO THE FIT METHOD OF THE ESTIMATOR
PREDISPATCH INT OR STRING OPTIONAL CONTROLS THE NUMBER OF JOBS THAT GET DISPATCHED DURING
PARALLEL EXECUTION REDUCING THIS NUMBER CAN BE USEFUL TO AVOID AN EXPLOSION OF MEMORY
CONSUMPTION WHEN MORE JOBS GET DISPATCHED THAN CPUS CAN PROCESS THIS PARAMETER CAN
BE
• NONE IN WHICH CASE ALL THE JOBS ARE IMMEDIATELY CREATED AND SPAWNED USE THIS FOR
LIGHTWEIGHT AND FASTRUNNING JOBS TO AVOID DELAYS DUE TO ONDEMAND SPAWNING OF THE JOBS
• AN INT GIVING THE EXACT NUMBER OF TOTAL JOBS THAT ARE SPAWNED
• A STRING GIVING AN EXPRESSION AS A FUNCTION OF NJOBS AS IN ‘2NJOBS’
RETURNTRAINSCORE BOOLEAN DEFAULTFALSE WHETHER TO INCLUDE TRAIN SCORES COMPUTING TRAIN
ING SCORES IS USED TO GET INSIGHTS ON HOW DIFFERENT PARAMETER SETTINGS IMPACT THE OVERFIT
TINGUNDERFITTING TRADEOFF HOWEVER COMPUTING THE SCORES ON THE TRAINING SET CAN BE COM
PUTATIONALLY EXPENSIVE AND IS NOT STRICTLY REQUIRED TO SELECT THE PARAMETERS THAT YIELD THE BEST
GENERALIZATION PERFORMANCE
RETURNESTIMATOR BOOLEAN DEFAULT FALSE WHETHER TO RETURN THE ESTIMATORS FITTED ON EACH SPLIT
ERRORSCORE ‘RAISE’ ‘RAISEDEPRECATING’ OR NUMERIC VALUE TO ASSIGN TO THE SCORE IF AN ERROR
OCCURS IN ESTIMATOR FITTING IF SET TO ‘RAISE’ THE ERROR IS RAISED IF SET TO ‘RAISEDEPRECATING’
A FUTUREWARNING IS PRINTED BEFORE THE ERROR IS RAISED IF A NUMERIC VALUE IS GIVEN FITFAILED
WARNING IS RAISED THIS PARAMETER DOES NOT AFFECT THE REFIT STEP WHICH WILL ALWAYS RAISE THE
ERROR DEFAULT IS ‘RAISEDEPRECATING’ BUT FROM VERSION 022 IT WILL CHANGE TO NPNAN
RETURNS
SCORES DICT OF FLOAT ARRAYS OF SHAPENSPLITS ARRAY OF SCORES OF THE ESTIMATOR FOR EACH RUN OF
THE CROSS VALIDATION
A DICT OF ARRAYS CONTAINING THE SCORETIME ARRAYS FOR EACH SCORER IS RETURNED THE POSSIBLE
KEYS FOR THIS DICT ARE
TESTSCORE THE SCORE ARRAY FOR TEST SCORES ON EACH CV SPLIT
TRAINSCORE THE SCORE ARRAY FOR TRAIN SCORES ON EACH CV SPLIT THIS IS AVAILABLE
ONLY IFRETURNTRAINSCORE PARAMETER IS TRUE
FITTIME THE TIME FOR FITTING THE ESTIMATOR ON THE TRAIN SET FOR EACH CV SPLIT
SCORETIME THE TIME FOR SCORING THE ESTIMATOR ON THE TEST SET FOR EACH CV
SPLIT NOTE TIME FOR SCORING ON THE TRAIN SET IS NOT INCLUDED EVEN IF
RETURNTRAINSCORE IS SET TOTRUE

ESTIMATOR THE ESTIMATOR OBJECTS FOR EACH CV SPLIT THIS IS AVAILABLE ONLY IF
RETURNESTIMATOR PARAMETER IS SET TO TRUE
SEE ALSO
SKLEARNMODELSELECTIONCROSSVALSCORE RUN CROSSVALIDATION FOR SINGLE METRIC EVALUATION
SKLEARNMODELSELECTIONCROSSVALPREDICT GET PREDICTIONS FROM EACH SPLIT OF CROSS
VALIDATION FOR DIAGNOSTIC PURPOSES
SKLEARNMETRICSMAKESCORER MAKE A SCORER FROM A PERFORMANCE METRIC OR LOSS FUNCTION
EXAMPLES
```
 FROM SKLEARN IMPORT DATASETS LINEARMODEL
 FROM SKLEARNMODELSELECTION IMPORT CROSSVALIDATE
 FROM SKLEARNMETRICSSCORER IMPORT MAKESCORER
 FROM SKLEARNMETRICS IMPORT CONFUSIONMATRIX
 FROM SKLEARNSVM IMPORT LINEARSVC
DIABETES  DATASETSLOADDIABETES
X  DIABETESDATA150
Y  DIABETESTARGET150
LASSO  LINEARMODELLASSO
SINGLE METRIC EVALUATION USING CROSSVALIDATE
CVRESULTS  CROSSVALIDATELASSO X Y CV3
SORTEDCVRESULTSKEYS
FITTIME SCORETIME TESTSCORE
CVRESULTSTESTSCORE
ARRAY033150734 008022311 003531764
MULTIPLE METRIC EVALUATION USING CROSSVALIDATE PLEASE REFER THE SCORING PARAMETER DOC FOR MORE IN
FORMATION
SCORES  CROSSVALIDATELASSO X Y CV3
 SCORINGR2 NEGMEANSQUAREDERROR
 RETURNTRAINSCORE TRUE
PRINTSCORESTESTNEGMEANSQUAREDERROR
36355 35733 61147
PRINTSCORESTRAINR2
028010158 039088426 022784852
SKLEARNMODELSELECTION CROSSVALPREDICT
SKLEARNMODELSELECTION CROSSVALPREDICT ESTIMATOR  XYNONE  GROUPSNONE
CV'WARN'  NJOBSNONE  VERBOSE0
FITPARAMSNONE PREDISPATCH'2NJOBS'
METHOD'PREDICT'
```
GENERATE CROSSVALIDATED ESTIMATES FOR EACH INPUT DATA POINT
THE DATA IS SPLIT ACCORDING TO THE CV PARAMETER EACH SAMPLE BELONGS TO EXACTLY ONE TEST SET AND ITS PREDICTION IS
COMPUTED WITH AN ESTIMATOR FITTED ON THE CORRESPONDING TRAINING SET
PASSING THESE PREDICTIONS INTO AN EVALUATION METRIC MAY NOT BE A VALID WAY TO MEASURE GENERALIZATION PERFOR
MANCE RESULTS CAN DIFFER FROM CROSSVALIDATE ANDCROSSVALSCORE UNLESS ALL TESTS SETS HAVE EQUAL
SIZE AND THE METRIC DECOMPOSES OVER SAMPLES

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READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT IMPLEMENTING ‘FIT’ AND ‘PREDICT’ THE OBJECT TO USE TO FIT THE DATA
XARRAYLIKE THE DATA TO FIT CAN BE FOR EXAMPLE A LIST OR AN ARRAY AT LEAST 2D
YARRAYLIKE OPTIONAL DEFAULT NONE THE TARGET VARIABLE TO TRY TO PREDICT IN THE CASE OF SUPER
VISED LEARNING
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED WHILE
SPLITTING THE DATASET INTO TRAINTEST SET ONLY USED IN CONJUNCTION WITH A “GROUP” CVINSTANCE
EGGROUPKFOLD
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSS VALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS IN A STRATIFIEDKFOLD
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF THE ESTIMATOR IS A CLASSIFIER AND YIS EITHER BINARY OR MULTICLASS
STRATIFIEDKFOLD IS USED IN ALL OTHER CASES KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF CPUS TO USE TO DO THE COMPUTA
TIONNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING
ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
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PARALLEL EXECUTION REDUCING THIS NUMBER CAN BE USEFUL TO AVOID AN EXPLOSION OF MEMORY
CONSUMPTION WHEN MORE JOBS GET DISPATCHED THAN CPUS CAN PROCESS THIS PARAMETER CAN
BE
• NONE IN WHICH CASE ALL THE JOBS ARE IMMEDIATELY CREATED AND SPAWNED USE THIS FOR
LIGHTWEIGHT AND FASTRUNNING JOBS TO AVOID DELAYS DUE TO ONDEMAND SPAWNING OF THE JOBS
• AN INT GIVING THE EXACT NUMBER OF TOTAL JOBS THAT ARE SPAWNED
• A STRING GIVING AN EXPRESSION AS A FUNCTION OF NJOBS AS IN ‘2NJOBS’
METHOD STRING OPTIONAL DEFAULT ‘PREDICT’ INVOKES THE PASSED METHOD NAME OF THE PASSED
ESTIMATOR FOR METHOD’PREDICTPROBA’ THE COLUMNS CORRESPOND TO THE CLASSES IN SORTED
ORDER
RETURNS
PREDICTIONS NDARRAY THIS IS THE RESULT OF CALLING METHOD
SEE ALSO
CROSSVALSCORE CALCULATE SCORE FOR EACH CV SPLIT

CROSSVALIDATE CALCULATE ONE OR MORE SCORES AND TIMINGS FOR EACH CV SPLIT
NOTES
IN THE CASE THAT ONE OR MORE CLASSES ARE ABSENT IN A TRAINING PORTION A DEFAULT SCORE NEEDS TO BE ASSIGNED TO ALL INSTANCES FOR THAT CLASS IF METHOD PRODUCES COLUMNS PER CLASS AS IN ‘DECISIONFUNCTION’ ‘PREDICTPROBA’ ‘PREDICTLOGPROBA’ FOR PREDICTPROBA THIS VALUE IS 0 IN ORDER TO ENSURE FINITE OUTPUT WE APPROXIMATE NEGATIVE INFINITY BY THE MINIMUM FINITE FLOAT VALUE FOR THE DTYPE IN OTHER CASES
EXAMPLES
FROM SKLEARN IMPORT DATASETS LINEARMODEL
FROM SKLEARNMODELSELECTION IMPORT CROSSVALPREDICT
DIABETES DATASETSLOADDIABETES
X DIABETESDATA150
Y DIABETESTARGET150
LASSO LINEARMODELLASSO
YPRED CROSSVALPREDICTLASSO X Y CV3
EXAMPLES USING SKLEARNMODELSELECTIONCROSSVALPREDICT
•PLOTTING CROSSVALIDATED PREDICTIONS
SKLEARNMODELSELECTION CROSSVALSCORE
SKLEARNMODELSELECTION CROSSVALSCORE ESTIMATOR XYNONE GROUPSNONE SCOR INGNONE CV’WARN’ NJOBSNONE VERBOSE0 FITPARAMSNONE PREDISPATCH‘2NJOBS’ ERRORSCORE‘RAISEDEPRECATING’
EVALUATE A SCORE BY CROSSVALIDATION
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT IMPLEMENTING ‘FIT’ THE OBJECT TO USE TO FIT THE DATA
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YARRAYLIKE OPTIONAL DEFAULT NONE THE TARGET VARIABLE TO TRY TO PREDICT IN THE CASE OF SUPER VISED LEARNING
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED WHILE SPLITTING THE DATASET INTO TRAINTEST SET ONLY USED IN CONJUNCTION WITH A “GROUP” CVINSTANCE EGGROUPKFOLD
SCORING STRING CALLABLE OR NONE OPTIONAL DEFAULT NONE A STRING SEE MODEL EVALUATION DOC UMENTATION OR A SCORER CALLABLE OBJECT FUNCTION WITH SIGNATURE SCORERESTIMATOR X Y WHICH SHOULD RETURN ONLY A SINGLE VALUE
SIMILAR TOCROSSVALIDATE BUT ONLY A SINGLE METRIC IS PERMITTED
IF NONE THE ESTIMATOR’S DEFAULT SCORER IF AVAILABLE IS USED

CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSS VALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS IN A STRATIFIEDKFOLD
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF THE ESTIMATOR IS A CLASSIFIER AND YIS EITHER BINARY OR MULTICLASS
STRATIFIEDKFOLD IS USED IN ALL OTHER CASES KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF CPUS TO USE TO DO THE COMPUTA
TIONNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING
ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
VERBOSE INTEGER OPTIONAL THE VERBOSITY LEVEL
FITPARAMS DICT OPTIONAL PARAMETERS TO PASS TO THE FIT METHOD OF THE ESTIMATOR
PREDISPATCH INT OR STRING OPTIONAL CONTROLS THE NUMBER OF JOBS THAT GET DISPATCHED DURING
PARALLEL EXECUTION REDUCING THIS NUMBER CAN BE USEFUL TO AVOID AN EXPLOSION OF MEMORY
CONSUMPTION WHEN MORE JOBS GET DISPATCHED THAN CPUS CAN PROCESS THIS PARAMETER CAN
BE
• NONE IN WHICH CASE ALL THE JOBS ARE IMMEDIATELY CREATED AND SPAWNED USE THIS FOR
LIGHTWEIGHT AND FASTRUNNING JOBS TO AVOID DELAYS DUE TO ONDEMAND SPAWNING OF THE JOBS
• AN INT GIVING THE EXACT NUMBER OF TOTAL JOBS THAT ARE SPAWNED
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ERRORSCORE ‘RAISE’ ‘RAISEDEPRECATING’ OR NUMERIC VALUE TO ASSIGN TO THE SCORE IF AN ERROR
OCCURS IN ESTIMATOR FITTING IF SET TO ‘RAISE’ THE ERROR IS RAISED IF SET TO ‘RAISEDEPRECATING’
A FUTUREWARNING IS PRINTED BEFORE THE ERROR IS RAISED IF A NUMERIC VALUE IS GIVEN FITFAILED
WARNING IS RAISED THIS PARAMETER DOES NOT AFFECT THE REFIT STEP WHICH WILL ALWAYS RAISE THE
ERROR DEFAULT IS ‘RAISEDEPRECATING’ BUT FROM VERSION 022 IT WILL CHANGE TO NPNAN
RETURNS
SCORES ARRAY OF FLOAT SHAPELENLISTCV ARRAY OF SCORES OF THE ESTIMATOR FOR EACH RUN OF THE
CROSS VALIDATION
SEE ALSO
SKLEARNMODELSELECTIONCROSSVALIDATE TO RUN CROSSVALIDATION ON MULTIPLE METRICS AND ALSO
TO RETURN TRAIN SCORES FIT TIMES AND SCORE TIMES
SKLEARNMODELSELECTIONCROSSVALPREDICT GET PREDICTIONS FROM EACH SPLIT OF CROSS
VALIDATION FOR DIAGNOSTIC PURPOSES
SKLEARNMETRICSMAKESCORER MAKE A SCORER FROM A PERFORMANCE METRIC OR LOSS FUNCTION

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EXAMPLES
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 FROM SKLEARN IMPORT DATASETS LINEARMODEL
 FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
DIABETES  DATASETSLOADDIABETES
X  DIABETESDATA150
Y  DIABETESTARGET150
LASSO  LINEARMODELLASSO
PRINTCROSSVALSCORELASSO X Y CV3
033150734 008022311 003531764
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EXAMPLES USING SKLEARNMODELSELECTIONCROSSVALSCORE
•MODEL SELECTION WITH PROBABILISTIC PCA AND FACTOR ANALYSIS FA
•CROSSVALIDATION ON DIGITS DATASET EXERCISE
•IMPUTING MISSING VALUES WITH VARIANTS OF ITERATIVEIMPUTER
•IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR
•UNDERFITTING VS OVERFITTING
•NESTED VERSUS NONNESTED CROSSVALIDATION
•SVMANOVA SVM WITH UNIVARIATE FEATURE SELECTION
SKLEARNMODELSELECTION LEARNINGCURVE
SKLEARNMODELSELECTION LEARNINGCURVE ESTIMATOR X Y GROUPSNONE
TRAINSIZESARRAY01 0325 0550775
1 CV’WARN’ SCORINGNONE EX
PLOITINCREMENTALLEARNINGFALSE NJOBSNONE
PREDISPATCH’ALL’ VERBOSE0 SHUFFLEFALSE RAN
DOMSTATENONE ERRORSCORE’RAISEDEPRECATING’
LEARNING CURVE
DETERMINES CROSSVALIDATED TRAINING AND TEST SCORES FOR DIFFERENT TRAINING SET SIZES
A CROSSVALIDATION GENERATOR SPLITS THE WHOLE DATASET K TIMES IN TRAINING AND TEST DATA SUBSETS OF THE TRAINING SET
WITH VARYING SIZES WILL BE USED TO TRAIN THE ESTIMATOR AND A SCORE FOR EACH TRAINING SUBSET SIZE AND THE TEST SET
WILL BE COMPUTED AFTERWARDS THE SCORES WILL BE AVERAGED OVER ALL K RUNS FOR EACH TRAINING SUBSET SIZE
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR OBJECT TYPE THAT IMPLEMENTS THE “FIT” AND “PREDICT” METHODS AN OBJECT OF THAT TYPE
WHICH IS CLONED FOR EACH VALIDATION
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IS THE NUMBER
OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NFEATURES OPTIONAL TARGET RELATIVE TO X FOR
CLASSIFICATION OR REGRESSION NONE FOR UNSUPERVISED LEARNING
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED WHILE
SPLITTING THE DATASET INTO TRAINTEST SET ONLY USED IN CONJUNCTION WITH A “GROUP” CVINSTANCE
EGGROUPKFOLD

TRAINSIZES ARRAYLIKE SHAPE NTICKS DTYPE FLOAT OR INT RELATIVE OR ABSOLUTE NUMBERS OF
TRAINING EXAMPLES THAT WILL BE USED TO GENERATE THE LEARNING CURVE IF THE DTYPE IS FLOAT
IT IS REGARDED AS A FRACTION OF THE MAXIMUM SIZE OF THE TRAINING SET THAT IS DETERMINED BY
THE SELECTED VALIDATION METHOD IE IT HAS TO BE WITHIN 0 1 OTHERWISE IT IS INTERPRETED
AS ABSOLUTE SIZES OF THE TRAINING SETS NOTE THAT FOR CLASSIFICATION THE NUMBER OF SAMPLES
USUALLY HAVE TO BE BIG ENOUGH TO CONTAIN AT LEAST ONE SAMPLE FROM EACH CLASS DEFAULT
NPLINSPACE01 10 5
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSS VALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS IN A STRATIFIEDKFOLD
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF THE ESTIMATOR IS A CLASSIFIER AND YIS EITHER BINARY OR MULTICLASS
STRATIFIEDKFOLD IS USED IN ALL OTHER CASES KFOLD IS USED
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CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
SCORING STRING CALLABLE OR NONE OPTIONAL DEFAULT NONE A STRING SEE MODEL EVALUATION DOC
UMENTATION OR A SCORER CALLABLE OBJECT FUNCTION WITH SIGNATURE SCORERESTIMATOR
X Y
EXPLOITINCREMENTALLEARNING BOOLEAN OPTIONAL DEFAULT FALSE IF THE ESTIMATOR SUPPORTS IN
CREMENTAL LEARNING THIS WILL BE USED TO SPEED UP FITTING FOR DIFFERENT TRAINING SET SIZES
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF JOBS TO RUN IN PARALLEL NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
PREDISPATCH INTEGER OR STRING OPTIONAL NUMBER OF PREDISPATCHED JOBS FOR PARALLEL EXECUTION
DEFAULT IS ALL THE OPTION CAN REDUCE THE ALLOCATED MEMORY THE STRING CAN BE AN EXPRESSION
LIKE ‘2NJOBS’
VERBOSE INTEGER OPTIONAL CONTROLS THE VERBOSITY THE HIGHER THE MORE MESSAGES
SHUFFLE BOOLEAN OPTIONAL WHETHER TO SHUFFLE TRAINING DATA BEFORE TAKING PREFIXES OF IT BASED
ON‘‘TRAINSIZES‘‘
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM USED WHEN SHUFFLE IS TRUE
ERRORSCORE ‘RAISE’ ‘RAISEDEPRECATING’ OR NUMERIC VALUE TO ASSIGN TO THE SCORE IF AN ERROR
OCCURS IN ESTIMATOR FITTING IF SET TO ‘RAISE’ THE ERROR IS RAISED IF SET TO ‘RAISEDEPRECATING’
A FUTUREWARNING IS PRINTED BEFORE THE ERROR IS RAISED IF A NUMERIC VALUE IS GIVEN FITFAILED
WARNING IS RAISED THIS PARAMETER DOES NOT AFFECT THE REFIT STEP WHICH WILL ALWAYS RAISE THE
ERROR DEFAULT IS ‘RAISEDEPRECATING’ BUT FROM VERSION 022 IT WILL CHANGE TO NPNAN
RETURNS
TRAINSIZESABS ARRAY SHAPE NUNIQUETICKS DTYPE INT NUMBERS OF TRAINING EXAMPLES THAT
HAS BEEN USED TO GENERATE THE LEARNING CURVE NOTE THAT THE NUMBER OF TICKS MIGHT BE LESS
THAN NTICKS BECAUSE DUPLICATE ENTRIES WILL BE REMOVED

TRAINSCORES ARRAY SHAPE NTICKS NCVFOLDS SCORES ON TRAINING SETS
TESTSCORES ARRAY SHAPE NTICKS NCVFOLDS SCORES ON TEST SET
NOTES
SEEEXAMPLESMODELSELECTIONPLOTLEARNINGCURVEPY
EXAMPLES USING SKLEARNMODELSELECTIONLEARNINGCURVE
•COMPARISON OF KERNEL RIDGE REGRESSION AND SVR
•PLOTTING LEARNING CURVES
SKLEARNMODELSELECTION PERMUTATIONTESTSCORE
SKLEARNMODELSELECTION PERMUTATIONTESTSCORE ESTIMATOR XY GROUPSNONE
CV'WARN' NPERMUTATIONS100
NJOBSNONE RANDOMSTATE0 VER
BOSE0 SCORINGNONE
EVALUATE THE SIGNIFICANCE OF A CROSSVALIDATED SCORE WITH PERMUTATIONS
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT IMPLEMENTING 'FIT' THE OBJECT TO USE TO FIT THE DATA
XARRAYLIKE OF SHAPE AT LEAST 2D THE DATA TO FIT
YARRAYLIKE THE TARGET VARIABLE TO TRY TO PREDICT IN THE CASE OF SUPERVISED LEARNING
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL LABELS TO CONSTRAIN PERMUTATION WITHIN
GROUPS IE YVALUES ARE PERMUTED AMONG SAMPLES WITH THE SAME GROUP IDENTIFIER WHEN NOT
SPECIFIEDYVALUES ARE PERMUTED AMONG ALL SAMPLES
WHEN A GROUPED CROSSVALIDATOR IS USED THE GROUP LABELS ARE ALSO PASSED ON TO THE SPLIT
METHOD OF THE CROSSVALIDATOR THE CROSSVALIDATOR USES THEM FOR GROUPING THE SAMPLES WHILE
SPLITTING THE DATASET INTO TRAINTEST SET
SCORING STRING CALLABLE OR NONE OPTIONAL DEFAULT NONE A SINGLE STRING SEE THE SCORING
PARAMETER DEFINING MODEL EVALUATION RULES OR A CALLABLE SEE DEFINING YOUR SCORING STRATEGY
FROM METRIC FUNCTIONS TO EVALUATE THE PREDICTIONS ON THE TEST SET
IF NONE THE ESTIMATOR'S SCORE METHOD IS USED
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSS VALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS IN A STRATIFIEDKFOLD
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES

FOR INTEGERNONE INPUTS IF THE ESTIMATOR IS A CLASSIFIER AND YIS EITHER BINARY OR MULTICLASS
STRATIFIEDKFOLD IS USED IN ALL OTHER CASES KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
NPERMUTATIONS INTEGER OPTIONAL NUMBER OF TIMES TO PERMUTE Y
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF CPUS TO USE TO DO THE COMPUTA
TIONNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING
ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT0 IF INT RANDOMSTATE
IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
VERBOSE INTEGER OPTIONAL THE VERBOSITY LEVEL
RETURNS
SCORE FLOAT THE TRUE SCORE WITHOUT PERMUTING TARGETS
PERMUTATIONSCORES ARRAY SHAPE NPERMUTATIONS THE SCORES OBTAINED FOR EACH PERMUTA
TIONS
PVALUE FLOAT THE PVALUE WHICH APPROXIMATES THE PROBABILITY THAT THE SCORE WOULD BE OBTAINED
BY CHANCE THIS IS CALCULATED AS
C 1 NPERMUTATIONS 1
WHERE C IS THE NUMBER OF PERMUTATIONS WHOSE SCORE THE TRUE SCORE
THE BEST POSSIBLE PVALUE IS 1NPERMUTATIONS 1 THE WORST IS 10
NOTES
THIS FUNCTION IMPLEMENTS TEST 1 IN
OJALA AND GARRIGA PERMUTATION TESTS FOR STUDYING CLASSIFIER PERFORMANCE THE JOURNAL OF MACHINE
LEARNING RESEARCH 2010 VOL 11
EXAMPLES USING SKLEARNMODELSELECTIONPERMUTATIONTESTSCORE
•TEST WITH PERMUTATIONS THE SIGNIFICANCE OF A CLASSIFICATION SCORE
SKLEARNMODELSELECTION VALIDATIONCURVE
SKLEARNMODELSELECTION VALIDATIONCURVE ESTIMATOR XYPARAMNAME PARAMRANGE
GROUPSNONE CV’WARN’ SCORINGNONE
NJOBSNONE PREDISPATCH’ALL’ VERBOSE0
ERRORSCORE‘RAISEDEPRECATING’
VALIDATION CURVE
DETERMINE TRAINING AND TEST SCORES FOR VARYING PARAMETER VALUES

COMPUTE SCORES FOR AN ESTIMATOR WITH DIFFERENT VALUES OF A SPECIFIED PARAMETER THIS IS SIMILAR TO GRID SEARCH WITH ONE PARAMETER HOWEVER THIS WILL ALSO COMPUTE TRAINING SCORES AND IS MERELY A UTILITY FOR PLOTTING THE RESULTS
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR OBJECT TYPE THAT IMPLEMENTS THE “FIT” AND “PREDICT” METHODS AN OBJECT OF THAT TYPE WHICH IS CLONED FOR EACH VALIDATION
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NFEATURES OPTIONAL TARGET RELATIVE TO X FOR CLASSIFICATION OR REGRESSION NONE FOR UNSUPERVISED LEARNING
PARAMNAME STRING NAME OF THE PARAMETER THAT WILL BE VARIED
PARAMRANGE ARRAYLIKE SHAPE NVALUES THE VALUES OF THE PARAMETER THAT WILL BE EVALUATED
GROUPS ARRAYLIKE WITH SHAPE NSAMPLES OPTIONAL GROUP LABELS FOR THE SAMPLES USED WHILE SPLITTING THE DATASET INTO TRAINTEST SET ONLY USED IN CONJUNCTION WITH A “GROUP” CVINSTANCE EGGROUPKFOLD
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLITTING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSS VALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS IN A STRATIFIEDKFOLD
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS IF THE ESTIMATOR IS A CLASSIFIER AND YIS EITHER BINARY OR MULTICLASS STRATIFIEDKFOLD IS USED IN ALL OTHER CASES KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN V022
SCORING STRING CALLABLE OR NONE OPTIONAL DEFAULT NONE A STRING SEE MODEL EVALUATION DOCUMENTATION OR A SCORER CALLABLE OBJECT FUNCTION WITH SIGNATURE SCORERESTIMATOR X Y
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF JOBS TO RUN IN PARALLEL NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
PREDISPATCH INTEGER OR STRING OPTIONAL NUMBER OF PREDISPATCHED JOBS FOR PARALLEL EXECUTION DEFAULT IS ALL THE OPTION CAN REDUCE THE ALLOCATED MEMORY THE STRING CAN BE AN EXPRESSION LIKE ‘2NJOBS’
VERBOSE INTEGER OPTIONAL CONTROLS THE VERBOSITY THE HIGHER THE MORE MESSAGES
ERRORSCORE ‘RAISE’ ‘RAISEDEPRECATING’ OR NUMERIC VALUE TO ASSIGN TO THE SCORE IF AN ERROR OCCURS IN ESTIMATOR FITTING IF SET TO ‘RAISE’ THE ERROR IS RAISED IF SET TO ‘RAISEDEPRECATING’ A FUTUREWARNING IS PRINTED BEFORE THE ERROR IS RAISED IF A NUMERIC VALUE IS GIVEN FITFAILED WARNING IS RAISED THIS PARAMETER DOES NOT AFFECT THE REFIT STEP WHICH WILL ALWAYS RAISE THE ERROR DEFAULT IS ‘RAISEDEPRECATING’ BUT FROM VERSION 022 IT WILL CHANGE TO NPNAN
RETURNS

TRAINSCORES ARRAY SHAPE NTICKS NCVFOLDS SCORES ON TRAINING SETS
TESTSCORES ARRAY SHAPE NTICKS NCVFOLDS SCORES ON TEST SET
NOTES
SEEPLOTTING VALIDATION CURVES
EXAMPLES USING SKLEARNMODELSELECTIONVALIDATIONCURVE
•PLOTTING VALIDATION CURVES
627SKLEARNMULTICLASS MULTICLASS AND MULTILABEL CLASSIFICATION
6271 MULTICLASS AND MULTILABEL CLASSIFICATION STRATEGIES
THIS MODULE IMPLEMENTS MULTICLASS LEARNING ALGORITHMS
• ONEVSTHEREST ONEVSALL
• ONEVSONE
• ERROR CORRECTING OUTPUT CODES
THE ESTIMATORS PROVIDED IN THIS MODULE ARE METAESTIMATORS THEY REQUIRE A BASE ESTIMATOR TO BE PROVIDED IN THEIR CONSTRUCTOR FOR EXAMPLE IT IS POSSIBLE TO USE THESE ESTIMATORS TO TURN A BINARY CLASSIFIER OR A REGRESSOR INTO A MULTICLASS CLASSIFIER IT IS ALSO POSSIBLE TO USE THESE ESTIMATORS WITH MULTICLASS ESTIMATORS IN THE HOPE THAT THEIR ACCURACY OR RUNTIME PERFORMANCE IMPROVES
ALL CLASSIFIERS IN SCIKITLEARN IMPLEMENT MULTICLASS CLASSIFICATION YOU ONLY NEED TO USE THIS MODULE IF YOU WANT TO EXPERIMENT WITH CUSTOM MULTICLASS STRATEGIES
THE ONEVSTHEREST METACLASSIFIER ALSO IMPLEMENTS A PREDICTPROBA METHOD SO LONG AS SUCH A METHOD IS IMPLEMENTED BY THE BASE CLASSIFIER THIS METHOD RETURNS PROBABILITIES OF CLASS MEMBERSHIP IN BOTH THE SINGLE LABEL AND MULTILABEL CASE NOTE THAT IN THE MULTILABEL CASE PROBABILITIES ARE THE MARGINAL PROBABILITY THAT A GIVEN SAMPLE FALLS IN THE GIVEN CLASS AS SUCH IN THE MULTILABEL CASE THE SUM OF THESE PROBABILITIES OVER ALL POSSIBLE LABELS FOR A GIVEN SAMPLE WILL NOT SUM TO UNITY AS THEY DO IN THE SINGLE LABEL CASE
USER GUIDE SEE THE MULTICLASS AND MULTILABEL ALGORITHMS SECTION FOR FURTHER DETAILS
MULTICLASSONEVSRESTCLASSIFIER ESTIMATOR
   ONEVSTHEREST OVR MULTICLASSMULTILABEL STRATEGY
MULTICLASSONEVSONECLASSIFIER ESTIMATOR
   ONEVSONE MULTICLASS STRATEGY
MULTICLASSOUTPUTCODECLASSIFIER ESTIMATOR
   ERRORCORRECTING OUTPUTCODE MULTICLASS STRATEGY
6272SKLEARNMULTICLASS ONEVSRESTCLASSIFIER
CLASSSKLEARNMULTICLASS ONEVSRESTCLASSIFIER ESTIMATOR NJOBSNONE
ONEVSTHEREST OVR MULTICLASSMULTILABEL STRATEGY
ALSO KNOWN AS ONEVSALL THIS STRATEGY CONSISTS IN FITTING ONE CLASSIFIER PER CLASS FOR EACH CLASSIFIER THE CLASS IS

FITTED AGAINST ALL THE OTHER CLASSES IN ADDITION TO ITS COMPUTATIONAL EFFICIENCY ONLY NCLASSES CLASSIFIERS ARE NEEDED ONE ADVANTAGE OF THIS APPROACH IS ITS INTERPRETABILITY SINCE EACH CLASS IS REPRESENTED BY ONE AND ONE CLASSIFIER ONLY IT IS POSSIBLE TO GAIN KNOWLEDGE ABOUT THE CLASS BY INSPECTING ITS CORRESPONDING CLASSIFIER THIS IS THE MOST COMMONLY USED STRATEGY FOR MULTICLASS CLASSIFICATION AND IS A FAIR DEFAULT CHOICE

THIS STRATEGY CAN ALSO BE USED FOR MULTILABEL LEARNING WHERE A CLASSIFIER IS USED TO PREDICT MULTIPLE LABELS FOR INSTANCE BY FITTING ON A 2D MATRIX IN WHICH CELL I J IS 1 IF SAMPLE I HAS LABEL J AND 0 OTHERWISE

IN THE MULTILABEL LEARNING LITERATURE OVR IS ALSO KNOWN AS THE BINARY RELEVANCE METHOD

READ MORE IN THE USER GUIDE

PARAMETERS

ESTIMATOR ESTIMATOR OBJECT AN ESTIMATOR OBJECT IMPLEMENTING FIT AND ONE OF DECISIONFUNCTION ORPREDICTPROBA

NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS

ATTRIBUTES

ESTIMATORS LIST OFNCLASSES ESTIMATORS ESTIMATORS USED FOR PREDICTIONS

CLASSES ARRAY SHAPE NCLASSES CLASS LABELS

LABELBINARIZER LABELBINARIZER OBJECT OBJECT USED TO TRANSFORM MULTICLASS LABELS TO BINARY LABELS AND VICEVERSA

MULTILABEL BOOLEAN WHETHER THIS IS A MULTILABEL CLASSIFIER

METHODS

DECISIONFUNCTION SELF X RETURNS THE DISTANCE OF EACH SAMPLE FROM THE DECISION BOUNDARY FOR EACH CLASS

FITSELF X Y FIT UNDERLYING ESTIMATORS

GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR

PARTIALFIT SELF X Y CLASSES PARTIALLY FIT UNDERLYING ESTIMATORS

PREDICT SELF X PREDICT MULTICLASS TARGETS USING UNDERLYING ESTIMATORS

PREDICTPROBA SELF X PROBABILITY ESTIMATES

SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS

SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

INIT SELFESTIMATOR NJOBSNONE

DECISIONFUNCTION SELFX

RETURNS THE DISTANCE OF EACH SAMPLE FROM THE DECISION BOUNDARY FOR EACH CLASS THIS CAN ONLY BE USED WITH ESTIMATORS WHICH IMPLEMENT THE DECISIONFUNCTION METHOD

PARAMETERS

XARRAYLIKE SHAPE NSAMPLES NFEATURES

RETURNS

TARRAYLIKE SHAPE NSAMPLES NCLASSES

FITSELFXY

SCIKITLEARN USER GUIDE RELEASE 0213
FIT UNDERLYING ESTIMATORS
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
YSPARSE ARRAYLIKE SHAPE NSAMPLES NSAMPLES NCLASSES MULTICLASS TARGETS
AN INDICATOR MATRIX TURNS ON MULTILABEL CLASSIFICATION
RETURNS
SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
MULTILABEL
WHETHER THIS IS A MULTILABEL CLASSIFIER
PARTIALFIT SELFXYCLASSESNONE
PARTIALLY FIT UNDERLYING ESTIMATORS
SHOULD BE USED WHEN MEMORY IS INEFFICIENT TO TRAIN ALL DATA CHUNKS OF DATA CAN BE PASSED IN SEVERAL
ITERATION
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
YSPARSE ARRAYLIKE SHAPE NSAMPLES NSAMPLES NCLASSES MULTICLASS TARGETS
AN INDICATOR MATRIX TURNS ON MULTILABEL CLASSIFICATION
CLASSES ARRAY SHAPE NCLASSES CLASSES ACROSS ALL CALLS TO PARTIALFIT CAN BE OBTAINED
VIANPUNIQUEYALL WHERE YALL IS THE TARGET VECTOR OF THE ENTIRE DATASET THIS
ARGUMENT IS ONLY REQUIRED IN THE FIRST CALL OF PARTIALFIT AND CAN BE OMITTED IN THE SUBSEQUENT
CALLS
RETURNS
SELF
PREDICTSELFX
PREDICT MULTICLASS TARGETS USING UNDERLYING ESTIMATORS
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
RETURNS
YSPARSE ARRAYLIKE SHAPE NSAMPLES NSAMPLES NCLASSES PREDICTED MULTICLASS
TARGETS
PREDICTPROBA SELFX
PROBABILITY ESTIMATES
THE RETURNED ESTIMATES FOR ALL CLASSES ARE ORDERED BY LABEL OF CLASSES

NOTE THAT IN THE MULTILABEL CASE EACH SAMPLE CAN HAVE ANY NUMBER OF LABELS THIS RETURNS THE MARGINAL PROBABILITY THAT THE GIVEN SAMPLE HAS THE LABEL IN QUESTION FOR EXAMPLE IT IS ENTIRELY CONSISTENT THAT TWO LABELS BOTH HAVE A 90 PROBABILITY OF APPLYING TO A GIVEN SAMPLE
IN THE SINGLE LABEL MULTICLASS CASE THE ROWS OF THE RETURNED MATRIX SUM TO 1
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
TSPARSE ARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE PROBABILITY OF THE SAMPLE FOR EACH CLASS IN THE MODEL WHERE CLASSES ARE ORDERED AS THEY ARE IN SELFCLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNMULTICLASSONEVSRESTCLASSIFIER
•MULTILABEL CLASSIFICATION
•RECEIVER OPERATING CHARACTERISTIC ROC
•PRECISIONRECALL
•CLASSIFIER CHAIN
6273SKLEARNMULTICLASS ONEVSONECLASSIFIER
CLASSSKLEARNMULTICLASS ONEVSONECLASSIFIER ESTIMATOR NJOBSNONE
ONEVSONE MULTICLASS STRATEGY
THIS STRATEGY CONSISTS IN FITTING ONE CLASSIFIER PER CLASS PAIR AT PREDICTION TIME THE CLASS WHICH RECEIVED THE MOST VOTES IS SELECTED SINCE IT REQUIRES TO FIT NCLASSES NCLASSES 1 2 CLASSIFIERS THIS METHOD IS USUALLY SLOWER THAN ONEVSTHEREST DUE TO ITS ONCLASSES2 COMPLEXITY HOWEVER THIS METHOD MAY BE ADVANTAGEOUS FOR ALGORITHMS SUCH AS KERNEL ALGORITHMS WHICH DON’T SCALE WELL WITH NSAMPLES THIS IS BECAUSE

EACH INDIVIDUAL LEARNING PROBLEM ONLY INVOLVES A SMALL SUBSET OF THE DATA WHEREAS WITH ONEVSTHEREST THE COMPLETE DATASET IS USED NCLASSES TIMES
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT AN ESTIMATOR OBJECT IMPLEMENTING FIT AND ONE OF DECISIONFUNCTION ORPREDICTPROBA
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
ATTRIBUTES
ESTIMATORS LIST OFNCLASSES NCLASSES 1 2 ESTIMATORS ESTIMATORS USED FOR PREDICTIONS
CLASSES NUMPY ARRAY OF SHAPE NCLASSES ARRAY CONTAINING LABELS
PAIRWISEINDICES LIST LENGTH LENESTIMATORS ORNONE INDICES OF SAMPLES USED WHEN TRAINING THE ESTIMATORS NONE WHENESTIMATOR DOES NOT HAVE PAIRWISE AT TRIBUTE
METHODS
DECISIONFUNCTION SELF X DECISION FUNCTION FOR THE ONEVSONECLASSIFIER
FITSELF X Y FIT UNDERLYING ESTIMATORS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y CLASSES PARTIALLY FIT UNDERLYING ESTIMATORS
PREDICT SELF X ESTIMATE THE BEST CLASS LABEL FOR EACH SAMPLE IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFESTIMATOR NJOBSNONE
DECISIONFUNCTION SELFX
DECISION FUNCTION FOR THE ONEVSONECLASSIFIER
THE DECISION VALUES FOR THE SAMPLES ARE COMPUTED BY ADDING THE NORMALIZED SUM OF PAIRWISE CLASSIFICATION CONFIDENCE LEVELS TO THE VOTES IN ORDER TO DISAMBIGUATE BETWEEN THE DECISION VALUES WHEN THE VOTES FOR ALL THE CLASSES ARE EQUAL LEADING TO A TIE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
YARRAYLIKE SHAPE NSAMPLES NCLASSES
FITSELFXY
FIT UNDERLYING ESTIMATORS
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
YARRAYLIKE SHAPE NSAMPLES MULTICLASS TARGETS

RETURNS
SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYCLASSESNONE
PARTIALLY FIT UNDERLYING ESTIMATORS
SHOULD BE USED WHEN MEMORY IS INEFFICIENT TO TRAIN ALL DATA CHUNKS OF DATA CAN BE PASSED IN SEVERAL
ITERATION WHERE THE FIRST CALL SHOULD HAVE AN ARRAY OF ALL TARGET VARIABLES
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
YARRAYLIKE SHAPE NSAMPLES MULTICLASS TARGETS
CLASSES ARRAY SHAPE NCLASSES CLASSES ACROSS ALL CALLS TO PARTIALFIT CAN BE OBTAINED
VIANPUNIQUEYALL WHERE YALL IS THE TARGET VECTOR OF THE ENTIRE DATASET THIS
ARGUMENT IS ONLY REQUIRED IN THE FIRST CALL OF PARTIALFIT AND CAN BE OMITTED IN THE SUBSEQUENT
CALLS
RETURNS
SELF
PREDICTSELFX
ESTIMATE THE BEST CLASS LABEL FOR EACH SAMPLE IN X
THIS IS IMPLEMENTED AS ARGMAXDECISIONFUNCTIONX AXIS1 WHICH WILL RETURN THE LABEL
OF THE CLASS WITH MOST VOTES BY ESTIMATORS PREDICTING THE OUTCOME OF A DECISION FOR EACH POSSIBLE CLASS PAIR
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
RETURNS
YNUMPY ARRAY OF SHAPE NSAMPLES PREDICTED MULTICLASS TARGETS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y

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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
6274SKLEARNMULTICLASS OUTPUTCODECLASSIFIER
CLASSSKLEARNMULTICLASS OUTPUTCODECLASSIFIER ESTIMATOR CODESIZE15 RAN
DOMSTATENONE NJOBSNONE
ERRORCORRECTING OUTPUTCODE MULTICLASS STRATEGY
OUTPUTCODE BASED STRATEGIES CONSIST IN REPRESENTING EACH CLASS WITH A BINARY CODE AN ARRAY OF 0S AND 1S AT
FITTING TIME ONE BINARY CLASSIFIER PER BIT IN THE CODE BOOK IS FITTED AT PREDICTION TIME THE CLASSIFIERS ARE USED TO
PROJECT NEW POINTS IN THE CLASS SPACE AND THE CLASS CLOSEST TO THE POINTS IS CHOSEN THE MAIN ADVANTAGE OF THESE
STRATEGIES IS THAT THE NUMBER OF CLASSIFIERS USED CAN BE CONTROLLED BY THE USER EITHER FOR COMPRESSING THE MODEL
0 CODESIZE 1 OR FOR MAKING THE MODEL MORE ROBUST TO ERRORS CODESIZE 1 SEE THE DOCUMENTATION FOR
MORE DETAILS
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT AN ESTIMATOR OBJECT IMPLEMENTING FIT AND ONE OF
DECISIONFUNCTION ORPREDICTPROBA
CODESIZE FLOAT PERCENTAGE OF THE NUMBER OF CLASSES TO BE USED TO CREATE THE CODE BOOK A NUM
BER BETWEEN 0 AND 1 WILL REQUIRE FEWER CLASSIFIERS THAN ONEVSTHEREST A NUMBER GREATER
THAN 1 WILL REQUIRE MORE CLASSIFIERS THAN ONEVSTHEREST
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE GENERATOR
USED TO INITIALIZE THE CODEBOOK IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER
GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE
THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTATION
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL
PROCESSORS SEE GLOSSARY FOR MORE DETAILS
ATTRIBUTES
ESTIMATORS LIST OFINTNCLASSES CODESIZE ESTIMATORS ESTIMATORS USED FOR PRE
DICTIONS
CLASSES NUMPY ARRAY OF SHAPE NCLASSES ARRAY CONTAINING LABELS
CODEBOOK NUMPY ARRAY OF SHAPE NCLASSES CODESIZE BINARY ARRAY CONTAINING THE CODE OF
EACH CLASS
REFERENCES
R2EDDAEEC08491 R2EDDAEEC08492 R2EDDAEEC08493
2128 CHAPTER 6 API REFERENCE

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METHODS
FITSELF X Y FIT UNDERLYING ESTIMATORS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT MULTICLASS TARGETS USING UNDERLYING ESTIMATORS
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFESTIMATOR CODESIZE15 RANDOMSTATENONE NJOBSNONE
FITSELFXY
FIT UNDERLYING ESTIMATORS
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
YNUMPY ARRAY OF SHAPE NSAMPLES MULTICLASS TARGETS
RETURNS
SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT MULTICLASS TARGETS USING UNDERLYING ESTIMATORS
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
RETURNS
YNUMPY ARRAY OF SHAPE NSAMPLES PREDICTED MULTICLASS TARGETS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
627SKLEARNMULTICLASS MULTICLASS AND MULTILABEL CLASSIFICATION 2129

SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
628SKLEARNMULTIOUTPUT MULTIOUTPUT REGRESSION AND CLASSIFICA
TION
THIS MODULE IMPLEMENTS MULTIOUTPUT REGRESSION AND CLASSIFICATION
THE ESTIMATORS PROVIDED IN THIS MODULE ARE METAESTIMATORS THEY REQUIRE A BASE ESTIMATOR TO BE PROVIDED IN THEIR
CONSTRUCTOR THE METAESTIMATOR EXTENDS SINGLE OUTPUT ESTIMATORS TO MULTIOUTPUT ESTIMATORS
USER GUIDE SEE THE MULTICLASS AND MULTILABEL ALGORITHMS SECTION FOR FURTHER DETAILS
MULTIOUTPUTCLASSIFIERCHAIN BASEESTIMATOR A MULTILABEL MODEL THAT ARRANGES BINARY CLASSIFIERS INTO A
CHAIN
MULTIOUTPUTMULTIOUTPUTREGRESSOR ESTIMATOR MULTI TARGET REGRESSION
MULTIOUTPUTMULTIOUTPUTCLASSIFIER ESTIMATOR MULTI TARGET CLASSIFICATION
MULTIOUTPUTREGRESSORCHAIN BASEESTIMATOR
  A MULTILABEL MODEL THAT ARRANGES REGRESSIONS INTO A CHAIN
6281SKLEARNMULTIOUTPUT CLASSIFIERCHAIN
CLASSSKLEARNMULTIOUTPUT CLASSIFIERCHAIN BASEESTIMATOR ORDERNONE CVNONE RAN
DOMSTATENONE
A MULTILABEL MODEL THAT ARRANGES BINARY CLASSIFIERS INTO A CHAIN
EACH MODEL MAKES A PREDICTION IN THE ORDER SPECIFIED BY THE CHAIN USING ALL OF THE AVAILABLE FEATURES PROVIDED TO
THE MODEL PLUS THE PREDICTIONS OF MODELS THAT ARE EARLIER IN THE CHAIN
READ MORE IN THE USER GUIDE
PARAMETERS
BASEESTIMATOR ESTIMATOR THE BASE ESTIMATOR FROM WHICH THE CLASSIFIER CHAIN IS BUILT
ORDER ARRAYLIKE SHAPENOUTPUTS OR 'RANDOM' OPTIONAL BY DEFAULT THE ORDER WILL BE DETER
MINED BY THE ORDER OF COLUMNS IN THE LABEL MATRIX Y
ORDER 0 1 2 YSHAPE1 1
THE ORDER OF THE CHAIN CAN BE EXPLICITLY SET BY PROVIDING A LIST OF INTEGERS FOR EXAMPLE FOR
A CHAIN OF LENGTH 5
ORDER 1 3 2 4 0
MEANS THAT THE FIRST MODEL IN THE CHAIN WILL MAKE PREDICTIONS FOR COLUMN 1 IN THE Y MATRIX
THE SECOND MODEL WILL MAKE PREDICTIONS FOR COLUMN 3 ETC

IF ORDER IS ‘RANDOM’ A RANDOM ORDERING WILL BE USED
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DEFAULTNONE DETERMINES WHETHER
TO USE CROSS VALIDATED PREDICTIONS OR TRUE LABELS FOR THE RESULTS OF PREVIOUS ESTIMATORS IN THE
CHAIN IF CV IS NONE THE TRUE LABELS ARE USED WHEN FITTING OTHERWISE POSSIBLE INPUTS FOR CV
ARE
• INTEGER TO SPECIFY THE NUMBER OF FOLDS IN A STRATIFIEDKFOLD
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
THE RANDOM NUMBER GENERATOR IS USED TO GENERATE RANDOM CHAIN ORDERS
ATTRIBUTES
CLASSES LIST A LIST OF ARRAYS OF LENGTH LENESTIMATORS CONTAINING THE CLASS LABELS FOR
EACH ESTIMATOR IN THE CHAIN
ESTIMATORS LIST A LIST OF CLONES OF BASEESTIMATOR
ORDER LIST THE ORDER OF LABELS IN THE CLASSIFIER CHAIN
SEE ALSO
REGRESSORCHAIN EQUIVALENT FOR REGRESSION
MULTIOUTPUTCLASSIFIER CLASSIFIES EACH OUTPUT INDEPENDENTLY RATHER THAN CHAINING
REFERENCES
JESSE READ BERNHARD PFAHRINGER GEOFF HOLMES EIBE FRANK “CLASSIFIER CHAINS FOR MULTILABEL CLASSIFICATION”
2009
METHODS
DECISIONFUNCTION SELF X EVALUATE THE DECISIONFUNCTION OF THE MODELS IN THE
CHAIN
FITSELF X Y FIT THE MODEL TO DATA MATRIX X AND TARGETS Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT ON THE DATA MATRIX X USING THE CLASSIFIERCHAIN
MODEL
PREDICTPROBA SELF X PREDICT PROBABILITY ESTIMATES
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFBASEESTIMATOR ORDERNONE CVNONE RANDOMSTATENONE
DECISIONFUNCTION SELFX
EVALUATE THE DECISIONFUNCTION OF THE MODELS IN THE CHAIN

PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
YDECISION ARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE DECISION FUNCTION OF THE
SAMPLE FOR EACH MODEL IN THE CHAIN
FITSELFXY
FIT THE MODEL TO DATA MATRIX X AND TARGETS Y
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
YARRAYLIKE SHAPE NSAMPLES NCLASSES THE TARGET VALUES
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT ON THE DATA MATRIX X USING THE CLASSIFIERCHAIN MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
RETURNS
YPRED ARRAYLIKE SHAPE NSAMPLES NCLASSES THE PREDICTED VALUES
PREDICTPROBA SELFX
PREDICT PROBABILITY ESTIMATES
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES
RETURNS
YPROB ARRAYLIKE SHAPE NSAMPLES NCLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS

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RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNMULTIOUTPUTCLASSIFIERCHAIN
•CLASSIFIER CHAIN
6282SKLEARNMULTIOUTPUT MULTIOUTPUTREGRESSOR
CLASSSKLEARNMULTIOUTPUT MULTIOUTPUTREGRESSOR ESTIMATOR NJOBSNONE
MULTI TARGET REGRESSION
THIS STRATEGY CONSISTS OF FITTING ONE REGRESSOR PER TARGET THIS IS A SIMPLE STRATEGY FOR EXTENDING REGRESSORS THAT
DO NOT NATIVELY SUPPORT MULTITARGET REGRESSION
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT AN ESTIMATOR OBJECT IMPLEMENTING FIT ANDPREDICT
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO RUN IN PARALLEL FOR FIT
NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL
PROCESSORS SEE GLOSSARY FOR MORE DETAILS
WHEN INDIVIDUAL ESTIMATORS ARE FAST TO TRAIN OR PREDICT USING NJOBS1 CAN RESULT IN SLOWER
PERFORMANCE DUE TO THE OVERHEAD OF SPAWNING PROCESSES
ATTRIBUTES
ESTIMATORS LIST OFNOUTPUT ESTIMATORS ESTIMATORS USED FOR PREDICTIONS
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE MODEL TO DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y SAMPLEWEIGHT INCREMENTALLY FIT THE MODEL TO DATA
PREDICT SELF X PREDICT MULTIOUTPUT VARIABLE USING A MODEL TRAINED FOR
EACH TARGET VARIABLE
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFESTIMATOR NJOBSNONE
FITSELFXYSAMPLEWEIGHTNONE
FIT THE MODEL TO DATA FIT A SEPARATE MODEL FOR EACH OUTPUT VARIABLE
628SKLEARNMULTIOUTPUT MULTIOUTPUT REGRESSION AND CLASSIFICATION 2133

PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
YSPARSE ARRAYLIKE SHAPE NSAMPLES NOUTPUTS MULTIOUTPUT TARGETS AN INDICATOR MA
TRIX TURNS ON MULTILABEL ESTIMATION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED ONLY SUPPORTED IF THE UNDERLYING REGRESSOR SUPPORTS SAMPLE
WEIGHTS
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYSAMPLEWEIGHTNONE
INCREMENTALLY FIT THE MODEL TO DATA FIT A SEPARATE MODEL FOR EACH OUTPUT VARIABLE
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
YSPARSE ARRAYLIKE SHAPE NSAMPLES NOUTPUTS MULTIOUTPUT TARGETS
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED ONLY SUPPORTED IF THE UNDERLYING REGRESSOR SUPPORTS SAMPLE
WEIGHTS
RETURNS
SELF OBJECT
PREDICTSELFX
PREDICT MULTIOUTPUT VARIABLE USING A MODEL TRAINED FOR EACH TARGET VARIABLE
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
RETURNS
YSPARSE ARRAYLIKE SHAPE NSAMPLES NOUTPUTS MULTIOUTPUT TARGETS PREDICTED ACROSS
MULTIPLE PREDICTORS NOTE SEPARATE MODELS ARE GENERATED FOR EACH PREDICTOR
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE REGRESSION SUM OF SQUARES YTRUE YTRUEMEAN 2SUM BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS

XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
R2 IS CALCULATED BY WEIGHTING ALL THE TARGETS EQUALLY USING MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNMULTIOUTPUTMULTIOUTPUTREGRESSOR
•COMPARING RANDOM FORESTS AND THE MULTIOUTPUT META ESTIMATOR
6283SKLEARNMULTIOUTPUT MULTIOUTPUTCLASSIFIER
CLASSSKLEARNMULTIOUTPUT MULTIOUTPUTCLASSIFIER ESTIMATOR NJOBSNONE
MULTI TARGET CLASSIFICATION
THIS STRATEGY CONSISTS OF FITTING ONE CLASSIFIER PER TARGET THIS IS A SIMPLE STRATEGY FOR EXTENDING CLASSIFIERS THAT
DO NOT NATIVELY SUPPORT MULTITARGET CLASSIFICATION
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT AN ESTIMATOR OBJECT IMPLEMENTING FITSCORE AND
PREDICTPROBA
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF JOBS TO USE FOR THE COMPUTA
TION IT DOES EACH TARGET VARIABLE IN Y IN PARALLEL NONE MEANS 1 UNLESS IN A JOBLIB
PARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE
DETAILS
ATTRIBUTES
ESTIMATORS LIST OFNOUTPUT ESTIMATORS ESTIMATORS USED FOR PREDICTIONS
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE MODEL TO DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y CLASSES SAMPLEWEIGHT INCREMENTALLY FIT THE MODEL TO DATA
CONTINUED ON NEXT PAGE

TABLE 6216 – CONTINUED FROM PREVIOUS PAGE
PREDICT SELF X PREDICT MULTIOUTPUT VARIABLE USING A MODEL TRAINED FOR
EACH TARGET VARIABLE
PREDICTPROBA SELF X PROBABILITY ESTIMATES
SCORE SELF X Y RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFESTIMATOR NJOBSNONE
FITSELFXYSAMPLEWEIGHTNONE
FIT THE MODEL TO DATA FIT A SEPARATE MODEL FOR EACH OUTPUT VARIABLE
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
YSPARSE ARRAYLIKE SHAPE NSAMPLES NOUTPUTS MULTIOUTPUT TARGETS AN INDICATOR MA
TRIX TURNS ON MULTILABEL ESTIMATION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED ONLY SUPPORTED IF THE UNDERLYING REGRESSOR SUPPORTS SAMPLE
WEIGHTS
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYCLASSESNONE SAMPLEWEIGHTNONE
INCREMENTALLY FIT THE MODEL TO DATA FIT A SEPARATE MODEL FOR EACH OUTPUT VARIABLE
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
YSPARSE ARRAYLIKE SHAPE NSAMPLES NOUTPUTS MULTIOUTPUT TARGETS
CLASSES LIST OF NUMPY ARRAYS SHAPE NOUTPUTS EACH ARRAY IS UNIQUE CLASSES FOR ONE OUTPUT
IN STRINT CAN BE OBTAINED BY VIA NPUNIQUEY I FOR I IN RANGEY
SHAPE1 WHERE Y IS THE TARGET MATRIX OF THE ENTIRE DATASET THIS ARGUMENT IS REQUIRED
FOR THE FIRST CALL TO PARTIALFIT AND CAN BE OMITTED IN THE SUBSEQUENT CALLS NOTE THAT Y DOESN’T
NEED TO CONTAIN ALL LABELS IN CLASSES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED ONLY SUPPORTED IF THE UNDERLYING REGRESSOR SUPPORTS SAMPLE
WEIGHTS
RETURNS
SELF OBJECT
PREDICTSELFX

PREDICT MULTIOUTPUT VARIABLE USING A MODEL TRAINED FOR EACH TARGET VARIABLE
PARAMETERS
XSPARSE ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
RETURNS
YSPARSE ARRAYLIKE SHAPE NSAMPLES NOUTPUTS MULTIOUTPUT TARGETS PREDICTED ACROSS
MULTIPLE PREDICTORS NOTE SEPARATE MODELS ARE GENERATED FOR EACH PREDICTOR
PREDICTPROBA SELFX
PROBABILITY ESTIMATES RETURNS PREDICTION PROBABILITIES FOR EACH CLASS OF EACH OUTPUT
THIS METHOD WILL RAISE A VALUEERROR IF ANY OF THE ESTIMATORS DO NOT HAVE PREDICTPROBA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES DATA
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES OR A LIST OF NOUTPUTS SUCH ARRAYS IF NOUTPUTS
1 THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS TO
THAT IN THE ATTRIBUTE CLASSES
SCORESELFXY
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES NOUTPUTS TRUE VALUES FOR X
RETURNS
SCORES FLOAT ACCURACYSCORE OF SELFPREDICTX VERSUS Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
6284SKLEARNMULTIOUTPUT REGRESSORCHAIN
CLASSSKLEARNMULTIOUTPUT REGRESSORCHAIN BASEESTIMATOR ORDERNONE CVNONE RAN
DOMSTATENONE
A MULTILABEL MODEL THAT ARRANGES REGRESSIONS INTO A CHAIN
EACH MODEL MAKES A PREDICTION IN THE ORDER SPECIFIED BY THE CHAIN USING ALL OF THE AVAILABLE FEATURES PROVIDED TO
THE MODEL PLUS THE PREDICTIONS OF MODELS THAT ARE EARLIER IN THE CHAIN
READ MORE IN THE USER GUIDE
PARAMETERS
BASEESTIMATOR ESTIMATOR THE BASE ESTIMATOR FROM WHICH THE CLASSIFIER CHAIN IS BUILT

ORDER ARRAYLIKE SHAPENOUTPUTS OR ‘RANDOM’ OPTIONAL BY DEFAULT THE ORDER WILL BE DETER
MINED BY THE ORDER OF COLUMNS IN THE LABEL MATRIX Y
ORDER 0 1 2 YSHAPE1 1
THE ORDER OF THE CHAIN CAN BE EXPLICITLY SET BY PROVIDING A LIST OF INTEGERS FOR EXAMPLE FOR
A CHAIN OF LENGTH 5
ORDER 1 3 2 4 0
MEANS THAT THE FIRST MODEL IN THE CHAIN WILL MAKE PREDICTIONS FOR COLUMN 1 IN THE Y MATRIX
THE SECOND MODEL WILL MAKE PREDICTIONS FOR COLUMN 3 ETC
IF ORDER IS ‘RANDOM’ A RANDOM ORDERING WILL BE USED
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DEFAULTNONE DETERMINES WHETHER
TO USE CROSS VALIDATED PREDICTIONS OR TRUE LABELS FOR THE RESULTS OF PREVIOUS ESTIMATORS IN THE
CHAIN IF CV IS NONE THE TRUE LABELS ARE USED WHEN FITTING OTHERWISE POSSIBLE INPUTS FOR CV
ARE
• INTEGER TO SPECIFY THE NUMBER OF FOLDS IN A STRATIFIEDKFOLD
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
THE RANDOM NUMBER GENERATOR IS USED TO GENERATE RANDOM CHAIN ORDERS
ATTRIBUTES
ESTIMATORS LIST A LIST OF CLONES OF BASEESTIMATOR
ORDER LIST THE ORDER OF LABELS IN THE CLASSIFIER CHAIN
SEE ALSO
CLASSIFIERCHAIN EQUIVALENT FOR CLASSIFICATION
MULTIOUTPUTREGRESSOR LEARNS EACH OUTPUT INDEPENDENTLY RATHER THAN CHAINING
METHODS
FITSELF X Y FIT THE MODEL TO DATA MATRIX X AND TARGETS Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT ON THE DATA MATRIX X USING THE CLASSIFIERCHAIN
MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFBASEESTIMATOR ORDERNONE CVNONE RANDOMSTATENONE
FITSELFXY
FIT THE MODEL TO DATA MATRIX X AND TARGETS Y

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PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
YARRAYLIKE SHAPE NSAMPLES NCLASSES THE TARGET VALUES
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT ON THE DATA MATRIX X USING THE CLASSIFIERCHAIN MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
RETURNS
YPRED ARRAYLIKE SHAPE NSAMPLES NCLASSES THE PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
628SKLEARNMULTIOUTPUT MULTIOUTPUT REGRESSION AND CLASSIFICATION 2139

SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
629SKLEARNNAIVEBAYES NAIVE BAYES
THESKLEARNNAIVEBAYES MODULE IMPLEMENTS NAIVE BAYES ALGORITHMS THESE ARE SUPERVISED LEARNING METHODS
BASED ON APPLYING BAYES' THEOREM WITH STRONG NAIVE FEATURE INDEPENDENCE ASSUMPTIONS
USER GUIDE SEE THE NAIVE BAYES SECTION FOR FURTHER DETAILS
NAIVEBAYESBERNOULLINB ALPHA BINARIZE NAIVE BAYES CLASSIFIER FOR MULTIVARIATE BERNOULLI MODELS
NAIVEBAYESGAUSSIANNB PRIORS VARSMOOTHING GAUSSIAN NAIVE BAYES GAUSSIANNB
NAIVEBAYESMULTINOMIALNB ALPHA NAIVE BAYES CLASSIFIER FOR MULTINOMIAL MODELS
NAIVEBAYESCOMPLEMENTNB ALPHA FITPRIOR THE COMPLEMENT NAIVE BAYES CLASSIFIER DESCRIBED IN REN
NIE ET AL
6291SKLEARNNAIVEBAYES BERNOULLINB
CLASSSKLEARNNAIVEBAYES BERNOULLINB ALPHA10 BINARIZE00 FITPRIORTRUE
CLASSPRIORNONE
NAIVE BAYES CLASSIFIER FOR MULTIVARIATE BERNOULLI MODELS
LIKE MULTINOMIALNB THIS CLASSIFIER IS SUITABLE FOR DISCRETE DATA THE DIFFERENCE IS THAT WHILE MULTINOMIALNB
WORKS WITH OCCURRENCE COUNTS BERNOULLINB IS DESIGNED FOR BINARYBOOLEAN FEATURES
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA FLOAT OPTIONAL DEFAULT10 ADDITIVE LAPLACELIDSTONE SMOOTHING PARAMETER 0 FOR
NO SMOOTHING
BINARIZE FLOAT OR NONE OPTIONAL DEFAULT00 THRESHOLD FOR BINARIZING MAPPING TO BOOLEANS
OF SAMPLE FEATURES IF NONE INPUT IS PRESUMED TO ALREADY CONSIST OF BINARY VECTORS
FITPRIOR BOOLEAN OPTIONAL DEFAULTTRUE WHETHER TO LEARN CLASS PRIOR PROBABILITIES OR NOT IF
FALSE A UNIFORM PRIOR WILL BE USED
CLASSPRIOR ARRAYLIKE SIZENCLASSES OPTIONAL DEFAULTNONE PRIOR PROBABILITIES OF THE
CLASSES IF SPECIFIED THE PRIORS ARE NOT ADJUSTED ACCORDING TO THE DATA
ATTRIBUTES
CLASSLOGPRIOR ARRAY SHAPE NCLASSES LOG PROBABILITY OF EACH CLASS SMOOTHED
FEATURELOGPROB ARRAY SHAPE NCLASSES NFEATURES EMPIRICAL LOG PROBABILITY OF FEA
TURES GIVEN A CLASS PXIY
CLASSCOUNT ARRAY SHAPE NCLASSES NUMBER OF SAMPLES ENCOUNTERED FOR EACH CLASS DURING
FITTING THIS VALUE IS WEIGHTED BY THE SAMPLE WEIGHT WHEN PROVIDED

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FEATURECOUNT ARRAY SHAPE NCLASSES NFEATURES NUMBER OF SAMPLES ENCOUNTERED FOR
EACH CLASS FEATURE DURING FITTING THIS VALUE IS WEIGHTED BY THE SAMPLE WEIGHT WHEN
PROVIDED
REFERENCES
CD MANNING P RAGHAVAN AND H SCHUETZE 2008 INTRODUCTION TO INFORMATION RETRIEVAL CAMBRIDGE UNIVER
SITY PRESS PP 234265 HTTPSNLPSTANFORDEDUIRBOOKHTMLHTMLEDITIONTHEBERNOULLIMODEL1HTML
A MCCALLUM AND K NIGAM 1998 A COMPARISON OF EVENT MODELS FOR NAIVE BAYES TEXT CLASSIFICATION PROC
AAAIICML98 WORKSHOP ON LEARNING FOR TEXT CATEGORIZATION PP 4148
V METSIS I ANDROUTSOPOULOS AND G PALIOURAS 2006 SPAM FILTERING WITH NAIVE BAYES – WHICH NAIVE BAYES
3RD CONF ON EMAIL AND ANTISPAM CEAS
EXAMPLES
```
 IMPORT NUMPY AS NP
X  NPRANDOMRANDINT2 SIZE6 100
Y  NPARRAY1 2 3 4 4 5
 FROM SKLEARNNAIVEBAYES IMPORT BERNOULLINB
CLF  BERNOULLINB
CLFFITX Y
BERNOULLINBALPHA10 BINARIZE00 CLASSPRIORNONE FITPRIORTRUE
PRINTCLFPREDICTX23
3
```
METHODS
FITSELF X Y SAMPLEWEIGHT FIT NAIVE BAYES CLASSIFIER ACCORDING TO X Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PARTIALFIT SELF X Y CLASSES SAMPLEWEIGHT INCREMENTAL FIT ON A BATCH OF SAMPLES
PREDICT SELF X PERFORM CLASSIFICATION ON AN ARRAY OF TEST VECTORS X
PREDICTLOGPROBA SELF X RETURN LOGPROBABILITY ESTIMATES FOR THE TEST VECTOR X
PREDICTPROBA SELF X RETURN PROBABILITY ESTIMATES FOR THE TEST VECTOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFALPHA10 BINARIZE00 FITPRIORTRUE CLASSPRIORNONE
FITSELFXYSAMPLEWEIGHTNONE
FIT NAIVE BAYES CLASSIFIER ACCORDING TO X Y
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES DEFAULTNONE WEIGHTS APPLIED TO INDI
VIDUAL SAMPLES 1 FOR UNWEIGHTED

RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT SELFXYCLASSESNONE SAMPLEWEIGHTNONE
INCREMENTAL FIT ON A BATCH OF SAMPLES
THIS METHOD IS EXPECTED TO BE CALLED SEVERAL TIMES CONSECUTIVELY ON DIFFERENT CHUNKS OF A DATASET SO AS TO
IMPLEMENT OUTOFCORE OR ONLINE LEARNING
THIS IS ESPECIALLY USEFUL WHEN THE WHOLE DATASET IS TOO BIG TO FIT IN MEMORY AT ONCE
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YARRAYLIKE SHAPE NSAMPLES TARGET VALUES
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VIDUAL SAMPLES 1 FOR UNWEIGHTED
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RETURNS
CARRAY SHAPE NSAMPLES PREDICTED TARGET VALUES FOR X
PREDICTLOGPROBA SELFX
RETURN LOGPROBABILITY ESTIMATES FOR THE TEST VECTOR X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS

CARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE LOGPROBABILITY OF THE SAMPLES
FOR EACH CLASS IN THE MODEL THE COLUMNS CORRESPOND TO THE CLASSES IN SORTED ORDER AS THEY
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PREDICTPROBA SELFX
RETURN PROBABILITY ESTIMATES FOR THE TEST VECTOR X
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XARRAYLIKE SHAPE NSAMPLES NFEATURES
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CARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE PROBABILITY OF THE SAMPLES FOR
EACH CLASS IN THE MODEL THE COLUMNS CORRESPOND TO THE CLASSES IN SORTED ORDER AS THEY
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SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
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SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
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OF A NESTED OBJECT
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EXAMPLES USING SKLEARNNAIVEBAYESBERNOULLNB
•HASHING FEATURE TRANSFORMATION USING TOTALLY RANDOM TREES
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
6292SKLEARNNAIVEBAYES GAUSSIANNB
CLASSSKLEARNNAIVEBAYES GAUSSIANNB PRIORSNONE VARSMOOTHING1E09
GAUSSIAN NAIVE BAYES GAUSSIANNB
CAN PERFORM ONLINE UPDATES TO MODEL PARAMETERS VIA PARTIALFIT METHOD FOR DETAILS ON ALGORITHM USED TO
UPDATE FEATURE MEANS AND VARIANCE ONLINE SEE STANFORD CS TECH REPORT STANCS79773 BY CHAN GOLUB AND
LEVEQUE
HTTPISTANFORDEDUPUBCSTRREPORTSCSTR79773CSTR79773PDF
629SKLEARNNAIVEBAYES NAIVE BAYES 2143

READ MORE IN THE USER GUIDE
PARAMETERS
PRIORS ARRAYLIKE SHAPE NCLASSES PRIOR PROBABILITIES OF THE CLASSES IF SPECIFIED THE PRIORS ARE NOT ADJUSTED ACCORDING TO THE DATA
VARSMOOTHING FLOAT OPTIONAL DEFAULT1E9 PORTION OF THE LARGEST VARIANCE OF ALL FEATURES THAT IS ADDED TO VARIANCES FOR CALCULATION STABILITY
ATTRIBUTES
CLASSPRIOR ARRAY SHAPE NCLASSES PROBABILITY OF EACH CLASS
CLASSCOUNT ARRAY SHAPE NCLASSES NUMBER OF TRAINING SAMPLES OBSERVED IN EACH CLASS
THETA ARRAY SHAPE NCLASSES NFEATURES MEAN OF EACH FEATURE PER CLASS
SIGMA ARRAY SHAPE NCLASSES NFEATURES VARIANCE OF EACH FEATURE PER CLASS
EPSILON FLOAT ABSOLUTE ADDITIVE VALUE TO VARIANCES
EXAMPLES
IMPORT NUMPY AS NP
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FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
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GET PARAMETERS FOR THIS ESTIMATOR
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CARRAY SHAPE NSAMPLES PREDICTED TARGET VALUES FOR X
629SKLEARNNAIVEBAYES NAIVE BAYES 2145

PREDICTLOGPROBA SELFX
RETURN LOGPROBABILITY ESTIMATES FOR THE TEST VECTOR X
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SELF
EXAMPLES USING SKLEARNNAIVEBAYESGAUSSIANNB
•COMPARISON OF CALIBRATION OF CLASSIFIERS
•PROBABILITY CALIBRATION CURVES
•PROBABILITY CALIBRATION OF CLASSIFIERS
•CLASSIFIER COMPARISON
•PLOT CLASS PROBABILITIES CALCULATED BY THE VOTINGCLASSIFIER

•PLOTTING LEARNING CURVES
•IMPORTANCE OF FEATURE SCALING
6293SKLEARNNAIVEBAYES MULTINOMIALNB
CLASSSKLEARNNAIVEBAYES MULTINOMIALNB ALPHA10 FITPRIORTRUE CLASSPRIORNONE
NAIVE BAYES CLASSIFIER FOR MULTINOMIAL MODELS
THE MULTINOMIAL NAIVE BAYES CLASSIFIER IS SUITABLE FOR CLASSIFICATION WITH DISCRETE FEATURES EG WORD COUNTS FOR TEXT CLASSIFICATION THE MULTINOMIAL DISTRIBUTION NORMALLY REQUIRES INTEGER FEATURE COUNTS HOWEVER IN PRACTICE FRACTIONAL COUNTS SUCH AS TFIDF MAY ALSO WORK
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA FLOAT OPTIONAL DEFAULT10 ADDITIVE LAPLACELIDSTONE SMOOTHING PARAMETER 0 FOR NO SMOOTHING
FITPRIOR BOOLEAN OPTIONAL DEFAULTTRUE WHETHER TO LEARN CLASS PRIOR PROBABILITIES OR NOT IF FALSE A UNIFORM PRIOR WILL BE USED
CLASSPRIOR ARRAYLIKE SIZE NCLASSES OPTIONAL DEFAULTNONE PRIOR PROBABILITIES OF THE CLASSES IF SPECIFIED THE PRIORS ARE NOT ADJUSTED ACCORDING TO THE DATA
ATTRIBUTES
CLASSLOGPRIOR ARRAY SHAPE NCLASSES SMOOTHED EMPIRICAL LOG PROBABILITY FOR EACH CLASS
INTERCEPT ARRAY SHAPE NCLASSES MIRRORS CLASSLOGPRIOR FOR INTERPRETING MULTI NOMIALNB AS A LINEAR MODEL
FEATURELOGPROB ARRAY SHAPE NCLASSES NFEATURES EMPIRICAL LOG PROBABILITY OF FEATURES GIVEN A CLASS PXIY
COEF ARRAY SHAPE NCLASSES NFEATURES MIRRORS FEATURELOGPROB FOR INTERPRETING MULTINOMIALNB AS A LINEAR MODEL
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FEATURECOUNT ARRAY SHAPE NCLASSES NFEATURES NUMBER OF SAMPLES ENCOUNTERED FOR EACH CLASS FEATURE DURING FITTING THIS VALUE IS WEIGHTED BY THE SAMPLE WEIGHT WHEN PROVIDED
NOTES
FOR THE RATIONALE BEHIND THE NAMES COEF ANDINTERCEPT IE NAIVE BAYES AS A LINEAR CLASSIFIER SEE J RENNIE ET AL 2003 TACKLING THE POOR ASSUMPTIONS OF NAIVE BAYES TEXT CLASSIFIERS ICML
REFERENCES
CD MANNING P RAGHAVAN AND H SCHUETZE 2008 INTRODUCTION TO INFORMATION RETRIEVAL CAMBRIDGE UNIVER SITY PRESS PP 234265 HTTPSNLPSTANFORDEDUIRBOOKHTMLHTMLEDITIONNAIVEBAYESTEXTCLASSIFICATION1 HTML

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EXAMPLES
IMPORT NUMPY AS NP
X NPRANDOMRANDINT5 SIZE6 100
Y NPARRAY1 2 3 4 5 6
FROM SKLEARNNAIVEBAYES IMPORT MULTINOMIALNB
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CLFFITX Y
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METHODS
FITSELF X Y SAMPLEWEIGHT FIT NAIVE BAYES CLASSIFIER ACCORDING TO X Y
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RETURNS
SELF
EXAMPLES USING SKLEARNNAIVEBAYESMULTINOMIALNB
•OUTOFCORE CLASSIFICATION OF TEXT DOCUMENTS
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
6294SKLEARNNAIVEBAYES COMPLEMENTNB
CLASSSKLEARNNAIVEBAYES COMPLEMENTNB ALPHA10 FITPRIORTRUE CLASSPRIORNONE NORMFALSE
THE COMPLEMENT NAIVE BAYES CLASSIFIER DESCRIBED IN RENNIE ET AL 2003
THE COMPLEMENT NAIVE BAYES CLASSIFIER WAS DESIGNED TO CORRECT THE "SEVERE ASSUMPTIONS" MADE BY THE STANDARD MULTINOMIAL NAIVE BAYES CLASSIFIER IT IS PARTICULARLY SUITED FOR IMBALANCED DATA SETS
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA FLOAT OPTIONAL DEFAULT10 ADDITIVE LAPLACELIDSTONE SMOOTHING PARAMETER 0 FOR NO SMOOTHING
FITPRIOR BOOLEAN OPTIONAL DEFAULTTRUE ONLY USED IN EDGE CASE WITH A SINGLE CLASS IN THE TRAINING SET
CLASSPRIOR ARRAYLIKE SIZE NCLASSES OPTIONAL DEFAULTNONE PRIOR PROBABILITIES OF THE CLASSES NOT USED
NORM BOOLEAN OPTIONAL DEFAULTFALSE WHETHER OR NOT A SECOND NORMALIZATION OF THE WEIGHTS IS PERFORMED THE DEFAULT BEHAVIOR MIRRORS THE IMPLEMENTATIONS FOUND IN MAHOUT AND WEKA WHICH DO NOT FOLLOW THE FULL ALGORITHM DESCRIBED IN TABLE 9 OF THE PAPER
ATTRIBUTES
CLASSLOGPRIOR ARRAY SHAPE NCLASSES SMOOTHED EMPIRICAL LOG PROBABILITY FOR EACH CLASS ONLY USED IN EDGE CASE WITH A SINGLE CLASS IN THE TRAINING SET

FEATURELOGPROB ARRAY SHAPE NCLASSES NFEATURES EMPIRICAL WEIGHTS FOR CLASS COMPLE
MENTS
CLASSCOUNT ARRAY SHAPE NCLASSES NUMBER OF SAMPLES ENCOUNTERED FOR EACH CLASS DURING
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FEATURECOUNT ARRAY SHAPE NCLASSES NFEATURES NUMBER OF SAMPLES ENCOUNTERED FOR EACH
CLASS FEATURE DURING FITTING THIS VALUE IS WEIGHTED BY THE SAMPLE WEIGHT WHEN PROVIDED
FEATUREALL ARRAY SHAPE NFEATURES NUMBER OF SAMPLES ENCOUNTERED FOR EACH FEATURE DUR
ING FITTING THIS VALUE IS WEIGHTED BY THE SAMPLE WEIGHT WHEN PROVIDED
REFERENCES
RENNIE J D SHIH L TEEVAN J KARGER D R 2003 TACKLING THE POOR ASSUMPTIONS OF NAIVE BAYES TEXT
CLASSIFIERS IN ICML V OL 3 PP 616623 HTTPSPEOPLECSAILMITEDUJRENNIEPAPERSICML03NBPDF
EXAMPLES
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 IMPORT NUMPY AS NP
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Y  NPARRAY1 2 3 4 5 6
 FROM SKLEARNNAIVEBAYES IMPORT COMPLEMENTNB
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COMPLEMENTNBALPHA10 CLASSPRIORNONE FITPRIORTRUE NORMFALSE
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METHODS
FITSELF X Y SAMPLEWEIGHT FIT NAIVE BAYES CLASSIFIER ACCORDING TO X Y
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•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
630SKLEARNNEIGHBORS NEAREST NEIGHBORS
THESKLEARNNEIGHBORS MODULE IMPLEMENTS THE KNEAREST NEIGHBORS ALGORITHM
USER GUIDE SEE THE NEAREST NEIGHBORS SECTION FOR FURTHER DETAILS
NEIGHBORSBALLTREE BALLTREE FOR FAST GENERALIZED NPOINT PROBLEMS
NEIGHBORSDISTANCEMETRIC DISTANCEMETRIC CLASS
NEIGHBORSKDTREE KDTREE FOR FAST GENERALIZED NPOINT PROBLEMS
CONTINUED ON NEXT PAGE

TABLE 6223 – CONTINUED FROM PREVIOUS PAGE
NEIGHBORSKERNELDENSITY BANDWIDTH KERNEL DENSITY ESTIMATION
NEIGHBORSKNEIGHBORSCLASSIFIER CLASSIFIER IMPLEMENTING THE KNEAREST NEIGHBORS VOTE
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REGRESSION BASED ON KNEAREST NEIGHBORS
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UNSUPERVISED OUTLIER DETECTION USING LOCAL OUTLIER FACTOR
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NEIGHBORSRADIUSNEIGHBORSCLASSIFIER CLASSIFIER IMPLEMENTING A VOTE AMONG NEIGHBORS WITHIN A
GIVEN RADIUS
NEIGHBORSRADIUSNEIGHBORSREGRESSOR RADIUS
REGRESSION BASED ON NEIGHBORS WITHIN A FIXED RADIUS
NEIGHBORSNEARESTCENTROID METRIC NEAREST CENTROID CLASSIFIER
NEIGHBORSNEARESTNEIGHBORS NNEIGHBORS
UNSUPERVISED LEARNER FOR IMPLEMENTING NEIGHBOR SEARCHES
NEIGHBORSNEIGHBORHOODCOMPONENTSANALYSIS NEIGHBORHOOD COMPONENTS ANALYSIS
6301SKLEARNNEIGHBORS BALLTREE
CLASSSKLEARNNEIGHBORS BALLTREE
BALLTREE FOR FAST GENERALIZED NPOINT PROBLEMS
BALLTREEX LEAFSIZE40 METRIC’MINKOWSKI’ KWARGS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES NSAMPLES IS THE NUMBER OF POINTS IN THE DATA
SET AND NFEATURES IS THE DIMENSION OF THE PARAMETER SPACE NOTE IF X IS A CCONTIGUOUS
ARRAY OF DOUBLES THEN DATA WILL NOT BE COPIED OTHERWISE AN INTERNAL COPY WILL BE MADE
LEAFSIZE POSITIVE INTEGER DEFAULT 40 NUMBER OF POINTS AT WHICH TO SWITCH TO BRUTEFORCE
CHANGING LEAFSIZE WILL NOT AFFECT THE RESULTS OF A QUERY BUT CAN SIGNIFICANTLY IMPACT THE
SPEED OF A QUERY AND THE MEMORY REQUIRED TO STORE THE CONSTRUCTED TREE THE AMOUNT OF
MEMORY NEEDED TO STORE THE TREE SCALES AS APPROXIMATELY NSAMPLES LEAFSIZE FOR A SPEC
IFIEDLEAFSIZE A LEAF NODE IS GUARANTEED TO SATISFY LEAFSIZE NPOINTS
2LEAFSIZE EXCEPT IN THE CASE THAT NSAMPLES LEAFSIZE
METRIC STRING OR DISTANCEMETRIC OBJECT THE DISTANCE METRIC TO USE FOR THE TREE DE
FAULT’MINKOWSKI’ WITH P2 THAT IS A EUCLIDEAN METRIC SEE THE DOCUMENTATION OF THE
DISTANCEMETRIC CLASS FOR A LIST OF AVAILABLE METRICS BALLTREEVALIDMETRICS GIVES A LIST OF THE
METRICS WHICH ARE VALID FOR BALLTREE
ADDITIONAL KEYWORDS ARE PASSED TO THE DISTANCE METRIC CLASS
ATTRIBUTES
DATA MEMORY VIEW THE TRAINING DATA
EXAMPLES
QUERY FOR KNEAREST NEIGHBORS
IMPORT NUMPY AS NP
RNG NPRANDOMRANDOMSTATE0
X RNGRANDOMSAMPLE10 3 10 POINTS IN 3 DIMENSIONS
TREE BALLTREEX LEAFSIZE2
DIST IND TREEQUERYX1 K3

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PRINTIND INDICES OF 3 CLOSEST NEIGHBORS
0 3 1
PRINTDIST DISTANCES TO 3 CLOSEST NEIGHBORS
 0 019662693 029473397
PICKLE AND UNPICKLE A TREE NOTE THAT THE STATE OF THE TREE IS SAVED IN THE PICKLE OPERATION THE TREE NEEDS NOT BE REBUILT UPON UNPICKLING
 IMPORT NUMPY AS NP
 IMPORT PICKLE
RNG NPRANDOMRANDOMSTATE0
X RNGRANDOMSAMPLE10 3 10 POINTS IN 3 DIMENSIONS
TREE BALLTREEX LEAFSIZE2
S PICKLEDUMPSTREE
TREECOPY PICKLELOADSS
DIST IND TREECOPYQUERYX1 K3
PRINTIND INDICES OF 3 CLOSEST NEIGHBORS
0 3 1
PRINTDIST DISTANCES TO 3 CLOSEST NEIGHBORS
 0 019662693 029473397
QUERY FOR NEIGHBORS WITHIN A GIVEN RADIUS
 IMPORT NUMPY AS NP
RNG NPRANDOMRANDOMSTATE0
X RNGRANDOMSAMPLE10 3 10 POINTS IN 3 DIMENSIONS
TREE BALLTREEX LEAFSIZE2
PRINTTREEQUERYRADIUSX1 R03 COUNTONLY TRUE
3
IND TREEQUERYRADIUSX1 R03
PRINTIND INDICES OF NEIGHBORS WITHIN DISTANCE 03
3 0 1
COMPUTE A GAUSSIAN KERNEL DENSITY ESTIMATE
 IMPORT NUMPY AS NP
RNG NPRANDOMRANDOMSTATE42
X RNGRANDOMSAMPLE100 3
TREE BALLTREEX
TREEKERNELDENSITYX3 H01 KERNELGAUSSIAN
ARRAY 694114649 783281226 72071716
COMPUTE A TWOPOINT AUTOCORRELATION FUNCTION
 IMPORT NUMPY AS NP
RNG NPRANDOMRANDOMSTATE0
X RNGRANDOMSAMPLE30 3
R NPLINSPACE0 1 5
TREE BALLTREEX
TREETWOPOINTCORRELATIONX R
ARRAY 30 62 278 580 820
METHODS
630SKLEARNNEIGHBORS NEAREST NEIGHBORS 2155

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KERNELDENSITY SELF X H KERNEL ATOL COMPUTE THE KERNEL DENSITY ESTIMATE AT POINTS X WITH
THE GIVEN KERNEL USING THE DISTANCE METRIC SPECIFIED AT
TREE CREATION
QUERY X K RETURNDISTANCE DUALTREE QUERY THE TREE FOR THE K NEAREST NEIGHBORS
QUERYRADIUS QUERYRADIUSSELF X R COUNTONLY FALSE
TWOPOINTCORRELATION COMPUTE THE TWOPOINT CORRELATION FUNCTION
GETARRAYS
GETNCALLS
GETTREESTATS
RESETNCALLS
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
KERNELDENSITY SELFXHKERNEL'GAUSSIAN' ATOL0 RTOL1E8 BREADTHFIRSTTRUE RE
TURNLOGFALSE
COMPUTE THE KERNEL DENSITY ESTIMATE AT POINTS X WITH THE GIVEN KERNEL USING THE DISTANCE METRIC SPECIFIED
AT TREE CREATION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES AN ARRAY OF POINTS TO QUERY LAST DIMENSION
SHOULD MATCH DIMENSION OF TRAINING DATA
HFLOAT THE BANDWIDTH OF THE KERNEL
KERNEL STRING SPECIFY THE KERNEL TO USE OPTIONS ARE 'GAUSSIAN' 'TOPHAT' 'EPANECHNIKOV'
'EXPONENTIAL' 'LINEAR' 'COSINE' DEFAULT IS KERNEL 'GAUSSIAN'
ATOL RTOL FLOAT DEFAULT 0 SPECIFY THE DESIRED RELATIVE AND ABSOLUTE TOLERANCE OF THE RE
SULT IF THE TRUE RESULT IS KTRUE THEN THE RETURNED RESULT KRET SATISFIES ABSKTRUE
KRET ATOL RTOL KRET THE DEFAULT IS ZERO IE MACHINE PRECISION FOR
BOTH
BREADTHFIRST BOOLEAN DEFAULT FALSE IF TRUE USE A BREADTHFIRST SEARCH IF FALSE DEFAULT
USE A DEPTHFIRST SEARCH BREADTHFIRST IS GENERALLY FASTER FOR COMPACT KERNELS ANDOR HIGH
TOLERANCES
RETURNLOG BOOLEAN DEFAULT FALSE RETURN THE LOGARITHM OF THE RESULT THIS CAN BE MORE
ACCURATE THAN RETURNING THE RESULT ITSELF FOR NARROW KERNELS
RETURNS
DENSITY NDARRAY THE ARRAY OF LOGDENSITY EVALUATIONS SHAPE XSHAPE1
QUERYXK1RETURNDISTANCETRUE DUALTREEFALSE BREADTHFIRSTFALSE
QUERY THE TREE FOR THE K NEAREST NEIGHBORS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES AN ARRAY OF POINTS TO QUERY
KINTEGER DEFAULT 1 THE NUMBER OF NEAREST NEIGHBORS TO RETURN
RETURNDISTANCE BOOLEAN DEFAULT TRUE IF TRUE RETURN A TUPLE D I OF DISTANCES AND
INDICES IF FALSE RETURN ARRAY I

DUALTREE BOOLEAN DEFAULT FALSE IF TRUE USE THE DUAL TREE FORMALISM FOR THE QUERY A TREE
IS BUILT FOR THE QUERY POINTS AND THE PAIR OF TREES IS USED TO EFFICIENTLY SEARCH THIS SPACE
THIS CAN LEAD TO BETTER PERFORMANCE AS THE NUMBER OF POINTS GROWS LARGE
BREADTHFIRST BOOLEAN DEFAULT FALSE IF TRUE THEN QUERY THE NODES IN A BREADTHFIRST
MANNER OTHERWISE QUERY THE NODES IN A DEPTHFIRST MANNER
SORTRESULTS BOOLEAN DEFAULT TRUE IF TRUE THEN DISTANCES AND INDICES OF EACH POINT ARE
SORTED ON RETURN SO THAT THE FIRST COLUMN CONTAINS THE CLOSEST POINTS OTHERWISE NEIGHBORS
ARE RETURNED IN AN ARBITRARY ORDER
RETURNS
IIF RETURNDISTANCE FALSE
DI IF RETURNDISTANCE TRUE
DARRAY OF DOUBLES SHAPE XSHAPE1 K EACH ENTRY GIVES THE LIST OF DISTANCES TO THE
NEIGHBORS OF THE CORRESPONDING POINT
IARRAY OF INTEGERS SHAPE XSHAPE1 K EACH ENTRY GIVES THE LIST OF INDICES OF NEIGH
BORS OF THE CORRESPONDING POINT
QUERYRADIUS
QUERYRADIUSSELF X R COUNTONLY FALSE
QUERY THE TREE FOR NEIGHBORS WITHIN A RADIUS R
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES AN ARRAY OF POINTS TO QUERY
RDISTANCE WITHIN WHICH NEIGHBORS ARE RETURNED R CAN BE A SINGLE VALUE OR AN ARRAY OF VALUES
OF SHAPE XSHAPE1 IF DIFFERENT RADII ARE DESIRED FOR EACH POINT
RETURNDISTANCE BOOLEAN DEFAULT FALSE IF TRUE RETURN DISTANCES TO NEIGHBORS OF EACH
POINT IF FALSE RETURN ONLY NEIGHBORS NOTE THAT UNLIKE THE QUERY METHOD SETTING RE
TURNDISTANCETRUE HERE ADDS TO THE COMPUTATION TIME NOT ALL DISTANCES NEED TO BE
CALCULATED EXPLICITLY FOR RETURNDISTANCEFALSE RESULTS ARE NOT SORTED BY DEFAULT SEE
SORTRESULTS KEYWORD
COUNTONLY BOOLEAN DEFAULT FALSE IF TRUE RETURN ONLY THE COUNT OF POINTS WITHIN DIS
TANCE R IF FALSE RETURN THE INDICES OF ALL POINTS WITHIN DISTANCE R IF RETURNDISTANCETRUE
SETTING COUNTONLYTRUE WILL RESULT IN AN ERROR
SORTRESULTS BOOLEAN DEFAULT FALSE IF TRUE THE DISTANCES AND INDICES WILL BE SORTED
BEFORE BEING RETURNED IF FALSE THE RESULTS WILL NOT BE SORTED IF RETURNDISTANCE FALSE
SETTING SORTRESULTS TRUE WILL RESULT IN AN ERROR
RETURNS
COUNT IF COUNTONLY TRUE
IND IF COUNTONLY FALSE AND RETURNDISTANCE FALSE
IND DIST IF COUNTONLY FALSE AND RETURNDISTANCE TRUE
COUNT ARRAY OF INTEGERS SHAPE XSHAPE1 EACH ENTRY GIVES THE NUMBER OF NEIGHBORS
WITHIN A DISTANCE R OF THE CORRESPONDING POINT
IND ARRAY OF OBJECTS SHAPE XSHAPE1 EACH ELEMENT IS A NUMPY INTEGER ARRAY LISTING
THE INDICES OF NEIGHBORS OF THE CORRESPONDING POINT NOTE THAT UNLIKE THE RESULTS OF A K
NEIGHBORS QUERY THE RETURNED NEIGHBORS ARE NOT SORTED BY DISTANCE BY DEFAULT

DIST ARRAY OF OBJECTS SHAPE XSHAPE1 EACH ELEMENT IS A NUMPY DOUBLE ARRAY LISTING
THE DISTANCES CORRESPONDING TO INDICES IN I
TWOPOINTCORRELATION
COMPUTE THE TWOPOINT CORRELATION FUNCTION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES AN ARRAY OF POINTS TO QUERY LAST DIMENSION
SHOULD MATCH DIMENSION OF TRAINING DATA
RARRAYLIKE A ONEDIMENSIONAL ARRAY OF DISTANCES
DUALTREE BOOLEAN DEFAULT FALSE IF TRUE USE A DUALTREE ALGORITHM OTHERWISE USE A
SINGLETREE ALGORITHM DUAL TREE ALGORITHMS CAN HAVE BETTER SCALING FOR LARGE N
RETURNS
COUNTS NDARRAY COUNTSI CONTAINS THE NUMBER OF PAIRS OF POINTS WITH DISTANCE LESS THAN OR
EQUAL TO RI
6302SKLEARNNEIGHBORS DISTANCEMETRIC
CLASSSKLEARNNEIGHBORS DISTANCEMETRIC
DISTANCEMETRIC CLASS
THIS CLASS PROVIDES A UNIFORM INTERFACE TO FAST DISTANCE METRIC FUNCTIONS THE VARIOUS METRICS CAN BE ACCESSED VIA
THEGETMETRIC CLASS METHOD AND THE METRIC STRING IDENTIFIER SEE BELOW FOR EXAMPLE TO USE THE EUCLIDEAN
DISTANCE
DIST DISTANCEMETRICGETMETRICEUCLIDEAN
X 0 1 2
3 4 5
DISTPAIRWISEX
ARRAY 0 519615242
 519615242 0
AVAILABLE METRICS
THE FOLLOWING LISTS THE STRING METRIC IDENTIFIERS AND THE ASSOCIATED DISTANCE METRIC CLASSES
METRICS INTENDED FOR REALVALUED VECTOR SPACES

IDENTIFIER CLASS NAME ARGS DISTANCE FUNCTION
“EUCLIDEAN” EUCLIDEANDISTANCE
•SQRTSUMX
Y2
“MANHATTAN” MANHATTANDISTANCE
•SUMX Y
“CHEBYSHEV” CHEBYSHEVDISTANCE
•MAXX Y
“MINKOWSKI” MINKOWSKIDISTANCE P SUMX
YP1P
“WMINKOWSKI” WMINKOWSKIDISTANCE P W SUMWX
YP1P
“SEUCLIDEAN” SEUCLIDEANDISTANCE V SQRTSUMX
Y2 V
“MAHALANOBIS” MAHALANOBISDISTANCE V OR VI SQRTX Y
V1 X Y
METRICS INTENDED FOR TWODIMENSIONAL VECTOR SPACES NOTE THAT THE HAVERSINE DISTANCE METRIC REQUIRES DATA IN THE FORM OF LATITUDE LONGITUDE AND BOTH INPUTS AND OUTPUTS ARE IN UNITS OF RADIANS
IDENTIFIER CLASS NAME DISTANCE FUNCTION
“HAVER
SINE”HAVERSINEDIS
TANCE2 ARCSINSQRTSIN205 DX
COSX1COSX2SIN205 DY
METRICS INTENDED FOR INTEGERVALUED VECTOR SPACES THOUGH INTENDED FOR INTEGERVALUED VECTORS THESE ARE ALSO VALID METRICS IN THE CASE OF REALVALUED VECTORS
IDENTIFIER CLASS NAME DISTANCE FUNCTION
“HAMMING” HAMMINGDISTANCE NUNEQUALX Y NTOT
“CANBERRA” CANBERRADISTANCE SUMX Y X Y
“BRAYCURTIS” BRAYCURTISDISTANCE SUMX Y SUMX SUMY
METRICS INTENDED FOR BOOLEANVALUED VECTOR SPACES ANY NONZERO ENTRY IS EVALUATED TO “TRUE” IN THE LISTINGS BELOW THE FOLLOWING ABBREVIATIONS ARE USED
• N NUMBER OF DIMENSIONS
• NTT NUMBER OF DIMS IN WHICH BOTH VALUES ARE TRUE
• NTF NUMBER OF DIMS IN WHICH THE FIRST VALUE IS TRUE SECOND IS FALSE
• NFT NUMBER OF DIMS IN WHICH THE FIRST VALUE IS FALSE SECOND IS TRUE
• NFF NUMBER OF DIMS IN WHICH BOTH VALUES ARE FALSE
• NNEQ NUMBER OF NONEQUAL DIMENSIONS NNEQ NTF NFT
• NNZ NUMBER OF NONZERO DIMENSIONS NNZ NTF NFT NTT

IDENTIFIER CLASS NAME DISTANCE FUNCTION
“JACCARD” JACCARDDISTANCE NNEQ NNZ
“MATCHING” MATCHINGDISTANCE NNEQ N
“DICE” DICEDISTANCE NNEQ NTT NNZ
“KULSINSKI” KULSINSKIDISTANCE NNEQ N NTT NNEQ N
“ROGERSTANIMOTO” ROGERSTANIMOTODISTANCE 2 NNEQ N NNEQ
“RUSSELLRAO” RUSSELLRAODISTANCE NNZ N
“SOKALMICHENER” SOKALMICHENERDISTANCE 2 NNEQ N NNEQ
“SOKALSNEATH” SOKALSNEATHDISTANCE NNEQ NNEQ 05 NTT
USERDEFINED DISTANCE
IDENTIFIER CLASS NAME ARGS
“PYFUNC” PYFUNCDISTANCE FUNC
HEREFUNC IS A FUNCTION WHICH TAKES TWO ONEDIMENSIONAL NUMPY ARRAYS AND RETURNS A DISTANCE NOTE THAT
IN ORDER TO BE USED WITHIN THE BALLTREE THE DISTANCE MUST BE A TRUE METRIC IE IT MUST SATISFY THE FOLLOWING
PROPERTIES
1 NONNEGATIVITY DX Y 0
2 IDENTITY DX Y 0 IF AND ONLY IF X Y
3 SYMMETRY DX Y DY X
4 TRIANGLE INEQUALITY DX Y DY Z DX Z
BECAUSE OF THE PYTHON OBJECT OVERHEAD INVOLVED IN CALLING THE PYTHON FUNCTION THIS WILL BE FAIRLY SLOW BUT IT
WILL HAVE THE SAME SCALING AS OTHER DISTANCES
METHODS
DISTTORDIST CONVERT THE TRUE DISTANCE TO THE REDUCED DISTANCE
GETMETRIC GET THE GIVEN DISTANCE METRIC FROM THE STRING IDENTIFIER
PAIRWISE COMPUTE THE PAIRWISE DISTANCES BETWEEN X AND Y
RDISTTODIST CONVERT THE REDUCED DISTANCE TO THE TRUE DISTANCE
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
DISTTORDIST
CONVERT THE TRUE DISTANCE TO THE REDUCED DISTANCE
THE REDUCED DISTANCE DEFINED FOR SOME METRICS IS A COMPUTATIONALLY MORE EFFICIENT MEASURE WHICH PRE
SERVES THE RANK OF THE TRUE DISTANCE FOR EXAMPLE IN THE EUCLIDEAN DISTANCE METRIC THE REDUCED DISTANCE IS
THE SQUAREDEUCLIDEAN DISTANCE
GETMETRIC
GET THE GIVEN DISTANCE METRIC FROM THE STRING IDENTIFIER
SEE THE DOCSTRING OF DISTANCEMETRIC FOR A LIST OF AVAILABLE METRICS
PARAMETERS
METRIC STRING OR CLASS NAME THE DISTANCE METRIC TO USE

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KWARGS ADDITIONAL ARGUMENTS WILL BE PASSED TO THE REQUESTED METRIC
PAIRWISE
COMPUTE THE PAIRWISE DISTANCES BETWEEN X AND Y
THIS IS A CONVENIENCE ROUTINE FOR THE SAKE OF TESTING FOR MANY METRICS THE UTILITIES IN
SCIPYSPATIALDISTANCECDIST AND SCIPYSPATIALDISTANCEPDIST WILL BE FASTER
PARAMETERS
XARRAYLIKE ARRAY OF SHAPE NX D REPRESENTING NX POINTS IN D DIMENSIONS
YARRAYLIKE OPTIONAL ARRAY OF SHAPE NY D REPRESENTING NY POINTS IN D DIMENSIONS
IF NOT SPECIFIED THEN YX
RETURNS
——
DIST NDARRAY THE SHAPE NX NY ARRAY OF PAIRWISE DISTANCES BETWEEN POINTS IN X AND Y
RDISTTODIST
CONVERT THE REDUCED DISTANCE TO THE TRUE DISTANCE
THE REDUCED DISTANCE DEFINED FOR SOME METRICS IS A COMPUTATIONALLY MORE EFFICIENT MEASURE WHICH PRE
SERVES THE RANK OF THE TRUE DISTANCE FOR EXAMPLE IN THE EUCLIDEAN DISTANCE METRIC THE REDUCED DISTANCE IS
THE SQUAREDEUCLIDEAN DISTANCE
6303SKLEARNNEIGHBORS KDTREE
CLASSSKLEARNNEIGHBORS KDTREE
KDTREE FOR FAST GENERALIZED NPOINT PROBLEMS
KDTREEX LEAFSIZE40 METRIC’MINKOWSKI’ KWARGS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES NSAMPLES IS THE NUMBER OF POINTS IN THE DATA
SET AND NFEATURES IS THE DIMENSION OF THE PARAMETER SPACE NOTE IF X IS A CCONTIGUOUS
ARRAY OF DOUBLES THEN DATA WILL NOT BE COPIED OTHERWISE AN INTERNAL COPY WILL BE MADE
LEAFSIZE POSITIVE INTEGER DEFAULT 40 NUMBER OF POINTS AT WHICH TO SWITCH TO BRUTEFORCE
CHANGING LEAFSIZE WILL NOT AFFECT THE RESULTS OF A QUERY BUT CAN SIGNIFICANTLY IMPACT THE
SPEED OF A QUERY AND THE MEMORY REQUIRED TO STORE THE CONSTRUCTED TREE THE AMOUNT OF
MEMORY NEEDED TO STORE THE TREE SCALES AS APPROXIMATELY NSAMPLES LEAFSIZE FOR A SPEC
IFIEDLEAFSIZE A LEAF NODE IS GUARANTEED TO SATISFY LEAFSIZE NPOINTS
2LEAFSIZE EXCEPT IN THE CASE THAT NSAMPLES LEAFSIZE
METRIC STRING OR DISTANCEMETRIC OBJECT THE DISTANCE METRIC TO USE FOR THE TREE DE
FAULT’MINKOWSKI’ WITH P2 THAT IS A EUCLIDEAN METRIC SEE THE DOCUMENTATION OF THE
DISTANCEMETRIC CLASS FOR A LIST OF AVAILABLE METRICS KDTREEVALIDMETRICS GIVES A LIST OF THE
METRICS WHICH ARE VALID FOR KDTREE
ADDITIONAL KEYWORDS ARE PASSED TO THE DISTANCE METRIC CLASS
ATTRIBUTES
DATA MEMORY VIEW THE TRAINING DATA
630SKLEARNNEIGHBORS NEAREST NEIGHBORS 2161

EXAMPLES
QUERY FOR KNEAREST NEIGHBORS
```
 IMPORT NUMPY AS NP
RNG  NPRANDOMRANDOMSTATE0
X  RNGRANDOMSAMPLE10 3  10 POINTS IN 3 DIMENSIONS
TREE  KDTREEX LEAFSIZE2
DIST IND  TREEQUERYX1 K3
PRINTIND  INDICES OF 3 CLOSEST NEIGHBORS
0 3 1
PRINTDIST  DISTANCES TO 3 CLOSEST NEIGHBORS
 0 019662693 029473397
```
PICKLE AND UNPICKLE A TREE NOTE THAT THE STATE OF THE TREE IS SAVED IN THE PICKLE OPERATION THE TREE NEEDS NOT BE REBUILT UPON UNPICKLING
```
 IMPORT NUMPY AS NP
 IMPORT PICKLE
RNG  NPRANDOMRANDOMSTATE0
X  RNGRANDOMSAMPLE10 3  10 POINTS IN 3 DIMENSIONS
TREE  KDTREEX LEAFSIZE2
S  PICKLEDUMPSTREE
TREECOPY  PICKLELOADSS
DIST IND  TREECOPYQUERYX1 K3
PRINTIND  INDICES OF 3 CLOSEST NEIGHBORS
0 3 1
PRINTDIST  DISTANCES TO 3 CLOSEST NEIGHBORS
 0 019662693 029473397
```
QUERY FOR NEIGHBORS WITHIN A GIVEN RADIUS
```
 IMPORT NUMPY AS NP
RNG  NPRANDOMRANDOMSTATE0
X  RNGRANDOMSAMPLE10 3  10 POINTS IN 3 DIMENSIONS
TREE  KDTREEX LEAFSIZE2
PRINTTREEQUERYRADIUSX1 R03 COUNTONLY TRUE
3
IND  TREEQUERYRADIUSX1 R03
PRINTIND  INDICES OF NEIGHBORS WITHIN DISTANCE 03
3 0 1
```
COMPUTE A GAUSSIAN KERNEL DENSITY ESTIMATE
```
 IMPORT NUMPY AS NP
RNG  NPRANDOMRANDOMSTATE42
X  RNGRANDOMSAMPLE100 3
TREE  KDTREEX
TREEKERNELDENSITYX3 H01 KERNELGAUSSIAN
ARRAY 694114649 783281226 72071716
```
COMPUTE A TWOPOINT AUTOCORRELATION FUNCTION
```
 IMPORT NUMPY AS NP
RNG  NPRANDOMRANDOMSTATE0
X  RNGRANDOMSAMPLE30 3
R  NPLINSPACE0 1 5
TREE  KDTREEX
```

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TREETWOPOINTCORRELATIONX R
ARRAY 30 62 278 580 820
METHODS
KERNELDENSITY SELF X H KERNEL ATOL COMPUTE THE KERNEL DENSITY ESTIMATE AT POINTS X WITH
THE GIVEN KERNEL USING THE DISTANCE METRIC SPECIFIED AT
TREE CREATION
QUERY X K RETURNDISTANCE DUALTREE QUERY THE TREE FOR THE K NEAREST NEIGHBORS
QUERYRADIUS QUERYRADIUSSELF X R COUNTONLY FALSE
TWOPOINTCORRELATION COMPUTE THE TWOPOINT CORRELATION FUNCTION
GETARRAYS
GETNCALLS
GETTREESTATS
RESETNCALLS
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
KERNELDENSITY SELFXHKERNEL'GAUSSIAN' ATOL0 RTOL1E8 BREADTHFIRSTTRUE RE
TURNLOGFALSE
COMPUTE THE KERNEL DENSITY ESTIMATE AT POINTS X WITH THE GIVEN KERNEL USING THE DISTANCE METRIC SPECIFIED
AT TREE CREATION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES AN ARRAY OF POINTS TO QUERY LAST DIMENSION
SHOULD MATCH DIMENSION OF TRAINING DATA
HFLOAT THE BANDWIDTH OF THE KERNEL
KERNEL STRING SPECIFY THE KERNEL TO USE OPTIONS ARE 'GAUSSIAN' 'TOPHAT' 'EPANECHNIKOV'
'EXPONENTIAL' 'LINEAR' 'COSINE' DEFAULT IS KERNEL 'GAUSSIAN'
ATOL RTOL FLOAT DEFAULT 0 SPECIFY THE DESIRED RELATIVE AND ABSOLUTE TOLERANCE OF THE RE
SULT IF THE TRUE RESULT IS KTRUE THEN THE RETURNED RESULT KRET SATISFIES ABSKTRUE
KRET ATOL RTOL KRET THE DEFAULT IS ZERO IE MACHINE PRECISION FOR
BOTH
BREADTHFIRST BOOLEAN DEFAULT FALSE IF TRUE USE A BREADTHFIRST SEARCH IF FALSE DEFAULT
USE A DEPTHFIRST SEARCH BREADTHFIRST IS GENERALLY FASTER FOR COMPACT KERNELS ANDOR HIGH
TOLERANCES
RETURNLOG BOOLEAN DEFAULT FALSE RETURN THE LOGARITHM OF THE RESULT THIS CAN BE MORE
ACCURATE THAN RETURNING THE RESULT ITSELF FOR NARROW KERNELS
RETURNS
DENSITY NDARRAY THE ARRAY OF LOGDENSITY EVALUATIONS SHAPE XSHAPE1
QUERYXK1RETURNDISTANCETRUE DUALTREEFALSE BREADTHFIRSTFALSE
QUERY THE TREE FOR THE K NEAREST NEIGHBORS
PARAMETERS
630SKLEARNNEIGHBORS NEAREST NEIGHBORS 2163

XARRAYLIKE SHAPE NSAMPLES NFEATURES AN ARRAY OF POINTS TO QUERY
KINTEGER DEFAULT 1 THE NUMBER OF NEAREST NEIGHBORS TO RETURN
RETURNDISTANCE BOOLEAN DEFAULT TRUE IF TRUE RETURN A TUPLE D I OF DISTANCES AND
INDICES IF FALSE RETURN ARRAY I
DUALTREE BOOLEAN DEFAULT FALSE IF TRUE USE THE DUAL TREE FORMALISM FOR THE QUERY A TREE
IS BUILT FOR THE QUERY POINTS AND THE PAIR OF TREES IS USED TO EFFICIENTLY SEARCH THIS SPACE
THIS CAN LEAD TO BETTER PERFORMANCE AS THE NUMBER OF POINTS GROWS LARGE
BREADTHFIRST BOOLEAN DEFAULT FALSE IF TRUE THEN QUERY THE NODES IN A BREADTHFIRST
MANNER OTHERWISE QUERY THE NODES IN A DEPTHFIRST MANNER
SORTRESULTS BOOLEAN DEFAULT TRUE IF TRUE THEN DISTANCES AND INDICES OF EACH POINT ARE
SORTED ON RETURN SO THAT THE FIRST COLUMN CONTAINS THE CLOSEST POINTS OTHERWISE NEIGHBORS
ARE RETURNED IN AN ARBITRARY ORDER
RETURNS
IIF RETURNDISTANCE FALSE
DI IF RETURNDISTANCE TRUE
DARRAY OF DOUBLES SHAPE XSHAPE1 K EACH ENTRY GIVES THE LIST OF DISTANCES TO THE
NEIGHBORS OF THE CORRESPONDING POINT
IARRAY OF INTEGERS SHAPE XSHAPE1 K EACH ENTRY GIVES THE LIST OF INDICES OF NEIGH
BORS OF THE CORRESPONDING POINT
QUERYRADIUS
QUERYRADIUSSELF X R COUNTONLY FALSE
QUERY THE TREE FOR NEIGHBORS WITHIN A RADIUS R
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES AN ARRAY OF POINTS TO QUERY
RDISTANCE WITHIN WHICH NEIGHBORS ARE RETURNED R CAN BE A SINGLE VALUE OR AN ARRAY OF VALUES
OF SHAPE XSHAPE1 IF DIFFERENT RADII ARE DESIRED FOR EACH POINT
RETURNDISTANCE BOOLEAN DEFAULT FALSE IF TRUE RETURN DISTANCES TO NEIGHBORS OF EACH
POINT IF FALSE RETURN ONLY NEIGHBORS NOTE THAT UNLIKE THE QUERY METHOD SETTING RE
TURNDISTANCETRUE HERE ADDS TO THE COMPUTATION TIME NOT ALL DISTANCES NEED TO BE
CALCULATED EXPLICITLY FOR RETURNDISTANCEFALSE RESULTS ARE NOT SORTED BY DEFAULT SEE
SORTRESULTS KEYWORD
COUNTONLY BOOLEAN DEFAULT FALSE IF TRUE RETURN ONLY THE COUNT OF POINTS WITHIN DIS
TANCE R IF FALSE RETURN THE INDICES OF ALL POINTS WITHIN DISTANCE R IF RETURNDISTANCETRUE
SETTING COUNTONLYTRUE WILL RESULT IN AN ERROR
SORTRESULTS BOOLEAN DEFAULT FALSE IF TRUE THE DISTANCES AND INDICES WILL BE SORTED
BEFORE BEING RETURNED IF FALSE THE RESULTS WILL NOT BE SORTED IF RETURNDISTANCE FALSE
SETTING SORTRESULTS TRUE WILL RESULT IN AN ERROR
RETURNS
COUNT IF COUNTONLY TRUE
IND IF COUNTONLY FALSE AND RETURNDISTANCE FALSE
IND DIST IF COUNTONLY FALSE AND RETURNDISTANCE TRUE

COUNT ARRAY OF INTEGERS SHAPE XSHAPE1 EACH ENTRY GIVES THE NUMBER OF NEIGHBORS
WITHIN A DISTANCE R OF THE CORRESPONDING POINT
IND ARRAY OF OBJECTS SHAPE XSHAPE1 EACH ELEMENT IS A NUMPY INTEGER ARRAY LISTING
THE INDICES OF NEIGHBORS OF THE CORRESPONDING POINT NOTE THAT UNLIKE THE RESULTS OF A K
NEIGHBORS QUERY THE RETURNED NEIGHBORS ARE NOT SORTED BY DISTANCE BY DEFAULT
DIST ARRAY OF OBJECTS SHAPE XSHAPE1 EACH ELEMENT IS A NUMPY DOUBLE ARRAY LISTING
THE DISTANCES CORRESPONDING TO INDICES IN I
TWOPOINTCORRELATION
COMPUTE THE TWOPOINT CORRELATION FUNCTION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES AN ARRAY OF POINTS TO QUERY LAST DIMENSION
SHOULD MATCH DIMENSION OF TRAINING DATA
RARRAYLIKE A ONEDIMENSIONAL ARRAY OF DISTANCES
DUALTREE BOOLEAN DEFAULT FALSE IF TRUE USE A DUALTREE ALGORITHM OTHERWISE USE A
SINGLETREE ALGORITHM DUAL TREE ALGORITHMS CAN HAVE BETTER SCALING FOR LARGE N
RETURNS
COUNTS NDARRAY COUNTSI CONTAINS THE NUMBER OF PAIRS OF POINTS WITH DISTANCE LESS THAN OR
EQUAL TO RI
6304SKLEARNNEIGHBORS KERNELDENSITY
CLASSSKLEARNNEIGHBORS KERNELDENSITY BANDWIDTH10 ALGORITHM’AUTO’ KERNEL’GAUSSIAN’
METRIC’EUCLIDEAN’ ATOL0 RTOL0 BREADTHFIRSTTRUE
LEAFSIZE40 METRICPARAMSNONE
KERNEL DENSITY ESTIMATION
READ MORE IN THE USER GUIDE
PARAMETERS
BANDWIDTH FLOAT THE BANDWIDTH OF THE KERNEL
ALGORITHM STRING THE TREE ALGORITHM TO USE VALID OPTIONS ARE ‘KDTREE’’BALLTREE’’AUTO’
DEFAULT IS ‘AUTO’
KERNEL STRING THE KERNEL TO USE VALID KERNELS ARE ‘GAUS
SIAN’’TOPHAT’’EPANECHNIKOV’’EXPONENTIAL’’LINEAR’’COSINE’ DEFAULT IS ‘GAUSSIAN’
METRIC STRING THE DISTANCE METRIC TO USE NOTE THAT NOT ALL METRICS ARE VALID WITH ALL ALGORITHMS
REFER TO THE DOCUMENTATION OF BALLTREE ANDKDTREE FOR A DESCRIPTION OF AVAILABLE ALGO
RITHMS NOTE THAT THE NORMALIZATION OF THE DENSITY OUTPUT IS CORRECT ONLY FOR THE EUCLIDEAN
DISTANCE METRIC DEFAULT IS ‘EUCLIDEAN’
ATOL FLOAT THE DESIRED ABSOLUTE TOLERANCE OF THE RESULT A LARGER TOLERANCE WILL GENERALLY LEAD
TO FASTER EXECUTION DEFAULT IS 0
RTOL FLOAT THE DESIRED RELATIVE TOLERANCE OF THE RESULT A LARGER TOLERANCE WILL GENERALLY LEAD TO
FASTER EXECUTION DEFAULT IS 1E8
BREADTHFIRST BOOLEAN IF TRUE DEFAULT USE A BREADTHFIRST APPROACH TO THE PROBLEM OTHERWISE
USE A DEPTHFIRST APPROACH
LEAFSIZE INT SPECIFY THE LEAF SIZE OF THE UNDERLYING TREE SEE BALLTREE ORKDTREE FOR
DETAILS DEFAULT IS 40

METRICPARAMS DICT ADDITIONAL PARAMETERS TO BE PASSED TO THE TREE FOR USE WITH THE METRIC
FOR MORE INFORMATION SEE THE DOCUMENTATION OF BALLTREE ORKDTREE
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE KERNEL DENSITY MODEL ON THE DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SAMPLE SELF NSAMPLES RANDOMSTATE GENERATE RANDOM SAMPLES FROM THE MODEL
SCORE SELF X Y COMPUTE THE TOTAL LOG PROBABILITY DENSITY UNDER THE
MODEL
SCORESAMPLES SELF X EVALUATE THE DENSITY MODEL ON THE DATA
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFBANDWIDTH10 ALGORITHM'AUTO' KERNEL'GAUSSIAN' METRIC'EUCLIDEAN' ATOL0
RTOL0 BREADTHFIRSTTRUE LEAFSIZE40 METRICPARAMSNONE
FITSELFXYNONE SAMPLEWEIGHTNONE
FIT THE KERNEL DENSITY MODEL ON THE DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES LIST OF NFEATURESDIMENSIONAL DATA POINTS
EACH ROW CORRESPONDS TO A SINGLE DATA POINT
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL LIST OF SAMPLE WEIGHTS ATTACHED
TO THE DATA X
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SAMPLESELFNSAMPLES1 RANDOMSTATENONE
GENERATE RANDOM SAMPLES FROM THE MODEL
CURRENTLY THIS IS IMPLEMENTED ONLY FOR GAUSSIAN AND TOPHAT KERNELS
PARAMETERS
NSAMPLES INT OPTIONAL NUMBER OF SAMPLES TO GENERATE DEFAULTS TO 1
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE DEFAULT TO NONE IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
RETURNS
XARRAYLIKE SHAPE NSAMPLES NFEATURES LIST OF SAMPLES
SCORESELFXYNONE
COMPUTE THE TOTAL LOG PROBABILITY DENSITY UNDER THE MODEL
PARAMETERS

SCIKITLEARN USER GUIDE RELEASE 0213
XARRAYLIKE SHAPE NSAMPLES NFEATURES LIST OF NFEATURESDIMENSIONAL DATA POINTS
EACH ROW CORRESPONDS TO A SINGLE DATA POINT
RETURNS
LOGPROB FLOAT TOTAL LOGLIKELIHOOD OF THE DATA IN X THIS IS NORMALIZED TO BE A PROBABILITY
DENSITY SO THE VALUE WILL BE LOW FOR HIGHDIMENSIONAL DATA
SCORESAMPLES SELFX
EVALUATE THE DENSITY MODEL ON THE DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES AN ARRAY OF POINTS TO QUERY LAST DIMENSION
SHOULD MATCH DIMENSION OF TRAINING DATA NFEATURES
RETURNS
DENSITY NDARRAY SHAPE NSAMPLES THE ARRAY OF LOGDENSITY EVALUATIONS THESE ARE NOR
MALIZED TO BE PROBABILITY DENSITIES SO VALUES WILL BE LOW FOR HIGHDIMENSIONAL DATA
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNNEIGHBORSKERNELDENSITY
•KERNEL DENSITY ESTIMATION
•KERNEL DENSITY ESTIMATE OF SPECIES DISTRIBUTIONS
•SIMPLE 1D KERNEL DENSITY ESTIMATION
6305SKLEARNNEIGHBORS KNEIGHBORSCLASSIFIER
CLASSSKLEARNNEIGHBORS KNEIGHBORSCLASSIFIER NNEIGHBORS5 WEIGHTS'UNIFORM' AL
GORITHM'AUTO' LEAFSIZE30 P2MET
RIC'MINKOWSKI' METRICPARAMSNONE
NJOBSNONE KWARGS
CLASSIFIER IMPLEMENTING THE KNEAREST NEIGHBORS VOTE
READ MORE IN THE USER GUIDE
PARAMETERS
NNEIGHBORS INT OPTIONAL DEFAULT 5 NUMBER OF NEIGHBORS TO USE BY DEFAULT FOR
KNEIGHBORS QUERIES
WEIGHTS STR OR CALLABLE OPTIONAL DEFAULT 'UNIFORM' WEIGHT FUNCTION USED IN PREDICTION POS
SIBLE VALUES
• 'UNIFORM' UNIFORM WEIGHTS ALL POINTS IN EACH NEIGHBORHOOD ARE WEIGHTED EQUALLY
• 'DISTANCE' WEIGHT POINTS BY THE INVERSE OF THEIR DISTANCE IN THIS CASE CLOSER NEIGHBORS
OF A QUERY POINT WILL HAVE A GREATER INFLUENCE THAN NEIGHBORS WHICH ARE FURTHER AWAY
630SKLEARNNEIGHBORS NEAREST NEIGHBORS 2167

• CALLABLE A USERDEFINED FUNCTION WHICH ACCEPTS AN ARRAY OF DISTANCES AND RETURNS AN ARRAY OF THE SAME SHAPE CONTAINING THE WEIGHTS
ALGORITHM ‘AUTO’ ‘BALLTREE’ ‘KDTREE’ ‘BRUTE’ OPTIONAL ALGORITHM USED TO COMPUTE THE NEAREST NEIGHBORS
• ‘BALLTREE’ WILL USE BALLTREE
• ‘KDTREE’ WILL USE KDTREE
• ‘BRUTE’ WILL USE A BRUTEFORCE SEARCH
• ‘AUTO’ WILL ATTEMPT TO DECIDE THE MOST APPROPRIATE ALGORITHM BASED ON THE VALUES PASSED TOFIT METHOD
NOTE FITTING ON SPARSE INPUT WILL OVERRIDE THE SETTING OF THIS PARAMETER USING BRUTE FORCE
LEAFSIZE INT OPTIONAL DEFAULT 30 LEAF SIZE PASSED TO BALLTREE OR KDTREE THIS CAN AFFECT THE SPEED OF THE CONSTRUCTION AND QUERY AS WELL AS THE MEMORY REQUIRED TO STORE THE TREE THE OPTIMAL VALUE DEPENDS ON THE NATURE OF THE PROBLEM
PINTEGER OPTIONAL DEFAULT 2 POWER PARAMETER FOR THE MINKOWSKI METRIC WHEN P 1 THIS IS EQUIVALENT TO USING MANHATTANDISTANCE L1 AND EUCLIDEANDISTANCE L2 FOR P 2 FOR ARBITRARY P MINKOWSKIDISTANCE LP IS USED
METRIC STRING OR CALLABLE DEFAULT ‘MINKOWSKI’ THE DISTANCE METRIC TO USE FOR THE TREE THE DEFAULT METRIC IS MINKOWSKI AND WITH P2 IS EQUIVALENT TO THE STANDARD EUCLIDEAN METRIC SEE THE DOCUMENTATION OF THE DISTANCEMETRIC CLASS FOR A LIST OF AVAILABLE METRICS
METRICPARAMS DICT OPTIONAL DEFAULT NONE ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC FUNCTION
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS DOESN’T AFFECT FIT METHOD
SEE ALSO
RADIUSNEIGHBORSCLASSIFIER
KNEIGHBORSREGRESSOR
RADIUSNEIGHBORSREGRESSOR
NEARESTNEIGHBORS
NOTES
SEE NEAREST NEIGHBORS IN THE ONLINE DOCUMENTATION FOR A DISCUSSION OF THE CHOICE OF ALGORITHM AND LEAFSIZE
WARNING REGARDING THE NEAREST NEIGHBORS ALGORITHMS IF IT IS FOUND THAT TWO NEIGHBORS NEIGHBOR K1 AND K HAVE IDENTICAL DISTANCES BUT DIFFERENT LABELS THE RESULTS WILL DEPEND ON THE ORDERING OF THE TRAINING DATA HTTPSENWIKIPEDIAORGWIKIKNEARESTNEIGHBORALGORITHM

EXAMPLES
```
X  0 1 2 3
Y  0 0 1 1
 FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSCLASSIFIER
NEIGH  KNEIGHBORSCLASSIFIERNNEIGHBORS3
NEIGHFITX Y
KNEIGHBORSCLASSIFIER
PRINTNEIGHPREDICT11
0
PRINTNEIGHPREDICTPROBA09
066666667 033333333
```
METHODS
FITSELF X Y FIT THE MODEL USING X AS TRAINING DATA AND Y AS TARGET VALUES
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
KNEIGHBORS SELF X NNEIGHBORS FINDS THE KNEIGHBORS OF A POINT
KNEIGHBORSGRAPH SELF X NNEIGHBORS MODE COMPUTES THE WEIGHTED GRAPH OF KNEIGHBORS FOR POINTS IN X
PREDICT SELF X PREDICT THE CLASS LABELS FOR THE PROVIDED DATA
PREDICTPROBA SELF X RETURN PROBABILITY ESTIMATES FOR THE TEST DATA X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNNEIGHBORS5 WEIGHTS'UNIFORM' ALGORITHM'AUTO' LEAFSIZE30 P2MET RIC'MINKOWSKI' METRICPARAMSNONE NJOBSNONE KWARGS
FITSELFXY
FIT THE MODEL USING X AS TRAINING DATA AND Y AS TARGET VALUES
PARAMETERS
XARRAYLIKE SPARSE MATRIX BALLTREE KDTREE TRAINING DATA IF ARRAY OR MATRIX SHAPE NSAMPLES NFEATURES OR NSAMPLES NSAMPLES IF METRIC'PRECOMPUTED'
YARRAYLIKE SPARSE MATRIX TARGET VALUES OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
KNEIGHBORS SELFXNONE NNEIGHBORSNONE RETURNDISTANCETRUE
FINDS THE KNEIGHBORS OF A POINT RETURNS INDICES OF AND DISTANCES TO THE NEIGHBORS OF EACH POINT
PARAMETERS

XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC ‘PRECOM
PUTED’ THE QUERY POINT OR POINTS IF NOT PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE
RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED ITS OWN NEIGHBOR
NNEIGHBORS INT NUMBER OF NEIGHBORS TO GET DEFAULT IS THE VALUE PASSED TO THE CONSTRUC
TOR
RETURNDISTANCE BOOLEAN OPTIONAL DEFAULTS TO TRUE IF FALSE DISTANCES WILL NOT BE RE
TURNED
RETURNS
DIST ARRAY ARRAY REPRESENTING THE LENGTHS TO POINTS ONLY PRESENT IF RETURNDISTANCETRUE
IND ARRAY INDICES OF THE NEAREST POINTS IN THE POPULATION MATRIX
EXAMPLES
IN THE FOLLOWING EXAMPLE WE CONSTRUCT A NEIGHBORSCLASSIFIER CLASS FROM AN ARRAY REPRESENTING OUR DATA SET
AND ASK WHO’S THE CLOSEST POINT TO 111
SAMPLES 0 0 0 0 5 0 1 1 5
FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH NEARESTNEIGHBORSNNEIGHBORS1
NEIGHFITSAMPLES
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
PRINTNEIGHKNEIGHBORS1 1 1
ARRAY05 ARRAY2
AS YOU CAN SEE IT RETURNS 05 AND 2 WHICH MEANS THAT THE ELEMENT IS AT DISTANCE 05 AND IS THE THIRD
ELEMENT OF SAMPLES INDEXES START AT 0 YOU CAN ALSO QUERY FOR MULTIPLE POINTS
X 0 1 0 1 0 1
NEIGHKNEIGHBORSX RETURNDISTANCE FALSE
ARRAY1
2
KNEIGHBORSGRAPH SELFXNONE NNEIGHBORSNONE MODE’CONNECTIVITY’
COMPUTES THE WEIGHTED GRAPH OF KNEIGHBORS FOR POINTS IN X
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC ‘PRECOM
PUTED’ THE QUERY POINT OR POINTS IF NOT PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE
RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED ITS OWN NEIGHBOR
NNEIGHBORS INT NUMBER OF NEIGHBORS FOR EACH SAMPLE DEFAULT IS VALUE PASSED TO THE
CONSTRUCTOR
MODE ‘CONNECTIVITY’ ‘DISTANCE’ OPTIONAL TYPE OF RETURNED MATRIX ‘CONNECTIVITY’ WILL
RETURN THE CONNECTIVITY MATRIX WITH ONES AND ZEROS IN ‘DISTANCE’ THE EDGES ARE EUCLIDEAN
DISTANCE BETWEEN POINTS
RETURNS
ASPARSE MATRIX IN CSR FORMAT SHAPE NSAMPLES NSAMPLESFIT NSAMPLESFIT IS THE
NUMBER OF SAMPLES IN THE FITTED DATA AI J IS ASSIGNED THE WEIGHT OF EDGE THAT CONNECTS I
TO J
SEE ALSO

NEARESTNEIGHBORSRADIUSNEIGHBORSGRAPH
EXAMPLES
X 0 3 1
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH NEARESTNEIGHBORSNNEIGHBORS2
NEIGHFITX
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
A NEIGHKNEIGHBORSGRAPHX
ATOARRAY
ARRAY1 0 1
0 1 1
1 0 1
PREDICTSELFX
PREDICT THE CLASS LABELS FOR THE PROVIDED DATA
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC ‘PRECOM
PUTED’ TEST SAMPLES
RETURNS
YARRAY OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS CLASS LABELS FOR EACH DATA SAMPLE
PREDICTPROBA SELFX
RETURN PROBABILITY ESTIMATES FOR THE TEST DATA X
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC ‘PRECOM
PUTED’ TEST SAMPLES
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES OR A LIST OF NOUTPUTS OF SUCH ARRAYS IF NOUTPUTS
 1 THE CLASS PROBABILITIES OF THE INPUT SAMPLES CLASSES ARE ORDERED BY LEXICOGRAPHIC
ORDER
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR

THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNNEIGHBORSKNEIGHBORSCLASSIFIER
•CLASSIFIER COMPARISON
•PLOT THE DECISION BOUNDARIES OF A VOTINGCLASSIFIER
•DIGITS CLASSIFICATION EXERCISE
•NEAREST NEIGHBORS CLASSIFICATION
•COMPARING NEAREST NEIGHBORS WITH AND WITHOUT NEIGHBORHOOD COMPONENTS ANALYSIS
•DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
6306SKLEARNNEIGHBORS KNEIGHBORSREGRESSOR
CLASSSKLEARNNEIGHBORS KNEIGHBORSREGRESSOR NNEIGHBORS5 WEIGHTS'UNIFORM' ALGO
RITHM'AUTO' LEAFSIZE30 P2MET
RIC'MINKOWSKI' METRICPARAMSNONE
NJOBSNONE KWARGS
REGRESSION BASED ON KNEAREST NEIGHBORS
THE TARGET IS PREDICTED BY LOCAL INTERPOLATION OF THE TARGETS ASSOCIATED OF THE NEAREST NEIGHBORS IN THE TRAINING SET
READ MORE IN THE USER GUIDE
PARAMETERS
NNEIGHBORS INT OPTIONAL DEFAULT 5 NUMBER OF NEIGHBORS TO USE BY DEFAULT FOR
KNEIGHBORS QUERIES
WEIGHTS STR OR CALLABLE WEIGHT FUNCTION USED IN PREDICTION POSSIBLE VALUES
• 'UNIFORM' UNIFORM WEIGHTS ALL POINTS IN EACH NEIGHBORHOOD ARE WEIGHTED EQUALLY
• 'DISTANCE' WEIGHT POINTS BY THE INVERSE OF THEIR DISTANCE IN THIS CASE CLOSER NEIGHBORS
OF A QUERY POINT WILL HAVE A GREATER INFLUENCE THAN NEIGHBORS WHICH ARE FURTHER AWAY
• CALLABLE A USERDEFINED FUNCTION WHICH ACCEPTS AN ARRAY OF DISTANCES AND RETURNS AN
ARRAY OF THE SAME SHAPE CONTAINING THE WEIGHTS
UNIFORM WEIGHTS ARE USED BY DEFAULT
ALGORITHM 'AUTO' 'BALLTREE' 'KDTREE' 'BRUTE' OPTIONAL ALGORITHM USED TO COMPUTE THE
NEAREST NEIGHBORS
• 'BALLTREE' WILL USE BALLTREE
• 'KDTREE' WILL USE KDTREE
• 'BRUTE' WILL USE A BRUTEFORCE SEARCH
• 'AUTO' WILL ATTEMPT TO DECIDE THE MOST APPROPRIATE ALGORITHM BASED ON THE VALUES PASSED
TOFIT METHOD

NOTE FITTING ON SPARSE INPUT WILL OVERRIDE THE SETTING OF THIS PARAMETER USING BRUTE FORCE
LEAFSIZE INT OPTIONAL DEFAULT 30 LEAF SIZE PASSED TO BALLTREE OR KDTREE THIS CAN AFFECT
THE SPEED OF THE CONSTRUCTION AND QUERY AS WELL AS THE MEMORY REQUIRED TO STORE THE TREE
THE OPTIMAL VALUE DEPENDS ON THE NATURE OF THE PROBLEM
PINTEGER OPTIONAL DEFAULT 2 POWER PARAMETER FOR THE MINKOWSKI METRIC WHEN P 1 THIS
IS EQUIVALENT TO USING MANHATTANDISTANCE L1 AND EUCLIDEANDISTANCE L2 FOR P 2 FOR
ARBITRARY P MINKOWSKIDISTANCE LP IS USED
METRIC STRING OR CALLABLE DEFAULT ‘MINKOWSKI’ THE DISTANCE METRIC TO USE FOR THE TREE THE
DEFAULT METRIC IS MINKOWSKI AND WITH P2 IS EQUIVALENT TO THE STANDARD EUCLIDEAN METRIC
SEE THE DOCUMENTATION OF THE DISTANCEMETRIC CLASS FOR A LIST OF AVAILABLE METRICS
METRICPARAMS DICT OPTIONAL DEFAULT NONE ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC
FUNCTION
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS
SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS DOESN’T AFFECT FIT METHOD
SEE ALSO
NEARESTNEIGHBORS
RADIUSNEIGHBORSREGRESSOR
KNEIGHBORSCLASSIFIER
RADIUSNEIGHBORSCLASSIFIER
NOTES
SEE NEAREST NEIGHBORS IN THE ONLINE DOCUMENTATION FOR A DISCUSSION OF THE CHOICE OF ALGORITHM AND
LEAFSIZE
WARNING REGARDING THE NEAREST NEIGHBORS ALGORITHMS IF IT IS FOUND THAT TWO NEIGHBORS NEIGHBOR K1 AND
K HAVE IDENTICAL DISTANCES BUT DIFFERENT LABELS THE RESULTS WILL DEPEND ON THE ORDERING OF THE TRAINING DATA
HTTPSENWIKIPEDIAORGWIKIKNEARESTNEIGHBORALGORITHM
EXAMPLES
X 0 1 2 3
Y 0 0 1 1
 FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSREGRESSOR
NEIGH KNEIGHBORSREGRESSORNNEIGHBORS2
NEIGHFITX Y
KNEIGHBORSREGRESSOR
PRINTNEIGHPREDICT15
05

METHODS
FITSELF X Y FIT THE MODEL USING X AS TRAINING DATA AND Y AS TARGET
VALUES
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
KNEIGHBORS SELF X NNEIGHBORS FINDS THE KNEIGHBORS OF A POINT
KNEIGHBORSGRAPH SELF X NNEIGHBORS MODE COMPUTES THE WEIGHTED GRAPH OF KNEIGHBORS FOR
POINTS IN X
PREDICT SELF X PREDICT THE TARGET FOR THE PROVIDED DATA
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNNEIGHBORS5 WEIGHTS'UNIFORM' ALGORITHM'AUTO' LEAFSIZE30 P2MET
RIC'MINKOWSKI' METRICPARAMSNONE NJOBSNONE KWARGS
FITSELFXY
FIT THE MODEL USING X AS TRAINING DATA AND Y AS TARGET VALUES
PARAMETERS
XARRAYLIKE SPARSE MATRIX BALLTREE KDTREE TRAINING DATA IF ARRAY OR MATRIX SHAPE
NSAMPLES NFEATURES OR NSAMPLES NSAMPLES IF METRIC'PRECOMPUTED'
YARRAYLIKE SPARSE MATRIX
TARGET VALUES ARRAY OF FLOAT VALUES SHAPE NSAMPLES OR NSAMPLES NOUTPUTS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
KNEIGHBORS SELFXNONE NNEIGHBORSNONE RETURNDISTANCETRUE
FINDS THE KNEIGHBORS OF A POINT RETURNS INDICES OF AND DISTANCES TO THE NEIGHBORS OF EACH POINT
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC 'PRECOM
PUTED' THE QUERY POINT OR POINTS IF NOT PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE
RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED ITS OWN NEIGHBOR
NNEIGHBORS INT NUMBER OF NEIGHBORS TO GET DEFAULT IS THE VALUE PASSED TO THE CONSTRUC
TOR
RETURNDISTANCE BOOLEAN OPTIONAL DEFAULTS TO TRUE IF FALSE DISTANCES WILL NOT BE RE
TURNED
RETURNS
DIST ARRAY ARRAY REPRESENTING THE LENGTHS TO POINTS ONLY PRESENT IF RETURNDISTANCETRUE
IND ARRAY INDICES OF THE NEAREST POINTS IN THE POPULATION MATRIX

EXAMPLES
IN THE FOLLOWING EXAMPLE WE CONSTRUCT A NEIGHBORSCLASSIFIER CLASS FROM AN ARRAY REPRESENTING OUR DATA SET
AND ASK WHO'S THE CLOSEST POINT TO 111
```
SAMPLES  0 0 0 0 5 0 1 1 5
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH  NEARESTNEIGHBORSNNEIGHBORS1
NEIGHFITSAMPLES
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
PRINTNEIGHKNEIGHBORS1 1 1
ARRAY05 ARRAY2
```
AS YOU CAN SEE IT RETURNS 05 AND 2 WHICH MEANS THAT THE ELEMENT IS AT DISTANCE 05 AND IS THE THIRD
ELEMENT OF SAMPLES INDEXES START AT 0 YOU CAN ALSO QUERY FOR MULTIPLE POINTS
```
X  0 1 0 1 0 1
NEIGHKNEIGHBORSX RETURNDISTANCE FALSE
ARRAY1
2
```
KNEIGHBORSGRAPH SELFXNONE NNEIGHBORSNONE MODE'CONNECTIVITY'
COMPUTES THE WEIGHTED GRAPH OF KNEIGHBORS FOR POINTS IN X
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC 'PRECOM
PUTED' THE QUERY POINT OR POINTS IF NOT PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE
RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED ITS OWN NEIGHBOR
NNEIGHBORS INT NUMBER OF NEIGHBORS FOR EACH SAMPLE DEFAULT IS VALUE PASSED TO THE
CONSTRUCTOR
MODE 'CONNECTIVITY' 'DISTANCE' OPTIONAL TYPE OF RETURNED MATRIX 'CONNECTIVITY' WILL
RETURN THE CONNECTIVITY MATRIX WITH ONES AND ZEROS IN 'DISTANCE' THE EDGES ARE EUCLIDEAN
DISTANCE BETWEEN POINTS
RETURNS
ASPARSE MATRIX IN CSR FORMAT SHAPE NSAMPLES NSAMPLESFIT NSAMPLESFIT IS THE
NUMBER OF SAMPLES IN THE FITTED DATA AI J IS ASSIGNED THE WEIGHT OF EDGE THAT CONNECTS I
TO J
SEE ALSO
NEARESTNEIGHBORSRADIUSNEIGHBORSGRAPH
EXAMPLES
```
X  0 3 1
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH  NEARESTNEIGHBORSNNEIGHBORS2
NEIGHFITX
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
A  NEIGHKNEIGHBORSGRAPHX
ATOARRAY
ARRAY1 0 1
```

0 1 1
1 0 1
PREDICTSELFX
PREDICT THE TARGET FOR THE PROVIDED DATA
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC ‘PRECOM
PUTED’ TEST SAMPLES
RETURNS
YARRAY OF INT SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNNEIGHBORSKNEIGHBORSREGRESSOR
•FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS

•IMPUTING MISSING VALUES WITH VARIANTS OF ITERATIVEIMPUTER
•NEAREST NEIGHBORS REGRESSION
6307SKLEARNNEIGHBORS LOCALOUTLIERFACTOR
CLASSSKLEARNNEIGHBORS LOCALOUTLIERFACTOR NNEIGHBORS20 ALGORITHM'AUTO'
LEAFSIZE30 METRIC'MINKOWSKI' P2MET
RICPARAMSNONE CONTAMINATION'LEGACY'
NOVELTYFALSE NJOBSNONE
UNSUPERVISED OUTLIER DETECTION USING LOCAL OUTLIER FACTOR LOF
THE ANOMALY SCORE OF EACH SAMPLE IS CALLED LOCAL OUTLIER FACTOR IT MEASURES THE LOCAL DEVIATION OF DENSITY OF A GIVEN SAMPLE WITH RESPECT TO ITS NEIGHBORS IT IS LOCAL IN THAT THE ANOMALY SCORE DEPENDS ON HOW ISOLATED THE OBJECT IS WITH RESPECT TO THE SURROUNDING NEIGHBORHOOD MORE PRECISELY LOCALITY IS GIVEN BY KNEAREST NEIGHBORS WHOSE DISTANCE IS USED TO ESTIMATE THE LOCAL DENSITY BY COMPARING THE LOCAL DENSITY OF A SAMPLE TO THE LOCAL DENSITIES OF ITS NEIGHBORS ONE CAN IDENTIFY SAMPLES THAT HAVE A SUBSTANTIALLY LOWER DENSITY THAN THEIR NEIGHBORS THESE ARE CONSIDERED OUTLIERS
PARAMETERS
NNEIGHBORS INT OPTIONAL DEFAULT20 NUMBER OF NEIGHBORS TO USE BY DEFAULT FOR KNEIGHBORS QUERIES IF NNEIGHBORS IS LARGER THAN THE NUMBER OF SAMPLES PROVIDED ALL SAMPLES WILL BE USED
ALGORITHM 'AUTO' 'BALLTREE' 'KDTREE' 'BRUTE' OPTIONAL ALGORITHM USED TO COMPUTE THE NEAREST NEIGHBORS
• 'BALLTREE' WILL USE BALLTREE
• 'KDTREE' WILL USE KDTREE
• 'BRUTE' WILL USE A BRUTEFORCE SEARCH
• 'AUTO' WILL ATTEMPT TO DECIDE THE MOST APPROPRIATE ALGORITHM BASED ON THE VALUES PASSED TOFIT METHOD
NOTE FITTING ON SPARSE INPUT WILL OVERRIDE THE SETTING OF THIS PARAMETER USING BRUTE FORCE
LEAFSIZE INT OPTIONAL DEFAULT30 LEAF SIZE PASSED TO BALLTREE ORKDTREE THIS CAN AFFECT THE SPEED OF THE CONSTRUCTION AND QUERY AS WELL AS THE MEMORY REQUIRED TO STORE THE TREE THE OPTIMAL VALUE DEPENDS ON THE NATURE OF THE PROBLEM
METRIC STRING OR CALLABLE DEFAULT 'MINKOWSKI' METRIC USED FOR THE DISTANCE COMPUTATION ANY METRIC FROM SCIKITLEARN OR SCIPYSPATIALDISTANCE CAN BE USED
IF 'PRECOMPUTED' THE TRAINING INPUT X IS EXPECTED TO BE A DISTANCE MATRIX
IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF INSTANCES ROWS AND THE RESULTING VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS AS INPUT AND RETURN ONE VALUE INDICATING THE DISTANCE BETWEEN THEM THIS WORKS FOR SCIPY'S METRICS BUT IS LESS EFFICIENT THAN PASSING THE METRIC NAME AS A STRING
VALID VALUES FOR METRIC ARE
• FROM SCIKITLEARN 'CITYBLOCK' 'COSINE' 'EUCLIDEAN' 'L1' 'L2' 'MANHATTAN'
• FROM SCIPYSPATIALDISTANCE 'BRAYCURTIS' 'CANBERRA' 'CHEBYSHEV' 'CORRELATION' 'DICE' 'HAMMING' 'JACCARD' 'KULSINSKI' 'MAHALANOBIS' 'MINKOWSKI' 'ROGERSTANIMOTO' 'RUS SELLRAO' 'SEUCLIDEAN' 'SOKALMICHENER' 'SOKALSNEATH' 'SQEUCLIDEAN' 'YULE'

SEE THE DOCUMENTATION FOR SCIPYSPATIALDISTANCE FOR DETAILS ON THESE METRICS HTTPSDOCS
SCIPYORGDOCSCIPYREFERENCESPATIALDISTANCEHTML
PINTEGER OPTIONAL DEFAULT2 PARAMETER FOR THE MINKOWSKI METRIC FROM SKLEARN
METRICSPAIRWISEPAIRWISEDISTANCES WHEN P 1 THIS IS EQUIVALENT TO
USING MANHATTANDISTANCE L1 AND EUCLIDEANDISTANCE L2 FOR P 2 FOR ARBITRARY P
MINKOWSKIDISTANCE LP IS USED
METRICPARAMS DICT OPTIONAL DEFAULTNONE ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC
FUNCTION
CONTAMINATION FLOAT IN 0 05 OPTIONAL DEFAULT01 THE AMOUNT OF CONTAMINATION OF THE
DATA SET IE THE PROPORTION OF OUTLIERS IN THE DATA SET WHEN FITTING THIS IS USED TO DEFINE THE
THRESHOLD ON THE DECISION FUNCTION IF “AUTO” THE DECISION FUNCTION THRESHOLD IS DETERMINED
AS IN THE ORIGINAL PAPER
CHANGED IN VERSION 020 THE DEFAULT VALUE OF CONTAMINATION WILL CHANGE FROM 01 IN
020 TOAUTO IN 022
NOVELTY BOOLEAN DEFAULT FALSE BY DEFAULT LOCALOUTLIERFACTOR IS ONLY MEANT TO BE USED FOR
OUTLIER DETECTION NOVELTYFALSE SET NOVELTY TO TRUE IF YOU WANT TO USE LOCALOUTLIERFACTOR
FOR NOVELTY DETECTION IN THIS CASE BE AWARE THAT THAT YOU SHOULD ONLY USE PREDICT DECI
SIONFUNCTION AND SCORESAMPLES ON NEW UNSEEN DATA AND NOT ON THE TRAINING SET
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGH
BORS SEARCH NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1
MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS AFFECTS ONLY KNEIGHBORS AND
KNEIGHBORSGRAPH METHODS
ATTRIBUTES
NEGATIVEOUTLIERFACTOR NUMPY ARRAY SHAPE NSAMPLES THE OPPOSITE LOF OF THE TRAIN
ING SAMPLES THE HIGHER THE MORE NORMAL INLIERS TEND TO HAVE A LOF SCORE CLOSE TO 1
NEGATIVEOUTLIERFACTOR CLOSE TO 1 WHILE OUTLIERS TEND TO HAVE A LARGER LOF
SCORE
THE LOCAL OUTLIER FACTOR LOF OF A SAMPLE CAPTURES ITS SUPPOSED ‘DEGREE OF ABNORMALITY’
IT IS THE AVERAGE OF THE RATIO OF THE LOCAL REACHABILITY DENSITY OF A SAMPLE AND THOSE OF ITS
KNEAREST NEIGHBORS
NNEIGHBORS INTEGER THE ACTUAL NUMBER OF NEIGHBORS USED FOR KNEIGHBORS QUERIES
OFFSET FLOAT OFFSET USED TO OBTAIN BINARY LABELS FROM THE RAW SCORES OBSERVATIONS HAVING A
NEGATIVEOUTLIERFACTOR SMALLER THAN OFFSET ARE DETECTED AS ABNORMAL THE OFFSET IS SET TO
15 INLIERS SCORE AROUND 1 EXCEPT WHEN A CONTAMINATION PARAMETER DIFFERENT THAN “AUTO”
IS PROVIDED IN THAT CASE THE OFFSET IS DEFINED IN SUCH A WAY WE OBTAIN THE EXPECTED NUMBER
OF OUTLIERS IN TRAINING
REFERENCES
RCA479BB498411
METHODS
FITSELF X Y FIT THE MODEL USING X AS TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
CONTINUED ON NEXT PAGE

TABLE 6230 – CONTINUED FROM PREVIOUS PAGE
KNEIGHBORS SELF X NNEIGHBORS FINDS THE KNEIGHBORS OF A POINT
KNEIGHBORSGRAPH SELF X NNEIGHBORS MODE COMPUTES THE WEIGHTED GRAPH OF KNEIGHBORS FOR
POINTS IN X
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNNEIGHBORS20 ALGORITHM'AUTO' LEAFSIZE30 METRIC'MINKOWSKI' P2MET
RICPARAMSNONE CONTAMINATION'LEGACY' NOVELTYFALSE NJOBSNONE
DECISIONFUNCTION
SHIFTED OPPOSITE OF THE LOCAL OUTLIER FACTOR OF X
BIGGER IS BETTER IE LARGE VALUES CORRESPOND TO INLIERS
THE SHIFT OFFSET ALLOWS A ZERO THRESHOLD FOR BEING AN OUTLIER ONLY AVAILABLE FOR NOVELTY DETECTION WHEN
NOVELTY IS SET TO TRUE THE ARGUMENT X IS SUPPOSED TO CONTAIN NEW DATA IF X CONTAINS A POINT FROM
TRAINING IT CONSIDERS THE LATER IN ITS OWN NEIGHBORHOOD ALSO THE SAMPLES IN X ARE NOT CONSIDERED IN THE
NEIGHBORHOOD OF ANY POINT
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE QUERY SAMPLE OR SAMPLES TO COMPUTE THE
LOCAL OUTLIER FACTOR WRT THE TRAINING SAMPLES
RETURNS
SHIFTEDOPPOSITELOFSCORES ARRAY SHAPE NSAMPLES THE SHIFTED OPPOSITE OF THE LOCAL
OUTLIER FACTOR OF EACH INPUT SAMPLES THE LOWER THE MORE ABNORMAL NEGATIVE SCORES
REPRESENT OUTLIERS POSITIVE SCORES REPRESENT INLIERS
FITSELFXYNONE
FIT THE MODEL USING X AS TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX BALLTREE KDTREE TRAINING DATA IF ARRAY OR MATRIX SHAPE
NSAMPLES NFEATURES OR NSAMPLES NSAMPLES IF METRIC'PRECOMPUTED'
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
SELF OBJECT
FITPREDICT
"FITS THE MODEL TO THE TRAINING SET X AND RETURNS THE LABELS
LABEL IS 1 FOR AN INLIER AND 1 FOR AN OUTLIER ACCORDING TO THE LOF SCORE AND THE CONTAMINATION PARAMETER
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES DEFAULTNONE THE QUERY SAMPLE OR SAMPLES
TO COMPUTE THE LOCAL OUTLIER FACTOR WRT TO THE TRAINING SAMPLES
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
ISINLIER ARRAY SHAPE NSAMPLES RETURNS 1 FOR ANOMALIESOUTLIERS AND 1 FOR INLIERS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

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DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
KNEIGHBORS SELFXNONE NNEIGHBORSNONE RETURNDISTANCETRUE
FINDS THE KNEIGHBORS OF A POINT RETURNS INDICES OF AND DISTANCES TO THE NEIGHBORS OF EACH POINT
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC ‘PRECOM
PUTED’ THE QUERY POINT OR POINTS IF NOT PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE
RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED ITS OWN NEIGHBOR
NNEIGHBORS INT NUMBER OF NEIGHBORS TO GET DEFAULT IS THE VALUE PASSED TO THE CONSTRUC
TOR
RETURNDISTANCE BOOLEAN OPTIONAL DEFAULTS TO TRUE IF FALSE DISTANCES WILL NOT BE RE
TURNED
RETURNS
DIST ARRAY ARRAY REPRESENTING THE LENGTHS TO POINTS ONLY PRESENT IF RETURNDISTANCETRUE
IND ARRAY INDICES OF THE NEAREST POINTS IN THE POPULATION MATRIX
EXAMPLES
IN THE FOLLOWING EXAMPLE WE CONSTRUCT A NEIGHBORSCLASSIFIER CLASS FROM AN ARRAY REPRESENTING OUR DATA SET
AND ASK WHO’S THE CLOSEST POINT TO 111
SAMPLES 0 0 0 0 5 0 1 1 5
FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH NEARESTNEIGHBORSNNEIGHBORS1
NEIGHFITSAMPLES
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
PRINTNEIGHKNEIGHBORS1 1 1
ARRAY05 ARRAY2
AS YOU CAN SEE IT RETURNS 05 AND 2 WHICH MEANS THAT THE ELEMENT IS AT DISTANCE 05 AND IS THE THIRD
ELEMENT OF SAMPLES INDEXES START AT 0 YOU CAN ALSO QUERY FOR MULTIPLE POINTS
X 0 1 0 1 0 1
NEIGHKNEIGHBORSX RETURNDISTANCE FALSE
ARRAY1
2
KNEIGHBORSGRAPH SELFXNONE NNEIGHBORSNONE MODE’CONNECTIVITY’
COMPUTES THE WEIGHTED GRAPH OF KNEIGHBORS FOR POINTS IN X
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC ‘PRECOM
PUTED’ THE QUERY POINT OR POINTS IF NOT PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE
RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED ITS OWN NEIGHBOR
NNEIGHBORS INT NUMBER OF NEIGHBORS FOR EACH SAMPLE DEFAULT IS VALUE PASSED TO THE
CONSTRUCTOR

MODE ‘CONNECTIVITY’ ‘DISTANCE’ OPTIONAL TYPE OF RETURNED MATRIX ‘CONNECTIVITY’ WILL
RETURN THE CONNECTIVITY MATRIX WITH ONES AND ZEROS IN ‘DISTANCE’ THE EDGES ARE EUCLIDEAN
DISTANCE BETWEEN POINTS
RETURNS
ASPARSE MATRIX IN CSR FORMAT SHAPE NSAMPLES NSAMPLESFIT NSAMPLESFIT IS THE
NUMBER OF SAMPLES IN THE FITTED DATA AI J IS ASSIGNED THE WEIGHT OF EDGE THAT CONNECTS I
TO J
SEE ALSO
NEARESTNEIGHBORSRADIUSNEIGHBORSGRAPH
EXAMPLES
```
X  0 3 1
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH  NEARESTNEIGHBORSNNEIGHBORS2
NEIGHFITX
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
A  NEIGHKNEIGHBORSGRAPHX
ATOARRAY
ARRAY1 0 1
0 1 1
1 0 1
```
PREDICT
PREDICT THE LABELS 1 INLIER 1 OUTLIER OF X ACCORDING TO LOF
THIS METHOD ALLOWS TO GENERALIZE PREDICTION TO NEW OBSERVATIONS NOT IN THE TRAINING SET ONLY AVAILABLE
FOR NOVELTY DETECTION WHEN NOVELTY IS SET TO TRUE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE QUERY SAMPLE OR SAMPLES TO COMPUTE THE
LOCAL OUTLIER FACTOR WRT TO THE TRAINING SAMPLES
RETURNS
ISINLIER ARRAY SHAPE NSAMPLES RETURNS 1 FOR ANOMALIESOUTLIERS AND 1 FOR INLIERS
SCORESAMPLES
OPPOSITE OF THE LOCAL OUTLIER FACTOR OF X
IT IS THE OPPOSITE AS BIGGER IS BETTER IE LARGE VALUES CORRESPOND TO INLIERS
ONLY AVAILABLE FOR NOVELTY DETECTION WHEN NOVELTY IS SET TO TRUE THE ARGUMENT X IS SUPPOSED TO CONTAIN
NEW DATA IF X CONTAINS A POINT FROM TRAINING IT CONSIDERS THE LATER IN ITS OWN NEIGHBORHOOD ALSO THE
SAMPLES IN X ARE NOT CONSIDERED IN THE NEIGHBORHOOD OF ANY POINT THE SCORESAMPLES ON TRAINING DATA IS
AVAILABLE BY CONSIDERING THE THE NEGATIVEOUTLIERFACTOR ATTRIBUTE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE QUERY SAMPLE OR SAMPLES TO COMPUTE THE
LOCAL OUTLIER FACTOR WRT THE TRAINING SAMPLES
RETURNS
OPPOSITELOFSCORES ARRAY SHAPE NSAMPLES THE OPPOSITE OF THE LOCAL OUTLIER FACTOR OF
EACH INPUT SAMPLES THE LOWER THE MORE ABNORMAL

SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNNEIGHBORSLOCALOUTLIERFACTOR
•COMPARING ANOMALY DETECTION ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS
•OUTLIER DETECTION WITH LOCAL OUTLIER FACTOR LOF
•NOVELTY DETECTION WITH LOCAL OUTLIER FACTOR LOF
6308SKLEARNNEIGHBORS RADIUSNEIGHBORSCLASSIFIER
CLASSSKLEARNNEIGHBORS RADIUSNEIGHBORSCLASSIFIER RADIUS10 WEIGHTS'UNIFORM' ALGORITHM'AUTO' LEAFSIZE30 P2METRIC'MINKOWSKI' OUTLIERLABELNONE METRICPARAMSNONE NJOBSNONE KWARGS
CLASSIFIER IMPLEMENTING A VOTE AMONG NEIGHBORS WITHIN A GIVEN RADIUS
READ MORE IN THE USER GUIDE
PARAMETERS
RADIUS FLOAT OPTIONAL DEFAULT 10 RANGE OF PARAMETER SPACE TO USE BY DEFAULT FOR RADIUSNEIGHBORS QUERIES
WEIGHTS STR OR CALLABLE WEIGHT FUNCTION USED IN PREDICTION POSSIBLE VALUES
• 'UNIFORM' UNIFORM WEIGHTS ALL POINTS IN EACH NEIGHBORHOOD ARE WEIGHTED EQUALLY
• 'DISTANCE' WEIGHT POINTS BY THE INVERSE OF THEIR DISTANCE IN THIS CASE CLOSER NEIGHBORS OF A QUERY POINT WILL HAVE A GREATER INFLUENCE THAN NEIGHBORS WHICH ARE FURTHER AWAY
• CALLABLE A USERDEFINED FUNCTION WHICH ACCEPTS AN ARRAY OF DISTANCES AND RETURNS AN ARRAY OF THE SAME SHAPE CONTAINING THE WEIGHTS
UNIFORM WEIGHTS ARE USED BY DEFAULT
ALGORITHM 'AUTO' 'BALLTREE' 'KDTREE' 'BRUTE' OPTIONAL ALGORITHM USED TO COMPUTE THE NEAREST NEIGHBORS
• 'BALLTREE' WILL USE BALLTREE
• 'KDTREE' WILL USE KDTREE
• 'BRUTE' WILL USE A BRUTEFORCE SEARCH
• 'AUTO' WILL ATTEMPT TO DECIDE THE MOST APPROPRIATE ALGORITHM BASED ON THE VALUES PASSED TOFIT METHOD
NOTE FITTING ON SPARSE INPUT WILL OVERRIDE THE SETTING OF THIS PARAMETER USING BRUTE FORCE

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LEAFSIZE INT OPTIONAL DEFAULT 30 LEAF SIZE PASSED TO BALLTREE OR KDTREE THIS CAN AFFECT
THE SPEED OF THE CONSTRUCTION AND QUERY AS WELL AS THE MEMORY REQUIRED TO STORE THE TREE
THE OPTIMAL VALUE DEPENDS ON THE NATURE OF THE PROBLEM
PINTEGER OPTIONAL DEFAULT 2 POWER PARAMETER FOR THE MINKOWSKI METRIC WHEN P 1 THIS
IS EQUIVALENT TO USING MANHATTANDISTANCE L1 AND EUCLIDEANDISTANCE L2 FOR P 2 FOR
ARBITRARY P MINKOWSKIDISTANCE LP IS USED
METRIC STRING OR CALLABLE DEFAULT ‘MINKOWSKI’ THE DISTANCE METRIC TO USE FOR THE TREE THE
DEFAULT METRIC IS MINKOWSKI AND WITH P2 IS EQUIVALENT TO THE STANDARD EUCLIDEAN METRIC
SEE THE DOCUMENTATION OF THE DISTANCEMETRIC CLASS FOR A LIST OF AVAILABLE METRICS
OUTLIERLABEL INT OPTIONAL DEFAULT NONE LABEL WHICH IS GIVEN FOR OUTLIER SAMPLES SAMPLES
WITH NO NEIGHBORS ON GIVEN RADIUS IF SET TO NONE VALUEERROR IS RAISED WHEN OUTLIER IS
DETECTED
METRICPARAMS DICT OPTIONAL DEFAULT NONE ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC
FUNCTION
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS
SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
SEE ALSO
KNEIGHBORSCLASSIFIER
RADIUSNEIGHBORSREGRESSOR
KNEIGHBORSREGRESSOR
NEARESTNEIGHBORS
NOTES
SEE NEAREST NEIGHBORS IN THE ONLINE DOCUMENTATION FOR A DISCUSSION OF THE CHOICE OF ALGORITHM AND
LEAFSIZE
HTTPSENWIKIPEDIAORGWIKIKNEARESTNEIGHBORALGORITHM
EXAMPLES
X 0 1 2 3
Y 0 0 1 1
 FROM SKLEARNNEIGHBORS IMPORT RADIUSNEIGHBORSCLASSIFIER
NEIGH RADIUSNEIGHBORSCLASSIFIERRADIUS10
NEIGHFITX Y
RADIUSNEIGHBORSCLASSIFIER
PRINTNEIGHPREDICT15
0
METHODS
630SKLEARNNEIGHBORS NEAREST NEIGHBORS 2183

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FITSELF X Y FIT THE MODEL USING X AS TRAINING DATA AND Y AS TARGET
VALUES
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT THE CLASS LABELS FOR THE PROVIDED DATA
RADIUSNEIGHBORS SELF X RADIUS FINDS THE NEIGHBORS WITHIN A GIVEN RADIUS OF A POINT OR
POINTS
RADIUSNEIGHBORSGRAPH SELF X RADIUS
MODECOMPUTES THE WEIGHTED GRAPH OF NEIGHBORS FOR POINTS
IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFRADIUS10 WEIGHTS'UNIFORM' ALGORITHM'AUTO' LEAFSIZE30 P2MET
RIC'MINKOWSKI' OUTLIERLABELNONE METRICPARAMSNONE NJOBSNONE KWARGS
FITSELFXY
FIT THE MODEL USING X AS TRAINING DATA AND Y AS TARGET VALUES
PARAMETERS
XARRAYLIKE SPARSE MATRIX BALLTREE KDTREE TRAINING DATA IF ARRAY OR MATRIX SHAPE
NSAMPLES NFEATURES OR NSAMPLES NSAMPLES IF METRIC'PRECOMPUTED'
YARRAYLIKE SPARSE MATRIX TARGET VALUES OF SHAPE NSAMPLES OR NSAMPLES
NOUTPUTS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT THE CLASS LABELS FOR THE PROVIDED DATA
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC 'PRECOM
PUTED' TEST SAMPLES
RETURNS
YARRAY OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS CLASS LABELS FOR EACH DATA SAMPLE
RADIUSNEIGHBORS SELFXNONE RADIUSNONE RETURNDISTANCETRUE
FINDS THE NEIGHBORS WITHIN A GIVEN RADIUS OF A POINT OR POINTS
RETURN THE INDICES AND DISTANCES OF EACH POINT FROM THE DATASET LYING IN A BALL WITH SIZE RADIUS AROUND
THE POINTS OF THE QUERY ARRAY POINTS LYING ON THE BOUNDARY ARE INCLUDED IN THE RESULTS
THE RESULT POINTS ARE NOTNECESSARILY SORTED BY DISTANCE TO THEIR QUERY POINT
PARAMETERS

XARRAYLIKE NSAMPLES NFEATURES OPTIONAL THE QUERY POINT OR POINTS IF NOT PROVIDED
NEIGHBORS OF EACH INDEXED POINT ARE RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED
ITS OWN NEIGHBOR
RADIUS FLOAT LIMITING DISTANCE OF NEIGHBORS TO RETURN DEFAULT IS THE VALUE PASSED TO THE
CONSTRUCTOR
RETURNDISTANCE BOOLEAN OPTIONAL DEFAULTS TO TRUE IF FALSE DISTANCES WILL NOT BE RE
TURNED
RETURNS
DIST ARRAY SHAPE NSAMPLES OF ARRAYS ARRAY REPRESENTING THE DISTANCES TO EACH POINT
ONLY PRESENT IF RETURNDISTANCETRUE THE DISTANCE VALUES ARE COMPUTED ACCORDING TO THE
METRIC CONSTRUCTOR PARAMETER
IND ARRAY SHAPE NSAMPLES OF ARRAYS AN ARRAY OF ARRAYS OF INDICES OF THE APPROXIMATE
NEAREST POINTS FROM THE POPULATION MATRIX THAT LIE WITHIN A BALL OF SIZE RADIUS AROUND THE
QUERY POINTS
NOTES
BECAUSE THE NUMBER OF NEIGHBORS OF EACH POINT IS NOT NECESSARILY EQUAL THE RESULTS FOR MULTIPLE QUERY
POINTS CANNOT BE FIT IN A STANDARD DATA ARRAY FOR EFFICIENCY RADIUSNEIGHBORS RETURNS ARRAYS OF
OBJECTS WHERE EACH OBJECT IS A 1D ARRAY OF INDICES OR DISTANCES
EXAMPLES
IN THE FOLLOWING EXAMPLE WE CONSTRUCT A NEIGHBORSCLASSIFIER CLASS FROM AN ARRAY REPRESENTING OUR DATA SET
AND ASK WHO’S THE CLOSEST POINT TO 1 1 1
```
 IMPORT NUMPY AS NP
SAMPLES  0 0 0 0 5 0 1 1 5
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH  NEARESTNEIGHBORSRADIUS16
NEIGHFITSAMPLES
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
RNG  NEIGHRADIUSNEIGHBORS1 1 1
PRINTNPASARRAYRNG00
15 05
PRINTNPASARRAYRNG10
1 2
```
THE FIRST ARRAY RETURNED CONTAINS THE DISTANCES TO ALL POINTS WHICH ARE CLOSER THAN 16 WHILE THE SECOND
ARRAY RETURNED CONTAINS THEIR INDICES IN GENERAL MULTIPLE POINTS CAN BE QUERIED AT THE SAME TIME
RADIUSNEIGHBORSGRAPH SELFXNONE RADIUSNONE MODE’CONNECTIVITY’
COMPUTES THE WEIGHTED GRAPH OF NEIGHBORS FOR POINTS IN X
NEIGHBORHOODS ARE RESTRICTED THE POINTS AT A DISTANCE LOWER THAN RADIUS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES OPTIONAL THE QUERY POINT OR POINTS IF NOT
PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE RETURNED IN THIS CASE THE QUERY POINT IS NOT
CONSIDERED ITS OWN NEIGHBOR
RADIUS FLOAT RADIUS OF NEIGHBORHOODS DEFAULT IS THE VALUE PASSED TO THE CONSTRUCTOR

MODE ‘CONNECTIVITY’ ‘DISTANCE’ OPTIONAL TYPE OF RETURNED MATRIX ‘CONNECTIVITY’ WILL
RETURN THE CONNECTIVITY MATRIX WITH ONES AND ZEROS IN ‘DISTANCE’ THE EDGES ARE EUCLIDEAN
DISTANCE BETWEEN POINTS
RETURNS
ASPARSE MATRIX IN CSR FORMAT SHAPE NSAMPLES NSAMPLES AI J IS ASSIGNED THE
WEIGHT OF EDGE THAT CONNECTS I TO J
SEE ALSO
KNEIGHBORSGRAPH
EXAMPLES
X 0 3 1
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH NEARESTNEIGHBORSRADIUS15
NEIGHFITX
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
A NEIGHRADIUSNEIGHBORSGRAPHX
ATOARRAY
ARRAY1 0 1
0 1 0
1 0 1
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF

6309SKLEARNNEIGHBORS RADIUSNEIGHBORSREGRESSOR
CLASSSKLEARNNEIGHBORS RADIUSNEIGHBORSREGRESSOR RADIUS10 WEIGHTS'UNIFORM' ALGO
RITHM'AUTO' LEAFSIZE30 P2MET
RIC'MINKOWSKI' METRICPARAMSNONE
NJOBSNONE KWARGS
REGRESSION BASED ON NEIGHBORS WITHIN A FIXED RADIUS
THE TARGET IS PREDICTED BY LOCAL INTERPOLATION OF THE TARGETS ASSOCIATED OF THE NEAREST NEIGHBORS IN THE TRAINING SET
READ MORE IN THE USER GUIDE
PARAMETERS
RADIUS FLOAT OPTIONAL DEFAULT 10 RANGE OF PARAMETER SPACE TO USE BY DEFAULT FOR
RADIUSNEIGHBORS QUERIES
WEIGHTS STR OR CALLABLE WEIGHT FUNCTION USED IN PREDICTION POSSIBLE VALUES
• 'UNIFORM' UNIFORM WEIGHTS ALL POINTS IN EACH NEIGHBORHOOD ARE WEIGHTED EQUALLY
• 'DISTANCE' WEIGHT POINTS BY THE INVERSE OF THEIR DISTANCE IN THIS CASE CLOSER NEIGHBORS
OF A QUERY POINT WILL HAVE A GREATER INFLUENCE THAN NEIGHBORS WHICH ARE FURTHER AWAY
• CALLABLE A USERDEFINED FUNCTION WHICH ACCEPTS AN ARRAY OF DISTANCES AND RETURNS AN
ARRAY OF THE SAME SHAPE CONTAINING THE WEIGHTS
UNIFORM WEIGHTS ARE USED BY DEFAULT
ALGORITHM 'AUTO' 'BALLTREE' 'KDTREE' 'BRUTE' OPTIONAL ALGORITHM USED TO COMPUTE THE
NEAREST NEIGHBORS
• 'BALLTREE' WILL USE BALLTREE
• 'KDTREE' WILL USE KDTREE
• 'BRUTE' WILL USE A BRUTEFORCE SEARCH
• 'AUTO' WILL ATTEMPT TO DECIDE THE MOST APPROPRIATE ALGORITHM BASED ON THE VALUES PASSED
TOFIT METHOD
NOTE FITTING ON SPARSE INPUT WILL OVERRIDE THE SETTING OF THIS PARAMETER USING BRUTE FORCE
LEAFSIZE INT OPTIONAL DEFAULT 30 LEAF SIZE PASSED TO BALLTREE OR KDTREE THIS CAN AFFECT
THE SPEED OF THE CONSTRUCTION AND QUERY AS WELL AS THE MEMORY REQUIRED TO STORE THE TREE
THE OPTIMAL VALUE DEPENDS ON THE NATURE OF THE PROBLEM
PINTEGER OPTIONAL DEFAULT 2 POWER PARAMETER FOR THE MINKOWSKI METRIC WHEN P 1 THIS
IS EQUIVALENT TO USING MANHATTANDISTANCE L1 AND EUCLIDEANDISTANCE L2 FOR P 2 FOR
ARBITRARY P MINKOWSKIDISTANCE LP IS USED
METRIC STRING OR CALLABLE DEFAULT 'MINKOWSKI' THE DISTANCE METRIC TO USE FOR THE TREE THE
DEFAULT METRIC IS MINKOWSKI AND WITH P2 IS EQUIVALENT TO THE STANDARD EUCLIDEAN METRIC
SEE THE DOCUMENTATION OF THE DISTANCEMETRIC CLASS FOR A LIST OF AVAILABLE METRICS
METRICPARAMS DICT OPTIONAL DEFAULT NONE ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC
FUNCTION
NJOBS INT OR NONE OPTIONAL DEFAULTNONE
THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS SEARCH NONE MEANS 1 UNLESS IN A
JOBLIBPARALLELBACKEND CONTEXT
1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
SEE ALSO
630SKLEARNNEIGHBORS NEAREST NEIGHBORS 2187

NEARESTNEIGHBORS
KNEIGHBORSREGRESSOR
KNEIGHBORSCLASSIFIER
RADIUSNEIGHBORSCLASSIFIER
NOTES
SEE NEAREST NEIGHBORS IN THE ONLINE DOCUMENTATION FOR A DISCUSSION OF THE CHOICE OF ALGORITHM AND
LEAFSIZE
HTTPSENWIKIPEDIAORGWIKIKNEARESTNEIGHBORALGORITHM
EXAMPLES
X 0 1 2 3
Y 0 0 1 1
 FROM SKLEARNNEIGHBORS IMPORT RADIUSNEIGHBORSREGRESSOR
NEIGH RADIUSNEIGHBORSREGRESSORRADIUS10
NEIGHFITX Y
RADIUSNEIGHBORSREGRESSOR
PRINTNEIGHPREDICT15
05
METHODS
FITSELF X Y FIT THE MODEL USING X AS TRAINING DATA AND Y AS TARGET
VALUES
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT THE TARGET FOR THE PROVIDED DATA
RADIUSNEIGHBORS SELF X RADIUS   FINDS THE NEIGHBORS WITHIN A GIVEN RADIUS OF A POINT OR
POINTS
RADIUSNEIGHBORSGRAPH SELF X RADIUS
MODECOMPUTES THE WEIGHTED GRAPH OF NEIGHBORS FOR POINTS
IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFRADIUS10 WEIGHTS’UNIFORM’ ALGORITHM’AUTO’ LEAFSIZE30 P2MET
RIC’MINKOWSKI’ METRICPARAMSNONE NJOBSNONE KWARGS
FITSELFXY
FIT THE MODEL USING X AS TRAINING DATA AND Y AS TARGET VALUES
PARAMETERS
XARRAYLIKE SPARSE MATRIX BALLTREE KDTREE TRAINING DATA IF ARRAY OR MATRIX SHAPE
NSAMPLES NFEATURES OR NSAMPLES NSAMPLES IF METRIC’PRECOMPUTED’
YARRAYLIKE SPARSE MATRIX
TARGET VALUES ARRAY OF FLOAT VALUES SHAPE NSAMPLES OR NSAMPLES NOUTPUTS

SCIKITLEARN USER GUIDE RELEASE 0213
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT THE TARGET FOR THE PROVIDED DATA
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC ‘PRECOM
PUTED’ TEST SAMPLES
RETURNS
YARRAY OF FLOAT SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TARGET VALUES
RADIUSNEIGHBORS SELFXNONE RADIUSNONE RETURNDISTANCETRUE
FINDS THE NEIGHBORS WITHIN A GIVEN RADIUS OF A POINT OR POINTS
RETURN THE INDICES AND DISTANCES OF EACH POINT FROM THE DATASET LYING IN A BALL WITH SIZE RADIUS AROUND
THE POINTS OF THE QUERY ARRAY POINTS LYING ON THE BOUNDARY ARE INCLUDED IN THE RESULTS
THE RESULT POINTS ARE NOTNECESSARILY SORTED BY DISTANCE TO THEIR QUERY POINT
PARAMETERS
XARRAYLIKE NSAMPLES NFEATURES OPTIONAL THE QUERY POINT OR POINTS IF NOT PROVIDED
NEIGHBORS OF EACH INDEXED POINT ARE RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED
ITS OWN NEIGHBOR
RADIUS FLOAT LIMITING DISTANCE OF NEIGHBORS TO RETURN DEFAULT IS THE VALUE PASSED TO THE
CONSTRUCTOR
RETURNDISTANCE BOOLEAN OPTIONAL DEFAULTS TO TRUE IF FALSE DISTANCES WILL NOT BE RE
TURNED
RETURNS
DIST ARRAY SHAPE NSAMPLES OF ARRAYS ARRAY REPRESENTING THE DISTANCES TO EACH POINT
ONLY PRESENT IF RETURNDISTANCETRUE THE DISTANCE VALUES ARE COMPUTED ACCORDING TO THE
METRIC CONSTRUCTOR PARAMETER
IND ARRAY SHAPE NSAMPLES OF ARRAYS AN ARRAY OF ARRAYS OF INDICES OF THE APPROXIMATE
NEAREST POINTS FROM THE POPULATION MATRIX THAT LIE WITHIN A BALL OF SIZE RADIUS AROUND THE
QUERY POINTS
NOTES
BECAUSE THE NUMBER OF NEIGHBORS OF EACH POINT IS NOT NECESSARILY EQUAL THE RESULTS FOR MULTIPLE QUERY
POINTS CANNOT BE FIT IN A STANDARD DATA ARRAY FOR EFFICIENCY RADIUSNEIGHBORS RETURNS ARRAYS OF
OBJECTS WHERE EACH OBJECT IS A 1D ARRAY OF INDICES OR DISTANCES
630SKLEARNNEIGHBORS NEAREST NEIGHBORS 2189

EXAMPLES
IN THE FOLLOWING EXAMPLE WE CONSTRUCT A NEIGHBORSCLASSIFIER CLASS FROM AN ARRAY REPRESENTING OUR DATA SET AND ASK WHO'S THE CLOSEST POINT TO 1 1 1

```
 IMPORT NUMPY AS NP
SAMPLES  0 0 0 0 5 0 1 1 5
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH  NEARESTNEIGHBORSRADIUS16
NEIGHFITSAMPLES
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
RNG  NEIGHRADIUSNEIGHBORS1 1 1
PRINTNPASARRAYRNG00
15 05
PRINTNPASARRAYRNG10
1 2
```

THE FIRST ARRAY RETURNED CONTAINS THE DISTANCES TO ALL POINTS WHICH ARE CLOSER THAN 16 WHILE THE SECOND ARRAY RETURNED CONTAINS THEIR INDICES IN GENERAL MULTIPLE POINTS CAN BE QUERIED AT THE SAME TIME

RADIUSNEIGHBORSGRAPH SELFXNONE RADIUSNONE MODE'CONNECTIVITY'

COMPUTES THE WEIGHTED GRAPH OF NEIGHBORS FOR POINTS IN X

NEIGHBORHOODS ARE RESTRICTED THE POINTS AT A DISTANCE LOWER THAN RADIUS

PARAMETERS

XARRAYLIKE SHAPE NSAMPLES NFEATURES OPTIONAL THE QUERY POINT OR POINTS IF NOT PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED ITS OWN NEIGHBOR

RADIUS FLOAT RADIUS OF NEIGHBORHOODS DEFAULT IS THE VALUE PASSED TO THE CONSTRUCTOR

MODE 'CONNECTIVITY' 'DISTANCE' OPTIONAL TYPE OF RETURNED MATRIX 'CONNECTIVITY' WILL RETURN THE CONNECTIVITY MATRIX WITH ONES AND ZEROS IN 'DISTANCE' THE EDGES ARE EUCLIDEAN DISTANCE BETWEEN POINTS

RETURNS

ASPARSE MATRIX IN CSR FORMAT SHAPE NSAMPLES NSAMPLES AI J IS ASSIGNED THE WEIGHT OF EDGE THAT CONNECTS I TO J

SEE ALSO

KNEIGHBORSGRAPH

EXAMPLES

```
X  0 3 1
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH  NEARESTNEIGHBORSRADIUS15
NEIGHFITX
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
A  NEIGHRADIUSNEIGHBORSGRAPHX
ATOARRAY
ARRAY1 0 1
0 1 0
1 0 1
```

SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
63010SKLEARNNEIGHBORS NEARESTCENTROID
CLASSSKLEARNNEIGHBORS NEARESTCENTROID METRIC’EUCLIDEAN’ SHRINKTHRESHOLDNONE
NEAREST CENTROID CLASSIFIER
EACH CLASS IS REPRESENTED BY ITS CENTROID WITH TEST SAMPLES CLASSIFIED TO THE CLASS WITH THE NEAREST CENTROID
READ MORE IN THE USER GUIDE
PARAMETERS
METRIC STRING OR CALLABLE THE METRIC TO USE WHEN CALCULATING DISTANCE BETWEEN INSTANCES IN
A FEATURE ARRAY IF METRIC IS A STRING OR CALLABLE IT MUST BE ONE OF THE OPTIONS ALLOWED BY
METRICSPAIRWISEPAIRWISEDISTANCES FOR ITS METRIC PARAMETER THE CENTROIDS FOR THE SAMPLES
CORRESPONDING TO EACH CLASS IS THE POINT FROM WHICH THE SUM OF THE DISTANCES ACCORDING TO
THE METRIC OF ALL SAMPLES THAT BELONG TO THAT PARTICULAR CLASS ARE MINIMIZED IF THE “MANHAT
TAN” METRIC IS PROVIDED THIS CENTROID IS THE MEDIAN AND FOR ALL OTHER METRICS THE CENTROID IS
NOW SET TO BE THE MEAN

SHRINKTHRESHOLD FLOAT OPTIONAL DEFAULT NONE THRESHOLD FOR SHRINKING CENTROIDS TO RE
MOVE FEATURES
ATTRIBUTES
CENTROIDS ARRAYLIKE SHAPE NCLASSES NFEATURES CENTROID OF EACH CLASS
SEE ALSO
SKLEARNNEIGHBORSKNEIGHBORSCLASSIFIER NEAREST NEIGHBORS CLASSIFIER
NOTES
WHEN USED FOR TEXT CLASSIFICATION WITH TFIDF VECTORS THIS CLASSIFIER IS ALSO KNOWN AS THE ROCCHIO CLASSIFIER
REFERENCES
TIBSHIRANI R HASTIE T NARASIMHAN B CHU G 2002 DIAGNOSIS OF MULTIPLE CANCER TYPES BY SHRUNKEN
CENTROIDS OF GENE EXPRESSION PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA
9910 65676572 THE NATIONAL ACADEMY OF SCIENCES
EXAMPLES
```
 FROM SKLEARNNEIGHBORSNEARESTCENTROID IMPORT NEARESTCENTROID
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 3 2 1 1 2 1 3 2
Y  NPARRAY1 1 1 2 2 2
CLF  NEARESTCENTROID
CLFFITX Y
NEARESTCENTROIDMETRICEUCLIDEAN SHRINKTHRESHOLDNONE
PRINTCLFPREDICT08 1
1
```
METHODS
FITSELF X Y FIT THE NEARESTCENTROID MODEL ACCORDING TO THE GIVEN
TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PERFORM CLASSIFICATION ON AN ARRAY OF TEST VECTORS X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFMETRIC’EUCLIDEAN’ SHRINKTHRESHOLDNONE
FITSELFXY
FIT THE NEARESTCENTROID MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES NOTE THAT

CENTROID SHRINKING CANNOT BE USED WITH SPARSE MATRICES
YARRAY SHAPE NSAMPLES TARGET VALUES INTEGERS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PERFORM CLASSIFICATION ON AN ARRAY OF TEST VECTORS X
THE PREDICTED CLASS C FOR EACH SAMPLE IN X IS RETURNED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
CARRAY SHAPE NSAMPLES
NOTES
IF THE METRIC CONSTRUCTOR PARAMETER IS “PRECOMPUTED” X IS ASSUMED TO BE THE DISTANCE MATRIX BETWEEN THE
DATA TO BE PREDICTED AND SELFCENTROIDS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF

EXAMPLES USING SKLEARNNEIGHBORSNEARESTCENTROID
•NEAREST CENTROID CLASSIFICATION
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
63011SKLEARNNEIGHBORS NEARESTNEIGHBORS
CLASSSKLEARNNEIGHBORS NEARESTNEIGHBORS NNEIGHBORS5 RADIUS10 ALGORITHM'AUTO'
LEAFSIZE30 METRIC'MINKOWSKI' P2MET
RICPARAMSNONE NJOBSNONE KWARGS
UNSUPERVISED LEARNER FOR IMPLEMENTING NEIGHBOR SEARCHES
READ MORE IN THE USER GUIDE
PARAMETERS
NNEIGHBORS INT OPTIONAL DEFAULT 5 NUMBER OF NEIGHBORS TO USE BY DEFAULT FOR
KNEIGHBORS QUERIES
RADIUS FLOAT OPTIONAL DEFAULT 10 RANGE OF PARAMETER SPACE TO USE BY DEFAULT FOR
RADIUSNEIGHBORS QUERIES
ALGORITHM 'AUTO' 'BALLTREE' 'KDTREE' 'BRUTE' OPTIONAL ALGORITHM USED TO COMPUTE THE
NEAREST NEIGHBORS
• 'BALLTREE' WILL USE BALLTREE
• 'KDTREE' WILL USE KDTREE
• 'BRUTE' WILL USE A BRUTEFORCE SEARCH
• 'AUTO' WILL ATTEMPT TO DECIDE THE MOST APPROPRIATE ALGORITHM BASED ON THE VALUES PASSED
TOFIT METHOD
NOTE FITTING ON SPARSE INPUT WILL OVERRIDE THE SETTING OF THIS PARAMETER USING BRUTE FORCE
LEAFSIZE INT OPTIONAL DEFAULT 30 LEAF SIZE PASSED TO BALLTREE OR KDTREE THIS CAN AFFECT
THE SPEED OF THE CONSTRUCTION AND QUERY AS WELL AS THE MEMORY REQUIRED TO STORE THE TREE
THE OPTIMAL VALUE DEPENDS ON THE NATURE OF THE PROBLEM
METRIC STRING OR CALLABLE DEFAULT 'MINKOWSKI' METRIC TO USE FOR DISTANCE COMPUTATION ANY
METRIC FROM SCIKITLEARN OR SCIPYSPATIALDISTANCE CAN BE USED
IF METRIC IS A CALLABLE FUNCTION IT IS CALLED ON EACH PAIR OF INSTANCES ROWS AND THE RESULTING
VALUE RECORDED THE CALLABLE SHOULD TAKE TWO ARRAYS AS INPUT AND RETURN ONE VALUE INDICATING
THE DISTANCE BETWEEN THEM THIS WORKS FOR SCIPY'S METRICS BUT IS LESS EFFICIENT THAN PASSING
THE METRIC NAME AS A STRING
DISTANCE MATRICES ARE NOT SUPPORTED
VALID VALUES FOR METRIC ARE
• FROM SCIKITLEARN 'CITYBLOCK' 'COSINE' 'EUCLIDEAN' 'L1' 'L2' 'MANHATTAN'
• FROM SCIPYSPATIALDISTANCE 'BRAYCURTIS' 'CANBERRA' 'CHEBYSHEV' 'CORRELATION' 'DICE'
'HAMMING' 'JACCARD' 'KULSINSKI' 'MAHALANOBIS' 'MINKOWSKI' 'ROGERSTANIMOTO' 'RUS
SELLRAO' 'SEUCLIDEAN' 'SOKALMICHENER' 'SOKALSNEATH' 'SQEUCLIDEAN' 'YULE'
SEE THE DOCUMENTATION FOR SCIPYSPATIALDISTANCE FOR DETAILS ON THESE METRICS

PINTEGER OPTIONAL DEFAULT 2 PARAMETER FOR THE MINKOWSKI METRIC FROM
SKLEARNMETRICSPAIRWISEPAIRWISEDISTANCES WHEN P 1 THIS IS EQUIVALENT TO US
ING MANHATTANDISTANCE L1 AND EUCLIDEANDISTANCE L2 FOR P 2 FOR ARBITRARY P
MINKOWSKIDISTANCE LP IS USED
METRICPARAMS DICT OPTIONAL DEFAULT NONE ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC
FUNCTION
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS
SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
SEE ALSO
KNEIGHBORSCLASSIFIER
RADIUSNEIGHBORSCLASSIFIER
KNEIGHBORSREGRESSOR
RADIUSNEIGHBORSREGRESSOR
BALLTREE
NOTES
SEE NEAREST NEIGHBORS IN THE ONLINE DOCUMENTATION FOR A DISCUSSION OF THE CHOICE OF ALGORITHM AND
LEAFSIZE
HTTPSENWIKIPEDIAORGWIKIKNEARESTNEIGHBORALGORITHM
EXAMPLES
 IMPORT NUMPY AS NP
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
SAMPLES 0 0 2 1 0 0 0 0 1
NEIGH NEARESTNEIGHBORS2 04
NEIGHFITSAMPLES
NEARESTNEIGHBORS
NEIGHKNEIGHBORS0 0 13 2 RETURNDISTANCE FALSE

ARRAY2 0
NBRS NEIGHRADIUSNEIGHBORS0 0 13 04 RETURNDISTANCE FALSE
NPASARRAYNBRS00
ARRAY2
METHODS
FITSELF X Y FIT THE MODEL USING X AS TRAINING DATA
CONTINUED ON NEXT PAGE

TABLE 6234 – CONTINUED FROM PREVIOUS PAGE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
KNEIGHBORS SELF X NNEIGHBORS FINDS THE KNEIGHBORS OF A POINT
KNEIGHBORSGRAPH SELF X NNEIGHBORS MODE COMPUTES THE WEIGHTED GRAPH OF KNEIGHBORS FOR
POINTS IN X
RADIUSNEIGHBORS SELF X RADIUS FINDS THE NEIGHBORS WITHIN A GIVEN RADIUS OF A POINT OR
POINTS
RADIUSNEIGHBORSGRAPH SELF X RADIUS
MODECOMPUTES THE WEIGHTED GRAPH OF NEIGHBORS FOR POINTS
IN X
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNNEIGHBORS5 RADIUS10 ALGORITHM'AUTO' LEAFSIZE30 METRIC'MINKOWSKI'
P2METRICPARAMSNONE NJOBSNONE KWARGS
FITSELFXYNONE
FIT THE MODEL USING X AS TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX BALLTREE KDTREE TRAINING DATA IF ARRAY OR MATRIX SHAPE
NSAMPLES NFEATURES OR NSAMPLES NSAMPLES IF METRIC'PRECOMPUTED'
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
KNEIGHBORS SELFXNONE NNEIGHBORSNONE RETURNDISTANCETRUE
FINDS THE KNEIGHBORS OF A POINT RETURNS INDICES OF AND DISTANCES TO THE NEIGHBORS OF EACH POINT
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC 'PRECOM
PUTED' THE QUERY POINT OR POINTS IF NOT PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE
RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED ITS OWN NEIGHBOR
NNEIGHBORS INT NUMBER OF NEIGHBORS TO GET DEFAULT IS THE VALUE PASSED TO THE CONSTRUC
TOR
RETURNDISTANCE BOOLEAN OPTIONAL DEFAULTS TO TRUE IF FALSE DISTANCES WILL NOT BE RE
TURNED
RETURNS
DIST ARRAY ARRAY REPRESENTING THE LENGTHS TO POINTS ONLY PRESENT IF RETURNDISTANCETRUE
IND ARRAY INDICES OF THE NEAREST POINTS IN THE POPULATION MATRIX
EXAMPLES
IN THE FOLLOWING EXAMPLE WE CONSTRUCT A NEIGHBORSCLASSIFIER CLASS FROM AN ARRAY REPRESENTING OUR DATA SET
AND ASK WHO'S THE CLOSEST POINT TO 111

SCIKITLEARN USER GUIDE RELEASE 0213
SAMPLES 0 0 0 0 5 0 1 1 5
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH NEARESTNEIGHBORSNNEIGHBORS1
NEIGHFITSAMPLES
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
PRINTNEIGHKNEIGHBORS1 1 1
ARRAY05 ARRAY2
AS YOU CAN SEE IT RETURNS 05 AND 2 WHICH MEANS THAT THE ELEMENT IS AT DISTANCE 05 AND IS THE THIRD
ELEMENT OF SAMPLES INDEXES START AT 0 YOU CAN ALSO QUERY FOR MULTIPLE POINTS
X 0 1 0 1 0 1
NEIGHKNEIGHBORSX RETURNDISTANCE FALSE
ARRAY1
2
KNEIGHBORSGRAPH SELFXNONE NNEIGHBORSNONE MODE’CONNECTIVITY’
COMPUTES THE WEIGHTED GRAPH OF KNEIGHBORS FOR POINTS IN X
PARAMETERS
XARRAYLIKE SHAPE NQUERY NFEATURES OR NQUERY NINDEXED IF METRIC ‘PRECOM
PUTED’ THE QUERY POINT OR POINTS IF NOT PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE
RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED ITS OWN NEIGHBOR
NNEIGHBORS INT NUMBER OF NEIGHBORS FOR EACH SAMPLE DEFAULT IS VALUE PASSED TO THE
CONSTRUCTOR
MODE ‘CONNECTIVITY’ ‘DISTANCE’ OPTIONAL TYPE OF RETURNED MATRIX ‘CONNECTIVITY’ WILL
RETURN THE CONNECTIVITY MATRIX WITH ONES AND ZEROS IN ‘DISTANCE’ THE EDGES ARE EUCLIDEAN
DISTANCE BETWEEN POINTS
RETURNS
ASPARSE MATRIX IN CSR FORMAT SHAPE NSAMPLES NSAMPLESFIT NSAMPLESFIT IS THE
NUMBER OF SAMPLES IN THE FITTED DATA AI J IS ASSIGNED THE WEIGHT OF EDGE THAT CONNECTS I
TO J
SEE ALSO
NEARESTNEIGHBORSRADIUSNEIGHBORSGRAPH
EXAMPLES
X 0 3 1
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH NEARESTNEIGHBORSNNEIGHBORS2
NEIGHFITX
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
A NEIGHKNEIGHBORSGRAPHX
ATOARRAY
ARRAY1 0 1
0 1 1
1 0 1
RADIUSNEIGHBORS SELFXNONE RADIUSNONE RETURNDISTANCETRUE
FINDS THE NEIGHBORS WITHIN A GIVEN RADIUS OF A POINT OR POINTS
630SKLEARNNEIGHBORS NEAREST NEIGHBORS 2197

RETURN THE INDICES AND DISTANCES OF EACH POINT FROM THE DATASET LYING IN A BALL WITH SIZE RADIUS AROUND
THE POINTS OF THE QUERY ARRAY POINTS LYING ON THE BOUNDARY ARE INCLUDED IN THE RESULTS
THE RESULT POINTS ARE NOTNECESSARILY SORTED BY DISTANCE TO THEIR QUERY POINT
PARAMETERS
XARRAYLIKE NSAMPLES NFEATURES OPTIONAL THE QUERY POINT OR POINTS IF NOT PROVIDED
NEIGHBORS OF EACH INDEXED POINT ARE RETURNED IN THIS CASE THE QUERY POINT IS NOT CONSIDERED
ITS OWN NEIGHBOR
RADIUS FLOAT LIMITING DISTANCE OF NEIGHBORS TO RETURN DEFAULT IS THE VALUE PASSED TO THE
CONSTRUCTOR
RETURNDISTANCE BOOLEAN OPTIONAL DEFAULTS TO TRUE IF FALSE DISTANCES WILL NOT BE RE
TURNED
RETURNS
DIST ARRAY SHAPE NSAMPLES OF ARRAYS ARRAY REPRESENTING THE DISTANCES TO EACH POINT
ONLY PRESENT IF RETURNDISTANCETRUE THE DISTANCE VALUES ARE COMPUTED ACCORDING TO THE
METRIC CONSTRUCTOR PARAMETER
IND ARRAY SHAPE NSAMPLES OF ARRAYS AN ARRAY OF ARRAYS OF INDICES OF THE APPROXIMATE
NEAREST POINTS FROM THE POPULATION MATRIX THAT LIE WITHIN A BALL OF SIZE RADIUS AROUND THE
QUERY POINTS
NOTES
BECAUSE THE NUMBER OF NEIGHBORS OF EACH POINT IS NOT NECESSARILY EQUAL THE RESULTS FOR MULTIPLE QUERY
POINTS CANNOT BE FIT IN A STANDARD DATA ARRAY FOR EFFICIENCY RADIUSNEIGHBORS RETURNS ARRAYS OF
OBJECTS WHERE EACH OBJECT IS A 1D ARRAY OF INDICES OR DISTANCES
EXAMPLES
IN THE FOLLOWING EXAMPLE WE CONSTRUCT A NEIGHBORSCLASSIFIER CLASS FROM AN ARRAY REPRESENTING OUR DATA SET
AND ASK WHO’S THE CLOSEST POINT TO 1 1 1
```
 IMPORT NUMPY AS NP
SAMPLES  0 0 0 0 5 0 1 1 5
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH  NEARESTNEIGHBORSRADIUS16
NEIGHFITSAMPLES
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
RNG  NEIGHRADIUSNEIGHBORS1 1 1
PRINTNPASARRAYRNG00
15 05
PRINTNPASARRAYRNG10
1 2
```
THE FIRST ARRAY RETURNED CONTAINS THE DISTANCES TO ALL POINTS WHICH ARE CLOSER THAN 16 WHILE THE SECOND
ARRAY RETURNED CONTAINS THEIR INDICES IN GENERAL MULTIPLE POINTS CAN BE QUERIED AT THE SAME TIME
RADIUSNEIGHBORSGRAPH SELFXNONE RADIUSNONE MODE’CONNECTIVITY’
COMPUTES THE WEIGHTED GRAPH OF NEIGHBORS FOR POINTS IN X
NEIGHBORHOODS ARE RESTRICTED THE POINTS AT A DISTANCE LOWER THAN RADIUS
PARAMETERS

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XARRAYLIKE SHAPE NSAMPLES NFEATURES OPTIONAL THE QUERY POINT OR POINTS IF NOT
PROVIDED NEIGHBORS OF EACH INDEXED POINT ARE RETURNED IN THIS CASE THE QUERY POINT IS NOT
CONSIDERED ITS OWN NEIGHBOR
RADIUS FLOAT RADIUS OF NEIGHBORHOODS DEFAULT IS THE VALUE PASSED TO THE CONSTRUCTOR
MODE ‘CONNECTIVITY’ ‘DISTANCE’ OPTIONAL TYPE OF RETURNED MATRIX ‘CONNECTIVITY’ WILL
RETURN THE CONNECTIVITY MATRIX WITH ONES AND ZEROS IN ‘DISTANCE’ THE EDGES ARE EUCLIDEAN
DISTANCE BETWEEN POINTS
RETURNS
ASPARSE MATRIX IN CSR FORMAT SHAPE NSAMPLES NSAMPLES AI J IS ASSIGNED THE
WEIGHT OF EDGE THAT CONNECTS I TO J
SEE ALSO
KNEIGHBORSGRAPH
EXAMPLES
X 0 3 1
 FROM SKLEARNNEIGHBORS IMPORT NEARESTNEIGHBORS
NEIGH NEARESTNEIGHBORSRADIUS15
NEIGHFITX
NEARESTNEIGHBORSALGORITHMAUTO LEAFSIZE30
A NEIGHRADIUSNEIGHBORSGRAPHX
ATOARRAY
ARRAY1 0 1
0 1 0
1 0 1
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
63012SKLEARNNEIGHBORS NEIGHBORHOODCOMPONENTSANALYSIS
CLASSSKLEARNNEIGHBORS NEIGHBORHOODCOMPONENTSANALYSIS NCOMPONENTSNONE
INIT’AUTO’ WARMSTARTFALSE
MAXITER50 TOL1E05
CALLBACKNONE VERBOSE0
RANDOMSTATENONE
NEIGHBORHOOD COMPONENTS ANALYSIS
NEIGHBORHOOD COMPONENT ANALYSIS NCA IS A MACHINE LEARNING ALGORITHM FOR METRIC LEARNING IT LEARNS A LINEAR
TRANSFORMATION IN A SUPERVISED FASHION TO IMPROVE THE CLASSIFICATION ACCURACY OF A STOCHASTIC NEAREST NEIGHBORS
RULE IN THE TRANSFORMED SPACE
READ MORE IN THE USER GUIDE
630SKLEARNNEIGHBORS NEAREST NEIGHBORS 2199

PARAMETERS
NCOMPONENTS INT OPTIONAL DEFAULTNONE PREFERRED DIMENSIONALITY OF THE PROJECTED SPACE
IF NONE IT WILL BE SET TO NFEATURES
INIT STRING OR NUMPY ARRAY OPTIONAL DEFAULT'AUTO' INITIALIZATION OF THE LINEAR TRANSFORMATION
POSSIBLE OPTIONS ARE 'AUTO' 'PCA' 'LDA' 'IDENTITY' 'RANDOM' AND A NUMPY ARRAY OF SHAPE
NFEATURESA NFEATURESB
'AUTO' DEPENDING ON NCOMPONENTS THE MOST REASONABLE INITIALIZATION WILL BE CHOSEN
IFNCOMPONENTS NCLASSES WE USE 'LDA' AS IT USES LABELS INFORMATION IF
NOT BUTNCOMPONENTS MINNFEATURES NSAMPLES WE USE 'PCA' AS IT
PROJECTS DATA IN MEANINGFUL DIRECTIONS THOSE OF HIGHER VARIANCE OTHERWISE WE JUST USE
'IDENTITY'
'PCA'NCOMPONENTS PRINCIPAL COMPONENTS OF THE INPUTS PASSED TO FIT WILL BE USED TO
INITIALIZE THE TRANSFORMATION SEE DECOMPOSITIONPCA
'LDA'MINNCOMPONENTS NCLASSES MOST DISCRIMINATIVE COMPONENTS OF THE
INPUTS PASSED TO FIT WILL BE USED TO INITIALIZE THE TRANSFORMATION IF
NCOMPONENTS NCLASSES THE REST OF THE COMPONENTS WILL BE ZERO SEE
DISCRIMINANTANALYSISLINEARDISCRIMINANTANALYSIS
'IDENTITY' IFNCOMPONENTS IS STRICTLY SMALLER THAN THE DIMENSIONALITY OF THE INPUTS
PASSED TOFIT THE IDENTITY MATRIX WILL BE TRUNCATED TO THE FIRST NCOMPONENTS ROWS
'RANDOM' THE INITIAL TRANSFORMATION WILL BE A RANDOM ARRAY OF SHAPE NCOMPONENTS
NFEATURES EACH VALUE IS SAMPLED FROM THE STANDARD NORMAL DISTRIBUTION
NUMPY ARRAY NFEATURESB MUST MATCH THE DIMENSIONALITY OF THE INPUTS PASSED TO FIT
AND NFEATURESA MUST BE LESS THAN OR EQUAL TO THAT IF NCOMPONENTS IS NOT NONE
NFEATURESA MUST MATCH IT
WARMSTART BOOL OPTIONAL DEFAULTFALSE IF TRUE AND FIT HAS BEEN CALLED BEFORE THE SOLU
TION OF THE PREVIOUS CALL TO FIT IS USED AS THE INITIAL LINEAR TRANSFORMATION NCOMPONENTS
ANDINIT WILL BE IGNORED
MAXITER INT OPTIONAL DEFAULT50 MAXIMUM NUMBER OF ITERATIONS IN THE OPTIMIZATION
TOLFLOAT OPTIONAL DEFAULT1E5 CONVERGENCE TOLERANCE FOR THE OPTIMIZATION
CALLBACK CALLABLE OPTIONAL DEFAULTNONE IF NOT NONE THIS FUNCTION IS CALLED AFTER EVERY
ITERATION OF THE OPTIMIZER TAKING AS ARGUMENTS THE CURRENT SOLUTION FLATTENED TRANSFORMATION
MATRIX AND THE NUMBER OF ITERATIONS THIS MIGHT BE USEFUL IN CASE ONE WANTS TO EXAMINE OR
STORE THE TRANSFORMATION FOUND AFTER EACH ITERATION
VERBOSE INT OPTIONAL DEFAULT0 IF 0 NO PROGRESS MESSAGES WILL BE PRINTED IF 1 PROGRESS
MESSAGES WILL BE PRINTED TO STDOUT IF 1 PROGRESS MESSAGES WILL BE PRINTED AND THE DISP
PARAMETER OF SCIPYOPTIMIZEMINIMIZE WILL BE SET TO VERBOSE 2
RANDOMSTATE INT OR NUMPYRANDOMSTATE OR NONE OPTIONAL DEFAULTNONE A PSEUDO RAN
DOM NUMBER GENERATOR OBJECT OR A SEED FOR IT IF INT IF INITRANDOM RANDOMSTATE
IS USED TO INITIALIZE THE RANDOM TRANSFORMATION IF INITPCA RANDOMSTATE IS
PASSED AS AN ARGUMENT TO PCA WHEN INITIALIZING THE TRANSFORMATION
ATTRIBUTES
COMPONENTS ARRAY SHAPE NCOMPONENTS NFEATURES THE LINEAR TRANSFORMATION LEARNED DUR
ING FITTING
NITER INT COUNTS THE NUMBER OF ITERATIONS PERFORMED BY THE OPTIMIZER

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REFERENCES
RF9B6BAEE82291 RF9B6BAEE82292
EXAMPLES
```
 FROM SKLEARNNEIGHBORSNCA IMPORT NEIGHBORHOODCOMPONENTSANALYSIS
 FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSCLASSIFIER
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNMODELSELECTION IMPORT TRAINTESTSPLIT
X Y  LOADIRISRETURNXY TRUE
XTRAIN XTEST YTRAIN YTEST  TRAINTESTSPLITX Y
STRATIFYY TESTSIZE07 RANDOMSTATE42
NCA  NEIGHBORHOODCOMPONENTSANALYSISRANDOMSTATE42
NCAFITXTRAIN YTRAIN
NEIGHBORHOODCOMPONENTSANALYSIS
KNN  KNEIGHBORSCLASSIFIERNNEIGHBORS3
KNNFITXTRAIN YTRAIN
KNEIGHBORSCLASSIFIER
PRINTKNNSCOREXTEST YTEST
0933333
KNNFITNCATRANSFORMXTRAIN YTRAIN
KNEIGHBORSCLASSIFIER
PRINTKNNSCORENCATRANSFORMXTEST YTEST
0961904
```
METHODS
FITSELF X Y FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X APPLIES THE LEARNED TRANSFORMATION TO THE GIVEN DATA
INIT SELFNCOMPONENTSNONE INIT’AUTO’ WARMSTARTFALSE MAXITER50 TOL1E05 CALL
BACKNONE VERBOSE0 RANDOMSTATENONE
FITSELFXY
FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE TRAINING SAMPLES
YARRAYLIKE SHAPE NSAMPLES THE CORRESPONDING TRAINING LABELS
RETURNS
SELF OBJECT RETURNS A TRAINED NEIGHBORHOODCOMPONENTSANALYSIS MODEL
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
630SKLEARNNEIGHBORS NEAREST NEIGHBORS 2201

XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
APPLIES THE LEARNED TRANSFORMATION TO THE GIVEN DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES DATA SAMPLES
RETURNS
XEMBEDDED ARRAY SHAPE NSAMPLES NCOMPONENTS THE DATA SAMPLES TRANSFORMED
RAISES
NOTFITTEDERROR IFFIT HAS NOT BEEN CALLED BEFORE
EXAMPLES USING SKLEARNNEIGHBORSNEIGHBORHOODCOMPONENTSANALYSIS
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
•COMPARING NEAREST NEIGHBORS WITH AND WITHOUT NEIGHBORHOOD COMPONENTS ANALYSIS
•DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
•NEIGHBORHOOD COMPONENTS ANALYSIS ILLUSTRATION
NEIGHBORSKNEIGHBORSGRAPH X NNEIGHBORS
COMPUTES THE WEIGHTED GRAPH OF KNEIGHBORS FOR POINTS
IN X
NEIGHBORSRADIUSNEIGHBORSGRAPH X RADIUS COMPUTES THE WEIGHTED GRAPH OF NEIGHBORS FOR POINTS IN
X

63013SKLEARNNEIGHBORS KNEIGHBORSGRAPH
SKLEARNNEIGHBORS KNEIGHBORSGRAPH X NNEIGHBORS MODE’CONNECTIVITY’ MET
RIC’MINKOWSKI’ P2METRICPARAMSNONE IN
CLUDESELFFALSE NJOBSNONE
COMPUTES THE WEIGHTED GRAPH OF KNEIGHBORS FOR POINTS IN X
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE OR BALLTREE SHAPE NSAMPLES NFEATURES SAMPLE DATA IN THE FORM OF A NUMPY
ARRAY OR A PRECOMPUTED BALLTREE
NNEIGHBORS INT NUMBER OF NEIGHBORS FOR EACH SAMPLE
MODE ‘CONNECTIVITY’ ‘DISTANCE’ OPTIONAL TYPE OF RETURNED MATRIX ‘CONNECTIVITY’ WILL RETURN
THE CONNECTIVITY MATRIX WITH ONES AND ZEROS AND ‘DISTANCE’ WILL RETURN THE DISTANCES BETWEEN
NEIGHBORS ACCORDING TO THE GIVEN METRIC
METRIC STRING DEFAULT ‘MINKOWSKI’ THE DISTANCE METRIC USED TO CALCULATE THE KNEIGHBORS FOR
EACH SAMPLE POINT THE DISTANCEMETRIC CLASS GIVES A LIST OF AVAILABLE METRICS THE DEFAULT
DISTANCE IS ‘EUCLIDEAN’ ‘MINKOWSKI’ METRIC WITH THE P PARAM EQUAL TO 2
PINT DEFAULT 2 POWER PARAMETER FOR THE MINKOWSKI METRIC WHEN P 1 THIS IS EQUIVALENT
TO USING MANHATTANDISTANCE L1 AND EUCLIDEANDISTANCE L2 FOR P 2 FOR ARBITRARY P
MINKOWSKIDISTANCE LP IS USED
METRICPARAMS DICT OPTIONAL ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC FUNCTION
INCLUDESELF BOOL DEFAULTFALSE WHETHER OR NOT TO MARK EACH SAMPLE AS THE FIRST NEAR
EST NEIGHBOR TO ITSELF IF NONE THEN TRUE IS USED FOR MODE’CONNECTIVITY’ AND FALSE FOR
MODE’DISTANCE’ AS THIS WILL PRESERVE BACKWARDS COMPATIBILITY
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS
SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RETURNS
ASPARSE MATRIX IN CSR FORMAT SHAPE NSAMPLES NSAMPLES AI J IS ASSIGNED THE WEIGHT
OF EDGE THAT CONNECTS I TO J
SEE ALSO
RADIUSNEIGHBORSGRAPH
EXAMPLES
X 0 3 1
 FROM SKLEARNNEIGHBORS IMPORT KNEIGHBORSGRAPH
A KNEIGHBORSGRAPHX 2 MODECONNECTIVITY INCLUDESELF TRUE
ATOARRAY
ARRAY1 0 1
0 1 1
1 0 1

EXAMPLES USING SKLEARNNEIGHBORSKNEIGHBORSGRAPH
•AGGLOMERATIVE CLUSTERING WITH AND WITHOUT STRUCTURE
•HIERARCHICAL CLUSTERING STRUCTURED VS UNSTRUCTURED WARD
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
63014SKLEARNNEIGHBORS RADIUSNEIGHBORSGRAPH
SKLEARNNEIGHBORS RADIUSNEIGHBORSGRAPH X RADIUS MODE'CONNECTIVITY' MET
RIC'MINKOWSKI' P2METRICPARAMSNONE
INCLUDESELFFALSE NJOBSNONE
COMPUTES THE WEIGHTED GRAPH OF NEIGHBORS FOR POINTS IN X
NEIGHBORHOODS ARE RESTRICTED THE POINTS AT A DISTANCE LOWER THAN RADIUS
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE OR BALLTREE SHAPE NSAMPLES NFEATURES SAMPLE DATA IN THE FORM OF A NUMPY
ARRAY OR A PRECOMPUTED BALLTREE
RADIUS FLOAT RADIUS OF NEIGHBORHOODS
MODE 'CONNECTIVITY' 'DISTANCE' OPTIONAL TYPE OF RETURNED MATRIX 'CONNECTIVITY' WILL RETURN
THE CONNECTIVITY MATRIX WITH ONES AND ZEROS AND 'DISTANCE' WILL RETURN THE DISTANCES BETWEEN
NEIGHBORS ACCORDING TO THE GIVEN METRIC
METRIC STRING DEFAULT 'MINKOWSKI' THE DISTANCE METRIC USED TO CALCULATE THE NEIGHBORS WITHIN
A GIVEN RADIUS FOR EACH SAMPLE POINT THE DISTANCEMETRIC CLASS GIVES A LIST OF AVAILABLE
METRICS THE DEFAULT DISTANCE IS 'EUCLIDEAN' 'MINKOWSKI' METRIC WITH THE PARAM EQUAL TO 2
PINT DEFAULT 2 POWER PARAMETER FOR THE MINKOWSKI METRIC WHEN P 1 THIS IS EQUIVALENT
TO USING MANHATTANDISTANCE L1 AND EUCLIDEANDISTANCE L2 FOR P 2 FOR ARBITRARY P
MINKOWSKIDISTANCE LP IS USED
METRICPARAMS DICT OPTIONAL ADDITIONAL KEYWORD ARGUMENTS FOR THE METRIC FUNCTION
INCLUDESELF BOOL DEFAULTFALSE WHETHER OR NOT TO MARK EACH SAMPLE AS THE FIRST NEAREST
NEIGHBOR TO ITSELF IF NONE THEN TRUE IS USED FOR MODE'CONNECTIVITY' AND FALSE FOR
MODE'DISTANCE' AS THIS WILL PRESERVE BACKWARDS COMPATIBILITY
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN FOR NEIGHBORS
SEARCHNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
RETURNS
ASPARSE MATRIX IN CSR FORMAT SHAPE NSAMPLES NSAMPLES AI J IS ASSIGNED THE WEIGHT
OF EDGE THAT CONNECTS I TO J
SEE ALSO
KNEIGHBORSGRAPH

EXAMPLES
X 0 3 1
 FROM SKLEARNNEIGHBORS IMPORT RADIUSNEIGHBORSGRAPH
A RADIUSNEIGHBORSGRAPHX 15 MODECONNECTIVITY
 INCLUDESELF TRUE
ATOARRAY
ARRAY1 0 1
0 1 0
1 0 1
631SKLEARNNEURALNETWORK NEURAL NETWORK MODELS
THESKLEARNNEURALNETWORK MODULE INCLUDES MODELS BASED ON NEURAL NETWORKS
USER GUIDE SEE THE NEURAL NETWORK MODELS SUPERVISED ANDNEURAL NETWORK MODELS UNSUPERVISED SECTIONS FOR
FURTHER DETAILS
NEURALNETWORKBERNOULLIRBM NCOMPONENTS
   BERNOULLI RESTRICTED BOLTZMANN MACHINE RBM
NEURALNETWORKMLPCLASSIFIER   MULTILAYER PERCEPTRON CLASSIFIER
NEURALNETWORKMLPREGRESSOR   MULTILAYER PERCEPTRON REGRESSOR
6311SKLEARNNEURALNETWORK BERNOULLIRBM
CLASSSKLEARNNEURALNETWORK BERNOULLIRBM NCOMPONENTS256 LEARNINGRATE01
BATCHSIZE10 NITER10 VERBOSE0 RAN
DOMSTATENONE
BERNOULLI RESTRICTED BOLTZMANN MACHINE RBM
A RESTRICTED BOLTZMANN MACHINE WITH BINARY VISIBLE UNITS AND BINARY HIDDEN UNITS PARAMETERS ARE ESTIMATED
USING STOCHASTIC MAXIMUM LIKELIHOOD SML ALSO KNOWN AS PERSISTENT CONTRASTIVE DIVERGENCE PCD 2
THE TIME COMPLEXITY OF THIS IMPLEMENTATION IS OD2ASSUMING D NFEATURES NCOMPONENTS
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT OPTIONAL NUMBER OF BINARY HIDDEN UNITS
LEARNINGRATE FLOAT OPTIONAL THE LEARNING RATE FOR WEIGHT UPDATES IT IS HIGHLY RECOMMENDED
TO TUNE THIS HYPERPARAMETER REASONABLE VALUES ARE IN THE 100 3 RANGE
BATCHSIZE INT OPTIONAL NUMBER OF EXAMPLES PER MINIBATCH
NITER INT OPTIONAL NUMBER OF ITERATIONSSWEEPS OVER THE TRAINING DATASET TO PERFORM DURING
TRAINING
VERBOSE INT OPTIONAL THE VERBOSITY LEVEL THE DEFAULT ZERO MEANS SILENT MODE
RANDOMSTATE INTEGER OR RANDOMSTATE OPTIONAL A RANDOM NUMBER GENERATOR INSTANCE TO DE
FINE THE STATE OF THE RANDOM PERMUTATIONS GENERATOR IF AN INTEGER IS GIVEN IT FIXES THE SEED
DEFAULTS TO THE GLOBAL NUMPY RANDOM NUMBER GENERATOR
ATTRIBUTES

INTERCEPTHIDDEN ARRAYLIKE SHAPE NCOMPONENTS BIASES OF THE HIDDEN UNITS
INTERCEPTVISIBLE ARRAYLIKE SHAPE NFEATURES BIASES OF THE VISIBLE UNITS
COMPONENTS ARRAYLIKE SHAPE NCOMPONENTS NFEATURES WEIGHT MATRIX WHERE NFEATURES
IN THE NUMBER OF VISIBLE UNITS AND NCOMPONENTS IS THE NUMBER OF HIDDEN UNITS
REFERENCES
1 HINTON G E OSINDERO S AND TEH Y A FAST LEARNING ALGORITHM FOR DEEP BELIEF NETS NEURAL COMPU
TATION 18 PP 15271554 HTTPSWWWCSTORONTOEDUHINTONABSPSFASTNCPDF
2 TIELEMAN T TRAINING RESTRICTED BOLTZMANN MACHINES USING APPROXIMATIONS TO THE LIKELIHOOD GRADI
ENT INTERNATIONAL CONFERENCE ON MACHINE LEARNING ICML 2008
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNNEURALNETWORK IMPORT BERNOULLIRBM
X  NPARRAY0 0 0 0 1 1 1 0 1 1 1 1
MODEL  BERNOULLIRBMNCOMPONENTS2
MODELFITX
BERNOULLIRBMBATCHSIZE10 LEARNINGRATE01 NCOMPONENTS2 NITER10
RANDOMSTATENONE VERBOSE0
```
METHODS
FITSELF X Y FIT THE MODEL TO THE DATA X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GIBBS SELF V PERFORM ONE GIBBS SAMPLING STEP
PARTIALFIT SELF X Y FIT THE MODEL TO THE DATA X WHICH SHOULD CONTAIN A PAR
TIAL SEGMENT OF THE DATA
SCORESAMPLES SELF X COMPUTE THE PSEUDOLIKELIHOOD OF X
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X COMPUTE THE HIDDEN LAYER ACTIVATION PROBABILITIES
PH1VX
INIT SELFNCOMPONENTS256 LEARNINGRATE01 BATCHSIZE10 NITER10 VERBOSE0 RAN
DOMSTATENONE
FITSELFXYNONE
FIT THE MODEL TO THE DATA X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING DATA
RETURNS
SELF BERNOULLIRBM THE FITTED MODEL
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT

FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GIBBSSELFV
PERFORM ONE GIBBS SAMPLING STEP
PARAMETERS
VARRAYLIKE SHAPE NSAMPLES NFEATURES VALUES OF THE VISIBLE LAYER TO START FROM
RETURNS
VNEW ARRAYLIKE SHAPE NSAMPLES NFEATURES VALUES OF THE VISIBLE LAYER AFTER ONE GIBBS
STEP
PARTIALFIT SELFXYNONE
FIT THE MODEL TO THE DATA X WHICH SHOULD CONTAIN A PARTIAL SEGMENT OF THE DATA
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TRAINING DATA
RETURNS
SELF BERNOULLIRBM THE FITTED MODEL
SCORESAMPLES SELFX
COMPUTE THE PSEUDOLIKELIHOOD OF X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES VALUES OF THE VISIBLE LAYER
MUST BE ALLBOOLEAN NOT CHECKED
RETURNS
PSEUDOLIKELIHOOD ARRAYLIKE SHAPE NSAMPLES VALUE OF THE PSEUDOLIKELIHOOD PROXY
FOR LIKELIHOOD
NOTES
THIS METHOD IS NOT DETERMINISTIC IT COMPUTES A QUANTITY CALLED THE FREE ENERGY ON X THEN ON A RANDOMLY
CORRUPTED VERSION OF X AND RETURNS THE LOG OF THE LOGISTIC FUNCTION OF THE DIFFERENCE

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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
COMPUTE THE HIDDEN LAYER ACTIVATION PROBABILITIES PH1VX
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA TO BE TRANSFORMED
RETURNS
HARRAY SHAPE NSAMPLES NCOMPONENTS LATENT REPRESENTATIONS OF THE DATA
EXAMPLES USING SKLEARNNEURALNETWORKBERNOULLIRBM
•RESTRICTED BOLTZMANN MACHINE FEATURES FOR DIGIT CLASSIFICATION
6312SKLEARNNEURALNETWORK MLPCLASSIFIER
CLASSSKLEARNNEURALNETWORK MLPCLASSIFIER HIDDENLAYERSIZES100 ACTIVA
TION'RELU' SOLVER'ADAM' ALPHA00001
BATCHSIZE'AUTO' LEARNINGRATE'CONSTANT'
LEARNINGRATEINIT0001 POWERT05
MAXITER200 SHUFFLETRUE RAN
DOMSTATENONE TOL00001 VER
BOSEFALSE WARMSTARTFALSE MOMEN
TUM09 NESTEROVSMOMENTUMTRUE
EARLYSTOPPINGFALSE VALIDATIONFRACTION01
BETA109 BETA20999 EPSILON1E08
NITERNOCHANGE10
MULTILAYER PERCEPTRON CLASSIFIER
THIS MODEL OPTIMIZES THE LOGLOSS FUNCTION USING LBFGS OR STOCHASTIC GRADIENT DESCENT
NEW IN VERSION 018
PARAMETERS
HIDDENLAYERSIZES TUPLE LENGTH NLAYERS 2 DEFAULT 100 THE ITH ELEMENT REPRESENTS THE
NUMBER OF NEURONS IN THE ITH HIDDEN LAYER
ACTIVATION 'IDENTITY' 'LOGISTIC' 'TANH' 'RELU' DEFAULT 'RELU' ACTIVATION FUNCTION FOR THE HID
DEN LAYER
• 'IDENTITY' NOOP ACTIVATION USEFUL TO IMPLEMENT LINEAR BOTTLENECK RETURNS FX X
• 'LOGISTIC' THE LOGISTIC SIGMOID FUNCTION RETURNS FX 1 1 EXPX
• 'TANH' THE HYPERBOLIC TAN FUNCTION RETURNS FX TANHX
• 'RELU' THE RECTIFIED LINEAR UNIT FUNCTION RETURNS FX MAX0 X
SOLVER 'LBFGS' 'SGD' 'ADAM' DEFAULT 'ADAM' THE SOLVER FOR WEIGHT OPTIMIZATION

• ‘LBFGS’ IS AN OPTIMIZER IN THE FAMILY OF QUASINEWTON METHODS
• ‘SGD’ REFERS TO STOCHASTIC GRADIENT DESCENT
• ‘ADAM’ REFERS TO A STOCHASTIC GRADIENTBASED OPTIMIZER PROPOSED BY KINGMA DIEDERIK AND JIMMY BA
NOTE THE DEFAULT SOLVER ‘ADAM’ WORKS PRETTY WELL ON RELATIVELY LARGE DATASETS WITH THOU SANDS OF TRAINING SAMPLES OR MORE IN TERMS OF BOTH TRAINING TIME AND VALIDATION SCORE FOR SMALL DATASETS HOWEVER ‘LBFGS’ CAN CONVERGE FASTER AND PERFORM BETTER
ALPHA FLOAT OPTIONAL DEFAULT 00001 L2 PENALTY REGULARIZATION TERM PARAMETER
BATCHSIZE INT OPTIONAL DEFAULT ‘AUTO’ SIZE OF MINIBATCHES FOR STOCHASTIC OPTIMIZERS IF THE SOLVER IS ‘LBFGS’ THE CLASSIFIER WILL NOT USE MINIBATCH WHEN SET TO “AUTO” BATCHSIZEMIN200 NSAMPLES
LEARNINGRATE ‘CONSTANT’ ‘INVSCALING’ ‘ADAPTIVE’ DEFAULT ‘CONSTANT’ LEARNING RATE SCHEDULE FOR WEIGHT UPDATES
• ‘CONSTANT’ IS A CONSTANT LEARNING RATE GIVEN BY ‘LEARNINGRATEINIT’
• ‘INVSCALING’ GRADUALLY DECREASES THE LEARNING RATE AT EACH TIME STEP ‘T’ USING AN IN VERSE SCALING EXPONENT OF ‘POWERT’ EFFECTIVELEARNINGRATE LEARNINGRATEINIT POWT POWERT
• ‘ADAPTIVE’ KEEPS THE LEARNING RATE CONSTANT TO ‘LEARNINGRATEINIT’ AS LONG AS TRAINING LOSS KEEPS DECREASING EACH TIME TWO CONSECUTIVE EPOCHS FAIL TO DECREASE TRAINING LOSS BY AT LEAST TOL OR FAIL TO INCREASE VALIDATION SCORE BY AT LEAST TOL IF ‘EARLYSTOPPING’ IS ON THE CURRENT LEARNING RATE IS DIVIDED BY 5
ONLY USED WHEN SOLVERSGD
LEARNINGRATEINIT DOUBLE OPTIONAL DEFAULT 0001 THE INITIAL LEARNING RATE USED IT CONTROLS THE STEPSIZE IN UPDATING THE WEIGHTS ONLY USED WHEN SOLVER’SGD’ OR ‘ADAM’
POWERT DOUBLE OPTIONAL DEFAULT 05 THE EXPONENT FOR INVERSE SCALING LEARNING RATE IT IS USED IN UPDATING EFFECTIVE LEARNING RATE WHEN THE LEARNINGRATE IS SET TO ‘INVSCALING’ ONLY USED WHEN SOLVER’SGD’
MAXITER INT OPTIONAL DEFAULT 200 MAXIMUM NUMBER OF ITERATIONS THE SOLVER ITERATES UNTIL CONVERGENCE DETERMINED BY ‘TOL’ OR THIS NUMBER OF ITERATIONS FOR STOCHASTIC SOLVERS ‘SGD’ ‘ADAM’ NOTE THAT THIS DETERMINES THE NUMBER OF EPOCHS HOW MANY TIMES EACH DATA POINT WILL BE USED NOT THE NUMBER OF GRADIENT STEPS
SHUFFLE BOOL OPTIONAL DEFAULT TRUE WHETHER TO SHUFFLE SAMPLES IN EACH ITERATION ONLY USED WHEN SOLVER’SGD’ OR ‘ADAM’
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
TOLFLOAT OPTIONAL DEFAULT 1E4 TOLERANCE FOR THE OPTIMIZATION WHEN THE LOSS OR SCORE IS NOT IMPROVING BY AT LEAST TOL FORNITERNOCHANGE CONSECUTIVE ITERATIONS UNLESS LEARNINGRATE IS SET TO ‘ADAPTIVE’ CONVERGENCE IS CONSIDERED TO BE REACHED AND TRAINING STOPS
VERBOSE BOOL OPTIONAL DEFAULT FALSE WHETHER TO PRINT PROGRESS MESSAGES TO STDOUT
WARMSTART BOOL OPTIONAL DEFAULT FALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY

MOMENTUM FLOAT DEFAULT 09 MOMENTUM FOR GRADIENT DESCENT UPDATE SHOULD BE BETWEEN 0
AND 1 ONLY USED WHEN SOLVER'SGD'
NESTEROVSMOMENTUM BOOLEAN DEFAULT TRUE WHETHER TO USE NESTEROV'S MOMENTUM ONLY
USED WHEN SOLVER'SGD' AND MOMENTUM 0
EARLYSTOPPING BOOL DEFAULT FALSE WHETHER TO USE EARLY STOPPING TO TERMINATE TRAINING WHEN
VALIDATION SCORE IS NOT IMPROVING IF SET TO TRUE IT WILL AUTOMATICALLY SET ASIDE 10 OF
TRAINING DATA AS VALIDATION AND TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT IMPROVING BY
AT LEAST TOL FOR NITERNOCHANGE CONSECUTIVE EPOCHS THE SPLIT IS STRATIFIED EXCEPT IN
A MULTILABEL SETTING ONLY EFFECTIVE WHEN SOLVER'SGD' OR 'ADAM'
VALIDATIONFRACTION FLOAT OPTIONAL DEFAULT 01 THE PROPORTION OF TRAINING DATA TO SET ASIDE AS
VALIDATION SET FOR EARLY STOPPING MUST BE BETWEEN 0 AND 1 ONLY USED IF EARLYSTOPPING IS
TRUE
BETA1 FLOAT OPTIONAL DEFAULT 09 EXPONENTIAL DECAY RATE FOR ESTIMATES OF FIRST MOMENT VECTOR
IN ADAM SHOULD BE IN 0 1 ONLY USED WHEN SOLVER'ADAM'
BETA2 FLOAT OPTIONAL DEFAULT 0999 EXPONENTIAL DECAY RATE FOR ESTIMATES OF SECOND MOMENT
VECTOR IN ADAM SHOULD BE IN 0 1 ONLY USED WHEN SOLVER'ADAM'
EPSILON FLOAT OPTIONAL DEFAULT 1E8 VALUE FOR NUMERICAL STABILITY IN ADAM ONLY USED WHEN
SOLVER'ADAM'
NITERNOCHANGE INT OPTIONAL DEFAULT 10 MAXIMUM NUMBER OF EPOCHS TO NOT MEET TOL
IMPROVEMENT ONLY EFFECTIVE WHEN SOLVER'SGD' OR 'ADAM'
NEW IN VERSION 020
ATTRIBUTES
CLASSES ARRAY OR LIST OF ARRAY OF SHAPE NCLASSES CLASS LABELS FOR EACH OUTPUT
LOSS FLOAT THE CURRENT LOSS COMPUTED WITH THE LOSS FUNCTION
COEFS LIST LENGTH NLAYERS 1 THE ITH ELEMENT IN THE LIST REPRESENTS THE WEIGHT MATRIX CORRE
SPONDING TO LAYER I
INTERCEPTS LIST LENGTH NLAYERS 1 THE ITH ELEMENT IN THE LIST REPRESENTS THE BIAS VECTOR COR
RESPONDING TO LAYER I 1
NITER INT THE NUMBER OF ITERATIONS THE SOLVER HAS RAN
NLAYERS INT NUMBER OF LAYERS
NOUTPUTS INT NUMBER OF OUTPUTS
OUTACTIVATION STRING NAME OF THE OUTPUT ACTIVATION FUNCTION
NOTES
MLPCLASSIFIER TRAINS ITERATIVELY SINCE AT EACH TIME STEP THE PARTIAL DERIVATIVES OF THE LOSS FUNCTION WITH RESPECT TO
THE MODEL PARAMETERS ARE COMPUTED TO UPDATE THE PARAMETERS
IT CAN ALSO HAVE A REGULARIZATION TERM ADDED TO THE LOSS FUNCTION THAT SHRINKS MODEL PARAMETERS TO PREVENT OVER
FITTING
THIS IMPLEMENTATION WORKS WITH DATA REPRESENTED AS DENSE NUMPY ARRAYS OR SPARSE SCIPY ARRAYS OF FLOATING POINT
VALUES

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HE KAIMING ET AL “DELVING DEEP INTO RECTIFIERS SURPASSING HUMANLEVEL PERFORMANCE ON IMAGENET CLASSI FICATION” ARXIV PREPRINT ARXIV150201852 2015
KINGMA DIEDERIK AND JIMMY BA “ADAM A METHOD FOR STOCHASTIC OPTIMIZATION” ARXIV PREPRINT ARXIV14126980 2014
METHODS
FITSELF X Y FIT THE MODEL TO DATA MATRIX X AND TARGETS Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE MULTILAYER PERCEPTRON CLASSIFIER
PREDICTLOGPROBA SELF X RETURN THE LOG OF PROBABILITY ESTIMATES
PREDICTPROBA SELF X PROBABILITY ESTIMATES
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELF HIDDENLAYERSIZES100 ACTIVATION’RELU’ SOLVER’ADAM’ AL PHA00001 BATCHSIZE’AUTO’ LEARNINGRATE’CONSTANT’ LEARNINGRATEINIT0001 POWERT05 MAXITER200 SHUFFLETRUE RANDOMSTATENONE TOL00001 VER BOSEFALSE WARMSTARTFALSE MOMENTUM09 NESTEROVSMOMENTUMTRUE EARLYSTOPPINGFALSE VALIDATIONFRACTION01 BETA109 BETA20999 EPSILON1E08 NITERNOCHANGE10
FITSELFXY
FIT THE MODEL TO DATA MATRIX X AND TARGETS Y
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUMBERS IN REGRESSION
RETURNS
SELF RETURNS A TRAINED MLP MODEL
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT
UPDATE THE MODEL WITH A SINGLE ITERATION OVER THE GIVEN DATA

PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES
CLASSES ARRAY SHAPE NCLASSES DEFAULT NONE CLASSES ACROSS ALL CALLS TO PARTIALFIT CAN BE
OBTAINED VIA NPUNIQUEYALL WHERE YALL IS THE TARGET VECTOR OF THE ENTIRE DATASET
THIS ARGUMENT IS REQUIRED FOR THE FIRST CALL TO PARTIALFIT AND CAN BE OMITTED IN THE SUBSE
QUENT CALLS NOTE THAT Y DOESN’T NEED TO CONTAIN ALL LABELS IN CLASSES
RETURNS
SELF RETURNS A TRAINED MLP MODEL
PREDICTSELFX
PREDICT USING THE MULTILAYER PERCEPTRON CLASSIFIER
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
RETURNS
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NCLASSES THE PREDICTED CLASSES
PREDICTLOGPROBA SELFX
RETURN THE LOG OF PROBABILITY ESTIMATES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE INPUT DATA
RETURNS
LOGYPROB ARRAYLIKE SHAPE NSAMPLES NCLASSES THE PREDICTED LOGPROBABILITY OF THE
SAMPLE FOR EACH CLASS IN THE MODEL WHERE CLASSES ARE ORDERED AS THEY ARE IN SELF
CLASSES EQUIVALENT TO LOGPREDICTPROBAX
PREDICTPROBA SELFX
PROBABILITY ESTIMATES
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
RETURNS
YPROB ARRAYLIKE SHAPE NSAMPLES NCLASSES THE PREDICTED PROBABILITY OF THE SAMPLE
FOR EACH CLASS IN THE MODEL WHERE CLASSES ARE ORDERED AS THEY ARE IN SELFCLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y

SCIKITLEARN USER GUIDE RELEASE 0213
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNNEURALNETWORKMLPCLASSIFIER
•CLASSIFIER COMPARISON
•VISUALIZATION OF MLP WEIGHTS ON MNIST
•VARYING REGULARIZATION IN MULTILAYER PERCEPTRON
•COMPARE STOCHASTIC LEARNING STRATEGIES FOR MLPCLASSIFIER
6313SKLEARNNEURALNETWORK MLPREGRESSOR
CLASSSKLEARNNEURALNETWORK MLPREGRESSOR HIDDENLAYERSIZES100 ACTIVA
TION'RELU' SOLVER'ADAM' ALPHA00001
BATCHSIZE'AUTO' LEARNINGRATE'CONSTANT'
LEARNINGRATEINIT0001 POWERT05
MAXITER200 SHUFFLETRUE RANDOMSTATENONE
TOL00001 VERBOSEFALSE WARMSTARTFALSE
MOMENTUM09 NESTEROVSMOMENTUMTRUE
EARLYSTOPPINGFALSE VALIDATIONFRACTION01
BETA109 BETA20999 EPSILON1E08
NITERNOCHANGE10
MULTILAYER PERCEPTRON REGRESSOR
THIS MODEL OPTIMIZES THE SQUAREDLOSS USING LBFGS OR STOCHASTIC GRADIENT DESCENT
NEW IN VERSION 018
PARAMETERS
HIDDENLAYERSIZES TUPLE LENGTH NLAYERS 2 DEFAULT 100 THE ITH ELEMENT REPRESENTS THE
NUMBER OF NEURONS IN THE ITH HIDDEN LAYER
ACTIVATION 'IDENTITY' 'LOGISTIC' 'TANH' 'RELU' DEFAULT 'RELU' ACTIVATION FUNCTION FOR THE HID
DEN LAYER
• 'IDENTITY' NOOP ACTIVATION USEFUL TO IMPLEMENT LINEAR BOTTLENECK RETURNS FX X
• 'LOGISTIC' THE LOGISTIC SIGMOID FUNCTION RETURNS FX 1 1 EXPX
• 'TANH' THE HYPERBOLIC TAN FUNCTION RETURNS FX TANHX
• 'RELU' THE RECTIFIED LINEAR UNIT FUNCTION RETURNS FX MAX0 X
SOLVER 'LBFGS' 'SGD' 'ADAM' DEFAULT 'ADAM' THE SOLVER FOR WEIGHT OPTIMIZATION
• 'LBFGS' IS AN OPTIMIZER IN THE FAMILY OF QUASINEWTON METHODS
• 'SGD' REFERS TO STOCHASTIC GRADIENT DESCENT
631SKLEARNNEURALNETWORK NEURAL NETWORK MODELS 2213

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• ‘CONSTANT’ IS A CONSTANT LEARNING RATE GIVEN BY ‘LEARNINGRATEINIT’
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LEARNINGRATEINIT DOUBLE OPTIONAL DEFAULT 0001 THE INITIAL LEARNING RATE USED IT CONTROLS THE STEPSIZE IN UPDATING THE WEIGHTS ONLY USED WHEN SOLVER‘SGD’ OR ‘ADAM’
POWERT DOUBLE OPTIONAL DEFAULT 05 THE EXPONENT FOR INVERSE SCALING LEARNING RATE IT IS USED IN UPDATING EFFECTIVE LEARNING RATE WHEN THE LEARNINGRATE IS SET TO ‘INVSCALING’ ONLY USED WHEN SOLVER‘SGD’
MAXITER INT OPTIONAL DEFAULT 200 MAXIMUM NUMBER OF ITERATIONS THE SOLVER ITERATES UNTIL CONVERGENCE DETERMINED BY ‘TOL’ OR THIS NUMBER OF ITERATIONS FOR STOCHASTIC SOLVERS ‘SGD’ ‘ADAM’ NOTE THAT THIS DETERMINES THE NUMBER OF EPOCHS HOW MANY TIMES EACH DATA POINT WILL BE USED NOT THE NUMBER OF GRADIENT STEPS
SHUFFLE BOOL OPTIONAL DEFAULT TRUE WHETHER TO SHUFFLE SAMPLES IN EACH ITERATION ONLY USED WHEN SOLVER‘SGD’ OR ‘ADAM’
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
TOLFLOAT OPTIONAL DEFAULT 1E4 TOLERANCE FOR THE OPTIMIZATION WHEN THE LOSS OR SCORE IS NOT IMPROVING BY AT LEAST TOL FORNITERNOCHANGE CONSECUTIVE ITERATIONS UNLESS LEARNINGRATE IS SET TO ‘ADAPTIVE’ CONVERGENCE IS CONSIDERED TO BE REACHED AND TRAINING STOPS
VERBOSE BOOL OPTIONAL DEFAULT FALSE WHETHER TO PRINT PROGRESS MESSAGES TO STDOUT
WARMSTART BOOL OPTIONAL DEFAULT FALSE WHEN SET TO TRUE REUSE THE SOLUTION OF THE PREVIOUS CALL TO FIT AS INITIALIZATION OTHERWISE JUST ERASE THE PREVIOUS SOLUTION SEE THE GLOSSARY
MOMENTUM FLOAT DEFAULT 09 MOMENTUM FOR GRADIENT DESCENT UPDATE SHOULD BE BETWEEN 0 AND 1 ONLY USED WHEN SOLVER‘SGD’

NESTEROVSMOMENTUM BOOLEAN DEFAULT TRUE WHETHER TO USE NESTEROV'S MOMENTUM ONLY
USED WHEN SOLVER'SGD' AND MOMENTUM 0
EARLYSTOPPING BOOL DEFAULT FALSE WHETHER TO USE EARLY STOPPING TO TERMINATE TRAINING WHEN
VALIDATION SCORE IS NOT IMPROVING IF SET TO TRUE IT WILL AUTOMATICALLY SET ASIDE 10 OF TRAINING
DATA AS VALIDATION AND TERMINATE TRAINING WHEN VALIDATION SCORE IS NOT IMPROVING BY AT LEAST
TOL FORNITERNOCHANGE CONSECUTIVE EPOCHS ONLY EFFECTIVE WHEN SOLVER'SGD' OR
'ADAM'
VALIDATIONFRACTION FLOAT OPTIONAL DEFAULT 01 THE PROPORTION OF TRAINING DATA TO SET ASIDE AS
VALIDATION SET FOR EARLY STOPPING MUST BE BETWEEN 0 AND 1 ONLY USED IF EARLYSTOPPING IS
TRUE
BETA1 FLOAT OPTIONAL DEFAULT 09 EXPONENTIAL DECAY RATE FOR ESTIMATES OF FIRST MOMENT VECTOR
IN ADAM SHOULD BE IN 0 1 ONLY USED WHEN SOLVER'ADAM'
BETA2 FLOAT OPTIONAL DEFAULT 0999 EXPONENTIAL DECAY RATE FOR ESTIMATES OF SECOND MOMENT
VECTOR IN ADAM SHOULD BE IN 0 1 ONLY USED WHEN SOLVER'ADAM'
EPSILON FLOAT OPTIONAL DEFAULT 1E8 VALUE FOR NUMERICAL STABILITY IN ADAM ONLY USED WHEN
SOLVER'ADAM'
NITERNOCHANGE INT OPTIONAL DEFAULT 10 MAXIMUM NUMBER OF EPOCHS TO NOT MEET TOL
IMPROVEMENT ONLY EFFECTIVE WHEN SOLVER'SGD' OR 'ADAM'
NEW IN VERSION 020
ATTRIBUTES
LOSS FLOAT THE CURRENT LOSS COMPUTED WITH THE LOSS FUNCTION
COEFS LIST LENGTH NLAYERS 1 THE ITH ELEMENT IN THE LIST REPRESENTS THE WEIGHT MATRIX CORRE
SPONDING TO LAYER I
INTERCEPTS LIST LENGTH NLAYERS 1 THE ITH ELEMENT IN THE LIST REPRESENTS THE BIAS VECTOR COR
RESPONDING TO LAYER I 1
NITER INT THE NUMBER OF ITERATIONS THE SOLVER HAS RAN
NLAYERS INT NUMBER OF LAYERS
NOUTPUTS INT NUMBER OF OUTPUTS
OUTACTIVATION STRING NAME OF THE OUTPUT ACTIVATION FUNCTION
NOTES
MLPREGRESSOR TRAINS ITERATIVELY SINCE AT EACH TIME STEP THE PARTIAL DERIVATIVES OF THE LOSS FUNCTION WITH RESPECT
TO THE MODEL PARAMETERS ARE COMPUTED TO UPDATE THE PARAMETERS
IT CAN ALSO HAVE A REGULARIZATION TERM ADDED TO THE LOSS FUNCTION THAT SHRINKS MODEL PARAMETERS TO PREVENT OVER
FITTING
THIS IMPLEMENTATION WORKS WITH DATA REPRESENTED AS DENSE AND SPARSE NUMPY ARRAYS OF FLOATING POINT VALUES
REFERENCES
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METHODS
FITSELF X Y FIT THE MODEL TO DATA MATRIX X AND TARGETS Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE MULTILAYER PERCEPTRON MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELF HIDDENLAYERSIZES100 ACTIVATION’RELU’ SOLVER’ADAM’ AL
PHA00001 BATCHSIZE’AUTO’ LEARNINGRATE’CONSTANT’ LEARNINGRATEINIT0001
POWERT05 MAXITER200 SHUFFLETRUE RANDOMSTATENONE TOL00001 VER
BOSEFALSE WARMSTARTFALSE MOMENTUM09 NESTEROVSMOMENTUMTRUE
EARLYSTOPPINGFALSE VALIDATIONFRACTION01 BETA109 BETA20999 EPSILON1E08
NITERNOCHANGE10
FITSELFXY
FIT THE MODEL TO DATA MATRIX X AND TARGETS Y
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE TARGET VALUES CLASS LABELS
IN CLASSIFICATION REAL NUMBERS IN REGRESSION
RETURNS
SELF RETURNS A TRAINED MLP MODEL
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PARTIALFIT
UPDATE THE MODEL WITH A SINGLE ITERATION OVER THE GIVEN DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
YARRAYLIKE SHAPE NSAMPLES THE TARGET VALUES
RETURNS
SELF RETURNS A TRAINED MLP MODEL

PREDICTSELFX
PREDICT USING THE MULTILAYER PERCEPTRON MODEL
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA
RETURNS
YARRAYLIKE SHAPE NSAMPLES NOUTPUTS THE PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNNEURALNETWORKMLPREGRESSOR
•PARTIAL DEPENDENCE PLOTS

632SKLEARNPIPELINE PIPELINE
THESKLEARNPIPELINE MODULE IMPLEMENTS UTILITIES TO BUILD A COMPOSITE ESTIMATOR AS A CHAIN OF TRANSFORMS AND ESTIMATORS
PIPELINEFEATUREUNION TRANSFORMERLIST CONCATENATES RESULTS OF MULTIPLE TRANSFORMER OBJECTS
PIPELINEPIPELINE STEPS MEMORY VERBOSE PIPELINE OF TRANSFORMS WITH A FINAL ESTIMATOR
6321SKLEARNPIPELINE FEATUREUNION
CLASSSKLEARNPIPELINE FEATUREUNION TRANSFORMERLIST NJOBSNONE TRANSFORMERWEIGHTSNONE VERBOSEFALSE
CONCATENATES RESULTS OF MULTIPLE TRANSFORMER OBJECTS
THIS ESTIMATOR APPLIES A LIST OF TRANSFORMER OBJECTS IN PARALLEL TO THE INPUT DATA THEN CONCATENATES THE RESULTS THIS IS USEFUL TO COMBINE SEVERAL FEATURE EXTRACTION MECHANISMS INTO A SINGLE TRANSFORMER
PARAMETERS OF THE TRANSFORMERS MAY BE SET USING ITS NAME AND THE PARAMETER NAME SEPARATED BY A ‘’ A TRANSFORMER MAY BE REPLACED ENTIRELY BY SETTING THE PARAMETER WITH ITS NAME TO ANOTHER TRANSFORMER OR REMOVED BY SETTING TO ‘DROP’ OR NONE
READ MORE IN THE USER GUIDE
PARAMETERS
TRANSFORMERLIST LIST OF STRING TRANSFORMER TUPLES LIST OF TRANSFORMER OBJECTS TO BE APPLIED TO THE DATA THE FIRST HALF OF EACH TUPLE IS THE NAME OF THE TRANSFORMER
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF JOBS TO RUN IN PARALLEL NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
TRANSFORMERWEIGHTS DICT OPTIONAL MULTIPLICATIVE WEIGHTS FOR FEATURES PER TRANSFORMER KEYS ARE TRANSFORMER NAMES VALUES THE WEIGHTS
VERBOSE BOOLEAN OPTIONALDEFAULTFALSE IF TRUE THE TIME ELAPSED WHILE FITTING EACH TRANS FORMER WILL BE PRINTED AS IT IS COMPLETED
SEE ALSO
SKLEARNPIPELINEMAKEUNION CONVENIENCE FUNCTION FOR SIMPLIFIED FEATURE UNION CONSTRUCTION
EXAMPLES
 FROM SKLEARNPIPELINE IMPORT FEATUREUNION
 FROM SKLEARNDECOMPOSITION IMPORT PCA TRUNCATEDSVD
UNION FEATUREUNIONPCA PCANCOMPONENTS1
 SVD TRUNCATEDSVDNCOMPONENTS2
X 0 1 3 2 2 5
UNIONFITTRANSFORMX
ARRAY 15 30 08
15 57 04

METHODS
FITSELF X Y FIT ALL TRANSFORMERS USING X
FITTRANSFORM SELF X Y FIT ALL TRANSFORMERS TRANSFORM THE DATA AND CONCATENATE
RESULTS
GETFEATURENAMES SELF GET FEATURE NAMES FROM ALL TRANSFORMERS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF KWARGS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM X SEPARATELY BY EACH TRANSFORMER CONCATE
NATE RESULTS
INIT SELFTRANSFORMERLIST NJOBSNONE TRANSFORMERWEIGHTSNONE VERBOSEFALSE
FITSELFXYNONE
FIT ALL TRANSFORMERS USING X
PARAMETERS
XITERABLE OR ARRAYLIKE DEPENDING ON TRANSFORMERS INPUT DATA USED TO FIT TRANSFORMERS
YARRAYLIKE SHAPE NSAMPLES OPTIONAL TARGETS FOR SUPERVISED LEARNING
RETURNS
SELF FEATUREUNION THIS ESTIMATOR
FITTRANSFORM SELFXYNONE FITPARAMS
FIT ALL TRANSFORMERS TRANSFORM THE DATA AND CONCATENATE RESULTS
PARAMETERS
XITERABLE OR ARRAYLIKE DEPENDING ON TRANSFORMERS INPUT DATA TO BE TRANSFORMED
YARRAYLIKE SHAPE NSAMPLES OPTIONAL TARGETS FOR SUPERVISED LEARNING
RETURNS
XT ARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES SUMNCOMPONENTS HSTACK OF RESULTS
OF TRANSFORMERS SUMNCOMPONENTS IS THE SUM OF NCOMPONENTS OUTPUT DIMENSION OVER
TRANSFORMERS
GETFEATURENAMES SELF
GET FEATURE NAMES FROM ALL TRANSFORMERS
RETURNS
FEATURENAMES LIST OF STRINGS NAMES OF THE FEATURES PRODUCED BY TRANSFORM
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFKWARGS
SET THE PARAMETERS OF THIS ESTIMATOR
632SKLEARNPIPELINE PIPELINE 2219

VALID PARAMETER KEYS CAN BE LISTED WITH GETPARAMS
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM X SEPARATELY BY EACH TRANSFORMER CONCATENATE RESULTS
PARAMETERS
XITERABLE OR ARRAYLIKE DEPENDING ON TRANSFORMERS INPUT DATA TO BE TRANSFORMED
RETURNS
XT ARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES SUMNCOMPONENTS HSTACK OF RESULTS
OF TRANSFORMERS SUMNCOMPONENTS IS THE SUM OF NCOMPONENTS OUTPUT DIMENSION OVER
TRANSFORMERS
EXAMPLES USING SKLEARNPIPELINEFEATUREUNION
•CONCATENATING MULTIPLE FEATURE EXTRACTION METHODS
6322SKLEARNPIPELINE PIPELINE
CLASSSKLEARNPIPELINE PIPELINE STEPS MEMORYNONE VERBOSEFALSE
PIPELINE OF TRANSFORMS WITH A FINAL ESTIMATOR
SEQUENTIALLY APPLY A LIST OF TRANSFORMS AND A FINAL ESTIMATOR INTERMEDIATE STEPS OF THE PIPELINE MUST BE ‘TRANS
FORMS’ THAT IS THEY MUST IMPLEMENT FIT AND TRANSFORM METHODS THE FINAL ESTIMATOR ONLY NEEDS TO IMPLEMENT FIT
THE TRANSFORMERS IN THE PIPELINE CAN BE CACHED USING MEMORY ARGUMENT
THE PURPOSE OF THE PIPELINE IS TO ASSEMBLE SEVERAL STEPS THAT CAN BE CROSSVALIDATED TOGETHER WHILE SETTING DIFFER
ENT PARAMETERS FOR THIS IT ENABLES SETTING PARAMETERS OF THE VARIOUS STEPS USING THEIR NAMES AND THE PARAMETER
NAME SEPARATED BY A ‘’ AS IN THE EXAMPLE BELOW A STEP’S ESTIMATOR MAY BE REPLACED ENTIRELY BY SETTING THE
PARAMETER WITH ITS NAME TO ANOTHER ESTIMATOR OR A TRANSFORMER REMOVED BY SETTING IT TO ‘PASSTHROUGH’ OR NONE
READ MORE IN THE USER GUIDE
PARAMETERS
STEPS LIST LIST OF NAME TRANSFORM TUPLES IMPLEMENTING FITTRANSFORM THAT ARE CHAINED IN THE
ORDER IN WHICH THEY ARE CHAINED WITH THE LAST OBJECT AN ESTIMATOR
MEMORY NONE STR OR OBJECT WITH THE JOBLIBMEMORY INTERFACE OPTIONAL USED TO CACHE THE FIT
TED TRANSFORMERS OF THE PIPELINE BY DEFAULT NO CACHING IS PERFORMED IF A STRING IS GIVEN
IT IS THE PATH TO THE CACHING DIRECTORY ENABLING CACHING TRIGGERS A CLONE OF THE TRANSFORM
ERS BEFORE FITTING THEREFORE THE TRANSFORMER INSTANCE GIVEN TO THE PIPELINE CANNOT BE IN
SPECTED DIRECTLY USE THE ATTRIBUTE NAMEDSTEPS ORSTEPS TO INSPECT ESTIMATORS WITHIN
THE PIPELINE CACHING THE TRANSFORMERS IS ADVANTAGEOUS WHEN FITTING IS TIME CONSUMING
VERBOSE BOOLEAN OPTIONAL IF TRUE THE TIME ELAPSED WHILE FITTING EACH STEP WILL BE PRINTED AS IT
IS COMPLETED
ATTRIBUTES
NAMEDSTEPS BUNCH OBJECT A DICTIONARY WITH ATTRIBUTE ACCESS READONLY ATTRIBUTE TO ACCESS
ANY STEP PARAMETER BY USER GIVEN NAME KEYS ARE STEP NAMES AND VALUES ARE STEPS PARAMETERS
SEE ALSO

SKLEARNPIPELINEMAKEPIPELINE CONVENIENCE FUNCTION FOR SIMPLIFIED PIPELINE CONSTRUCTION
EXAMPLES

```
 FROM SKLEARN IMPORT SVM
 FROM SKLEARNDATASETS IMPORT SAMPLESGENERATOR
 FROM SKLEARNFEATURESELECTION IMPORT SELECTKBEST
 FROM SKLEARNFEATURESELECTION IMPORT FREGRESSION
 FROM SKLEARNPIPELINE IMPORT PIPELINE
 GENERATE SOME DATA TO PLAY WITH
X Y  SAMPLESGENERATORMAKECLASSIFICATION
 NINFORMATIVE5 NREDUNDANT0 RANDOMSTATE42
 ANOVA SVMC
ANOVAFILTER  SELECTKBESTFREGRESSION K5
CLF  SVMSVCKERNELLINEAR
ANOVASVM  PIPELINEANOVA ANOVAFILTER SVC CLF
 YOU CAN SET THE PARAMETERS USING THE NAMES ISSUED
 FOR INSTANCE FIT USING A K OF 10 IN THE SELECTKBEST
 AND A PARAMETER C OF THE SVM
ANOVASVMSETPARAMSANOVAK10 SVCC1FITX Y

PIPELINEMEMORYNONE
STEPSANOVA SELECTKBEST
SVC SVC VERBOSEFALSE
PREDICTION  ANOVASVMPREDICTX
ANOVASVMSCOREX Y
083
 GETTING THE SELECTED FEATURES CHOSEN BY ANOVAFILTER
ANOVASVMANOVAGETSUPPORT

ARRAYFALSE FALSE TRUE TRUE FALSE FALSE TRUE TRUE FALSE
TRUE FALSE TRUE TRUE FALSE TRUE FALSE TRUE TRUE
FALSE FALSE
 ANOTHER WAY TO GET SELECTED FEATURES CHOSEN BY ANOVAFILTER
ANOVASVMNAMEDSTEPSANOVAGETSUPPORT

ARRAYFALSE FALSE TRUE TRUE FALSE FALSE TRUE TRUE FALSE
TRUE FALSE TRUE TRUE FALSE TRUE FALSE TRUE TRUE
FALSE FALSE
 INDEXING CAN ALSO BE USED TO EXTRACT A SUBPIPELINE
SUBPIPELINE  ANOVASVM1
SUBPIPELINE
PIPELINEMEMORYNONE STEPSANOVA  VERBOSEFALSE
COEF  ANOVASVM1COEF
ANOVASVMSVC ISANOVASVM1
TRUE
COEFSHAPE
1 10
SUBPIPELINEINVERSETRANSFORMCOEFSHAPE
1 20
METHODS
632SKLEARNPIPELINE  PIPELINE 2221
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DECISIONFUNCTION SELF X APPLY TRANSFORMS AND DECISIONFUNCTION OF THE FINAL ES
TIMATOR
FITSELF X Y FIT THE MODEL
FITPREDICT SELF X Y APPLIES FITPREDICT OF LAST STEP IN PIPELINE AFTER TRANS
FORMS
FITTRANSFORM SELF X Y FIT THE MODEL AND TRANSFORM WITH THE FINAL ESTIMATOR
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICTPARAMS APPLY TRANSFORMS TO THE DATA AND PREDICT WITH THE FINAL
ESTIMATOR
PREDICTLOGPROBA SELF X APPLY TRANSFORMS AND PREDICTLOGPROBA OF THE FINAL ES
TIMATOR
PREDICTPROBA SELF X APPLY TRANSFORMS AND PREDICTPROBA OF THE FINAL ESTIMA
TOR
SCORE SELF X Y SAMPLEWEIGHT APPLY TRANSFORMS AND SCORE WITH THE FINAL ESTIMATOR
SETPARAMS SELF KWARGS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFSTEPS MEMORYNONE VERBOSEFALSE
DECISIONFUNCTION SELFX
APPLY TRANSFORMS AND DECISIONFUNCTION OF THE FINAL ESTIMATOR
PARAMETERS
XITERABLE DATA TO PREDICT ON MUST FULFILL INPUT REQUIREMENTS OF FIRST STEP OF THE PIPELINE
RETURNS
YSCORE ARRAYLIKE SHAPE NSAMPLES NCLASSES
FITSELFXYNONE FITPARAMS
FIT THE MODEL
FIT ALL THE TRANSFORMS ONE AFTER THE OTHER AND TRANSFORM THE DATA THEN FIT THE TRANSFORMED DATA USING THE FINAL
ESTIMATOR
PARAMETERS
XITERABLE TRAINING DATA MUST FULFILL INPUT REQUIREMENTS OF FIRST STEP OF THE PIPELINE
YITERABLE DEFAULTNONE TRAINING TARGETS MUST FULFILL LABEL REQUIREMENTS FOR ALL STEPS OF
THE PIPELINE
FITPARAMS DICT OF STRING OBJECT PARAMETERS PASSED TO THE FIT METHOD OF EACH STEP
WHERE EACH PARAMETER NAME IS PREFIXED SUCH THAT PARAMETER PFOR STEPSHAS KEYSP
RETURNS
SELF PIPELINE THIS ESTIMATOR
FITPREDICT SELFXYNONE FITPARAMS
APPLIES FITPREDICT OF LAST STEP IN PIPELINE AFTER TRANSFORMS
APPLIES FITTRANSFORMS OF A PIPELINE TO THE DATA FOLLOWED BY THE FITPREDICT METHOD OF THE FINAL ESTIMATOR IN
THE PIPELINE VALID ONLY IF THE FINAL ESTIMATOR IMPLEMENTS FITPREDICT
PARAMETERS
XITERABLE TRAINING DATA MUST FULFILL INPUT REQUIREMENTS OF FIRST STEP OF THE PIPELINE
YITERABLE DEFAULTNONE TRAINING TARGETS MUST FULFILL LABEL REQUIREMENTS FOR ALL STEPS OF
THE PIPELINE

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FITPARAMS DICT OF STRING OBJECT PARAMETERS PASSED TO THE FIT METHOD OF EACH STEP
WHERE EACH PARAMETER NAME IS PREFIXED SUCH THAT PARAMETER PFOR STEPSHAS KEYSP
RETURNS
YPRED ARRAYLIKE
FITTRANSFORM SELFXYNONE FITPARAMS
FIT THE MODEL AND TRANSFORM WITH THE FINAL ESTIMATOR
FITS ALL THE TRANSFORMS ONE AFTER THE OTHER AND TRANSFORMS THE DATA THEN USES FITTRANSFORM ON TRANSFORMED
DATA WITH THE FINAL ESTIMATOR
PARAMETERS
XITERABLE TRAINING DATA MUST FULFILL INPUT REQUIREMENTS OF FIRST STEP OF THE PIPELINE
YITERABLE DEFAULTNONE TRAINING TARGETS MUST FULFILL LABEL REQUIREMENTS FOR ALL STEPS OF
THE PIPELINE
FITPARAMS DICT OF STRING OBJECT PARAMETERS PASSED TO THE FIT METHOD OF EACH STEP
WHERE EACH PARAMETER NAME IS PREFIXED SUCH THAT PARAMETER PFOR STEPSHAS KEYSP
RETURNS
XTARRAYLIKE SHAPE NSAMPLES NTRANSFORMEDFEATURES TRANSFORMED SAMPLES
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM
APPLY INVERSE TRANSFORMATIONS IN REVERSE ORDER
ALL ESTIMATORS IN THE PIPELINE MUST SUPPORT INVERSETRANSFORM
PARAMETERS
XTARRAYLIKE SHAPE NSAMPLES NTRANSFORMEDFEATURES DATA SAMPLES WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES MUST
FULFILL INPUT REQUIREMENTS OF LAST STEP OF PIPELINE’S INVERSETRANSFORM METHOD
RETURNS
XTARRAYLIKE SHAPE NSAMPLES NFEATURES
PREDICTSELFXPREDICTPARAMS
APPLY TRANSFORMS TO THE DATA AND PREDICT WITH THE FINAL ESTIMATOR
PARAMETERS
XITERABLE DATA TO PREDICT ON MUST FULFILL INPUT REQUIREMENTS OF FIRST STEP OF THE PIPELINE
PREDICTPARAMS DICT OF STRING OBJECT PARAMETERS TO THE PREDICT CALLED AT THE END OF
ALL TRANSFORMATIONS IN THE PIPELINE NOTE THAT WHILE THIS MAY BE USED TO RETURN UNCERTAINTIES
FROM SOME MODELS WITH RETURNSTD OR RETURNCOV UNCERTAINTIES THAT ARE GENERATED BY THE
TRANSFORMATIONS IN THE PIPELINE ARE NOT PROPAGATED TO THE FINAL ESTIMATOR
RETURNS
632SKLEARNPIPELINE PIPELINE 2223

YPRED ARRAYLIKE
PREDICTLOGPROBA SELFX
APPLY TRANSFORMS AND PREDICTLOGPROBA OF THE FINAL ESTIMATOR
PARAMETERS
XITERABLE DATA TO PREDICT ON MUST FULFILL INPUT REQUIREMENTS OF FIRST STEP OF THE PIPELINE
RETURNS
YSCORE ARRAYLIKE SHAPE NSAMPLES NCLASSES
PREDICTPROBA SELFX
APPLY TRANSFORMS AND PREDICTPROBA OF THE FINAL ESTIMATOR
PARAMETERS
XITERABLE DATA TO PREDICT ON MUST FULFILL INPUT REQUIREMENTS OF FIRST STEP OF THE PIPELINE
RETURNS
YPROBA ARRAYLIKE SHAPE NSAMPLES NCLASSES
SCORESELFXYNONE SAMPLEWEIGHTNONE
APPLY TRANSFORMS AND SCORE WITH THE FINAL ESTIMATOR
PARAMETERS
XITERABLE DATA TO PREDICT ON MUST FULFILL INPUT REQUIREMENTS OF FIRST STEP OF THE PIPELINE
YITERABLE DEFAULTNONE TARGETS USED FOR SCORING MUST FULFILL LABEL REQUIREMENTS FOR ALL
STEPS OF THE PIPELINE
SAMPLEWEIGHT ARRAYLIKE DEFAULTNONE IF NOT NONE THIS ARGUMENT IS PASSED AS
SAMPLEWEIGHT KEYWORD ARGUMENT TO THE SCORE METHOD OF THE FINAL ESTIMATOR
RETURNS
SCORE FLOAT
SETPARAMS SELFKWARGS
SET THE PARAMETERS OF THIS ESTIMATOR
VALID PARAMETER KEYS CAN BE LISTED WITH GETPARAMS
RETURNS
SELF
TRANSFORM
APPLY TRANSFORMS AND TRANSFORM WITH THE FINAL ESTIMATOR
THIS ALSO WORKS WHERE FINAL ESTIMATOR IS NONE ALL PRIOR TRANSFORMATIONS ARE APPLIED
PARAMETERS
XITERABLE DATA TO TRANSFORM MUST FULFILL INPUT REQUIREMENTS OF FIRST STEP OF THE PIPELINE
RETURNS
XTARRAYLIKE SHAPE NSAMPLES NTRANSFORMEDFEATURES

EXAMPLES USING SKLEARNPIPELINEPIPELINE
•EXPLICIT FEATURE MAP APPROXIMATION FOR RBF KERNELS
•FEATURE AGGLOMERATION VS UNIVARIATE SELECTION
•CONCATENATING MULTIPLE FEATURE EXTRACTION METHODS
•PIPELINING CHAINING A PCA AND A LOGISTIC REGRESSION
•COLUMN TRANSFORMER WITH MIXED TYPES
•SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV
•COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
•UNDERFITTING VS OVERFITTING
•BALANCE MODEL COMPLEXITY AND CROSSVALIDATED SCORE
•SAMPLE PIPELINE FOR TEXT FEATURE EXTRACTION AND EVALUATION
•COMPARING NEAREST NEIGHBORS WITH AND WITHOUT NEIGHBORHOOD COMPONENTS ANALYSIS
•RESTRICTED BOLTZMANN MACHINE FEATURES FOR DIGIT CLASSIFICATION
•SVMANOVA SVM WITH UNIVARIATE FEATURE SELECTION
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
PIPELINEMAKEPIPELINE STEPS KWARGS CONSTRUCT A PIPELINE FROM THE GIVEN ESTIMATORS
PIPELINEMAKEUNION TRANSFORMERS KWARGS CONSTRUCT A FEATUREUNION FROM THE GIVEN TRANSFORMERS
6323SKLEARNPIPELINE MAKEPIPELINE
SKLEARNPIPELINE MAKEPIPELINE STEPS KWARGS
CONSTRUCT A PIPELINE FROM THE GIVEN ESTIMATORS
THIS IS A SHORTHAND FOR THE PIPELINE CONSTRUCTOR IT DOES NOT REQUIRE AND DOES NOT PERMIT NAMING THE ESTIMATORS
INSTEAD THEIR NAMES WILL BE SET TO THE LOWERCASE OF THEIR TYPES AUTOMATICALLY
PARAMETERS
STEPS LIST OF ESTIMATORS
MEMORY NONE STR OR OBJECT WITH THE JOBLIBMEMORY INTERFACE OPTIONAL USED TO CACHE THE FIT
TED TRANSFORMERS OF THE PIPELINE BY DEFAULT NO CACHING IS PERFORMED IF A STRING IS GIVEN
IT IS THE PATH TO THE CACHING DIRECTORY ENABLING CACHING TRIGGERS A CLONE OF THE TRANSFORM
ERS BEFORE FITTING THEREFORE THE TRANSFORMER INSTANCE GIVEN TO THE PIPELINE CANNOT BE IN
SPECTED DIRECTLY USE THE ATTRIBUTE NAMEDSTEPS ORSTEPS TO INSPECT ESTIMATORS WITHIN
THE PIPELINE CACHING THE TRANSFORMERS IS ADVANTAGEOUS WHEN FITTING IS TIME CONSUMING
VERBOSE BOOLEAN OPTIONAL IF TRUE THE TIME ELAPSED WHILE FITTING EACH STEP WILL BE PRINTED AS IT
IS COMPLETED
RETURNS
PPIPELINE
SEE ALSO
SKLEARNPIPELINEPIPELINE CLASS FOR CREATING A PIPELINE OF TRANSFORMS WITH A FINAL ESTIMATOR

EXAMPLES
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 FROM SKLEARNNAIVEBAYES IMPORT GAUSSIANNB
 FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
MAKEPIPELINESTANDARDSCALER GAUSSIANNBPRIORS NONE

PIPELINEMEMORYNONE
STEPSSTANDARDSCALER
STANDARDSCALERCOPYTRUE WITHMEANTRUE WITHSTDTRUE
GAUSSIANNB
GAUSSIANNBPRIORSNONE VARSMOOTHING1E09
VERBOSEFALSE
```
EXAMPLES USING SKLEARNPIPELINEMAKEPIPELINE
•FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES
•PIPELINE ANOVA SVM
•IMPUTING MISSING VALUES WITH VARIANTS OF ITERATIVEIMPUTER
•IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR
•POLYNOMIAL INTERPOLATION
•ROBUST LINEAR ESTIMATOR FITTING
•DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
•USING FUNCTIONTRANSFORMER TO SELECT COLUMNS
•IMPORTANCE OF FEATURE SCALING
•FEATURE DISCRETIZATION
•CLUSTERING TEXT DOCUMENTS USING KMEANS
6324SKLEARNPIPELINE MAKEUNION
SKLEARNPIPELINE MAKEUNION TRANSFORMERS KWARGS
CONSTRUCT A FEATUREUNION FROM THE GIVEN TRANSFORMERS
THIS IS A SHORTHAND FOR THE FEATUREUNION CONSTRUCTOR IT DOES NOT REQUIRE AND DOES NOT PERMIT NAMING THE TRANSFORMERS INSTEAD THEY WILL BE GIVEN NAMES AUTOMATICALLY BASED ON THEIR TYPES IT ALSO DOES NOT ALLOW WEIGHTING
PARAMETERS
TRANSFORMERS LIST OF ESTIMATORS
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF JOBS TO RUN IN PARALLEL NONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
VERBOSE BOOLEAN OPTIONALDEFAULTFALSE IF TRUE THE TIME ELAPSED WHILE FITTING EACH TRANS FORMER WILL BE PRINTED AS IT IS COMPLETED
RETURNS
FFEATUREUNION

SEE ALSO
SKLEARNPIPELINEFEATUREUNION CLASS FOR CONCATENATING THE RESULTS OF MULTIPLE TRANSFORMER OBJECTS
EXAMPLES
```
 FROM SKLEARNDECOMPOSITION IMPORT PCA TRUNCATEDSVD
 FROM SKLEARNPIPELINE IMPORT MAKEUNION
MAKEUNIONPCA TRUNCATEDSVD
FEATUREUNIONNJOBSNONE
TRANSFORMERLISTPCA
PCACOPYTRUE ITERATEDPOWERAUTO
NCOMPONENTSNONE RANDOMSTATENONE
SVDSOLVERAUTO TOL00 WHITENFALSE
TRUNCATEDSVD
TRUNCATEDSVDALGORITHMRANDOMIZED
NCOMPONENTS2 NITER5
RANDOMSTATENONE TOL00
TRANSFORMERWEIGHTSNONE VERBOSEFALSE
```
EXAMPLES USING SKLEARNPIPELINEMAKEUNION
•IMPUTING MISSING VALUES BEFORE BUILDING AN ESTIMATOR
633SKLEARNINSPECTION INSPECTION
THESKLEARNINSPECTION MODULE INCLUDES TOOLS FOR MODEL INSPECTION
INSPECTIONPARTIALDEPENDENCE ESTIMATOR X
   PARTIAL DEPENDENCE OF FEATURES
INSPECTIONPLOTPARTIALDEPENDENCE
   PARTIAL DEPENDENCE PLOTS
6331SKLEARNINSPECTION PARTIALDEPENDENCE
SKLEARNINSPECTION PARTIALDEPENDENCE ESTIMATOR XFEATURES RESPONSEMETHOD‘AUTO’
PERCENTILES005 095 GRIDRESOLUTION100
METHOD‘AUTO’
PARTIAL DEPENDENCE OF FEATURES
PARTIAL DEPENDENCE OF A FEATURE OR A SET OF FEATURES CORRESPONDS TO THE AVERAGE RESPONSE OF AN ESTIMATOR FOR EACH POSSIBLE VALUE OF THE FEATURE
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR BASEESTIMATOR A FITTED ESTIMATOR OBJECT IMPLEMENTING PREDICT PREDICTPROBA OR DECISIONFUNCTION MULTIOUTPUTMULTICLASS CLASSIFIERS ARE NOT SUPPORTED
XARRAYLIKE SHAPE NSAMPLES NFEATURES XIS USED BOTH TO GENERATE A GRID OF VALUES FOR THE FEATURES AND TO COMPUTE THE AVERAGED PREDICTIONS WHEN METHOD IS ‘BRUTE’

FEATURES LIST OR ARRAYLIKE OF INT THE TARGET FEATURES FOR WHICH THE PARTIAL DEPENDENCY SHOULD
BE COMPUTED
RESPONSEMETHOD ‘AUTO’ ‘PREDICTPROBA’ OR ‘DECISIONFUNCTION’ OPTIONAL DEFAULT’AUTO’
SPECIFIES WHETHER TO USE PREDICTPROBA ORDECISIONFUNCTION AS THE TARGET RESPONSE FOR
REGRESSORS THIS PARAMETER IS IGNORED AND THE RESPONSE IS ALWAYS THE OUTPUT OF PREDICT BY
DEFAULT PREDICTPROBA IS TRIED FIRST AND WE REVERT TO DECISIONFUNCTION IF IT DOESN’T EXIST IF
METHOD IS ‘RECURSION’ THE RESPONSE IS ALWAYS THE OUTPUT OF DECISIONFUNCTION
PERCENTILES TUPLE OF FLOAT OPTIONAL DEFAULT005 095 THE LOWER AND UPPER PERCENTILE USED
TO CREATE THE EXTREME VALUES FOR THE GRID MUST BE IN 0 1
GRIDRESOLUTION INT OPTIONAL DEFAULT100 THE NUMBER OF EQUALLY SPACED POINTS ON THE GRID
FOR EACH TARGET FEATURE
METHOD STR OPTIONAL DEFAULT’AUTO’ THE METHOD USED TO CALCULATE THE AVERAGED PREDICTIONS
• ‘RECURSION’ IS ONLY SUPPORTED FOR OBJECTS INHERITING FROM BASEGRADIENTBOOSTING
BUT IS MORE EFFICIENT IN TERMS OF SPEED WITH THIS METHOD XIS ONLY USED TO BUILD THE
GRID AND THE PARTIAL DEPENDENCES ARE COMPUTED USING THE TRAINING DATA THIS METHOD DOES
NOT ACCOUNT FOR THE INIT PREDICOR OF THE BOOSTING PROCESS WHICH MAY LEAD TO INCORRECT
VALUES SEE WARNING BELOW WITH THIS METHOD THE TARGET RESPONSE OF A CLASSIFIER IS ALWAYS
THE DECISION FUNCTION NOT THE PREDICTED PROBABILITIES
• ‘BRUTE’ IS SUPPORTED FOR ANY ESTIMATOR BUT IS MORE COMPUTATIONALLY INTENSIVE
• IF ‘AUTO’ THEN ‘RECURSION’ WILL BE USED FOR BASEGRADIENTBOOSTING ESTIMATORS WITH
INITNONE AND ‘BRUTE’ FOR ALL OTHER
RETURNS
AVERAGEDPREDICTIONS NDARRAY SHAPE NOUTPUTS LENVALUES0 LENVALUES1 THE PRE
DICTIONS FOR ALL THE POINTS IN THE GRID AVERAGED OVER ALL SAMPLES IN X OR OVER THE TRAINING DATA
IFMETHOD IS ‘RECURSION’ NOUTPUTS CORRESPONDS TO THE NUMBER OF CLASSES IN A MULTI
CLASS SETTING OR TO THE NUMBER OF TASKS FOR MULTIOUTPUT REGRESSION FOR CLASSICAL REGRESSION
AND BINARY CLASSIFICATION NOUTPUTS1 NVALUESFEATUREJ CORRESPONDS TO THE
SIZEVALUESJ
VALUES SEQ OF 1D NDARRAYS THE VALUES WITH WHICH THE GRID HAS BEEN CREATED THE GENERATED GRID
IS A CARTESIAN PRODUCT OF THE ARRAYS IN VALUES LENVALUES LENFEATURES
THE SIZE OF EACH ARRAY VALUESJ IS EITHERGRIDRESOLUTION OR THE NUMBER OF
UNIQUE VALUES IN X J WHICHEVER IS SMALLER
WARNING THE ‘RECURSION’ METHOD ONLY WORKS FOR GRADIENT BOOSTING ESTIMATORS AND UNLIKE THE ‘BRUTE’
METHOD IT DOES NOT ACCOUNT FOR THE INIT PREDICTOR OF THE BOOSTING PROCESS IN PRACTICE THIS WILL PRODUCE THE
SAME VALUES AS ‘BRUTE’ UP TO A CONSTANT OFFSET IN THE TARGET RESPONSE PROVIDED THAT INIT IS A CONSANT ESTIMATOR
WHICH IS THE DEFAULT HOWEVER AS SOON AS INIT IS NOT A CONSTANT ESTIMATOR THE PARTIAL DEPENDENCE VALUES
ARE INCORRECT FOR ‘RECURSION’
SEE ALSO
SKLEARNINSPECTIONPLOTPARTIALDEPENDENCE PLOT PARTIAL DEPENDENCE

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EXAMPLES
X 0 0 2 1 0 0
Y 0 1
FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGCLASSIFIER
GB GRADIENTBOOSTINGCLASSIFIERRANDOMSTATE0FITX Y
PARTIALDEPENDENCEGB FEATURES0 XX PERCENTILES0 1
GRIDRESOLUTION2
ARRAY452 452 ARRAY 0 1
EXAMPLES USING SKLEARNINSPECTIONPARTIALDEPENDENCE
•PARTIAL DEPENDENCE PLOTS
6332SKLEARNINSPECTION PLOTPARTIALDEPENDENCE
SKLEARNINSPECTION PLOTPARTIALDEPENDENCE ESTIMATOR XFEATURES FEATURENAMESNONE
TARGETNONE RESPONSEMETHOD'AUTO'
NCOLS3 GRIDRESOLUTION100 PER
CENTILES005 095 METHOD'AUTO'
NJOBSNONE VERBOSE0 FIGNONE
LINEKWNONE CONTOURKWNONE
PARTIAL DEPENDENCE PLOTS
THELENFEATURES PLOTS ARE ARRANGED IN A GRID WITH NCOLS COLUMNS TWOWAY PARTIAL DEPENDENCE PLOTS
ARE PLOTTED AS CONTOUR PLOTS
READ MORE IN THE USER GUIDE
PARAMETERS
ESTIMATOR BASEESTIMATOR A FITTED ESTIMATOR OBJECT IMPLEMENTING PREDICT PREDICTPROBA OR
DECISIONFUNCTION MULTIOUTPUTMULTICLASS CLASSIFIERS ARE NOT SUPPORTED
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA TO USE TO BUILD THE GRID OF VALUES ON
WHICH THE DEPENDENCE WILL BE EVALUATED THIS IS USUALLY THE TRAINING DATA
FEATURES LIST OF INT STR PAIR OF INT PAIR OF STR THE TARGET FEATURES FOR WHICH TO CREATE THE
PDPS IF FEATURESI IS AN INT OR A STRING A ONEWAY PDP IS CREATED IF FEATURESI IS A TUPLE A
TWOWAY PDP IS CREATED EACH TUPLE MUST BE OF SIZE 2 IF ANY ENTRY IS A STRING THEN IT MUST
BE INFEATURENAMES
FEATURENAMES SEQ OF STR SHAPE NFEATURES OPTIONAL NAME OF EACH FEATURE FEA
TURENAMESI HOLDS THE NAME OF THE FEATURE WITH INDEX I BY DEFAULT THE NAME OF THE FEATURE
CORRESPONDS TO THEIR NUMERICAL INDEX
TARGET INT OPTIONAL DEFAULTNONE
• IN A MULTICLASS SETTING SPECIFIES THE CLASS FOR WHICH THE PDPS SHOULD BE COMPUTED NOTE
THAT FOR BINARY CLASSIFICATION THE POSITIVE CLASS INDEX 1 IS ALWAYS USED
• IN A MULTIOUTPUT SETTING SPECIFIES THE TASK FOR WHICH THE PDPS SHOULD BE COMPUTED
IGNORED IN BINARY CLASSIFICATION OR CLASSICAL REGRESSION SETTINGS
RESPONSEMETHOD 'AUTO' 'PREDICTPROBA' OR 'DECISIONFUNCTION' OPTIONAL DEFAULT'AUTO'
SPECIFIES WHETHER TO USE PREDICTPROBA ORDECISIONFUNCTION AS THE TARGET RESPONSE FOR
REGRESSORS THIS PARAMETER IS IGNORED AND THE RESPONSE IS ALWAYS THE OUTPUT OF PREDICT BY
633SKLEARNINSPECTION INSPECTION 2229

DEFAULT PREDICTPROBA IS TRIED FIRST AND WE REVERT TO DECISIONFUNCTION IF IT DOESN'T EXIST IF
METHOD IS 'RECURSION' THE RESPONSE IS ALWAYS THE OUTPUT OF DECISIONFUNCTION
NCOLS INT OPTIONAL DEFAULT3 THE MAXIMUM NUMBER OF COLUMNS IN THE GRID PLOT
GRIDRESOLUTION INT OPTIONAL DEFAULT100 THE NUMBER OF EQUALLY SPACED POINTS ON THE AXES
OF THE PLOTS FOR EACH TARGET FEATURE
PERCENTILES TUPLE OF FLOAT OPTIONAL DEFAULT005 095 THE LOWER AND UPPER PERCENTILE USED
TO CREATE THE EXTREME VALUES FOR THE PDP AXES MUST BE IN 0 1
METHOD STR OPTIONAL DEFAULT'AUTO' THE METHOD TO USE TO CALCULATE THE PARTIAL DEPENDENCE
PREDICTIONS
• 'RECURSION' IS ONLY SUPPORTED FOR OBJECTS INHERITING FROM BASEGRADIENTBOOSTING
BUT IS MORE EFFICIENT IN TERMS OF SPEED WITH THIS METHOD XIS OPTIONAL AND IS ONLY USED
TO BUILD THE GRID AND THE PARTIAL DEPENDENCES ARE COMPUTED USING THE TRAINING DATA THIS
METHOD DOES NOT ACCOUNT FOR THE INIT PREDICOR OF THE BOOSTING PROCESS WHICH MAY LEAD
TO INCORRECT VALUES SEE WARNING BELOW WITH THIS METHOD THE TARGET RESPONSE OF A CLASSI
FIER IS ALWAYS THE DECISION FUNCTION NOT THE PREDICTED PROBABILITIES
• 'BRUTE' IS SUPPORTED FOR ANY ESTIMATOR BUT IS MORE COMPUTATIONALLY INTENSIVE
• IF 'AUTO' THEN 'RECURSION' WILL BE USED FOR BASEGRADIENTBOOSTING ESTIMATORS WITH
INITNONE AND 'BRUTE' FOR ALL OTHER
UNLIKE THE 'BRUTE' METHOD 'RECURSION' DOES NOT ACCOUNT FOR THE INIT PREDICTOR OF THE BOOST
ING PROCESS IN PRACTICE THIS STILL PRODUCES THE SAME PLOTS UP TO A CONSTANT OFFSET IN THE TARGET
RESPONSE
NJOBS INT OPTIONAL DEFAULTNONE THE NUMBER OF CPUS TO USE TO COMPUTE THE PARTIAL DEPEN
DENCESNONE MEANS 1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS
USING ALL PROCESSORS SEE GLOSSARY FOR MORE DETAILS
VERBOSE INT OPTIONAL DEFAULT0 VERBOSE OUTPUT DURING PD COMPUTATIONS
FIGMATPLOTLIB FIGURE OBJECT OPTIONAL DEFAULTNONE A FIGURE OBJECT ONTO WHICH THE PLOTS WILL
BE DRAWN AFTER THE FIGURE HAS BEEN CLEARED BY DEFAULT A NEW ONE IS CREATED
LINEKW DICT OPTIONAL DICT WITH KEYWORDS PASSED TO THE MATPLOTLIBPYPLOTPLOT CALL
FOR ONEWAY PARTIAL DEPENDENCE PLOTS
CONTOURKW DICT OPTIONAL DICT WITH KEYWORDS PASSED TO THE MATPLOTLIBPYPLOTPLOT
CALL FOR TWOWAY PARTIAL DEPENDENCE PLOTS
WARNING THE 'RECURSION' METHOD ONLY WORKS FOR GRADIENT BOOSTING ESTIMATORS AND UNLIKE THE 'BRUTE'
METHOD IT DOES NOT ACCOUNT FOR THE INIT PREDICTOR OF THE BOOSTING PROCESS IN PRACTICE THIS WILL PRODUCE THE
SAME VALUES AS 'BRUTE' UP TO A CONSTANT OFFSET IN THE TARGET RESPONSE PROVIDED THAT INIT IS A CONSANT ESTIMATOR
WHICH IS THE DEFAULT HOWEVER AS SOON AS INIT IS NOT A CONSTANT ESTIMATOR THE PARTIAL DEPENDENCE VALUES
ARE INCORRECT FOR 'RECURSION'
SEE ALSO
SKLEARNINSPECTIONPARTIALDEPENDENCE RETURN RAW PARTIAL DEPENDENCE VALUES

EXAMPLES
 FROM SKLEARNDATASETS IMPORT MAKEFRIEDMAN1
 FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGREGRESSOR
X Y MAKEFRIEDMAN1
CLF GRADIENTBOOSTINGREGRESSORNESTIMATORS10FITX Y
PLOTPARTIALDEPENDENCECLF X 0 0 1
EXAMPLES USING SKLEARNINSPECTIONPLOTPARTIALDEPENDENCE
•PARTIAL DEPENDENCE PLOTS
634SKLEARNPREPROCESSING PREPROCESSING AND NORMALIZATION
THESKLEARNPREPROCESSING MODULE INCLUDES SCALING CENTERING NORMALIZATION BINARIZATION AND IMPUTATION
METHODS
USER GUIDE SEE THE PREPROCESSING DATA SECTION FOR FURTHER DETAILS
PREPROCESSINGBINARIZER THRESHOLD COPY BINARIZE DATA SET FEATURE VALUES TO 0 OR 1 ACCORDING TO A
THRESHOLD
PREPROCESSINGFUNCTIONTRANSFORMER FUNC
   CONSTRUCTS A TRANSFORMER FROM AN ARBITRARY CALLABLE
PREPROCESSINGKBINSDISCRETIZER NBINS
   BIN CONTINUOUS DATA INTO INTERVALS
PREPROCESSINGKERNELCENTERER CENTER A KERNEL MATRIX
PREPROCESSINGLABELBINARIZER NEGLABEL
   BINARIZE LABELS IN A ONEVSALL FASHION
PREPROCESSINGLABELENCODER ENCODE LABELS WITH VALUE BETWEEN 0 AND NCLASSES1
PREPROCESSINGMULTILABELBINARIZER CLASSES
   TRANSFORM BETWEEN ITERABLE OF ITERABLES AND A MULTILABEL
FORMAT
PREPROCESSINGMAXABSSCALER COPY SCALE EACH FEATURE BY ITS MAXIMUM ABSOLUTE VALUE
PREPROCESSINGMINMAXSCALER FEATURERANGE
COPYTRANSFORMS FEATURES BY SCALING EACH FEATURE TO A GIVEN
RANGE
PREPROCESSINGNORMALIZER NORM COPY NORMALIZE SAMPLES INDIVIDUALLY TO UNIT NORM
PREPROCESSINGONEHOTENCODER NVALUES   ENCODE CATEGORICAL INTEGER FEATURES AS A ONEHOT NUMERIC
ARRAY
PREPROCESSINGORDINALENCODER CATEGORIES
DTYPEENCODE CATEGORICAL FEATURES AS AN INTEGER ARRAY
PREPROCESSINGPOLYNOMIALFEATURES DEGREE
   GENERATE POLYNOMIAL AND INTERACTION FEATURES
PREPROCESSINGPOWERTRANSFORMER METHOD
   APPLY A POWER TRANSFORM FEATUREWISE TO MAKE DATA MORE
GAUSSIANLIKE
PREPROCESSINGQUANTILETRANSFORMER   TRANSFORM FEATURES USING QUANTILES INFORMATION
PREPROCESSINGROBUSTSCALER WITHCENTERING
   SCALE FEATURES USING STATISTICS THAT ARE ROBUST TO OUTLIERS
PREPROCESSINGSTANDARDSCALER COPY   STANDARDIZE FEATURES BY REMOVING THE MEAN AND SCALING TO
UNIT VARIANCE

6341SKLEARNPREPROCESSING BINARIZER
CLASSSKLEARNPREPROCESSING BINARIZER THRESHOLD00 COPYTRUE
BINARIZE DATA SET FEATURE VALUES TO 0 OR 1 ACCORDING TO A THRESHOLD
VALUES GREATER THAN THE THRESHOLD MAP TO 1 WHILE VALUES LESS THAN OR EQUAL TO THE THRESHOLD MAP TO 0 WITH THE DEFAULT THRESHOLD OF 0 ONLY POSITIVE VALUES MAP TO 1
BINARIZATION IS A COMMON OPERATION ON TEXT COUNT DATA WHERE THE ANALYST CAN DECIDE TO ONLY CONSIDER THE PRESENCE OR ABSENCE OF A FEATURE RATHER THAN A QUANTIFIED NUMBER OF OCCURRENCES FOR INSTANCE
IT CAN ALSO BE USED AS A PREPROCESSING STEP FOR ESTIMATORS THAT CONSIDER BOOLEAN RANDOM VARIABLES EG MODELLED USING THE BERNOULLI DISTRIBUTION IN A BAYESIAN SETTING
READ MORE IN THE USER GUIDE
PARAMETERS
THRESHOLD FLOAT OPTIONAL 00 BY DEFAULT FEATURE VALUES BELOW OR EQUAL TO THIS ARE REPLACED BY 0 ABOVE IT BY 1 THRESHOLD MAY NOT BE LESS THAN 0 FOR OPERATIONS ON SPARSE MATRICES
COPY BOOLEAN OPTIONAL DEFAULT TRUE SET TO FALSE TO PERFORM INPLACE BINARIZATION AND AVOID A COPY IF THE INPUT IS ALREADY A NUMPY ARRAY OR A SCIPYSPARSE CSR MATRIX
SEE ALSO
BINARIZE EQUIVALENT FUNCTION WITHOUT THE ESTIMATOR API
NOTES
IF THE INPUT IS A SPARSE MATRIX ONLY THE NONZERO VALUES ARE SUBJECT TO UPDATE BY THE BINARIZER CLASS
THIS ESTIMATOR IS STATELESS BESIDES CONSTRUCTOR PARAMETERS THE FIT METHOD DOES NOTHING BUT IS USEFUL WHEN USED IN A PIPELINE
EXAMPLES
FROM SKLEARNPREPROCESSING IMPORT BINARIZER
X 1 1 2
2 0 0
0 1 1
TRANSFORMER BINARIZERFITX FIT DOES NOTHING
TRANSFORMER
BINARIZERCOPYTRUE THRESHOLD00
TRANSFORMERTRANSFORMX
ARRAY1 0 1
1 0 0
0 1 0
METHODS
FITSELF X Y DO NOTHING AND RETURN THE ESTIMATOR UNCHANGED
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
CONTINUED ON NEXT PAGE

TABLE 6247 – CONTINUED FROM PREVIOUS PAGE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X COPY BINARIZE EACH ELEMENT OF X
INIT SELFTHRESHOLD00 COPYTRUE
FITSELFXYNONE
DO NOTHING AND RETURN THE ESTIMATOR UNCHANGED
THIS METHOD IS JUST THERE TO IMPLEMENT THE USUAL API AND HENCE WORK IN PIPELINES
PARAMETERS
XARRAYLIKE
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFXCOPYNONE
BINARIZE EACH ELEMENT OF X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA TO BINARIZE ELEMENT
BY ELEMENT SCIPYSPARSE MATRICES SHOULD BE IN CSR FORMAT TO AVOID AN UNNECESSARY COPY
COPY BOOL COPY THE INPUT X OR NOT

6342SKLEARNPREPROCESSING FUNCTIONTRANSFORMER
CLASSSKLEARNPREPROCESSING FUNCTIONTRANSFORMER FUNCNONE INVERSEFUNCNONE VAL
IDATENONE ACCEPTSPARSEFALSE
PASSY'DEPRECATED'
CHECKINVERSETRUE KWARGSNONE
INVKWARGSNONE
CONSTRUCTS A TRANSFORMER FROM AN ARBITRARY CALLABLE
A FUNCTIONTRANSFORMER FORWARDS ITS X AND OPTIONALLY Y ARGUMENTS TO A USERDEFINED FUNCTION OR FUNCTION
OBJECT AND RETURNS THE RESULT OF THIS FUNCTION THIS IS USEFUL FOR STATELESS TRANSFORMATIONS SUCH AS TAKING THE LOG
OF FREQUENCIES DOING CUSTOM SCALING ETC
NOTE IF A LAMBDA IS USED AS THE FUNCTION THEN THE RESULTING TRANSFORMER WILL NOT BE PICKLEABLE
NEW IN VERSION 017
READ MORE IN THE USER GUIDE
PARAMETERS
FUNC CALLABLE OPTIONAL DEFAULTNONE THE CALLABLE TO USE FOR THE TRANSFORMATION THIS WILL BE
PASSED THE SAME ARGUMENTS AS TRANSFORM WITH ARGS AND KWARGS FORWARDED IF FUNC IS NONE
THEN FUNC WILL BE THE IDENTITY FUNCTION
INVERSEFUNC CALLABLE OPTIONAL DEFAULTNONE THE CALLABLE TO USE FOR THE INVERSE TRANSFORMA
TION THIS WILL BE PASSED THE SAME ARGUMENTS AS INVERSE TRANSFORM WITH ARGS AND KWARGS
FORWARDED IF INVERSEFUNC IS NONE THEN INVERSEFUNC WILL BE THE IDENTITY FUNCTION
VALIDATE BOOL OPTIONAL DEFAULTTRUE INDICATE THAT THE INPUT X ARRAY SHOULD BE CHECKED BEFORE
CALLINGFUNC THE POSSIBILITIES ARE
• IF FALSE THERE IS NO INPUT VALIDATION
• IF TRUE THEN X WILL BE CONVERTED TO A 2DIMENSIONAL NUMPY ARRAY OR SPARSE MATRIX IF THE
CONVERSION IS NOT POSSIBLE AN EXCEPTION IS RAISED
DEPRECATED SINCE VERSION 020 VALIDATETRUE AS DEFAULT WILL BE REPLACED BY
VALIDATEFALSE IN 022
ACCEPTSPARSE BOOLEAN OPTIONAL INDICATE THAT FUNC ACCEPTS A SPARSE MATRIX AS INPUT IF VALIDATE
IS FALSE THIS HAS NO EFFECT OTHERWISE IF ACCEPTSPARSE IS FALSE SPARSE MATRIX INPUTS WILL
CAUSE AN EXCEPTION TO BE RAISED
PASSY BOOL OPTIONAL DEFAULTFALSE INDICATE THAT TRANSFORM SHOULD FORWARD THE Y ARGUMENT TO
THE INNER CALLABLE
DEPRECATED SINCE VERSION 019
CHECKINVERSE BOOL DEFAULTTRUE WHETHER TO CHECK THAT OR FUNC FOLLOWED BY
INVERSEFUNC LEADS TO THE ORIGINAL INPUTS IT CAN BE USED FOR A SANITY CHECK RAISING
A WARNING WHEN THE CONDITION IS NOT FULFILLED
NEW IN VERSION 020
KWARGS DICT OPTIONAL DICTIONARY OF ADDITIONAL KEYWORD ARGUMENTS TO PASS TO FUNC
INVKWARGS DICT OPTIONAL DICTIONARY OF ADDITIONAL KEYWORD ARGUMENTS TO PASS TO IN
VERSEFUNC

METHODS
FITSELF X Y FIT TRANSFORMER BY CHECKING X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X TRANSFORM X USING THE INVERSE FUNCTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM X USING THE FORWARD FUNCTION
INIT SELF FUNCNONE INVERSEFUNCNONE VALIDATENONE ACCEPTSPARSEFALSE
PASSY'DEPRECATED' CHECKINVERSETRUE KWARGSNONE INVKWARGSNONE
FITSELFXYNONE
FIT TRANSFORMER BY CHECKING X
IFVALIDATE ISTRUE XWILL BE CHECKED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT ARRAY
RETURNS
SELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFX
TRANSFORM X USING THE INVERSE FUNCTION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT ARRAY
RETURNS
XOUT ARRAYLIKE SHAPE NSAMPLES NFEATURES TRANSFORMED INPUT

SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM X USING THE FORWARD FUNCTION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT ARRAY
RETURNS
XOUT ARRAYLIKE SHAPE NSAMPLES NFEATURES TRANSFORMED INPUT
EXAMPLES USING SKLEARNPREPROCESSINGFUNCTIONTRANSFORMER
•USING FUNCTIONTRANSFORMER TO SELECT COLUMNS
6343SKLEARNPREPROCESSING KBINSDISCRETIZER
CLASSSKLEARNPREPROCESSING KBINSDISCRETIZER NBINS5 ENCODE'ONEHOT' STRATEGY'QUANTILE'
BIN CONTINUOUS DATA INTO INTERVALS
READ MORE IN THE USER GUIDE
PARAMETERS
NBINS INT OR ARRAYLIKE SHAPE NFEATURES DEFAULT5 THE NUMBER OF BINS TO PRODUCE
RAISES VALUEERROR IF NBINS 2
ENCODE 'ONEHOT' 'ONEHOTDENSE' 'ORDINAL' DEFAULT'ONEHOT' METHOD USED TO ENCODE THE TRANSFORMED RESULT
ONEHOT ENCODE THE TRANSFORMED RESULT WITH ONEHOT ENCODING AND RETURN A SPARSE MATRIX IGNORED FEATURES ARE ALWAYS STACKED TO THE RIGHT
ONEHOTDENSE ENCODE THE TRANSFORMED RESULT WITH ONEHOT ENCODING AND RETURN A DENSE ARRAY IGNORED FEATURES ARE ALWAYS STACKED TO THE RIGHT
ORDINAL RETURN THE BIN IDENTIFIER ENCODED AS AN INTEGER VALUE
STRATEGY 'UNIFORM' 'QUANTILE' 'KMEANS' DEFAULT'QUANTILE' STRATEGY USED TO DEFINE THE WIDTHS OF THE BINS
UNIFORM ALL BINS IN EACH FEATURE HAVE IDENTICAL WIDTHS
QUANTILE ALL BINS IN EACH FEATURE HAVE THE SAME NUMBER OF POINTS
KMEANS VALUES IN EACH BIN HAVE THE SAME NEAREST CENTER OF A 1D KMEANS CLUSTER
ATTRIBUTES
NBINS INT ARRAY SHAPE NFEATURES NUMBER OF BINS PER FEATURE BINS WHOSE WIDTH ARE TOO SMALL IE 1E8 ARE REMOVED WITH A WARNING

BINEDGES ARRAY OF ARRAYS SHAPE NFEATURES THE EDGES OF EACH BIN CONTAIN ARRAYS OF
VARYING SHAPES NBINS IGNORED FEATURES WILL HAVE EMPTY ARRAYS
SEE ALSO
SKLEARNPREPROCESSINGBINARIZER CLASS USED TO BIN VALUES AS 0OR1BASED ON A PARAMETER
THRESHOLD
NOTES
IN BIN EDGES FOR FEATURE I THE FIRST AND LAST VALUES ARE USED ONLY FOR INVERSETRANSFORM DURING TRANSFORM
BIN EDGES ARE EXTENDED TO
NPCONCATENATENPINF BINEDGESI11 NPINF
YOU CAN COMBINE KBINSDISCRETIZER WITHSKLEARNCOMPOSECOLUMNTRANSFORMER IF YOU ONLY
WANT TO PREPROCESS PART OF THE FEATURES
KBINSDISCRETIZER MIGHT PRODUCE CONSTANT FEATURES EG WHEN ENCODE ONEHOT AND CERTAIN BINS
DO NOT CONTAIN ANY DATA THESE FEATURES CAN BE REMOVED WITH FEATURE SELECTION ALGORITHMS EG SKLEARN
FEATURESELECTIONVARIANCETHRESHOLD
EXAMPLES
```
X  2 1 4 1
 1 2 3 05
  0 3 2 05
  1 4 1 2
EST  KBINSDISCRETIZERNBINS3 ENCODEORDINAL STRATEGYUNIFORM
ESTFITX
KBINSDISCRETIZER
XT  ESTTRANSFORMX
XT
ARRAY 0 0 0 0
 1 1 1 0
 2 2 2 1
 2 2 2 2
```
SOMETIMES IT MAY BE USEFUL TO CONVERT THE DATA BACK INTO THE ORIGINAL FEATURE SPACE THE
INVERSETRANSFORM FUNCTION CONVERTS THE BINNED DATA INTO THE ORIGINAL FEATURE SPACE EACH VALUE WILL
BE EQUAL TO THE MEAN OF THE TWO BIN EDGES
```
ESTBINEDGES0
ARRAY2 1 0 1
ESTINVERSETRANSFORMXT
ARRAY15 15 35 05
05 25 25 05
 05 35 15 05
 05 35 15 15
```
METHODS

FITSELF X Y FITS THE ESTIMATOR
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF XT TRANSFORMS DISCRETIZED DATA BACK TO ORIGINAL FEATURE
SPACE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X DISCRETIZES THE DATA
INIT SELFNBINS5 ENCODE’ONEHOT’ STRATEGY’QUANTILE’
FITSELFXYNONE
FITS THE ESTIMATOR
PARAMETERS
XNUMERIC ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA TO BE DISCRETIZED
YIGNORED
RETURNS
SELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFXT
TRANSFORMS DISCRETIZED DATA BACK TO ORIGINAL FEATURE SPACE
NOTE THAT THIS FUNCTION DOES NOT REGENERATE THE ORIGINAL DATA DUE TO DISCRETIZATION ROUNDING
PARAMETERS
XTNUMERIC ARRAYLIKE SHAPE NSAMPLE NFEATURES TRANSFORMED DATA IN THE BINNED SPACE
RETURNS
XINV NUMERIC ARRAYLIKE DATA IN THE ORIGINAL FEATURE SPACE

SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
DISCRETIZES THE DATA
PARAMETERS
XNUMERIC ARRAYLIKE SHAPE NSAMPLES NFEATURES DATA TO BE DISCRETIZED
RETURNS
XTNUMERIC ARRAYLIKE OR SPARSE MATRIX DATA IN THE BINNED SPACE
EXAMPLES USING SKLEARNPREPROCESSINGKBINSDISCRETIZER
•USING KBINSDISCRETIZER TO DISCRETIZE CONTINUOUS FEATURES
•DEMONSTRATING THE DIFFERENT STRATEGIES OF KBINSDISCRETIZER
•FEATURE DISCRETIZATION
6344SKLEARNPREPROCESSING KERNELCENTERER
CLASSSKLEARNPREPROCESSING KERNELCENTERER
CENTER A KERNEL MATRIX
LET KX Z BE A KERNEL DEFINED BY PHIXT PHIZ WHERE PHI IS A FUNCTION MAPPING X TO A HILBERT SPACE
KERNELCENTERER CENTERS IE NORMALIZE TO HAVE ZERO MEAN THE DATA WITHOUT EXPLICITLY COMPUTING PHIX IT IS
EQUIVALENT TO CENTERING PHIX WITH SKLEARNPREPROCESSINGSTANDARDSCALERWITHSTDFALSE
READ MORE IN THE USER GUIDE
EXAMPLES
```
 FROM SKLEARNPREPROCESSING IMPORT KERNELCENTERER
 FROM SKLEARNMETRICSPAIRWISE IMPORT PAIRWISEKERNELS
X   1 2 2
  2 1 3
  4 1 2
K  PAIRWISEKERNELSX METRICLINEAR
K
ARRAY 9 2 2
 2 14 13
 2 13 21
TRANSFORMER  KERNELCENTERERFITK
TRANSFORMER
KERNELCENTERER
TRANSFORMERTRANSFORMK
ARRAY 5 0 5
```

0 14 14
5 14 19
METHODS
FITSELF K Y FIT KERNELCENTERER
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF K COPY CENTER KERNEL MATRIX
INIT SELF
FITSELFKYNONE
FIT KERNELCENTERER
PARAMETERS
KNUMPY ARRAY OF SHAPE NSAMPLES NSAMPLES KERNEL MATRIX
RETURNS
SELF RETURNS AN INSTANCE OF SELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF

TRANSFORM SELFKCOPYTRUE
CENTER KERNEL MATRIX
PARAMETERS
KNUMPY ARRAY OF SHAPE NSAMPLES1 NSAMPLES2 KERNEL MATRIX
COPY BOOLEAN OPTIONAL DEFAULT TRUE SET TO FALSE TO PERFORM INPLACE COMPUTATION
RETURNS
KNEW NUMPY ARRAY OF SHAPE NSAMPLES1 NSAMPLES2
6345SKLEARNPREPROCESSING LABELBINARIZER
CLASSSKLEARNPREPROCESSING LABELBINARIZER NEGLABEL0 POSLABEL1
SPARSEOUTPUTFALSE
BINARIZE LABELS IN A ONEVSALL FASHION
SEVERAL REGRESSION AND BINARY CLASSIFICATION ALGORITHMS ARE AVAILABLE IN SCIKITLEARN A SIMPLE WAY TO EXTEND
THESE ALGORITHMS TO THE MULTICLASS CLASSIFICATION CASE IS TO USE THE SOCALLED ONEVSALL SCHEME
AT LEARNING TIME THIS SIMPLY CONSISTS IN LEARNING ONE REGRESSOR OR BINARY CLASSIFIER PER CLASS IN DOING SO ONE
NEEDS TO CONVERT MULTICLASS LABELS TO BINARY LABELS BELONG OR DOES NOT BELONG TO THE CLASS LABELBINARIZER
MAKES THIS PROCESS EASY WITH THE TRANSFORM METHOD
AT PREDICTION TIME ONE ASSIGNS THE CLASS FOR WHICH THE CORRESPONDING MODEL GAVE THE GREATEST CONFIDENCE LA
BELBINARIZER MAKES THIS EASY WITH THE INVERSETRANSFORM METHOD
READ MORE IN THE USER GUIDE
PARAMETERS
NEGLABEL INT DEFAULT 0 VALUE WITH WHICH NEGATIVE LABELS MUST BE ENCODED
POSLABEL INT DEFAULT 1 VALUE WITH WHICH POSITIVE LABELS MUST BE ENCODED
SPARSEOUTPUT BOOLEAN DEFAULT FALSE TRUE IF THE RETURNED ARRAY FROM TRANSFORM IS DESIRED TO
BE IN SPARSE CSR FORMAT
ATTRIBUTES
CLASSES ARRAY OF SHAPE NCLASS HOLDS THE LABEL FOR EACH CLASS
YTYPE STR REPRESENTS THE TYPE OF THE TARGET DATA AS EVALUATED BY
UTILSMULTICLASSTYPEOFTARGET POSSIBLE TYPE ARE ‘CONTINUOUS’ ‘CONTINUOUSMULTIOUTPUT’
‘BINARY’ ‘MULTICLASS’ ‘MULTICLASSMULTIOUTPUT’ ‘MULTILABELINDICATOR’ AND ‘UNKNOWN’
SPARSEINPUT BOOLEAN TRUE IF THE INPUT DATA TO TRANSFORM IS GIVEN AS A SPARSE MATRIX FALSE
OTHERWISE
SEE ALSO
LABELBINARIZE FUNCTION TO PERFORM THE TRANSFORM OPERATION OF LABELBINARIZER WITH FIXED CLASSES
SKLEARNPREPROCESSINGONEHOTENCODER ENCODE CATEGORICAL FEATURES USING A ONEHOT AKA ONEOFK
SCHEME
634SKLEARNPREPROCESSING PREPROCESSING AND NORMALIZATION 2241

EXAMPLES
```
 FROM SKLEARN IMPORT PREPROCESSING
LB  PREPROCESSINGLABELBINARIZER
LBFIT1 2 6 4 2
LABELBINARIZERNEGLABEL0 POSLABEL1 SPARSEOUTPUTFALSE
LBCLASSES
ARRAY1 2 4 6
LBTRANSFORM1 6
ARRAY1 0 0 0
0 0 0 1
```
BINARY TARGETS TRANSFORM TO A COLUMN VECTOR
```
LB  PREPROCESSINGLABELBINARIZER
LBFITTRANSFORMYES NO NO YES
ARRAY1
0
0
1
```
PASSING A 2D MATRIX FOR MULTILABEL CLASSIFICATION
```
 IMPORT NUMPY AS NP
LBFITNPARRAY0 1 1 1 0 0
LABELBINARIZERNEGLABEL0 POSLABEL1 SPARSEOUTPUTFALSE
LBCLASSES
ARRAY0 1 2
LBTRANSFORM0 1 2 1
ARRAY1 0 0
0 1 0
0 0 1
0 1 0
```
METHODS

FITSELF Y FIT LABEL BINARIZER

FITTRANSFORM SELF Y FIT LABEL BINARIZER AND TRANSFORM MULTICLASS LABELS TO BINARY LABELS

GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR

INVERSETRANSFORM SELF Y THRESHOLD TRANSFORM BINARY LABELS BACK TO MULTICLASS LABELS

SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR

TRANSFORM SELF Y TRANSFORM MULTICLASS LABELS TO BINARY LABELS

INIT SELFNEGLABEL0 POSLABEL1 SPARSEOUTPUTFALSE

FITSELFY

FIT LABEL BINARIZER

PARAMETERS

YARRAY OF SHAPE NSAMPLES OR NSAMPLES NCLASSES TARGET VALUES THE 2D MATRIX SHOULD ONLY CONTAIN 0 AND 1 REPRESENTS MULTILABEL CLASSIFICATION

RETURNS

SELF RETURNS AN INSTANCE OF SELF
FITTRANSFORM SELFY
FIT LABEL BINARIZER AND TRANSFORM MULTICLASS LABELS TO BINARY LABELS
THE OUTPUT OF TRANSFORM IS SOMETIMES REFERRED TO AS THE 1OFK CODING SCHEME
PARAMETERS
YARRAY OR SPARSE MATRIX OF SHAPE NSAMPLES OR NSAMPLES NCLASSES TARGET VALUES
THE 2D MATRIX SHOULD ONLY CONTAIN 0 AND 1 REPRESENTS MULTILABEL CLASSIFICATION SPARSE
MATRIX CAN BE CSR CSC COO DOK OR LIL
RETURNS
YARRAY OR CSR MATRIX OF SHAPE NSAMPLES NCLASSES SHAPE WILL BE NSAMPLES 1 FOR
BINARY PROBLEMS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFYTHRESHOLDNONE
TRANSFORM BINARY LABELS BACK TO MULTICLASS LABELS
PARAMETERS
YNUMPY ARRAY OR SPARSE MATRIX WITH SHAPE NSAMPLES NCLASSES TARGET VALUES ALL
SPARSE MATRICES ARE CONVERTED TO CSR BEFORE INVERSE TRANSFORMATION
THRESHOLD FLOAT OR NONE THRESHOLD USED IN THE BINARY AND MULTILABEL CASES
USE 0 WHEN YCONTAINS THE OUTPUT OF DECISIONFUNCTION CLASSIFIER USE 05 WHEN YCON
TAINS THE OUTPUT OF PREDICTPROBA
IF NONE THE THRESHOLD IS ASSUMED TO BE HALF WAY BETWEEN NEGLABEL AND POSLABEL
RETURNS
YNUMPY ARRAY OR CSR MATRIX OF SHAPE NSAMPLES TARGET VALUES
NOTES
IN THE CASE WHEN THE BINARY LABELS ARE FRACTIONAL PROBABILISTIC INVERSETRANSFORM CHOOSES THE CLASS WITH
THE GREATEST VALUE TYPICALLY THIS ALLOWS TO USE THE OUTPUT OF A LINEAR MODEL’S DECISIONFUNCTION METHOD
DIRECTLY AS THE INPUT OF INVERSETRANSFORM
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS

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SELF
TRANSFORM SELFY
TRANSFORM MULTICLASS LABELS TO BINARY LABELS
THE OUTPUT OF TRANSFORM IS SOMETIMES REFERRED TO BY SOME AUTHORS AS THE 1OFK CODING SCHEME
PARAMETERS
YARRAY OR SPARSE MATRIX OF SHAPE NSAMPLES OR NSAMPLES NCLASSES TARGET VALUES
THE 2D MATRIX SHOULD ONLY CONTAIN 0 AND 1 REPRESENTS MULTILABEL CLASSIFICATION SPARSE
MATRIX CAN BE CSR CSC COO DOK OR LIL
RETURNS
YNUMPY ARRAY OR CSR MATRIX OF SHAPE NSAMPLES NCLASSES SHAPE WILL BE NSAMPLES
1 FOR BINARY PROBLEMS
6346SKLEARNPREPROCESSING LABELENCODER
CLASSSKLEARNPREPROCESSING LABELENCODER
ENCODE LABELS WITH VALUE BETWEEN 0 AND NCLASSES1
READ MORE IN THE USER GUIDE
ATTRIBUTES
CLASSES ARRAY OF SHAPE NCLASS HOLDS THE LABEL FOR EACH CLASS
SEE ALSO
SKLEARNPREPROCESSINGORDINALENCODER ENCODE CATEGORICAL FEATURES USING A ONEHOT OR ORDINAL
ENCODING SCHEME
EXAMPLES
LABELENCODER CAN BE USED TO NORMALIZE LABELS
 FROM SKLEARN IMPORT PREPROCESSING
LE PREPROCESSINGLABELENCODER
LEFIT1 2 2 6
LABELENCODER
LECLASSES
ARRAY1 2 6
LETRANSFORM1 1 2 6
ARRAY0 0 1 2
LEINVERSETRANSFORM0 0 1 2
ARRAY1 1 2 6
IT CAN ALSO BE USED TO TRANSFORM NONNUMERICAL LABELS AS LONG AS THEY ARE HASHABLE AND COMPARABLE TO NUMERICAL
LABELS
LE PREPROCESSINGLABELENCODER
LEFITPARIS PARIS TOKYO AMSTERDAM
LABELENCODER
LISTLECLASSES
AMSTERDAM PARIS TOKYO
LETRANSFORMTOKYO TOKYO PARIS
ARRAY2 2 1

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LISTLEINVERSETRANSFORM2 2 1
TOKYO TOKYO PARIS
METHODS
FITSELF Y FIT LABEL ENCODER
FITTRANSFORM SELF Y FIT LABEL ENCODER AND RETURN ENCODED LABELS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF Y TRANSFORM LABELS BACK TO ORIGINAL ENCODING
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF Y TRANSFORM LABELS TO NORMALIZED ENCODING
INIT SELFARGS KWARGS
INITIALIZE SELF SEE HELPTYPESELF FOR ACCURATE SIGNATURE
FITSELFY
FIT LABEL ENCODER
PARAMETERS
YARRAYLIKE OF SHAPE NSAMPLES TARGET VALUES
RETURNS
SELF RETURNS AN INSTANCE OF SELF
FITTRANSFORM SELFY
FIT LABEL ENCODER AND RETURN ENCODED LABELS
PARAMETERS
YARRAYLIKE OF SHAPE NSAMPLES TARGET VALUES
RETURNS
YARRAYLIKE OF SHAPE NSAMPLES
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFY
TRANSFORM LABELS BACK TO ORIGINAL ENCODING
PARAMETERS
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
YNUMPY ARRAY OF SHAPE NSAMPLES

SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFY
TRANSFORM LABELS TO NORMALIZED ENCODING
PARAMETERS
YARRAYLIKE OF SHAPE NSAMPLES TARGET VALUES
RETURNS
YARRAYLIKE OF SHAPE NSAMPLES
6347SKLEARNPREPROCESSING MULTILABELBINARIZER
CLASSSKLEARNPREPROCESSING MULTILABELBINARIZER CLASSESNONE SPARSEOUTPUTFALSE
TRANSFORM BETWEEN ITERABLE OF ITERABLES AND A MULTILABEL FORMAT
ALTHOUGH A LIST OF SETS OR TUPLES IS A VERY INTUITIVE FORMAT FOR MULTILABEL DATA IT IS UNWIELDY TO PROCESS THIS
TRANSFORMER CONVERTS BETWEEN THIS INTUITIVE FORMAT AND THE SUPPORTED MULTILABEL FORMAT A SAMPLES X CLASSES
BINARY MATRIX INDICATING THE PRESENCE OF A CLASS LABEL
PARAMETERS
CLASSES ARRAYLIKE OF SHAPE NCLASSES OPTIONAL INDICATES AN ORDERING FOR THE CLASS LABELS ALL
ENTRIES SHOULD BE UNIQUE CANNOT CONTAIN DUPLICATE CLASSES
SPARSEOUTPUT BOOLEAN DEFAULT FALSE SET TO TRUE IF OUTPUT BINARY ARRAY IS DESIRED IN CSR
SPARSE FORMAT
ATTRIBUTES
CLASSES ARRAY OF LABELS A COPY OF THE CLASSES PARAMETER WHERE PROVIDED OR OTHERWISE THE
SORTED SET OF CLASSES FOUND WHEN FITTING
SEE ALSO
SKLEARNPREPROCESSINGONEHOTENCODER ENCODE CATEGORICAL FEATURES USING A ONEHOT AKA ONEOFK
SCHEME
EXAMPLES
```
 FROM SKLEARNPREPROCESSING IMPORT MULTILABELBINARIZER
MLB  MULTILABELBINARIZER
MLBFITTRANSFORM1 2 3
ARRAY1 1 0
0 0 1
MLBCLASSES
ARRAY1 2 3
```

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MLBFITTRANSFORMSCIFI THRILLER COMEDY
ARRAY0 1 1
1 0 0
LISTMLBCLASSES
COMEDY SCIFI THRILLER
METHODS
FITSELF Y FIT THE LABEL SETS BINARIZER STORING CLASSES
FITTRANSFORM SELF Y FIT THE LABEL SETS BINARIZER AND TRANSFORM THE GIVEN LABEL
SETS
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF YT TRANSFORM THE GIVEN INDICATOR MATRIX INTO LABEL SETS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF Y TRANSFORM THE GIVEN LABEL SETS
INIT SELFCLASSESNONE SPARSEOUTPUTFALSE
FITSELFY
FIT THE LABEL SETS BINARIZER STORING CLASSES
PARAMETERS
YITERABLE OF ITERABLES A SET OF LABELS ANY ORDERABLE AND HASHABLE OBJECT FOR EACH SAMPLE
IF THECLASSES PARAMETER IS SET YWILL NOT BE ITERATED
RETURNS
SELF RETURNS THIS MULTILABELBINARIZER INSTANCE
FITTRANSFORM SELFY
FIT THE LABEL SETS BINARIZER AND TRANSFORM THE GIVEN LABEL SETS
PARAMETERS
YITERABLE OF ITERABLES A SET OF LABELS ANY ORDERABLE AND HASHABLE OBJECT FOR EACH SAMPLE
IF THECLASSES PARAMETER IS SET YWILL NOT BE ITERATED
RETURNS
YINDICATOR ARRAY OR CSR MATRIX SHAPE NSAMPLES NCLASSES A MATRIX SUCH THAT
YINDICATORI J 1 IFFCLASSESJ IS INYI AND 0 OTHERWISE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFYT
TRANSFORM THE GIVEN INDICATOR MATRIX INTO LABEL SETS
PARAMETERS

YTARRAY OR SPARSE MATRIX OF SHAPE NSAMPLES NCLASSES A MATRIX CONTAINING ONLY 1S ANDS
0S
RETURNS
YLIST OF TUPLES THE SET OF LABELS FOR EACH SAMPLE SUCH THAT YI CONSISTS OF
CLASSESJ FOR EACHYTI J 1
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFY
TRANSFORM THE GIVEN LABEL SETS
PARAMETERS
YITERABLE OF ITERABLES A SET OF LABELS ANY ORDERABLE AND HASHABLE OBJECT FOR EACH SAMPLE
IF THECLASSES PARAMETER IS SET YWILL NOT BE ITERATED
RETURNS
YINDICATOR ARRAY OR CSR MATRIX SHAPE NSAMPLES NCLASSES A MATRIX SUCH THAT
YINDICATORI J 1 IFFCLASSESJ IS INYI AND 0 OTHERWISE
6348SKLEARNPREPROCESSING MAXABSSCALER
CLASSSKLEARNPREPROCESSING MAXABSSCALER COPYTRUE
SCALE EACH FEATURE BY ITS MAXIMUM ABSOLUTE VALUE
THIS ESTIMATOR SCALES AND TRANSLATES EACH FEATURE INDIVIDUALLY SUCH THAT THE MAXIMAL ABSOLUTE VALUE OF EACH
FEATURE IN THE TRAINING SET WILL BE 10 IT DOES NOT SHIFTCENTER THE DATA AND THUS DOES NOT DESTROY ANY SPARSITY
THIS SCALER CAN ALSO BE APPLIED TO SPARSE CSR OR CSC MATRICES
NEW IN VERSION 017
PARAMETERS
COPY BOOLEAN OPTIONAL DEFAULT IS TRUE SET TO FALSE TO PERFORM INPLACE SCALING AND AVOID A
COPY IF THE INPUT IS ALREADY A NUMPY ARRAY
ATTRIBUTES
SCALE NDARRAY SHAPE NFEATURES PER FEATURE RELATIVE SCALING OF THE DATA
NEW IN VERSION 017 SCALE ATTRIBUTE
MAXABS NDARRAY SHAPE NFEATURES PER FEATURE MAXIMUM ABSOLUTE VALUE
NSAMPLESSEEN INT THE NUMBER OF SAMPLES PROCESSED BY THE ESTIMATOR WILL BE RESET ON
NEW CALLS TO FIT BUT INCREMENTS ACROSS PARTIALFIT CALLS
SEE ALSO
MAXABSSCALE EQUIVALENT FUNCTION WITHOUT THE ESTIMATOR API

NOTES
NANS ARE TREATED AS MISSING VALUES DISREGARDED IN FIT AND MAINTAINED IN TRANSFORM
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
EXAMPLES
```
 FROM SKLEARNPREPROCESSING IMPORT MAXABSSCALER
X   1 1 2
  2 0 0
  0 1 1
TRANSFORMER  MAXABSSCALERFITX
TRANSFORMER
MAXABSSCALERCOPYTRUE
TRANSFORMERTRANSFORMX
ARRAY 05 1  1
 1  0  0
 0  1  05
```
METHODS
FITSELF X Y COMPUTE THE MAXIMUM ABSOLUTE VALUE TO BE USED FOR
LATER SCALING
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X SCALE BACK THE DATA TO THE ORIGINAL REPRESENTATION
PARTIALFIT SELF X Y ONLINE COMPUTATION OF MAX ABSOLUTE VALUE OF X FOR LATER
SCALING
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X SCALE THE DATA
INIT SELFCOPYTRUE
FITSELFXYNONE
COMPUTE THE MAXIMUM ABSOLUTE VALUE TO BE USED FOR LATER SCALING
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA USED TO COMPUTE THE
PERFEATURE MINIMUM AND MAXIMUM USED FOR LATER SCALING ALONG THE FEATURES AXIS
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS

XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFX
SCALE BACK THE DATA TO THE ORIGINAL REPRESENTATION
PARAMETERS
XARRAYLIKE SPARSE MATRIX THE DATA THAT SHOULD BE TRANSFORMED BACK
PARTIALFIT SELFXYNONE
ONLINE COMPUTATION OF MAX ABSOLUTE VALUE OF X FOR LATER SCALING ALL OF X IS PROCESSED AS A SINGLE BATCH
THIS IS INTENDED FOR CASES WHEN FIT IS NOT FEASIBLE DUE TO VERY LARGE NUMBER OF NSAMPLES OR BECAUSE X
IS READ FROM A CONTINUOUS STREAM
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA USED TO COMPUTE THE
MEAN AND STANDARD DEVIATION USED FOR LATER SCALING ALONG THE FEATURES AXIS
YIGNORED
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
SCALE THE DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX THE DATA THAT SHOULD BE SCALED
EXAMPLES USING SKLEARNPREPROCESSINGMAXABSSCALER
•COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS
6349SKLEARNPREPROCESSING MINMAXSCALER
CLASSSKLEARNPREPROCESSING MINMAXSCALER FEATURERANGE0 1COPYTRUE
TRANSFORMS FEATURES BY SCALING EACH FEATURE TO A GIVEN RANGE
THIS ESTIMATOR SCALES AND TRANSLATES EACH FEATURE INDIVIDUALLY SUCH THAT IT IS IN THE GIVEN RANGE ON THE TRAINING SET
EG BETWEEN ZERO AND ONE

THE TRANSFORMATION IS GIVEN BY
XSTD X XMINAXIS0 XMAXAXIS0 XMINAXIS0
XSCALED XSTD MAX MIN MIN
WHERE MIN MAX FEATURERANGE
THE TRANSFORMATION IS CALCULATED AS
XSCALED SCALE X MIN XMINAXIS0 SCALE
WHERE SCALE MAX MIN XMAXAXIS0 XMINAXIS0
THIS TRANSFORMATION IS OFTEN USED AS AN ALTERNATIVE TO ZERO MEAN UNIT VARIANCE SCALING
READ MORE IN THE USER GUIDE
PARAMETERS
FEATURERANGE TUPLE MIN MAX DEFAULT0 1 DESIRED RANGE OF TRANSFORMED DATA
COPY BOOLEAN OPTIONAL DEFAULT TRUE SET TO FALSE TO PERFORM INPLACE ROW NORMALIZATION AND
AVOID A COPY IF THE INPUT IS ALREADY A NUMPY ARRAY
ATTRIBUTES
MIN NDARRAY SHAPE NFEATURES PER FEATURE ADJUSTMENT FOR MINIMUM EQUIVALENT TO MIN
XMINAXIS0 SELFSCALE
SCALE NDARRAY SHAPE NFEATURES PER FEATURE RELATIVE SCALING OF THE DATA EQUIVALENT TO MAX
 MIN XMAXAXIS0 XMINAXIS0
NEW IN VERSION 017 SCALE ATTRIBUTE
DATAMIN NDARRAY SHAPE NFEATURES PER FEATURE MINIMUM SEEN IN THE DATA
NEW IN VERSION 017 DATAMIN
DATAMAX NDARRAY SHAPE NFEATURES PER FEATURE MAXIMUM SEEN IN THE DATA
NEW IN VERSION 017 DATAMAX
DATARANGE NDARRAY SHAPE NFEATURES PER FEATURE RANGE DATAMAX
DATAMIN SEEN IN THE DATA
NEW IN VERSION 017 DATARANGE
SEE ALSO
MINMAXSCALE EQUIVALENT FUNCTION WITHOUT THE ESTIMATOR API
NOTES
NANS ARE TREATED AS MISSING VALUES DISREGARDED IN FIT AND MAINTAINED IN TRANSFORM
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
EXAMPLES

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FROM SKLEARNPREPROCESSING IMPORT MINMAXSCALER
DATA 1 2 05 6 0 10 1 18
SCALER MINMAXSCALER
PRINTSCALERFITDATA
MINMAXSCALERCOPYTRUE FEATURERANGE0 1
PRINTSCALERDATAMAX
1 18
PRINTSCALERTRANSFORMDATA
0 0
025 025
05 05
1 1
PRINTSCALERTRANSFORM2 2
15 0
METHODS
FITSELF X Y COMPUTE THE MINIMUM AND MAXIMUM TO BE USED FOR
LATER SCALING
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X UNDO THE SCALING OF X ACCORDING TO FEATURERANGE
PARTIALFIT SELF X Y ONLINE COMPUTATION OF MIN AND MAX ON X FOR LATER SCAL
ING
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X SCALING FEATURES OF X ACCORDING TO FEATURERANGE
INIT SELFFEATURERANGE0 1COPYTRUE
FITSELFXYNONE
COMPUTE THE MINIMUM AND MAXIMUM TO BE USED FOR LATER SCALING
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA USED TO COMPUTE THE PERFEATURE MIN
IMUM AND MAXIMUM USED FOR LATER SCALING ALONG THE FEATURES AXIS
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFX
UNDO THE SCALING OF X ACCORDING TO FEATURERANGE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT DATA THAT WILL BE TRANSFORMED IT CANNOT
BE SPARSE
PARTIALFIT SELFXYNONE
ONLINE COMPUTATION OF MIN AND MAX ON X FOR LATER SCALING ALL OF X IS PROCESSED AS A SINGLE BATCH THIS IS
INTENDED FOR CASES WHEN FIT IS NOT FEASIBLE DUE TO VERY LARGE NUMBER OF NSAMPLES OR BECAUSE X IS READ
FROM A CONTINUOUS STREAM
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA USED TO COMPUTE THE MEAN AND STAN
DARD DEVIATION USED FOR LATER SCALING ALONG THE FEATURES AXIS
YIGNORED
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
SCALING FEATURES OF X ACCORDING TO FEATURERANGE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES INPUT DATA THAT WILL BE TRANSFORMED
EXAMPLES USING SKLEARNPREPROCESSINGMINMAXSCALER
•COMPARE STOCHASTIC LEARNING STRATEGIES FOR MLPCLASSIFIER
•COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS
63410SKLEARNPREPROCESSING NORMALIZER
CLASSSKLEARNPREPROCESSING NORMALIZER NORM’L2’ COPYTRUE
NORMALIZE SAMPLES INDIVIDUALLY TO UNIT NORM
EACH SAMPLE IE EACH ROW OF THE DATA MATRIX WITH AT LEAST ONE NON ZERO COMPONENT IS RESCALED INDEPENDENTLY
OF OTHER SAMPLES SO THAT ITS NORM L1 OR L2 EQUALS ONE
THIS TRANSFORMER IS ABLE TO WORK BOTH WITH DENSE NUMPY ARRAYS AND SCIPYSPARSE MATRIX USE CSR FORMAT IF YOU
WANT TO AVOID THE BURDEN OF A COPY CONVERSION

SCALING INPUTS TO UNIT NORMS IS A COMMON OPERATION FOR TEXT CLASSIFICATION OR CLUSTERING FOR INSTANCE FOR INSTANCE THE DOT PRODUCT OF TWO L2NORMALIZED TFIDF VECTORS IS THE COSINE SIMILARITY OF THE VECTORS AND IS THE BASE SIMILARITY METRIC FOR THE VECTOR SPACE MODEL COMMONLY USED BY THE INFORMATION RETRIEVAL COMMUNITY
READ MORE IN THE USER GUIDE
PARAMETERS
NORM ‘L1’ ‘L2’ OR ‘MAX’ OPTIONAL ‘L2’ BY DEFAULT THE NORM TO USE TO NORMALIZE EACH NON ZERO SAMPLE
COPY BOOLEAN OPTIONAL DEFAULT TRUE SET TO FALSE TO PERFORM INPLACE ROW NORMALIZATION AND AVOID A COPY IF THE INPUT IS ALREADY A NUMPY ARRAY OR A SCIPYSPARSE CSR MATRIX
SEE ALSO
NORMALIZE EQUIVALENT FUNCTION WITHOUT THE ESTIMATOR API
NOTES
THIS ESTIMATOR IS STATELESS BESIDES CONSTRUCTOR PARAMETERS THE FIT METHOD DOES NOTHING BUT IS USEFUL WHEN USED IN A PIPELINE
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM PLESPREPROCESSINGPLOTALLSCALINGPY
EXAMPLES
FROM SKLEARNPREPROCESSING IMPORT NORMALIZER
X 4 1 2 2
1 3 9 3
5 7 5 1
TRANSFORMER NORMALIZERFITX FIT DOES NOTHING
TRANSFORMER
NORMALIZERCOPYTRUE NORML2
TRANSFORMERTRANSFORMX
ARRAY08 02 04 04
01 03 09 03
05 07 05 01
METHODS
FITSELF X Y DO NOTHING AND RETURN THE ESTIMATOR UNCHANGED
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X COPY SCALE EACH NON ZERO ROW OF X TO UNIT NORM
INIT SELFNORM’L2’ COPYTRUE
FITSELFXYNONE
DO NOTHING AND RETURN THE ESTIMATOR UNCHANGED
THIS METHOD IS JUST THERE TO IMPLEMENT THE USUAL API AND HENCE WORK IN PIPELINES

PARAMETERS
XARRAYLIKE
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFXCOPYNONE
SCALE EACH NON ZERO ROW OF X TO UNIT NORM
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA TO NORMALIZE ROW
BY ROW SCIPYSPARSE MATRICES SHOULD BE IN CSR FORMAT TO AVOID AN UNNECESSARY COPY
COPY BOOL OPTIONAL DEFAULT NONE COPY THE INPUT X OR NOT
EXAMPLES USING SKLEARNPREPROCESSINGNORMALIZER
•COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS
•CLUSTERING TEXT DOCUMENTS USING KMEANS

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63411SKLEARNPREPROCESSING ONEHOTENCODER
CLASSSKLEARNPREPROCESSING ONEHOTENCODER NVALUESNONE CATEGORICALFEATURESNONE
CATEGORIESNONE DROPNONE SPARSETRUE
DTYPECLASS ‘NUMPYFLOAT64’ HAN
DLEUNKNOWN’ERROR’
ENCODE CATEGORICAL INTEGER FEATURES AS A ONEHOT NUMERIC ARRAY
THE INPUT TO THIS TRANSFORMER SHOULD BE AN ARRAYLIKE OF INTEGERS OR STRINGS DENOTING THE VALUES TAKEN ON BY
CATEGORICAL DISCRETE FEATURES THE FEATURES ARE ENCODED USING A ONEHOT AKA ‘ONEOFK’ OR ‘DUMMY’ ENCODING
SCHEME THIS CREATES A BINARY COLUMN FOR EACH CATEGORY AND RETURNS A SPARSE MATRIX OR DENSE ARRAY
BY DEFAULT THE ENCODER DERIVES THE CATEGORIES BASED ON THE UNIQUE VALUES IN EACH FEATURE ALTERNATIVELY YOU CAN
ALSO SPECIFY THE CATEGORIES MANUALLY THE ONEHOTENCODER PREVIOUSLY ASSUMED THAT THE INPUT FEATURES TAKE
ON VALUES IN THE RANGE 0 MAXVALUES THIS BEHAVIOUR IS DEPRECATED
THIS ENCODING IS NEEDED FOR FEEDING CATEGORICAL DATA TO MANY SCIKITLEARN ESTIMATORS NOTABLY LINEAR MODELS AND
SVMS WITH THE STANDARD KERNELS
NOTE A ONEHOT ENCODING OF Y LABELS SHOULD USE A LABELBINARIZER INSTEAD
READ MORE IN THE USER GUIDE
PARAMETERS
CATEGORIES ‘AUTO’ OR A LIST OF LISTSARRAYS OF VALUES DEFAULT’AUTO’ CATEGORIES UNIQUE VALUES
PER FEATURE
• ‘AUTO’ DETERMINE CATEGORIES AUTOMATICALLY FROM THE TRAINING DATA
• LIST CATEGORIESI HOLDS THE CATEGORIES EXPECTED IN THE ITH COLUMN THE PASSED
CATEGORIES SHOULD NOT MIX STRINGS AND NUMERIC VALUES WITHIN A SINGLE FEATURE AND SHOULD
BE SORTED IN CASE OF NUMERIC VALUES
THE USED CATEGORIES CAN BE FOUND IN THE CATEGORIES ATTRIBUTE
DROP ‘FIRST’ OR A LISTARRAY OF SHAPE NFEATURES DEFAULTNONE SPECIFIES A METHODOLOGY TO
USE TO DROP ONE OF THE CATEGORIES PER FEATURE THIS IS USEFUL IN SITUATIONS WHERE PERFECTLY
COLLINEAR FEATURES CAUSE PROBLEMS SUCH AS WHEN FEEDING THE RESULTING DATA INTO A NEURAL
NETWORK OR AN UNREGULARIZED REGRESSION
• NONE RETAIN ALL FEATURES THE DEFAULT
• ‘FIRST’ DROP THE FIRST CATEGORY IN EACH FEATURE IF ONLY ONE CATEGORY IS PRESENT THE FEATURE
WILL BE DROPPED ENTIRELY
• ARRAY DROPI IS THE CATEGORY IN FEATURE X I THAT SHOULD BE DROPPED
SPARSE BOOLEAN DEFAULTTRUE WILL RETURN SPARSE MATRIX IF SET TRUE ELSE WILL RETURN AN ARRAY
DTYPE NUMBER TYPE DEFAULTNPFLOAT DESIRED DTYPE OF OUTPUT
HANDLEUNKNOWN ‘ERROR’ OR ‘IGNORE’ DEFAULT’ERROR’ WHETHER TO RAISE AN ERROR OR IGNORE IF
AN UNKNOWN CATEGORICAL FEATURE IS PRESENT DURING TRANSFORM DEFAULT IS TO RAISE WHEN THIS
PARAMETER IS SET TO ‘IGNORE’ AND AN UNKNOWN CATEGORY IS ENCOUNTERED DURING TRANSFORM THE
RESULTING ONEHOT ENCODED COLUMNS FOR THIS FEATURE WILL BE ALL ZEROS IN THE INVERSE TRANSFORM
AN UNKNOWN CATEGORY WILL BE DENOTED AS NONE
NVALUES ‘AUTO’ INT OR ARRAY OF INTS DEFAULT’AUTO’ NUMBER OF VALUES PER FEATURE
• ‘AUTO’ DETERMINE VALUE RANGE FROM TRAINING DATA
•INTNUMBER OF CATEGORICAL VALUES PER FEATURE EACH FEATURE VALUE SHOULD BE IN
RANGENVALUES

•ARRAY NVALUESI IS THE NUMBER OF CATEGORICAL VALUES IN X I EACH FEATURE
VALUE SHOULD BE IN RANGENVALUESI
DEPRECATED SINCE VERSION 020 THE NVALUES KEYWORD WAS DEPRECATED IN VERSION 020
AND WILL BE REMOVED IN 022 USE CATEGORIES INSTEAD
CATEGORICALFEATURES ‘ALL’ OR ARRAY OF INDICES OR MASK DEFAULT’ALL’ SPECIFY WHAT FEATURES ARE
TREATED AS CATEGORICAL
• ‘ALL’ ALL FEATURES ARE TREATED AS CATEGORICAL
• ARRAY OF INDICES ARRAY OF CATEGORICAL FEATURE INDICES
• MASK ARRAY OF LENGTH NFEATURES AND WITH DTYPEBOOL
NONCATEGORICAL FEATURES ARE ALWAYS STACKED TO THE RIGHT OF THE MATRIX
DEPRECATED SINCE VERSION 020 THE CATEGORICALFEATURES KEYWORD WAS DEPRECATED
IN VERSION 020 AND WILL BE REMOVED IN 022 YOU CAN USE THE COLUMNTRANSFORMER
INSTEAD
ATTRIBUTES
CATEGORIES LIST OF ARRAYS THE CATEGORIES OF EACH FEATURE DETERMINED DURING FITTING IN ORDER
OF THE FEATURES IN X AND CORRESPONDING WITH THE OUTPUT OF TRANSFORM THIS INCLUDES THE
CATEGORY SPECIFIED IN DROP IF ANY
DROPIDX ARRAY OF SHAPE NFEATURES DROPIDXI IS THE INDEX IN CATEGORIESI
OF THE CATEGORY TO BE DROPPED FOR EACH FEATURE NONE IF ALL THE TRANSFORMED FEATURES WILL BE
RETAINED
ACTIVEFEATURES ARRAY INDICES FOR ACTIVE FEATURES MEANING VALUES THAT ACTUALLY OCCUR IN THE
TRAINING SET ONLY AVAILABLE WHEN NVALUES IS AUTO
DEPRECATED SINCE VERSION 020 THE ACTIVEFEATURES ATTRIBUTE WAS DEPRECATED IN VER
SION 020 AND WILL BE REMOVED IN 022
FEATUREINDICES ARRAY OF SHAPE NFEATURES INDICES TO FEATURE RANGES FEATURE
IIN THE ORIGINAL DATA IS MAPPED TO FEATURES FROM FEATUREINDICESI TO
FEATUREINDICESI1 AND THEN POTENTIALLY MASKED BY ACTIVEFEATURES AF
TERWARDS
DEPRECATED SINCE VERSION 020 THE FEATUREINDICES ATTRIBUTE WAS DEPRECATED IN VER
SION 020 AND WILL BE REMOVED IN 022
NVALUES ARRAY OF SHAPE NFEATURES MAXIMUM NUMBER OF VALUES PER FEATURE
DEPRECATED SINCE VERSION 020 THE NVALUES ATTRIBUTE WAS DEPRECATED IN VERSION 020
AND WILL BE REMOVED IN 022
SEE ALSO
SKLEARNPREPROCESSINGORDINALENCODER PERFORMS AN ORDINAL INTEGER ENCODING OF THE CATEGORICAL
FEATURES
SKLEARNFEATUREEXTRACTIONDICTVECTORIZER PERFORMS A ONEHOT ENCODING OF DICTIONARY ITEMS
ALSO HANDLES STRINGVALUED FEATURES
SKLEARNFEATUREEXTRACTIONFEATUREHASHER PERFORMS AN APPROXIMATE ONEHOT ENCODING OF DIC
TIONARY ITEMS OR STRINGS
SKLEARNPREPROCESSINGLABELBINARIZER BINARIZES LABELS IN A ONEVSALL FASHION

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SKLEARNPREPROCESSINGMULTILABELBINARIZER TRANSFORMS BETWEEN ITERABLE OF ITERABLES AND A
MULTILABEL FORMAT EG A SAMPLES X CLASSES BINARY MATRIX INDICATING THE PRESENCE OF A CLASS LABEL
EXAMPLES
GIVEN A DATASET WITH TWO FEATURES WE LET THE ENCODER FIND THE UNIQUE VALUES PER FEATURE AND TRANSFORM THE DATA
TO A BINARY ONEHOT ENCODING
 FROM SKLEARNPREPROCESSING IMPORT ONEHOTENCODER
ENC ONEHOTENCODERHANDLEUNKNOWNIGNORE
X MALE 1 FEMALE 3 FEMALE 2
ENCFITX

ONEHOTENCODERCATEGORICALFEATURESNONE CATEGORIESNONE DROPNONE
DTYPE NUMPYFLOAT64 HANDLEUNKNOWNIGNORE
NVALUESNONE SPARSETRUE
ENCCATEGORIES
ARRAYFEMALE MALE DTYPEOBJECT ARRAY1 2 3 DTYPEOBJECT
ENCTRANSFORMFEMALE 1 MALE 4TOARRAY
ARRAY1 0 1 0 0
0 1 0 0 0
ENCINVERSETRANSFORM0 1 1 0 0 0 0 0 1 0
ARRAYMALE 1
NONE 2 DTYPEOBJECT
ENCGETFEATURENAMES
ARRAYX0FEMALE X0MALE X11 X12 X13 DTYPEOBJECT
DROPENC ONEHOTENCODERDROPFIRSTFITX
DROPENCCATEGORIES
ARRAYFEMALE MALE DTYPEOBJECT ARRAY1 2 3 DTYPEOBJECT
DROPENCTRANSFORMFEMALE 1 MALE 2TOARRAY
ARRAY0 0 0
1 1 0
METHODS
FITSELF X Y FIT ONEHOTENCODER TO X
FITTRANSFORM SELF X Y FIT ONEHOTENCODER TO X THEN TRANSFORM X
GETFEATURENAMES SELF INPUTFEATURES RETURN FEATURE NAMES FOR OUTPUT FEATURES
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X CONVERT THE BACK DATA TO THE ORIGINAL REPRESENTATION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM X USING ONEHOT ENCODING
INIT SELFNVALUESNONE CATEGORICALFEATURESNONE CATEGORIESNONE DROPNONE
SPARSETRUE DTYPECLASS ‘NUMPYFLOAT64’ HANDLEUNKNOWN’ERROR’
FITSELFXYNONE
FIT ONEHOTENCODER TO X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA TO DETERMINE THE CATEGORIES OF EACH

FEATURE
RETURNS
SELF
FITTRANSFORM SELFXYNONE
FIT ONEHOTENCODER TO X THEN TRANSFORM X
EQUIVALENT TO FITXTRANSFORMX BUT MORE CONVENIENT
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA TO ENCODE
RETURNS
XOUT SPARSE MATRIX IF SPARSETRUE ELSE A 2D ARRAY TRANSFORMED INPUT
GETFEATURENAMES SELFINPUTFEATURESNONE
RETURN FEATURE NAMES FOR OUTPUT FEATURES
PARAMETERS
INPUTFEATURES LIST OF STRING LENGTH NFEATURES OPTIONAL STRING NAMES FOR INPUT FEATURES IF
AVAILABLE BY DEFAULT “X0” “X1” “XNFEATURES” IS USED
RETURNS
OUTPUTFEATURENAMES ARRAY OF STRING LENGTH NOUTPUTFEATURES
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFX
CONVERT THE BACK DATA TO THE ORIGINAL REPRESENTATION
IN CASE UNKNOWN CATEGORIES ARE ENCOUNTERED ALL ZEROS IN THE ONEHOT ENCODING NONE IS USED TO REPRESENT
THIS CATEGORY
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NENCODEDFEATURES THE TRANSFORMED
DATA
RETURNS
XTR ARRAYLIKE SHAPE NSAMPLES NFEATURES INVERSE TRANSFORMED ARRAY
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF

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TRANSFORM SELFX
TRANSFORM X USING ONEHOT ENCODING
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA TO ENCODE
RETURNS
XOUT SPARSE MATRIX IF SPARSETRUE ELSE A 2D ARRAY TRANSFORMED INPUT
EXAMPLES USING SKLEARNPREPROCESSINGONEHOTENCODER
•COLUMN TRANSFORMER WITH MIXED TYPES
•FEATURE TRANSFORMATIONS WITH ENSEMBLES OF TREES
63412SKLEARNPREPROCESSING ORDINALENCODER
CLASSSKLEARNPREPROCESSING ORDINALENCODER CATEGORIES'AUTO' DTYPECLASS
'NUMPYFLOAT64'
ENCODE CATEGORICAL FEATURES AS AN INTEGER ARRAY
THE INPUT TO THIS TRANSFORMER SHOULD BE AN ARRAYLIKE OF INTEGERS OR STRINGS DENOTING THE VALUES TAKEN ON BY CATEGORICAL DISCRETE FEATURES THE FEATURES ARE CONVERTED TO ORDINAL INTEGERS THIS RESULTS IN A SINGLE COLUMN OF INTEGERS 0 TO NCATEGORIES 1 PER FEATURE
READ MORE IN THE USER GUIDE
PARAMETERS
CATEGORIES 'AUTO' OR A LIST OF LISTSARRAYS OF VALUES CATEGORIES UNIQUE VALUES PER FEATURE
• 'AUTO' DETERMINE CATEGORIES AUTOMATICALLY FROM THE TRAINING DATA
• LIST CATEGORIESI HOLDS THE CATEGORIES EXPECTED IN THE ITH COLUMN THE PASSED CATEGORIES SHOULD NOT MIX STRINGS AND NUMERIC VALUES AND SHOULD BE SORTED IN CASE OF NUMERIC VALUES
THE USED CATEGORIES CAN BE FOUND IN THE CATEGORIES ATTRIBUTE
DTYPE NUMBER TYPE DEFAULT NPFLOAT64 DESIRED DTYPE OF OUTPUT
ATTRIBUTES
CATEGORIES LIST OF ARRAYS THE CATEGORIES OF EACH FEATURE DETERMINED DURING FITTING IN ORDER OF THE FEATURES IN X AND CORRESPONDING WITH THE OUTPUT OF TRANSFORM
SEE ALSO
SKLEARNPREPROCESSINGONEHOTENCODER PERFORMS A ONEHOT ENCODING OF CATEGORICAL FEATURES
SKLEARNPREPROCESSINGLABELENCODER ENCODES TARGET LABELS WITH VALUES BETWEEN 0 AND NCLASSES 1
EXAMPLES
GIVEN A DATASET WITH TWO FEATURES WE LET THE ENCODER FIND THE UNIQUE VALUES PER FEATURE AND TRANSFORM THE DATA TO AN ORDINAL ENCODING

FROM SKLEARNPREPROCESSING IMPORT ORDINALENCODER
ENC ORDINALENCODER
X MALE 1 FEMALE 3 FEMALE 2
ENCFITX

ORDINALENCODERCATEGORIESAUTO DTYPE NUMPYFLOAT64
ENCCATEGORIES
ARRAYFEMALE MALE DTYPEOBJECT ARRAY1 2 3 DTYPEOBJECT
ENCTRANSFORMFEMALE 3 MALE 1
ARRAY0 2
1 0
ENCINVERSETRANSFORM1 0 0 1
ARRAYMALE 1
FEMALE 2 DTYPEOBJECT
METHODS
FITSELF X Y FIT THE ORDINALENCODER TO X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X CONVERT THE DATA BACK TO THE ORIGINAL REPRESENTATION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM X TO ORDINAL CODES
INIT SELFCATEGORIES‘AUTO’ DTYPECLASS ‘NUMPYFLOAT64’
FITSELFXYNONE
FIT THE ORDINALENCODER TO X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA TO DETERMINE THE CATEGORIES OF EACH
FEATURE
RETURNS
SELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS

DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFX
CONVERT THE DATA BACK TO THE ORIGINAL REPRESENTATION
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NENCODEDFEATURES THE TRANSFORMED
DATA
RETURNS
XTR ARRAYLIKE SHAPE NSAMPLES NFEATURES INVERSE TRANSFORMED ARRAY
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM X TO ORDINAL CODES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA TO ENCODE
RETURNS
XOUT SPARSE MATRIX OR A 2D ARRAY TRANSFORMED INPUT
63413SKLEARNPREPROCESSING POLYNOMIALFEATURES
CLASSSKLEARNPREPROCESSING POLYNOMIALFEATURES DEGREE2 INTERACTIONONLYFALSE IN
CLUDEBIASTRUE ORDER’C’
GENERATE POLYNOMIAL AND INTERACTION FEATURES
GENERATE A NEW FEATURE MATRIX CONSISTING OF ALL POLYNOMIAL COMBINATIONS OF THE FEATURES WITH DEGREE LESS THAN
OR EQUAL TO THE SPECIFIED DEGREE FOR EXAMPLE IF AN INPUT SAMPLE IS TWO DIMENSIONAL AND OF THE FORM A B THE
DEGREE2 POLYNOMIAL FEATURES ARE 1 A B A2 AB B2
PARAMETERS
DEGREE INTEGER THE DEGREE OF THE POLYNOMIAL FEATURES DEFAULT 2
INTERACTIONONLY BOOLEAN DEFAULT FALSE IF TRUE ONLY INTERACTION FEATURES ARE PRODUCED FEA
TURES THAT ARE PRODUCTS OF AT MOST DEGREE DISTINCT INPUT FEATURES SO NOT X12
X0X23 ETC
INCLUDEBIAS BOOLEAN IF TRUE DEFAULT THEN INCLUDE A BIAS COLUMN THE FEATURE IN WHICH ALL
POLYNOMIAL POWERS ARE ZERO IE A COLUMN OF ONES ACTS AS AN INTERCEPT TERM IN A LINEAR
MODEL

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ORDER STR IN ‘C’ ‘F’ DEFAULT ‘C’ ORDER OF OUTPUT ARRAY IN THE DENSE CASE ‘F’ ORDER IS FASTER
TO COMPUTE BUT MAY SLOW DOWN SUBSEQUENT ESTIMATORS
NEW IN VERSION 021
ATTRIBUTES
POWERS ARRAY SHAPE NOUTPUTFEATURES NINPUTFEATURES POWERSI J IS THE EXPONENT OF
THE JTH INPUT IN THE ITH OUTPUT
NINPUTFEATURES INT THE TOTAL NUMBER OF INPUT FEATURES
NOUTPUTFEATURES INT THE TOTAL NUMBER OF POLYNOMIAL OUTPUT FEATURES THE NUMBER OF OUT
PUT FEATURES IS COMPUTED BY ITERATING OVER ALL SUITABLY SIZED COMBINATIONS OF INPUT FEATURES
NOTES
BE AWARE THAT THE NUMBER OF FEATURES IN THE OUTPUT ARRAY SCALES POLYNOMIALLY IN THE NUMBER OF FEATURES OF THE
INPUT ARRAY AND EXPONENTIALLY IN THE DEGREE HIGH DEGREES CAN CAUSE OVERFITTING
SEEEXAMPLESLINEARMODELPLOTPOLYNOMIALINTERPOLATIONPY
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNPREPROCESSING IMPORT POLYNOMIALFEATURES
X  NPARANGE6RESHAPE3 2
X
ARRAY0 1
2 3
4 5
POLY  POLYNOMIALFEATURES2
POLYFITTRANSFORMX
ARRAY 1 0 1 0 0 1
 1 2 3 4 6 9
 1 4 5 16 20 25
POLY  POLYNOMIALFEATURESINTERACTIONONLY TRUE
POLYFITTRANSFORMX
ARRAY 1 0 1 0
 1 2 3 6
 1 4 5 20
```
METHODS
FITSELF X Y COMPUTE NUMBER OF OUTPUT FEATURES
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETFEATURENAMES SELF INPUTFEATURES RETURN FEATURE NAMES FOR OUTPUT FEATURES
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X TRANSFORM DATA TO POLYNOMIAL FEATURES
INIT SELFDEGREE2 INTERACTIONONLYFALSE INCLUDEBIASTRUE ORDER’C’
FITSELFXYNONE

COMPUTE NUMBER OF OUTPUT FEATURES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA
RETURNS
SELF INSTANCE
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETFEATURENAMES SELFINPUTFEATURESNONE
RETURN FEATURE NAMES FOR OUTPUT FEATURES
PARAMETERS
INPUTFEATURES LIST OF STRING LENGTH NFEATURES OPTIONAL STRING NAMES FOR INPUT FEATURES IF
AVAILABLE BY DEFAULT “X0” “X1” “XNFEATURES” IS USED
RETURNS
OUTPUTFEATURENAMES LIST OF STRING LENGTH NOUTPUTFEATURES
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
TRANSFORM DATA TO POLYNOMIAL FEATURES
PARAMETERS
XARRAYLIKE OR CSRCSC SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA TO TRANS
FORM ROW BY ROW

PREFER CSR OVER CSC FOR SPARSE INPUT FOR SPEED BUT CSC IS REQUIRED IF THE DEGREE IS 4
OR HIGHER IF THE DEGREE IS LESS THAN 4 AND THE INPUT FORMAT IS CSC IT WILL BE CONVERTED TO
CSR HAVE ITS POLYNOMIAL FEATURES GENERATED THEN CONVERTED BACK TO CSC
IF THE DEGREE IS 2 OR 3 THE METHOD DESCRIBED IN “LEVERAGING SPARSITY TO SPEED UP POLYNO
MIAL FEATURE EXPANSIONS OF CSR MATRICES USING KSIMPLEX NUMBERS” BY ANDREW NYS
TROM AND JOHN HUGHES IS USED WHICH IS MUCH FASTER THAN THE METHOD USED ON CSC INPUT
FOR THIS REASON A CSC INPUT WILL BE CONVERTED TO CSR AND THE OUTPUT WILL BE CONVERTED
BACK TO CSC PRIOR TO BEING RETURNED HENCE THE PREFERENCE OF CSR
RETURNS
XPNPNDARRAY OR CSRCSC SPARSE MATRIX SHAPE NSAMPLES NP THE MATRIX OF FEATURES
WHERE NP IS THE NUMBER OF POLYNOMIAL FEATURES GENERATED FROM THE COMBINATION OF INPUTS
EXAMPLES USING SKLEARNPREPROCESSINGPOLYNOMIALFEATURES
•POLYNOMIAL INTERPOLATION
•ROBUST LINEAR ESTIMATOR FITTING
•UNDERFITTING VS OVERFITTING
63414SKLEARNPREPROCESSING POWERTRANSFORMER
CLASSSKLEARNPREPROCESSING POWERTRANSFORMER METHOD’YEOJOHNSON’ STANDARDIZETRUE
COPYTRUE
APPLY A POWER TRANSFORM FEATUREWISE TO MAKE DATA MORE GAUSSIANLIKE
POWER TRANSFORMS ARE A FAMILY OF PARAMETRIC MONOTONIC TRANSFORMATIONS THAT ARE APPLIED TO MAKE DATA MORE
GAUSSIANLIKE THIS IS USEFUL FOR MODELING ISSUES RELATED TO HETEROSCEDASTICITY NONCONSTANT VARIANCE OR OTHER
SITUATIONS WHERE NORMALITY IS DESIRED
CURRENTLY POWERTRANSFORMER SUPPORTS THE BOXCOX TRANSFORM AND THE YEOJOHNSON TRANSFORM THE OPTIMAL
PARAMETER FOR STABILIZING VARIANCE AND MINIMIZING SKEWNESS IS ESTIMATED THROUGH MAXIMUM LIKELIHOOD
BOXCOX REQUIRES INPUT DATA TO BE STRICTLY POSITIVE WHILE YEOJOHNSON SUPPORTS BOTH POSITIVE OR NEGATIVE DATA
BY DEFAULT ZEROMEAN UNITVARIANCE NORMALIZATION IS APPLIED TO THE TRANSFORMED DATA
READ MORE IN THE USER GUIDE
PARAMETERS
METHOD STR DEFAULT’YEOJOHNSON’ THE POWER TRANSFORM METHOD AVAILABLE METHODS ARE
• ‘YEOJOHNSON’ RF3E1504535DE1 WORKS WITH POSITIVE AND NEGATIVE VALUES
• ‘BOXCOX’ RF3E1504535DE2 ONLY WORKS WITH STRICTLY POSITIVE VALUES
STANDARDIZE BOOLEAN DEFAULTTRUE SET TO TRUE TO APPLY ZEROMEAN UNITVARIANCE NORMALIZA
TION TO THE TRANSFORMED OUTPUT
COPY BOOLEAN OPTIONAL DEFAULTTRUE SET TO FALSE TO PERFORM INPLACE COMPUTATION DURING
TRANSFORMATION
ATTRIBUTES
LAMBDAS ARRAY OF FLOAT SHAPE NFEATURES THE PARAMETERS OF THE POWER TRANSFORMATION FOR
THE SELECTED FEATURES
SEE ALSO
634SKLEARNPREPROCESSING PREPROCESSING AND NORMALIZATION 2265

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POWERTRANSFORM EQUIVALENT FUNCTION WITHOUT THE ESTIMATOR API
QUANTILETRANSFORMER MAPS DATA TO A STANDARD NORMAL DISTRIBUTION WITH THE PARAMETER
OUTPUTDISTRIBUTIONNORMAL
NOTES
NANS ARE TREATED AS MISSING VALUES DISREGARDED IN FIT AND MAINTAINED IN TRANSFORM
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
REFERENCES
RF3E1504535DE1 RF3E1504535DE2
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNPREPROCESSING IMPORT POWERTRANSFORMER
PT  POWERTRANSFORMER
DATA  1 2 3 2 4 5
PRINTPTFITDATA
POWERTRANSFORMERCOPYTRUE METHODYEOJOHNSON STANDARDIZETRUE
PRINTPTLAMBDAS
 1386 3100
PRINTPTTRANSFORMDATA
1316 0707
 0209 0707
 1106 1414
```
METHODS
FITSELF X Y ESTIMATE THE OPTIMAL PARAMETER LAMBDA FOR EACH FEATURE
FITTRANSFORM SELF X Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X APPLY THE INVERSE POWER TRANSFORMATION USING THE FITTED
LAMBDAS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X APPLY THE POWER TRANSFORM TO EACH FEATURE USING THE FIT
TED LAMBDAS
INIT SELFMETHOD’YEOJOHNSON’ STANDARDIZETRUE COPYTRUE
FITSELFXYNONE
ESTIMATE THE OPTIMAL PARAMETER LAMBDA FOR EACH FEATURE
THE OPTIMAL LAMBDA PARAMETER FOR MINIMIZING SKEWNESS IS ESTIMATED ON EACH FEATURE INDEPENDENTLY USING
MAXIMUM LIKELIHOOD
PARAMETERS

XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA USED TO ESTIMATE THE OPTIMAL TRANS
FORMATION PARAMETERS
YIGNORED
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFX
APPLY THE INVERSE POWER TRANSFORMATION USING THE FITTED LAMBDAS
THE INVERSE OF THE BOXCOX TRANSFORMATION IS GIVEN BY
IF LAMBDA 0
X EXPXTRANS
ELSE
X XTRANS LAMBDA 11 LAMBDA
THE INVERSE OF THE YEOJOHNSON TRANSFORMATION IS GIVEN BY
IFX 0AND LAMBDA 0
X EXPXTRANS 1
ELIFX 0AND LAMBDA 0
X XTRANS LAMBDA 11 LAMBDA 1
ELIFX 0AND LAMBDA 2
X 1 2 LAMBDAXTRANS 1 1 2 LAMBDA
ELIFX 0AND LAMBDA 2
X 1 EXPXTRANS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE TRANSFORMED DATA
RETURNS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE ORIGINAL DATA
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
APPLY THE POWER TRANSFORM TO EACH FEATURE USING THE FITTED LAMBDAS

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PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA TO BE TRANSFORMED USING A POWER
TRANSFORMATION
RETURNS
XTRANS ARRAYLIKE SHAPE NSAMPLES NFEATURES THE TRANSFORMED DATA
EXAMPLES USING SKLEARNPREPROCESSINGPOWERTRANSFORMER
•MAP DATA TO A NORMAL DISTRIBUTION
•COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS
63415SKLEARNPREPROCESSING QUANTILETRANSFORMER
CLASSSKLEARNPREPROCESSING QUANTILETRANSFORMER NQUANTILES1000 OUT
PUTDISTRIBUTION'UNIFORM' IG
NOREIMPLICITZEROSFALSE SUBSAM
PLE100000 RANDOMSTATENONE
COPYTRUE
TRANSFORM FEATURES USING QUANTILES INFORMATION
THIS METHOD TRANSFORMS THE FEATURES TO FOLLOW A UNIFORM OR A NORMAL DISTRIBUTION THEREFORE FOR A GIVEN FEATURE
THIS TRANSFORMATION TENDS TO SPREAD OUT THE MOST FREQUENT VALUES IT ALSO REDUCES THE IMPACT OF MARGINAL OUTLIERS
THIS IS THEREFORE A ROBUST PREPROCESSING SCHEME
THE TRANSFORMATION IS APPLIED ON EACH FEATURE INDEPENDENTLY FIRST AN ESTIMATE OF THE CUMULATIVE DISTRIBUTION
FUNCTION OF A FEATURE IS USED TO MAP THE ORIGINAL VALUES TO A UNIFORM DISTRIBUTION THE OBTAINED VALUES ARE THEN
MAPPED TO THE DESIRED OUTPUT DISTRIBUTION USING THE ASSOCIATED QUANTILE FUNCTION FEATURES VALUES OF NEWUNSEEN
DATA THAT FALL BELOW OR ABOVE THE FITTED RANGE WILL BE MAPPED TO THE BOUNDS OF THE OUTPUT DISTRIBUTION NOTE THAT
THIS TRANSFORM IS NONLINEAR IT MAY DISTORT LINEAR CORRELATIONS BETWEEN VARIABLES MEASURED AT THE SAME SCALE BUT
RENDERS VARIABLES MEASURED AT DIFFERENT SCALES MORE DIRECTLY COMPARABLE
READ MORE IN THE USER GUIDE
PARAMETERS
NQUANTILES INT OPTIONAL DEFAULT1000 OR NSAMPLES NUMBER OF QUANTILES TO BE COMPUTED
IT CORRESPONDS TO THE NUMBER OF LANDMARKS USED TO DISCRETIZE THE CUMULATIVE DISTRIBUTION
FUNCTION IF NQUANTILES IS LARGER THAN THE NUMBER OF SAMPLES NQUANTILES IS SET TO THE
NUMBER OF SAMPLES AS A LARGER NUMBER OF QUANTILES DOES NOT GIVE A BETTER APPROXIMATION OF
THE CUMULATIVE DISTRIBUTION FUNCTION ESTIMATOR
OUTPUTDISTRIBUTION STR OPTIONAL DEFAULT'UNIFORM' MARGINAL DISTRIBUTION FOR THE TRANS
FORMED DATA THE CHOICES ARE 'UNIFORM' DEFAULT OR 'NORMAL'
IGNOREIMPLICITZEROS BOOL OPTIONAL DEFAULTFALSE ONLY APPLIES TO SPARSE MATRICES IF TRUE
THE SPARSE ENTRIES OF THE MATRIX ARE DISCARDED TO COMPUTE THE QUANTILE STATISTICS IF FALSE
THESE ENTRIES ARE TREATED AS ZEROS
SUBSAMPLE INT OPTIONAL DEFAULT1E5 MAXIMUM NUMBER OF SAMPLES USED TO ESTIMATE THE
QUANTILES FOR COMPUTATIONAL EFFICIENCY NOTE THAT THE SUBSAMPLING PROCEDURE MAY DIFFER
FOR VALUEIDENTICAL SPARSE AND DENSE MATRICES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS

THE RANDOMSTATE INSTANCE USED BY NPRANDOM NOTE THAT THIS IS USED BY SUBSAMPLING AND
SMOOTHING NOISE
COPY BOOLEAN OPTIONAL DEFAULTTRUE SET TO FALSE TO PERFORM INPLACE TRANSFORMATION AND
AVOID A COPY IF THE INPUT IS ALREADY A NUMPY ARRAY
ATTRIBUTES
NQUANTILES INTEGER THE ACTUAL NUMBER OF QUANTILES USED TO DISCRETIZE THE CUMULATIVE DISTRI
BUTION FUNCTION
QUANTILES NDARRAY SHAPE NQUANTILES NFEATURES THE VALUES CORRESPONDING THE QUANTILES OF
REFERENCE
REFERENCES NDARRAY SHAPENQUANTILES QUANTILES OF REFERENCES
SEE ALSO
QUANTILETRANSFORM EQUIVALENT FUNCTION WITHOUT THE ESTIMATOR API
POWERTRANSFORMER PERFORM MAPPING TO A NORMAL DISTRIBUTION USING A POWER TRANSFORM
STANDARDSCALER PERFORM STANDARDIZATION THAT IS FASTER BUT LESS ROBUST TO OUTLIERS
ROBUSTSCALER PERFORM ROBUST STANDARDIZATION THAT REMOVES THE INFLUENCE OF OUTLIERS BUT DOES NOT PUT OUTLIERS
AND INLIERS ON THE SAME SCALE
NOTES
NANS ARE TREATED AS MISSING VALUES DISREGARDED IN FIT AND MAINTAINED IN TRANSFORM
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNPREPROCESSING IMPORT QUANTILETRANSFORMER
RNG  NPRANDOMRANDOMSTATE0
X  NPSORTRNGNORMALLOC05 SCALE025 SIZE25 1 AXIS0
QT  QUANTILETRANSFORMERNQUANTILES10 RANDOMSTATE0
QTFITTRANSFORMX
```
ARRAY
METHODS
FITSELF X Y COMPUTE THE QUANTILES USED FOR TRANSFORMING
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X BACKPROJECTION TO THE ORIGINAL SPACE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X FEATUREWISE TRANSFORMATION OF THE DATA

INIT SELFNQUANTILES1000 OUTPUTDISTRIBUTION’UNIFORM’ IGNOREIMPLICITZEROSFALSE SUB
SAMPLE100000 RANDOMSTATENONE COPYTRUE
FITSELFXYNONE
COMPUTE THE QUANTILES USED FOR TRANSFORMING
PARAMETERS
XNDARRAY OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA USED TO SCALE
ALONG THE FEATURES AXIS IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED INTO
A SPARSECSCMATRIX ADDITIONALLY THE SPARSE MATRIX NEEDS TO BE NONNEGATIVE IF
IGNOREIMPLICITZEROS IS FALSE
RETURNS
SELF OBJECT
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFX
BACKPROJECTION TO THE ORIGINAL SPACE
PARAMETERS
XNDARRAY OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA USED TO SCALE
ALONG THE FEATURES AXIS IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED INTO
A SPARSECSCMATRIX ADDITIONALLY THE SPARSE MATRIX NEEDS TO BE NONNEGATIVE IF
IGNOREIMPLICITZEROS IS FALSE
RETURNS
XTNDARRAY OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE PROJECTED DATA
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS

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SELF
TRANSFORM SELFX
FEATUREWISE TRANSFORMATION OF THE DATA
PARAMETERS
XNDARRAY OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA USED TO SCALE
ALONG THE FEATURES AXIS IF A SPARSE MATRIX IS PROVIDED IT WILL BE CONVERTED INTO
A SPARSECSCMATRIX ADDITIONALLY THE SPARSE MATRIX NEEDS TO BE NONNEGATIVE IF
IGNOREIMPLICITZEROS IS FALSE
RETURNS
XTNDARRAY OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE PROJECTED DATA
EXAMPLES USING SKLEARNPREPROCESSINGQUANTILETRANSFORMER
•EFFECT OF TRANSFORMING THE TARGETS IN REGRESSION MODEL
•MAP DATA TO A NORMAL DISTRIBUTION
•COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS
63416SKLEARNPREPROCESSING ROBUSTSCALER
CLASSSKLEARNPREPROCESSING ROBUSTSCALER WITHCENTERINGTRUE WITHSCALINGTRUE QUAN
TILERANGE250 750 COPYTRUE
SCALE FEATURES USING STATISTICS THAT ARE ROBUST TO OUTLIERS
THIS SCALER REMOVES THE MEDIAN AND SCALES THE DATA ACCORDING TO THE QUANTILE RANGE DEFAULTS TO IQR INTERQUARTILE
RANGE THE IQR IS THE RANGE BETWEEN THE 1ST QUARTILE 25TH QUANTILE AND THE 3RD QUARTILE 75TH QUANTILE
CENTERING AND SCALING HAPPEN INDEPENDENTLY ON EACH FEATURE BY COMPUTING THE RELEVANT STATISTICS ON THE SAMPLES
IN THE TRAINING SET MEDIAN AND INTERQUARTILE RANGE ARE THEN STORED TO BE USED ON LATER DATA USING THE TRANSFORM
METHOD
STANDARDIZATION OF A DATASET IS A COMMON REQUIREMENT FOR MANY MACHINE LEARNING ESTIMATORS TYPICALLY THIS IS
DONE BY REMOVING THE MEAN AND SCALING TO UNIT VARIANCE HOWEVER OUTLIERS CAN OFTEN INFLUENCE THE SAMPLE MEAN
 VARIANCE IN A NEGATIVE WAY IN SUCH CASES THE MEDIAN AND THE INTERQUARTILE RANGE OFTEN GIVE BETTER RESULTS
NEW IN VERSION 017
READ MORE IN THE USER GUIDE
PARAMETERS
WITHCENTERING BOOLEAN TRUE BY DEFAULT IF TRUE CENTER THE DATA BEFORE SCALING THIS WILL
CAUSETRANSFORM TO RAISE AN EXCEPTION WHEN ATTEMPTED ON SPARSE MATRICES BECAUSE CEN
TERING THEM ENTAILS BUILDING A DENSE MATRIX WHICH IN COMMON USE CASES IS LIKELY TO BE TOO
LARGE TO FIT IN MEMORY
WITHSCALING BOOLEAN TRUE BY DEFAULT IF TRUE SCALE THE DATA TO INTERQUARTILE RANGE
QUANTILERANGE TUPLE QMIN QMAX 00 QMIN QMAX 1000 DEFAULT 250 750
1ST QUANTILE 3RD QUANTILE IQR QUANTILE RANGE USED TO CALCULATE SCALE
NEW IN VERSION 018
COPY BOOLEAN OPTIONAL DEFAULT IS TRUE IF FALSE TRY TO AVOID A COPY AND DO INPLACE SCALING
INSTEAD THIS IS NOT GUARANTEED TO ALWAYS WORK INPLACE EG IF THE DATA IS NOT A NUMPY ARRAY
OR SCIPYSPARSE CSR MATRIX A COPY MAY STILL BE RETURNED

ATTRIBUTES
CENTER ARRAY OF FLOATS THE MEDIAN VALUE FOR EACH FEATURE IN THE TRAINING SET
SCALE ARRAY OF FLOATS THE SCALED INTERQUARTILE RANGE FOR EACH FEATURE IN THE TRAINING SET
NEW IN VERSION 017 SCALE ATTRIBUTE
SEE ALSO
ROBUSTSCALE EQUIVALENT FUNCTION WITHOUT THE ESTIMATOR API
SKLEARNDECOMPOSITIONPCA FURTHER REMOVES THE LINEAR CORRELATION ACROSS FEATURES WITH
‘WHITENTRUE’
NOTES
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
HTTPSENWIKIPEDIAORGWIKIMEDIAN HTTPSENWIKIPEDIAORGWIKIINTERQUARTILERANGE
EXAMPLES
```
 FROM SKLEARNPREPROCESSING IMPORT ROBUSTSCALER
X   1 2 2
  2 1 3
  4 1 2
TRANSFORMER  ROBUSTSCALERFITX
TRANSFORMER
ROBUSTSCALERCOPYTRUE QUANTILERANGE250 750 WITHCENTERINGTRUE
WITHSCALINGTRUE
TRANSFORMERTRANSFORMX
ARRAY 0  2  0
1  0  04
 1  0  16
```
METHODS
FITSELF X Y COMPUTE THE MEDIAN AND QUANTILES TO BE USED FOR SCAL
ING
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X SCALE BACK THE DATA TO THE ORIGINAL REPRESENTATION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X CENTER AND SCALE THE DATA
INIT SELFWITHCENTERINGTRUE WITHSCALINGTRUE QUANTILERANGE250 750 COPYTRUE
FITSELFXYNONE
COMPUTE THE MEDIAN AND QUANTILES TO BE USED FOR SCALING
PARAMETERS

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XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA USED TO COMPUTE THE MEDIAN AND
QUANTILES USED FOR LATER SCALING ALONG THE FEATURES AXIS
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFX
SCALE BACK THE DATA TO THE ORIGINAL REPRESENTATION
PARAMETERS
XARRAYLIKE THE DATA USED TO SCALE ALONG THE SPECIFIED AXIS
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
CENTER AND SCALE THE DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX THE DATA USED TO SCALE ALONG THE SPECIFIED AXIS
EXAMPLES USING SKLEARNPREPROCESSINGROBUSTSCALER
•COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS
63417SKLEARNPREPROCESSING STANDARDSCALER
CLASSSKLEARNPREPROCESSING STANDARDSCALER COPYTRUE WITHMEANTRUE WITHSTDTRUE
STANDARDIZE FEATURES BY REMOVING THE MEAN AND SCALING TO UNIT VARIANCE
634SKLEARNPREPROCESSING PREPROCESSING AND NORMALIZATION 2273

THE STANDARD SCORE OF A SAMPLE XIS CALCULATED AS
Z X U S
WHEREUIS THE MEAN OF THE TRAINING SAMPLES OR ZERO IF WITHMEANFALSE ANDSIS THE STANDARD DEVIATION OF
THE TRAINING SAMPLES OR ONE IF WITHSTDFALSE
CENTERING AND SCALING HAPPEN INDEPENDENTLY ON EACH FEATURE BY COMPUTING THE RELEVANT STATISTICS ON THE SAMPLES
IN THE TRAINING SET MEAN AND STANDARD DEVIATION ARE THEN STORED TO BE USED ON LATER DATA USING THE TRANSFORM
METHOD
STANDARDIZATION OF A DATASET IS A COMMON REQUIREMENT FOR MANY MACHINE LEARNING ESTIMATORS THEY MIGHT BEHAVE
BADLY IF THE INDIVIDUAL FEATURES DO NOT MORE OR LESS LOOK LIKE STANDARD NORMALLY DISTRIBUTED DATA EG GAUSSIAN
WITH 0 MEAN AND UNIT VARIANCE
FOR INSTANCE MANY ELEMENTS USED IN THE OBJECTIVE FUNCTION OF A LEARNING ALGORITHM SUCH AS THE RBF KERNEL OF
SUPPORT VECTOR MACHINES OR THE L1 AND L2 REGULARIZERS OF LINEAR MODELS ASSUME THAT ALL FEATURES ARE CENTERED
AROUND 0 AND HAVE VARIANCE IN THE SAME ORDER IF A FEATURE HAS A VARIANCE THAT IS ORDERS OF MAGNITUDE LARGER
THAT OTHERS IT MIGHT DOMINATE THE OBJECTIVE FUNCTION AND MAKE THE ESTIMATOR UNABLE TO LEARN FROM OTHER FEATURES
CORRECTLY AS EXPECTED
THIS SCALER CAN ALSO BE APPLIED TO SPARSE CSR OR CSC MATRICES BY PASSING WITHMEANFALSE TO AVOID
BREAKING THE SPARSITY STRUCTURE OF THE DATA
READ MORE IN THE USER GUIDE
PARAMETERS
COPY BOOLEAN OPTIONAL DEFAULT TRUE IF FALSE TRY TO AVOID A COPY AND DO INPLACE SCALING IN
STEAD THIS IS NOT GUARANTEED TO ALWAYS WORK INPLACE EG IF THE DATA IS NOT A NUMPY ARRAY
OR SCIPYSPARSE CSR MATRIX A COPY MAY STILL BE RETURNED
WITHMEAN BOOLEAN TRUE BY DEFAULT IF TRUE CENTER THE DATA BEFORE SCALING THIS DOES NOT
WORK AND WILL RAISE AN EXCEPTION WHEN ATTEMPTED ON SPARSE MATRICES BECAUSE CENTERING
THEM ENTAILS BUILDING A DENSE MATRIX WHICH IN COMMON USE CASES IS LIKELY TO BE TOO LARGE TO
FIT IN MEMORY
WITHSTD BOOLEAN TRUE BY DEFAULT IF TRUE SCALE THE DATA TO UNIT VARIANCE OR EQUIVALENTLY UNIT
STANDARD DEVIATION
ATTRIBUTES
SCALE NDARRAY OR NONE SHAPE NFEATURES PER FEATURE RELATIVE SCALING OF THE DATA THIS IS
CALCULATED USING NPSQRTVAR EQUAL TONONE WHENWITHSTDFALSE
NEW IN VERSION 017 SCALE
MEAN NDARRAY OR NONE SHAPE NFEATURES THE MEAN VALUE FOR EACH FEATURE IN THE TRAINING
SET EQUAL TO NONE WHENWITHMEANFALSE
VAR NDARRAY OR NONE SHAPE NFEATURES THE VARIANCE FOR EACH FEATURE IN THE TRAINING SET
USED TO COMPUTE SCALE EQUAL TONONE WHENWITHSTDFALSE
NSAMPLESSEEN INT OR ARRAY SHAPE NFEATURES THE NUMBER OF SAMPLES PROCESSED BY THE
ESTIMATOR FOR EACH FEATURE IF THERE ARE NOT MISSING SAMPLES THE NSAMPLESSEEN WILL
BE AN INTEGER OTHERWISE IT WILL BE AN ARRAY WILL BE RESET ON NEW CALLS TO FIT BUT INCREMENTS
ACROSSPARTIALFIT CALLS
SEE ALSO
SCALE EQUIVALENT FUNCTION WITHOUT THE ESTIMATOR API

SKLEARNDECOMPOSITIONPCA FURTHER REMOVES THE LINEAR CORRELATION ACROSS FEATURES WITH
‘WHITENTRUE’
NOTES
NANS ARE TREATED AS MISSING VALUES DISREGARDED IN FIT AND MAINTAINED IN TRANSFORM
WE USE A BIASED ESTIMATOR FOR THE STANDARD DEVIATION EQUIVALENT TO NUMPYSTDX DDOF0 NOTE THAT THE
CHOICE OFDDOF IS UNLIKELY TO AFFECT MODEL PERFORMANCE
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
EXAMPLES
```
 FROM SKLEARNPREPROCESSING IMPORT STANDARDSCALER
DATA  0 0 0 0 1 1 1 1
SCALER  STANDARDSCALER
PRINTSCALERFITDATA
STANDARDSCALERCOPYTRUE WITHMEANTRUE WITHSTDTRUE
PRINTSCALERMEAN
05 05
PRINTSCALERTRANSFORMDATA
1 1
1 1
 1 1
 1 1
PRINTSCALERTRANSFORM2 2
3 3
```
METHODS
FITSELF X Y COMPUTE THE MEAN AND STD TO BE USED FOR LATER SCALING
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
INVERSETRANSFORM SELF X COPY SCALE BACK THE DATA TO THE ORIGINAL REPRESENTATION
PARTIALFIT SELF X Y ONLINE COMPUTATION OF MEAN AND STD ON X FOR LATER SCAL
ING
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X COPY PERFORM STANDARDIZATION BY CENTERING AND SCALING
INIT SELFCOPYTRUE WITHMEANTRUE WITHSTDTRUE
FITSELFXYNONE
COMPUTE THE MEAN AND STD TO BE USED FOR LATER SCALING
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA USED TO COMPUTE THE
MEAN AND STANDARD DEVIATION USED FOR LATER SCALING ALONG THE FEATURES AXIS
YIGNORED

FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
INVERSETRANSFORM SELFXCOPYNONE
SCALE BACK THE DATA TO THE ORIGINAL REPRESENTATION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA USED TO SCALE ALONG THE FEATURES AXIS
COPY BOOL OPTIONAL DEFAULT NONE COPY THE INPUT X OR NOT
RETURNS
XTR ARRAYLIKE SHAPE NSAMPLES NFEATURES TRANSFORMED ARRAY
PARTIALFIT SELFXYNONE
ONLINE COMPUTATION OF MEAN AND STD ON X FOR LATER SCALING ALL OF X IS PROCESSED AS A SINGLE BATCH THIS IS
INTENDED FOR CASES WHEN FIT IS NOT FEASIBLE DUE TO VERY LARGE NUMBER OF NSAMPLES OR BECAUSE X IS READ
FROM A CONTINUOUS STREAM
THE ALGORITHM FOR INCREMENTAL MEAN AND STD IS GIVEN IN EQUATION 15AB IN CHAN TONY F GENE H GOLUB
AND RANDALL J LEVEQUE “ALGORITHMS FOR COMPUTING THE SAMPLE VARIANCE ANALYSIS AND RECOMMENDATIONS”
THE AMERICAN STATISTICIAN 373 1983 242247
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA USED TO COMPUTE THE
MEAN AND STANDARD DEVIATION USED FOR LATER SCALING ALONG THE FEATURES AXIS
YIGNORED
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF

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TRANSFORM SELFXCOPYNONE
PERFORM STANDARDIZATION BY CENTERING AND SCALING
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA USED TO SCALE ALONG THE FEATURES AXIS
COPY BOOL OPTIONAL DEFAULT NONE COPY THE INPUT X OR NOT
EXAMPLES USING SKLEARNPREPROCESSINGSTANDARDSCALER
•PREDICTION LATENCY
•CLASSIFIER COMPARISON
•DEMO OF DBSCAN CLUSTERING ALGORITHM
•COMPARING DIFFERENT HIERARCHICAL LINKAGE METHODS ON TOY DATASETS
•COMPARING DIFFERENT CLUSTERING ALGORITHMS ON TOY DATASETS
•COLUMN TRANSFORMER WITH MIXED TYPES
•MNIST CLASSFIFICATION USING MULTINOMIAL LOGISTIC L1
•L1 PENALTY AND SPARSITY IN LOGISTIC REGRESSION
•COMPARING NEAREST NEIGHBORS WITH AND WITHOUT NEIGHBORHOOD COMPONENTS ANALYSIS
•DIMENSIONALITY REDUCTION WITH NEIGHBORHOOD COMPONENTS ANALYSIS
•VARYING REGULARIZATION IN MULTILAYER PERCEPTRON
•IMPORTANCE OF FEATURE SCALING
•FEATURE DISCRETIZATION
•COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS
•SVMANOVA SVM WITH UNIVARIATE FEATURE SELECTION
•RBF SVM PARAMETERS
PREPROCESSINGADDDUMMYFEATURE X VALUE AUGMENT DATASET WITH AN ADDITIONAL DUMMY FEATURE
PREPROCESSINGBINARIZE X THRESHOLD COPY BOOLEAN THRESHOLDING OF ARRAYLIKE OR SCIPYSPARSE MATRIX
PREPROCESSINGLABELBINARIZE Y CLASSES BINARIZE LABELS IN A ONEVSALL FASHION
PREPROCESSINGMAXABSSCALE X AXIS COPY SCALE EACH FEATURE TO THE 1 1 RANGE WITHOUT BREAKING THE
SPARSITY
PREPROCESSINGMINMAXSCALE X TRANSFORMS FEATURES BY SCALING EACH FEATURE TO A GIVEN
RANGE
PREPROCESSINGNORMALIZE X NORM AXIS SCALE INPUT VECTORS INDIVIDUALLY TO UNIT NORM VECTOR
LENGTH
PREPROCESSINGQUANTILETRANSFORM X AXIS
  TRANSFORM FEATURES USING QUANTILES INFORMATION
PREPROCESSINGROBUSTSCALE X AXIS STANDARDIZE A DATASET ALONG ANY AXIS
PREPROCESSINGSCALE X AXIS WITHMEAN STANDARDIZE A DATASET ALONG ANY AXIS
PREPROCESSINGPOWERTRANSFORM X METHOD
  POWER TRANSFORMS ARE A FAMILY OF PARAMETRIC MONO
TONIC TRANSFORMATIONS THAT ARE APPLIED TO MAKE DATA MORE
GAUSSIANLIKE
634SKLEARNPREPROCESSING PREPROCESSING AND NORMALIZATION 2277

63418SKLEARNPREPROCESSING ADDDUMMYFEATURE
SKLEARNPREPROCESSING ADDDUMMYFEATURE XVALUE10
AUGMENT DATASET WITH AN ADDITIONAL DUMMY FEATURE
THIS IS USEFUL FOR FITTING AN INTERCEPT TERM WITH IMPLEMENTATIONS WHICH CANNOT OTHERWISE FIT IT DIRECTLY
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES DATA
VALUE FLOAT VALUE TO USE FOR THE DUMMY FEATURE
RETURNS
XARRAY SPARSE MATRIX SHAPE NSAMPLES NFEATURES 1 SAME DATA WITH DUMMY FEATURE
ADDED AS FIRST COLUMN
EXAMPLES
 FROM SKLEARNPREPROCESSING IMPORT ADDDUMMYFEATURE
ADDDUMMYFEATURE0 1 1 0
ARRAY1 0 1
1 1 0
63419SKLEARNPREPROCESSING BINARIZE
SKLEARNPREPROCESSING BINARIZE XTHRESHOLD00 COPYTRUE
BOOLEAN THRESHOLDING OF ARRAYLIKE OR SCIPYSPARSE MATRIX
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA TO BINARIZE ELEMENT BY
ELEMENT SCIPYSPARSE MATRICES SHOULD BE IN CSR OR CSC FORMAT TO AVOID AN UNNECESSARY
COPY
THRESHOLD FLOAT OPTIONAL 00 BY DEFAULT FEATURE VALUES BELOW OR EQUAL TO THIS ARE REPLACED BY
0 ABOVE IT BY 1 THRESHOLD MAY NOT BE LESS THAN 0 FOR OPERATIONS ON SPARSE MATRICES
COPY BOOLEAN OPTIONAL DEFAULT TRUE SET TO FALSE TO PERFORM INPLACE BINARIZATION AND AVOID A
COPY IF THE INPUT IS ALREADY A NUMPY ARRAY OR A SCIPYSPARSE CSR CSC MATRIX AND IF AXIS
IS 1
SEE ALSO
BINARIZER PERFORMS BINARIZATION USING THE TRANSFORMER API EG AS PART OF A PREPROCESSING SKLEARN
PIPELINEPIPELINE
63420SKLEARNPREPROCESSING LABELBINARIZE
SKLEARNPREPROCESSING LABELBINARIZE Y CLASSES NEGLABEL0 POSLABEL1
SPARSEOUTPUTFALSE
BINARIZE LABELS IN A ONEVSALL FASHION

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SEVERAL REGRESSION AND BINARY CLASSIFICATION ALGORITHMS ARE AVAILABLE IN SCIKITLEARN A SIMPLE WAY TO EXTEND THESE ALGORITHMS TO THE MULTICLASS CLASSIFICATION CASE IS TO USE THE SOCALLED ONEVSALL SCHEME
THIS FUNCTION MAKES IT POSSIBLE TO COMPUTE THIS TRANSFORMATION FOR A FIXED SET OF CLASS LABELS KNOWN AHEAD OF TIME
PARAMETERS
YARRAYLIKE SEQUENCE OF INTEGER LABELS OR MULTILABEL DATA TO ENCODE
CLASSES ARRAYLIKE OF SHAPE NCLASSES UNIQUELY HOLDS THE LABEL FOR EACH CLASS
NEGLABEL INT DEFAULT 0 VALUE WITH WHICH NEGATIVE LABELS MUST BE ENCODED
POSLABEL INT DEFAULT 1 VALUE WITH WHICH POSITIVE LABELS MUST BE ENCODED
SPARSEOUTPUT BOOLEAN DEFAULT FALSE SET TO TRUE IF OUTPUT BINARY ARRAY IS DESIRED IN CSR SPARSE FORMAT
RETURNS
YNUMPY ARRAY OR CSR MATRIX OF SHAPE NSAMPLES NCLASSES SHAPE WILL BE NSAMPLES 1 FOR BINARY PROBLEMS
SEE ALSO
LABELBINARIZER CLASS USED TO WRAP THE FUNCTIONALITY OF LABELBINARIZE AND ALLOW FOR FITTING TO CLASSES INDEPENDENTLY OF THE TRANSFORM OPERATION
EXAMPLES
FROM SKLEARNPREPROCESSING IMPORT LABELBINARIZE
LABELBINARIZE1 6 CLASSES1 2 4 6
ARRAY1 0 0 0
0 0 0 1
THE CLASS ORDERING IS PRESERVED
LABELBINARIZE1 6 CLASSES1 6 4 2
ARRAY1 0 0 0
0 1 0 0
BINARY TARGETS TRANSFORM TO A COLUMN VECTOR
LABELBINARIZEYES NO NO YES CLASSESNO YES
ARRAY1
0
0
1
EXAMPLES USING SKLEARNPREPROCESSINGLABELBINARIZE
•RECEIVER OPERATING CHARACTERISTIC ROC
•PRECISIONRECALL

63421SKLEARNPREPROCESSING MAXABSSCALE
SKLEARNPREPROCESSING MAXABSSCALE XAXIS0 COPYTRUE
SCALE EACH FEATURE TO THE 1 1 RANGE WITHOUT BREAKING THE SPARSITY
THIS ESTIMATOR SCALES EACH FEATURE INDIVIDUALLY SUCH THAT THE MAXIMAL ABSOLUTE VALUE OF EACH FEATURE IN THE TRAINING SET WILL BE 10
THIS SCALER CAN ALSO BE APPLIED TO SPARSE CSR OR CSC MATRICES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA
AXIS INT 0 BY DEFAULT AXIS USED TO SCALE ALONG IF 0 INDEPENDENTLY SCALE EACH FEATURE OTHER WISE IF 1 SCALE EACH SAMPLE
COPY BOOLEAN OPTIONAL DEFAULT IS TRUE SET TO FALSE TO PERFORM INPLACE SCALING AND AVOID A COPY IF THE INPUT IS ALREADY A NUMPY ARRAY
SEE ALSO
MAXABSSCALER PERFORMS SCALING TO THE 1 1 RANGE USING THE‘‘TRANSFORMER‘‘ API EG AS PART OF A PREPRO CESSINGSKLEARNPIPELINEPIPELINE
NOTES
NANS ARE TREATED AS MISSING VALUES DISREGARDED TO COMPUTE THE STATISTICS AND MAINTAINED DURING THE DATA TRANS FORMATION
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM PLESPREPROCESSINGPLOTALLSCALINGPY
63422SKLEARNPREPROCESSING MINMAXSCALE
SKLEARNPREPROCESSING MINMAXSCALE XFEATURERANGE0 1AXIS0 COPYTRUE
TRANSFORMS FEATURES BY SCALING EACH FEATURE TO A GIVEN RANGE
THIS ESTIMATOR SCALES AND TRANSLATES EACH FEATURE INDIVIDUALLY SUCH THAT IT IS IN THE GIVEN RANGE ON THE TRAINING SET IE BETWEEN ZERO AND ONE
THE TRANSFORMATION IS GIVEN BY WHEN AXIS0
XSTD X XMINAXIS0 XMAXAXIS0 XMINAXIS0
XSCALED XSTD MAX MIN MIN
WHERE MIN MAX FEATURERANGE
THE TRANSFORMATION IS CALCULATED AS WHEN AXIS0
XSCALED SCALE X MIN XMINAXIS0 SCALE
WHERE SCALE MAX MIN XMAXAXIS0 XMINAXIS0
THIS TRANSFORMATION IS OFTEN USED AS AN ALTERNATIVE TO ZERO MEAN UNIT VARIANCE SCALING
READ MORE IN THE USER GUIDE
NEW IN VERSION 017 MINMAXSCALE FUNCTION INTERFACE TO SKLEARNPREPROCESSINGMINMAXSCALER
PARAMETERS

XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA
FEATURERANGE TUPLE MIN MAX DEFAULT0 1 DESIRED RANGE OF TRANSFORMED DATA
AXIS INT 0 BY DEFAULT AXIS USED TO SCALE ALONG IF 0 INDEPENDENTLY SCALE EACH FEATURE OTHER
WISE IF 1 SCALE EACH SAMPLE
COPY BOOLEAN OPTIONAL DEFAULT IS TRUE SET TO FALSE TO PERFORM INPLACE SCALING AND AVOID A
COPY IF THE INPUT IS ALREADY A NUMPY ARRAY
SEE ALSO
MINMAXSCALER PERFORMS SCALING TO A GIVEN RANGE USING THE‘‘TRANSFORMER‘‘ API EG AS PART OF A PREPROCESS
INGSKLEARNPIPELINEPIPELINE
NOTES
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
EXAMPLES USING SKLEARNPREPROCESSINGMINMAXSCALE
•COMPARE THE EFFECT OF DIFFERENT SCALERS ON DATA WITH OUTLIERS
63423SKLEARNPREPROCESSING NORMALIZE
SKLEARNPREPROCESSING NORMALIZE XNORM‘L2’ AXIS1 COPYTRUE RETURNNORMFALSE
SCALE INPUT VECTORS INDIVIDUALLY TO UNIT NORM VECTOR LENGTH
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE DATA TO NORMALIZE ELEMENT
BY ELEMENT SCIPYSPARSE MATRICES SHOULD BE IN CSR FORMAT TO AVOID AN UNNECESSARY COPY
NORM ‘L1’ ‘L2’ OR ‘MAX’ OPTIONAL ‘L2’ BY DEFAULT THE NORM TO USE TO NORMALIZE EACH NON
ZERO SAMPLE OR EACH NONZERO FEATURE IF AXIS IS 0
AXIS 0 OR 1 OPTIONAL 1 BY DEFAULT AXIS USED TO NORMALIZE THE DATA ALONG IF 1 INDEPENDENTLY
NORMALIZE EACH SAMPLE OTHERWISE IF 0 NORMALIZE EACH FEATURE
COPY BOOLEAN OPTIONAL DEFAULT TRUE SET TO FALSE TO PERFORM INPLACE ROW NORMALIZATION AND
AVOID A COPY IF THE INPUT IS ALREADY A NUMPY ARRAY OR A SCIPYSPARSE CSR MATRIX AND IF AXIS
IS 1
RETURNNORM BOOLEAN DEFAULT FALSE WHETHER TO RETURN THE COMPUTED NORMS
RETURNS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES NORMALIZED INPUT X
NORMS ARRAY SHAPE NSAMPLES IF AXIS1 ELSE NFEATURES AN ARRAY OF NORMS ALONG GIVEN
AXIS FOR X WHEN X IS SPARSE A NOTIMPLEMENTEDERROR WILL BE RAISED FOR NORM ‘L1’ OR ‘L2’
SEE ALSO
NORMALIZER PERFORMS NORMALIZATION USING THE TRANSFORMER API EG AS PART OF A PREPROCESSING
SKLEARNPIPELINEPIPELINE

NOTES
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
63424SKLEARNPREPROCESSING QUANTILETRANSFORM
SKLEARNPREPROCESSING QUANTILETRANSFORM X AXIS0 NQUANTILES1000 OUT
PUTDISTRIBUTION'UNIFORM' IG
NOREIMPLICITZEROSFALSE SUBSAMPLE100000
RANDOMSTATENONE COPY'WARN'
TRANSFORM FEATURES USING QUANTILES INFORMATION
THIS METHOD TRANSFORMS THE FEATURES TO FOLLOW A UNIFORM OR A NORMAL DISTRIBUTION THEREFORE FOR A GIVEN FEATURE
THIS TRANSFORMATION TENDS TO SPREAD OUT THE MOST FREQUENT VALUES IT ALSO REDUCES THE IMPACT OF MARGINAL OUTLIERS
THIS IS THEREFORE A ROBUST PREPROCESSING SCHEME
THE TRANSFORMATION IS APPLIED ON EACH FEATURE INDEPENDENTLY FIRST AN ESTIMATE OF THE CUMULATIVE DISTRIBUTION
FUNCTION OF A FEATURE IS USED TO MAP THE ORIGINAL VALUES TO A UNIFORM DISTRIBUTION THE OBTAINED VALUES ARE THEN
MAPPED TO THE DESIRED OUTPUT DISTRIBUTION USING THE ASSOCIATED QUANTILE FUNCTION FEATURES VALUES OF NEWUNSEEN
DATA THAT FALL BELOW OR ABOVE THE FITTED RANGE WILL BE MAPPED TO THE BOUNDS OF THE OUTPUT DISTRIBUTION NOTE THAT
THIS TRANSFORM IS NONLINEAR IT MAY DISTORT LINEAR CORRELATIONS BETWEEN VARIABLES MEASURED AT THE SAME SCALE BUT
RENDERS VARIABLES MEASURED AT DIFFERENT SCALES MORE DIRECTLY COMPARABLE
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX THE DATA TO TRANSFORM
AXIS INT DEFAULT0 AXIS USED TO COMPUTE THE MEANS AND STANDARD DEVIATIONS ALONG IF 0
TRANSFORM EACH FEATURE OTHERWISE IF 1 TRANSFORM EACH SAMPLE
NQUANTILES INT OPTIONAL DEFAULT1000 OR NSAMPLES NUMBER OF QUANTILES TO BE COMPUTED
IT CORRESPONDS TO THE NUMBER OF LANDMARKS USED TO DISCRETIZE THE CUMULATIVE DISTRIBUTION
FUNCTION IF NQUANTILES IS LARGER THAN THE NUMBER OF SAMPLES NQUANTILES IS SET TO THE
NUMBER OF SAMPLES AS A LARGER NUMBER OF QUANTILES DOES NOT GIVE A BETTER APPROXIMATION OF
THE CUMULATIVE DISTRIBUTION FUNCTION ESTIMATOR
OUTPUTDISTRIBUTION STR OPTIONAL DEFAULT'UNIFORM' MARGINAL DISTRIBUTION FOR THE TRANS
FORMED DATA THE CHOICES ARE 'UNIFORM' DEFAULT OR 'NORMAL'
IGNOREIMPLICITZEROS BOOL OPTIONAL DEFAULTFALSE ONLY APPLIES TO SPARSE MATRICES IF TRUE
THE SPARSE ENTRIES OF THE MATRIX ARE DISCARDED TO COMPUTE THE QUANTILE STATISTICS IF FALSE
THESE ENTRIES ARE TREATED AS ZEROS
SUBSAMPLE INT OPTIONAL DEFAULT1E5 MAXIMUM NUMBER OF SAMPLES USED TO ESTIMATE THE
QUANTILES FOR COMPUTATIONAL EFFICIENCY NOTE THAT THE SUBSAMPLING PROCEDURE MAY DIFFER
FOR VALUEIDENTICAL SPARSE AND DENSE MATRICES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM NOTE THAT THIS IS USED BY SUBSAMPLING AND
SMOOTHING NOISE
COPY BOOLEAN OPTIONAL DEFAULT"WARN" SET TO FALSE TO PERFORM INPLACE TRANSFORMATION AND
AVOID A COPY IF THE INPUT IS ALREADY A NUMPY ARRAY IF TRUE A COPY OF XIS TRANSFORMED
LEAVING THE ORIGINAL XUNCHANGED

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DEPRECATED SINCE VERSION 021 THE DEFAULT VALUE OF PARAMETER COPY WILL BE CHANGED FROM
FALSE TO TRUE IN 023 THE CURRENT DEFAULT OF FALSE IS BEING CHANGED TO MAKE IT MORE CON
SISTENT WITH THE DEFAULT COPY VALUES OF OTHER FUNCTIONS IN SKLEARNPREPROCESSING
DATA FURTHERMORE THE CURRENT DEFAULT OF FALSE MAY HAVE UNEXPECTED SIDE EFFECTS BY MOD
IFYING THE VALUE OF XINPLACE
RETURNS
XTNDARRAY OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE TRANSFORMED DATA
SEE ALSO
QUANTILETRANSFORMER PERFORMS QUANTILEBASED SCALING USING THE TRANSFORMER API EG AS PART OF A
PREPROCESSING SKLEARNPIPELINEPIPELINE
POWERTRANSFORM MAPS DATA TO A NORMAL DISTRIBUTION USING A POWER TRANSFORMATION
SCALE PERFORMS STANDARDIZATION THAT IS FASTER BUT LESS ROBUST TO OUTLIERS
ROBUSTSCALE PERFORMS ROBUST STANDARDIZATION THAT REMOVES THE INFLUENCE OF OUTLIERS BUT DOES NOT PUT OUT
LIERS AND INLIERS ON THE SAME SCALE
NOTES
NANS ARE TREATED AS MISSING VALUES DISREGARDED IN FIT AND MAINTAINED IN TRANSFORM
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
EXAMPLES
 IMPORT NUMPY AS NP
 FROM SKLEARNPREPROCESSING IMPORT QUANTILETRANSFORM
RNG NPRANDOMRANDOMSTATE0
X NPSORTRNGNORMALLOC05 SCALE025 SIZE25 1 AXIS0
QUANTILETRANSFORMX NQUANTILES10 RANDOMSTATE0 COPY TRUE

ARRAY
EXAMPLES USING SKLEARNPREPROCESSINGQUANTILETRANSFORM
•EFFECT OF TRANSFORMING THE TARGETS IN REGRESSION MODEL
63425SKLEARNPREPROCESSING ROBUSTSCALE
SKLEARNPREPROCESSING ROBUSTSCALE XAXIS0 WITHCENTERINGTRUE WITHSCALINGTRUE
QUANTILERANGE250 750 COPYTRUE
STANDARDIZE A DATASET ALONG ANY AXIS
CENTER TO THE MEDIAN AND COMPONENT WISE SCALE ACCORDING TO THE INTERQUARTILE RANGE
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE THE DATA TO CENTER AND SCALE

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AXIS INT 0 BY DEFAULT AXIS USED TO COMPUTE THE MEDIANS AND IQR ALONG IF 0 INDEPENDENTLY
SCALE EACH FEATURE OTHERWISE IF 1 SCALE EACH SAMPLE
WITHCENTERING BOOLEAN TRUE BY DEFAULT IF TRUE CENTER THE DATA BEFORE SCALING
WITHSCALING BOOLEAN TRUE BY DEFAULT IF TRUE SCALE THE DATA TO UNIT VARIANCE OR EQUIVALENTLY
UNIT STANDARD DEVIATION
QUANTILERANGE TUPLE QMIN QMAX 00 QMIN QMAX 1000 DEFAULT 250 750
1ST QUANTILE 3RD QUANTILE IQR QUANTILE RANGE USED TO CALCULATE SCALE
NEW IN VERSION 018
COPY BOOLEAN OPTIONAL DEFAULT IS TRUE SET TO FALSE TO PERFORM INPLACE ROW NORMALIZATION AND
AVOID A COPY IF THE INPUT IS ALREADY A NUMPY ARRAY OR A SCIPYSPARSE CSR MATRIX AND IF AXIS
IS 1
SEE ALSO
ROBUSTSCALER PERFORMS CENTERING AND SCALING USING THE TRANSFORMER API EG AS PART OF A PREPROCESS
INGSKLEARNPIPELINEPIPELINE
NOTES
THIS IMPLEMENTATION WILL REFUSE TO CENTER SCIPYSPARSE MATRICES SINCE IT WOULD MAKE THEM NONSPARSE AND WOULD
POTENTIALLY CRASH THE PROGRAM WITH MEMORY EXHAUSTION PROBLEMS
INSTEAD THE CALLER IS EXPECTED TO EITHER SET EXPLICITLY WITHCENTERINGFALSE IN THAT CASE ONLY VARIANCE
SCALING WILL BE PERFORMED ON THE FEATURES OF THE CSR MATRIX OR TO CALL XTOARRAY IF HESHE EXPECTS THE
MATERIALIZED DENSE ARRAY TO FIT IN MEMORY
TO AVOID MEMORY COPY THE CALLER SHOULD PASS A CSR MATRIX
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
63426SKLEARNPREPROCESSING SCALE
SKLEARNPREPROCESSING SCALEXAXIS0 WITHMEANTRUE WITHSTDTRUE COPYTRUE
STANDARDIZE A DATASET ALONG ANY AXIS
CENTER TO THE MEAN AND COMPONENT WISE SCALE TO UNIT VARIANCE
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SPARSE MATRIX THE DATA TO CENTER AND SCALE
AXIS INT 0 BY DEFAULT AXIS USED TO COMPUTE THE MEANS AND STANDARD DEVIATIONS ALONG IF 0
INDEPENDENTLY STANDARDIZE EACH FEATURE OTHERWISE IF 1 STANDARDIZE EACH SAMPLE
WITHMEAN BOOLEAN TRUE BY DEFAULT IF TRUE CENTER THE DATA BEFORE SCALING
WITHSTD BOOLEAN TRUE BY DEFAULT IF TRUE SCALE THE DATA TO UNIT VARIANCE OR EQUIVALENTLY UNIT
STANDARD DEVIATION
COPY BOOLEAN OPTIONAL DEFAULT TRUE SET TO FALSE TO PERFORM INPLACE ROW NORMALIZATION AND
AVOID A COPY IF THE INPUT IS ALREADY A NUMPY ARRAY OR A SCIPYSPARSE CSC MATRIX AND IF AXIS
IS 1

SEE ALSO
STANDARDSCALER PERFORMS SCALING TO UNIT VARIANCE USING THE‘‘TRANSFORMER‘‘ API EG AS PART OF A PREPRO
CESSINGSKLEARNPIPELINEPIPELINE
NOTES
THIS IMPLEMENTATION WILL REFUSE TO CENTER SCIPYSPARSE MATRICES SINCE IT WOULD MAKE THEM NONSPARSE AND WOULD
POTENTIALLY CRASH THE PROGRAM WITH MEMORY EXHAUSTION PROBLEMS
INSTEAD THE CALLER IS EXPECTED TO EITHER SET EXPLICITLY WITHMEANFALSE IN THAT CASE ONLY VARIANCE SCALING
WILL BE PERFORMED ON THE FEATURES OF THE CSC MATRIX OR TO CALL XTOARRAY IF HESHE EXPECTS THE MATERIALIZED
DENSE ARRAY TO FIT IN MEMORY
TO AVOID MEMORY COPY THE CALLER SHOULD PASS A CSC MATRIX
NANS ARE TREATED AS MISSING VALUES DISREGARDED TO COMPUTE THE STATISTICS AND MAINTAINED DURING THE DATA TRANS
FORMATION
WE USE A BIASED ESTIMATOR FOR THE STANDARD DEVIATION EQUIVALENT TO NUMPYSTDX DDOF0 NOTE THAT THE
CHOICE OFDDOF IS UNLIKELY TO AFFECT MODEL PERFORMANCE
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
EXAMPLES USING SKLEARNPREPROCESSINGSCALE
•A DEMO OF KMEANS CLUSTERING ON THE HANDWRITTEN DIGITS DATA
63427SKLEARNPREPROCESSING POWERTRANSFORM
SKLEARNPREPROCESSING POWERTRANSFORM XMETHOD’WARN’ STANDARDIZETRUE COPYTRUE
POWER TRANSFORMS ARE A FAMILY OF PARAMETRIC MONOTONIC TRANSFORMATIONS THAT ARE APPLIED TO MAKE DATA MORE
GAUSSIANLIKE THIS IS USEFUL FOR MODELING ISSUES RELATED TO HETEROSCEDASTICITY NONCONSTANT VARIANCE OR OTHER
SITUATIONS WHERE NORMALITY IS DESIRED
CURRENTLY POWERTRANSFORM SUPPORTS THE BOXCOX TRANSFORM AND THE YEOJOHNSON TRANSFORM THE OPTIMAL PA
RAMETER FOR STABILIZING VARIANCE AND MINIMIZING SKEWNESS IS ESTIMATED THROUGH MAXIMUM LIKELIHOOD
BOXCOX REQUIRES INPUT DATA TO BE STRICTLY POSITIVE WHILE YEOJOHNSON SUPPORTS BOTH POSITIVE OR NEGATIVE DATA
BY DEFAULT ZEROMEAN UNITVARIANCE NORMALIZATION IS APPLIED TO THE TRANSFORMED DATA
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE DATA TO BE TRANSFORMED USING A POWER TRANS
FORMATION
METHOD STR THE POWER TRANSFORM METHOD AVAILABLE METHODS ARE
• ‘YEOJOHNSON’ 1 WORKS WITH POSITIVE AND NEGATIVE VALUES
• ‘BOXCOX’ 2 ONLY WORKS WITH STRICTLY POSITIVE VALUES
THE DEFAULT METHOD WILL BE CHANGED FROM ‘BOXCOX’ TO ‘YEOJOHNSON’ IN VERSION 023 TO
SUPPRESS THE FUTUREWARNING EXPLICITLY SET THE PARAMETER

STANDARDIZE BOOLEAN DEFAULTTRUE SET TO TRUE TO APPLY ZEROMEAN UNITVARIANCE NORMALIZA
TION TO THE TRANSFORMED OUTPUT
COPY BOOLEAN OPTIONAL DEFAULTTRUE SET TO FALSE TO PERFORM INPLACE COMPUTATION DURING
TRANSFORMATION
RETURNS
XTRANS ARRAYLIKE SHAPE NSAMPLES NFEATURES THE TRANSFORMED DATA
SEE ALSO
POWERTRANSFORMER EQUIVALENT TRANSFORMATION WITH THE TRANSFORMER API EG AS PART OF A PREPROCESS
INGSKLEARNPIPELINEPIPELINE
QUANTILETRANSFORM MAPS DATA TO A STANDARD NORMAL DISTRIBUTION WITH THE PARAMETER
OUTPUTDISTRIBUTIONNORMAL
NOTES
NANS ARE TREATED AS MISSING VALUES DISREGARDED IN FIT AND MAINTAINED IN TRANSFORM
FOR A COMPARISON OF THE DIFFERENT SCALERS TRANSFORMERS AND NORMALIZERS SEE EXAM
PLESPREPROCESSINGPLOTALLSCALINGPY
REFERENCES
12
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNPREPROCESSING IMPORT POWERTRANSFORM
DATA  1 2 3 2 4 5
PRINTPOWERTRANSFORMDATA METHODBOXCOX
1332 0707
 0256 0707
 1076 1414
```
635SKLEARNRANDOMPROJECTION RANDOM PROJECTION
RANDOM PROJECTION TRANSFORMERS
RANDOM PROJECTIONS ARE A SIMPLE AND COMPUTATIONALLY EFFICIENT WAY TO REDUCE THE DIMENSIONALITY OF THE DATA BY TRADING
A CONTROLLED AMOUNT OF ACCURACY AS ADDITIONAL VARIANCE FOR FASTER PROCESSING TIMES AND SMALLER MODEL SIZES
THE DIMENSIONS AND DISTRIBUTION OF RANDOM PROJECTIONS MATRICES ARE CONTROLLED SO AS TO PRESERVE THE PAIRWISE DISTANCES
BETWEEN ANY TWO SAMPLES OF THE DATASET
THE MAIN THEORETICAL RESULT BEHIND THE EFFICIENCY OF RANDOM PROJECTION IS THE JOHNSONLINDENSTRAUSS LEMMA QUOTING
WIKIPEDIA

IN MATHEMATICS THE JOHNSONLINDENSTRAUSS LEMMA IS A RESULT CONCERNING LOWDISTORTION EMBEDDINGS OF POINTS FROM HIGHDIMENSIONAL INTO LOWDIMENSIONAL EUCLIDEAN SPACE THE LEMMA STATES THAT A SMALL SET OF POINTS IN A HIGHDIMENSIONAL SPACE CAN BE EMBEDDED INTO A SPACE OF MUCH LOWER DIMENSION IN SUCH A WAY THAT DISTANCES BETWEEN THE POINTS ARE NEARLY PRESERVED THE MAP USED FOR THE EMBEDDING IS AT LEAST LIPSCHITZ AND CAN EVEN BE TAKEN TO BE AN ORTHOGONAL PROJECTION
USER GUIDE SEE THE RANDOM PROJECTION SECTION FOR FURTHER DETAILS
RANDOMPROJECTION
GAUSSIANRANDOMPROJECTION REDUCE DIMENSIONALITY THROUGH GAUSSIAN RANDOM PROJEC TION
RANDOMPROJECTION
SPARSERANDOMPROJECTION REDUCE DIMENSIONALITY THROUGH SPARSE RANDOM PROJECTION
6351SKLEARNRANDOMPROJECTION GAUSSIANRANDOMPROJECTION
CLASSSKLEARNRANDOMPROJECTION GAUSSIANRANDOMPROJECTION NCOMPONENTS’AUTO’ EPS01 RAN DOMSTATENONE
REDUCE DIMENSIONALITY THROUGH GAUSSIAN RANDOM PROJECTION
THE COMPONENTS OF THE RANDOM MATRIX ARE DRAWN FROM N0 1 NCOMPONENTS
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT OR ‘AUTO’ OPTIONAL DEFAULT ‘AUTO’ DIMENSIONALITY OF THE TARGET PROJECTION SPACE
NCOMPONENTS CAN BE AUTOMATICALLY ADJUSTED ACCORDING TO THE NUMBER OF SAMPLES IN THE DATASET AND THE BOUND GIVEN BY THE JOHNSONLINDENSTRAUSS LEMMA IN THAT CASE THE QUALITY OF THE EMBEDDING IS CONTROLLED BY THE EPS PARAMETER
IT SHOULD BE NOTED THAT JOHNSONLINDENSTRAUSS LEMMA CAN YIELD VERY CONSERVATIVE ESTIMATED OF THE REQUIRED NUMBER OF COMPONENTS AS IT MAKES NO ASSUMPTION ON THE STRUCTURE OF THE DATASET
EPS STRICTLY POSITIVE FLOAT OPTIONAL DEFAULT01 PARAMETER TO CONTROL THE QUALITY OF THE EMBED DING ACCORDING TO THE JOHNSONLINDENSTRAUSS LEMMA WHEN NCOMPONENTS IS SET TO ‘AUTO’ SMALLER VALUES LEAD TO BETTER EMBEDDING AND HIGHER NUMBER OF DIMENSIONS NCOMPONENTS IN THE TARGET PROJECTION SPACE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE CONTROL THE PSEUDO RANDOM NUMBER GENERATOR USED TO GENERATE THE MATRIX AT FIT TIME IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES
NCOMPONENT INT CONCRETE NUMBER OF COMPONENTS COMPUTED WHEN NCOMPONENTS”AUTO”
COMPONENTS NUMPY ARRAY OF SHAPE NCOMPONENTS NFEATURES RANDOM MATRIX USED FOR THE PROJECTION
SEE ALSO
SPARSERANDOMPROJECTION

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EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNRANDOMPROJECTION IMPORT GAUSSIANRANDOMPROJECTION
RNG  NPRANDOMRANDOMSTATE42
X  RNGRAND100 10000
TRANSFORMER  GAUSSIANRANDOMPROJECTIONRANDOMSTATERNG
XNEW  TRANSFORMERFITTRANSFORMX
XNEWSHAPE
```
100 3947
METHODS
FITSELF X Y GENERATE A SPARSE RANDOM PROJECTION MATRIX
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X PROJECT THE DATA BY USING MATRIX PRODUCT WITH THE RAN
DOM MATRIX
INIT SELFNCOMPONENTS‘AUTO’ EPS01 RANDOMSTATENONE
FITSELFXYNONE
GENERATE A SPARSE RANDOM PROJECTION MATRIX
PARAMETERS
XNUMPY ARRAY OR SCIPYSPARSE OF SHAPE NSAMPLES NFEATURES TRAINING SET ONLY THE
SHAPE IS USED TO FIND OPTIMAL RANDOM MATRIX DIMENSIONS BASED ON THE THEORY REFERENCED IN
THE AFORE MENTIONED PAPERS
YIGNORED
RETURNS
SELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS

RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
PROJECT THE DATA BY USING MATRIX PRODUCT WITH THE RANDOM MATRIX
PARAMETERS
XNUMPY ARRAY OR SCIPYSPARSE OF SHAPE NSAMPLES NFEATURES THE INPUT DATA TO PROJECT
INTO A SMALLER DIMENSIONAL SPACE
RETURNS
XNEW NUMPY ARRAY OR SCIPY SPARSE OF SHAPE NSAMPLES NCOMPONENTS PROJECTED ARRAY
6352SKLEARNRANDOMPROJECTION SPARSERANDOMPROJECTION
CLASSSKLEARNRANDOMPROJECTION SPARSERANDOMPROJECTION NCOMPONENTS'AUTO'
DENSITY'AUTO' EPS01
DENSEOUTPUTFALSE RAN
DOMSTATENONE
REDUCE DIMENSIONALITY THROUGH SPARSE RANDOM PROJECTION
SPARSE RANDOM MATRIX IS AN ALTERNATIVE TO DENSE RANDOM PROJECTION MATRIX THAT GUARANTEES SIMILAR EMBEDDING
QUALITY WHILE BEING MUCH MORE MEMORY EFFICIENT AND ALLOWING FASTER COMPUTATION OF THE PROJECTED DATA
IF WE NOTES 1 DENSITY THE COMPONENTS OF THE RANDOM MATRIX ARE DRAWN FROM
• SQRTS SQRTNCOMPONENTS WITH PROBABILITY 1 2S
• 0 WITH PROBABILITY 1 1 S
• SQRTS SQRTNCOMPONENTS WITH PROBABILITY 1 2S
READ MORE IN THE USER GUIDE
PARAMETERS
NCOMPONENTS INT OR 'AUTO' OPTIONAL DEFAULT 'AUTO' DIMENSIONALITY OF THE TARGET PROJECTION
SPACE
NCOMPONENTS CAN BE AUTOMATICALLY ADJUSTED ACCORDING TO THE NUMBER OF SAMPLES IN THE
DATASET AND THE BOUND GIVEN BY THE JOHNSONLINDENSTRAUSS LEMMA IN THAT CASE THE QUALITY
OF THE EMBEDDING IS CONTROLLED BY THE EPS PARAMETER
IT SHOULD BE NOTED THAT JOHNSONLINDENSTRAUSS LEMMA CAN YIELD VERY CONSERVATIVE ESTIMATED
OF THE REQUIRED NUMBER OF COMPONENTS AS IT MAKES NO ASSUMPTION ON THE STRUCTURE OF THE
DATASET
DENSITY FLOAT IN RANGE 0 1 OPTIONAL DEFAULT'AUTO' RATIO OF NONZERO COMPONENT IN THE
RANDOM PROJECTION MATRIX
635SKLEARNRANDOMPROJECTION RANDOM PROJECTION 2289

IF DENSITY ‘AUTO’ THE VALUE IS SET TO THE MINIMUM DENSITY AS RECOMMENDED BY PING LI ET
AL 1 SQRTNFEATURES
USE DENSITY 1 30 IF YOU WANT TO REPRODUCE THE RESULTS FROM ACHLIOPTAS 2001
EPS STRICTLY POSITIVE FLOAT OPTIONAL DEFAULT01 PARAMETER TO CONTROL THE QUALITY OF THE EM
BEDDING ACCORDING TO THE JOHNSONLINDENSTRAUSS LEMMA WHEN NCOMPONENTS IS SET TO ‘AUTO’
SMALLER VALUES LEAD TO BETTER EMBEDDING AND HIGHER NUMBER OF DIMENSIONS NCOMPONENTS
IN THE TARGET PROJECTION SPACE
DENSEOUTPUT BOOLEAN OPTIONAL DEFAULTFALSE IF TRUE ENSURE THAT THE OUTPUT OF THE RANDOM
PROJECTION IS A DENSE NUMPY ARRAY EVEN IF THE INPUT AND RANDOM PROJECTION MATRIX ARE BOTH
SPARSE IN PRACTICE IF THE NUMBER OF COMPONENTS IS SMALL THE NUMBER OF ZERO COMPONENTS IN
THE PROJECTED DATA WILL BE VERY SMALL AND IT WILL BE MORE CPU AND MEMORY EFFICIENT TO USE A
DENSE REPRESENTATION
IF FALSE THE PROJECTED DATA USES A SPARSE REPRESENTATION IF THE INPUT IS SPARSE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE CONTROL THE
PSEUDO RANDOM NUMBER GENERATOR USED TO GENERATE THE MATRIX AT FIT TIME IF INT RANDOMSTATE
IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
ATTRIBUTES
NCOMPONENT INT CONCRETE NUMBER OF COMPONENTS COMPUTED WHEN NCOMPONENTS”AUTO”
COMPONENTS CSR MATRIX WITH SHAPE NCOMPONENTS NFEATURES RANDOM MATRIX USED FOR
THE PROJECTION
DENSITY FLOAT IN RANGE 00 10 CONCRETE DENSITY COMPUTED FROM WHEN DENSITY “AUTO”
SEE ALSO
GAUSSIANRANDOMPROJECTION
REFERENCES
R0FECF191E4B81 R0FECF191E4B82
EXAMPLES
```
IMPORT NUMPY AS NP
FROM SKLEARNRANDOMPROJECTION IMPORT SPARSERANDOMPROJECTION
RNG NPRANDOMRANDOMSTATE42
X RNGRAND100 10000
TRANSFORMER SPARSERANDOMPROJECTIONRANDOMSTATERNG
XNEW TRANSFORMERFITTRANSFORMX
XNEWSHAPE
100 3947
VERY FEW COMPONENTS ARE NONZERO
NPMEANTRANSFORMERCOMPONENTS 0
00100
```

METHODS
FITSELF X Y GENERATE A SPARSE RANDOM PROJECTION MATRIX
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X PROJECT THE DATA BY USING MATRIX PRODUCT WITH THE RAN
DOM MATRIX
INIT SELFNCOMPONENTS'AUTO' DENSITY'AUTO' EPS01 DENSEOUTPUTFALSE RAN
DOMSTATENONE
FITSELFXYNONE
GENERATE A SPARSE RANDOM PROJECTION MATRIX
PARAMETERS
XNUMPY ARRAY OR SCIPYSPARSE OF SHAPE NSAMPLES NFEATURES TRAINING SET ONLY THE
SHAPE IS USED TO FIND OPTIMAL RANDOM MATRIX DIMENSIONS BASED ON THE THEORY REFERENCED IN
THE AFORE MENTIONED PAPERS
YIGNORED
RETURNS
SELF
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF

TRANSFORM SELFX
PROJECT THE DATA BY USING MATRIX PRODUCT WITH THE RANDOM MATRIX
PARAMETERS
XNUMPY ARRAY OR SCIPYSPARSE OF SHAPE NSAMPLES NFEATURES THE INPUT DATA TO PROJECT
INTO A SMALLER DIMENSIONAL SPACE
RETURNS
XNEW NUMPY ARRAY OR SCIPY SPARSE OF SHAPE NSAMPLES NCOMPONENTS PROJECTED ARRAY
EXAMPLES USING SKLEARNRANDOMPROJECTIONSPARSERANDOMPROJECTION
•THE JOHNSONLINDENSTRAUSS BOUND FOR EMBEDDING WITH RANDOM PROJECTIONS
•MANIFOLD LEARNING ON HANDWRITTEN DIGITS LOCALLY LINEAR EMBEDDING ISOMAP
RANDOMPROJECTION
JOHNSONLINDENSTRAUSSMINDIM FIND A 'SAFE' NUMBER OF COMPONENTS TO RANDOMLY PROJECT TO
6353SKLEARNRANDOMPROJECTION JOHNSONLINDENSTRAUSSMINDIM
SKLEARNRANDOMPROJECTION JOHNSONLINDENSTRAUSSMINDIM NSAMPLES EPS01
FIND A 'SAFE' NUMBER OF COMPONENTS TO RANDOMLY PROJECT TO
THE DISTORTION INTRODUCED BY A RANDOM PROJECTION PONLY CHANGES THE DISTANCE BETWEEN TWO POINTS BY A FACTOR 1
EPS IN AN EUCLIDEAN SPACE WITH GOOD PROBABILITY THE PROJECTION PIS AN EPSEMBEDDING AS DEFINED BY
1 EPS U V2 PU PV2 1 EPS U V2
WHERE U AND V ARE ANY ROWS TAKEN FROM A DATASET OF SHAPE NSAMPLES NFEATURES EPS IS IN 0 1 AND P IS A
PROJECTION BY A RANDOM GAUSSIAN N0 1 MATRIX WITH SHAPE NCOMPONENTS NFEATURES OR A SPARSE ACHLIOPTAS
MATRIX
THE MINIMUM NUMBER OF COMPONENTS TO GUARANTEE THE EPSEMBEDDING IS GIVEN BY
NCOMPONENTS 4 LOGNSAMPLES EPS2 2 EPS3 3
NOTE THAT THE NUMBER OF DIMENSIONS IS INDEPENDENT OF THE ORIGINAL NUMBER OF FEATURES BUT INSTEAD DEPENDS ON
THE SIZE OF THE DATASET THE LARGER THE DATASET THE HIGHER IS THE MINIMAL DIMENSIONALITY OF AN EPSEMBEDDING
READ MORE IN THE USER GUIDE
PARAMETERS
NSAMPLES INT OR NUMPY ARRAY OF INT GREATER THAN 0 NUMBER OF SAMPLES IF AN ARRAY IS GIVEN
IT WILL COMPUTE A SAFE NUMBER OF COMPONENTS ARRAYWISE
EPS FLOAT OR NUMPY ARRAY OF FLOAT IN 01 OPTIONAL DEFAULT01 MAXIMUM DISTORTION RATE AS
DEFINED BY THE JOHNSONLINDENSTRAUSS LEMMA IF AN ARRAY IS GIVEN IT WILL COMPUTE A SAFE
NUMBER OF COMPONENTS ARRAYWISE
RETURNS
NCOMPONENTS INT OR NUMPY ARRAY OF INT THE MINIMAL NUMBER OF COMPONENTS TO GUARANTEE
WITH GOOD PROBABILITY AN EPSEMBEDDING WITH NSAMPLES

REFERENCES
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EXAMPLES
JOHNSONLINDENSTRAUSSMINDIM1E6 EPS05
663
JOHNSONLINDENSTRAUSSMINDIM1E6 EPS05 01 001
ARRAY 663 11841 1112658
JOHNSONLINDENSTRAUSSMINDIM1E4 1E5 1E6 EPS01
ARRAY 7894 9868 11841
EXAMPLES USING SKLEARNRANDOMPROJECTIONJOHNSONLINDENSTRAUSSMINDIM
•THE JOHNSONLINDENSTRAUSS BOUND FOR EMBEDDING WITH RANDOM PROJECTIONS
636SKLEARNSEMISUPERVISED SEMISUPERVISED LEARNING
THESKLEARNSEMISUPERVISED MODULE IMPLEMENTS SEMISUPERVISED LEARNING ALGORITHMS THESE ALGORITHMS
UTILIZED SMALL AMOUNTS OF LABELED DATA AND LARGE AMOUNTS OF UNLABELED DATA FOR CLASSIFICATION TASKS THIS MODULE
INCLUDES LABEL PROPAGATION
USER GUIDE SEE THE SEMISUPERVISED SECTION FOR FURTHER DETAILS
SEMISUPERVISEDLABELPROPAGATION KERNEL
LABEL PROPAGATION CLASSIFIER
SEMISUPERVISEDLABELSPREADING KERNEL
LABELSPREADING MODEL FOR SEMISUPERVISED LEARNING
6361SKLEARNSEMISUPERVISED LABELPROPAGATION
CLASSSKLEARNSEMISUPERVISED LABELPROPAGATION KERNEL’RBF’ GAMMA20 NNEIGHBORS7
MAXITER1000 TOL0001 NJOBSNONE
LABEL PROPAGATION CLASSIFIER
READ MORE IN THE USER GUIDE
PARAMETERS
KERNEL ‘KNN’ ‘RBF’ CALLABLE STRING IDENTIFIER FOR KERNEL FUNCTION TO USE OR THE KERNEL FUNCTION
ITSELF ONLY ‘RBF’ AND ‘KNN’ STRINGS ARE VALID INPUTS THE FUNCTION PASSED SHOULD TAKE TWO
INPUTS EACH OF SHAPE NSAMPLES NFEATURES AND RETURN A NSAMPLES NSAMPLES SHAPED
WEIGHT MATRIX
GAMMA FLOAT PARAMETER FOR RBF KERNEL
NNEIGHBORS INTEGER 0 PARAMETER FOR KNN KERNEL

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MAXITER INTEGER CHANGE MAXIMUM NUMBER OF ITERATIONS ALLOWED
TOLFLOAT CONVERGENCE TOLERANCE THRESHOLD TO CONSIDER THE SYSTEM AT STEADY STATE
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS
1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
ATTRIBUTES
XARRAY SHAPE NSAMPLES NFEATURES INPUT ARRAY
CLASSES ARRAY SHAPE NCLASSES THE DISTINCT LABELS USED IN CLASSIFYING INSTANCES
LABELDISTRIBUTIONS ARRAY SHAPE NSAMPLES NCLASSES CATEGORICAL DISTRIBUTION FOR EACH
ITEM
TRANSDUCTION ARRAY SHAPE NSAMPLES LABEL ASSIGNED TO EACH ITEM VIA THE TRANSDUCTION
NITER INT NUMBER OF ITERATIONS RUN
SEE ALSO
LABELSPREADING ALTERNATE LABEL PROPAGATION STRATEGY MORE ROBUST TO NOISE
REFERENCES
XIAOJIN ZHU AND ZOUBIN GHAHRAMANI LEARNING FROM LABELED AND UNLABELED DATA WITH LABEL PROPAGATION TECH
NICAL REPORT CMUCALD02107 CARNEGIE MELLON UNIVERSITY 2002 HTTPPAGESCSWISCEDUJERRYZHUPUB
CMUCALD02107PDF
EXAMPLES
 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT DATASETS
 FROM SKLEARNSEMISUPERVISED IMPORT LABELPROPAGATION
LABELPROPMODEL LABELPROPAGATION
IRIS DATASETSLOADIRIS
RNG NPRANDOMRANDOMSTATE42
RANDOMUNLABELEDPOINTS RNGRANDLENIRISTARGET 03
LABELS NPCOPYIRISTARGET
LABELSRANDOMUNLABELEDPOINTS 1
LABELPROPMODELFITIRISDATA LABELS

LABELPROPAGATION
METHODS
FITSELF X Y
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PERFORMS INDUCTIVE INFERENCE ACROSS THE MODEL
PREDICTPROBA SELF X PREDICT PROBABILITY FOR EACH POSSIBLE OUTCOME
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
CONTINUED ON NEXT PAGE

TABLE 6270 – CONTINUED FROM PREVIOUS PAGE
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFKERNEL’RBF’ GAMMA20 NNEIGHBORS7 MAXITER1000 TOL0001 NJOBSNONE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PERFORMS INDUCTIVE INFERENCE ACROSS THE MODEL
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
YARRAYLIKE SHAPE NSAMPLES PREDICTIONS FOR INPUT DATA
PREDICTPROBA SELFX
PREDICT PROBABILITY FOR EACH POSSIBLE OUTCOME
COMPUTE THE PROBABILITY ESTIMATES FOR EACH SINGLE SAMPLE IN X AND EACH POSSIBLE OUTCOME SEEN DURING
TRAINING CATEGORICAL DISTRIBUTION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
PROBABILITIES ARRAY SHAPE NSAMPLES NCLASSES NORMALIZED PROBABILITY DISTRIBUTIONS
ACROSS CLASS LABELS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT

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RETURNS
SELF
6362SKLEARNSEMISUPERVISED LABELSPREADING
CLASSSKLEARNSEMISUPERVISED LABELSPREADING KERNEL'RBF' GAMMA20 NNEIGHBORS7
ALPHA02 MAXITER30 TOL0001
NJOBSNONE
LABELSPREADING MODEL FOR SEMISUPERVISED LEARNING
THIS MODEL IS SIMILAR TO THE BASIC LABEL PROPAGATION ALGORITHM BUT USES AFFINITY MATRIX BASED ON THE NORMALIZED
GRAPH LAPLACIAN AND SOFT CLAMPING ACROSS THE LABELS
READ MORE IN THE USER GUIDE
PARAMETERS
KERNEL 'KNN' 'RBF' CALLABLE STRING IDENTIFIER FOR KERNEL FUNCTION TO USE OR THE KERNEL FUNCTION
ITSELF ONLY 'RBF' AND 'KNN' STRINGS ARE VALID INPUTS THE FUNCTION PASSED SHOULD TAKE TWO
INPUTS EACH OF SHAPE NSAMPLES NFEATURES AND RETURN A NSAMPLES NSAMPLES SHAPED
WEIGHT MATRIX
GAMMA FLOAT PARAMETER FOR RBF KERNEL
NNEIGHBORS INTEGER 0 PARAMETER FOR KNN KERNEL
ALPHA FLOAT CLAMPING FACTOR A VALUE IN 0 1 THAT SPECIFIES THE RELATIVE AMOUNT THAT AN INSTANCE
SHOULD ADOPT THE INFORMATION FROM ITS NEIGHBORS AS OPPOSED TO ITS INITIAL LABEL ALPHA0
MEANS KEEPING THE INITIAL LABEL INFORMATION ALPHA1 MEANS REPLACING ALL INITIAL INFORMATION
MAXITER INTEGER MAXIMUM NUMBER OF ITERATIONS ALLOWED
TOLFLOAT CONVERGENCE TOLERANCE THRESHOLD TO CONSIDER THE SYSTEM AT STEADY STATE
NJOBS INT OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF PARALLEL JOBS TO RUN NONE MEANS
1 UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
ATTRIBUTES
XARRAY SHAPE NSAMPLES NFEATURES INPUT ARRAY
CLASSES ARRAY SHAPE NCLASSES THE DISTINCT LABELS USED IN CLASSIFYING INSTANCES
LABELDISTRIBUTIONS ARRAY SHAPE NSAMPLES NCLASSES CATEGORICAL DISTRIBUTION FOR EACH
ITEM
TRANSDUCTION ARRAY SHAPE NSAMPLES LABEL ASSIGNED TO EACH ITEM VIA THE TRANSDUCTION
NITER INT NUMBER OF ITERATIONS RUN
SEE ALSO
LABELPROPAGATION UNREGULARIZED GRAPH BASED SEMISUPERVISED LEARNING
REFERENCES
DENGYONG ZHOU OLIVIER BOUSQUET THOMAS NAVIN LAL JASON WESTON BERNHARD SCHOELKOPF LEARNING WITH
LOCAL AND GLOBAL CONSISTENCY 2004 HTTPCITESEERISTPSUEDUVIEWDOCSUMMARYDOI10111153219

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EXAMPLES
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 IMPORT NUMPY AS NP
 FROM SKLEARN IMPORT DATASETS
 FROM SKLEARNSEMISUPERVISED IMPORT LABELSPREADING
LABELPROPMODEL  LABELSPREADING
IRIS  DATASETSLOADIRIS
RNG  NPRANDOMRANDOMSTATE42
RANDOMUNLABELEDPOINTS  RNGRANDLENIRISTARGET  03
LABELS  NPCOPYIRISTARGET
LABELSRANDOMUNLABELEDPOINTS  1
LABELPROPMODELFITIRISDATA LABELS

LABELSPREADING
```
METHODS
FITSELF X Y FIT A SEMISUPERVISED LABEL PROPAGATION MODEL BASED
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PERFORMS INDUCTIVE INFERENCE ACROSS THE MODEL
PREDICTPROBA SELF X PREDICT PROBABILITY FOR EACH POSSIBLE OUTCOME
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFKERNEL’RBF’ GAMMA20 NNEIGHBORS7 ALPHA02 MAXITER30 TOL0001
NJOBSNONE
FITSELFXY
FIT A SEMISUPERVISED LABEL PROPAGATION MODEL BASED
ALL THE INPUT DATA IS PROVIDED MATRIX X LABELED AND UNLABELED AND CORRESPONDING LABEL MATRIX Y WITH A
DEDICATED MARKER VALUE FOR UNLABELED SAMPLES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES A NSAMPLES BY NSAMPLES SIZE MATRIX
WILL BE CREATED FROM THIS
YARRAYLIKE SHAPE NSAMPLES NLABELEDSAMPLES UNLABELED POINTS ARE MARKED AS 1
ALL UNLABELED SAMPLES WILL BE TRANSDUCTIVELY ASSIGNED LABELS
RETURNS
SELF RETURNS AN INSTANCE OF SELF
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES

PREDICTSELFX
PERFORMS INDUCTIVE INFERENCE ACROSS THE MODEL
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
YARRAYLIKE SHAPE NSAMPLES PREDICTIONS FOR INPUT DATA
PREDICTPROBA SELFX
PREDICT PROBABILITY FOR EACH POSSIBLE OUTCOME
COMPUTE THE PROBABILITY ESTIMATES FOR EACH SINGLE SAMPLE IN X AND EACH POSSIBLE OUTCOME SEEN DURING
TRAINING CATEGORICAL DISTRIBUTION
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
PROBABILITIES ARRAY SHAPE NSAMPLES NCLASSES NORMALIZED PROBABILITY DISTRIBUTIONS
ACROSS CLASS LABELS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNSEMISUPERVISEDLABELSPREADING
•DECISION BOUNDARY OF LABEL PROPAGATION VERSUS SVM ON THE IRIS DATASET
•LABEL PROPAGATION LEARNING A COMPLEX STRUCTURE
•LABEL PROPAGATION DIGITS DEMONSTRATING PERFORMANCE
•LABEL PROPAGATION DIGITS ACTIVE LEARNING

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THESKLEARNSVM MODULE INCLUDES SUPPORT VECTOR MACHINE ALGORITHMS
USER GUIDE SEE THE SUPPORT VECTOR MACHINES SECTION FOR FURTHER DETAILS
6371 ESTIMATORS
SVMLINEARSVC PENALTY LOSS DUAL TOL C LINEAR SUPPORT VECTOR CLASSIFICATION
SVMLINEARSVR EPSILON TOL C LOSS LINEAR SUPPORT VECTOR REGRESSION
SVMNUSVC NU KERNEL DEGREE GAMMA NUSUPPORT VECTOR CLASSIFICATION
SVMNUSVR NU C KERNEL DEGREE GAMMA NU SUPPORT VECTOR REGRESSION
SVMONECLASSSVM KERNEL DEGREE GAMMA UNSUPERVISED OUTLIER DETECTION
SVMSVC C KERNEL DEGREE GAMMA COEF0 CSUPPORT VECTOR CLASSIFICATION
SVMSVR KERNEL DEGREE GAMMA COEF0 TOL EPSILONSUPPORT VECTOR REGRESSION
SKLEARNSVM LINEARSVC
CLASSSKLEARNSVM LINEARSVC PENALTY’L2’ LOSS’SQUAREDHINGE’ DUALTRUE TOL00001
C10 MULTICLASS’OVR’ FITINTERCEPTTRUE INTERCEPTSCALING1
CLASSWEIGHTNONE VERBOSE0 RANDOMSTATENONE MAXITER1000
LINEAR SUPPORT VECTOR CLASSIFICATION
SIMILAR TO SVC WITH PARAMETER KERNEL’LINEAR’ BUT IMPLEMENTED IN TERMS OF LIBLINEAR RATHER THAN LIBSVM SO IT HAS MORE FLEXIBILITY IN THE CHOICE OF PENALTIES AND LOSS FUNCTIONS AND SHOULD SCALE BETTER TO LARGE NUMBERS OF SAMPLES
THIS CLASS SUPPORTS BOTH DENSE AND SPARSE INPUT AND THE MULTICLASS SUPPORT IS HANDLED ACCORDING TO A ONEVSTHE REST SCHEME
READ MORE IN THE USER GUIDE
PARAMETERS
PENALTY STRING ‘L1’ OR ‘L2’ DEFAULT’L2’ SPECIFIES THE NORM USED IN THE PENALIZATION THE ‘L2’ PENALTY IS THE STANDARD USED IN SVC THE ‘L1’ LEADS TO COEF VECTORS THAT ARE SPARSE
LOSS STRING ‘HINGE’ OR ‘SQUAREDHINGE’ DEFAULT’SQUAREDHINGE’ SPECIFIES THE LOSS FUNCTION ‘HINGE’ IS THE STANDARD SVM LOSS USED EG BY THE SVC CLASS WHILE ‘SQUAREDHINGE’ IS THE SQUARE OF THE HINGE LOSS
DUAL BOOL DEFAULTTRUE SELECT THE ALGORITHM TO EITHER SOLVE THE DUAL OR PRIMAL OPTIMIZATION PROBLEM PREFER DUALFALSE WHEN NSAMPLES NFEATURES
TOLFLOAT OPTIONAL DEFAULT1E4 TOLERANCE FOR STOPPING CRITERIA
CFLOAT OPTIONAL DEFAULT10 PENALTY PARAMETER C OF THE ERROR TERM
MULTICLASS STRING ‘OVR’ OR ‘CRAMMERSINGER’ DEFAULT’OVR’ DETERMINES THE MULTICLASS STRATEGY IF YCONTAINS MORE THAN TWO CLASSES OVR TRAINS NCLASSES ONEVSREST CLAS SIFIERS WHILE CRAMMERSINGER OPTIMIZES A JOINT OBJECTIVE OVER ALL CLASSES WHILE CRAMMERSINGER IS INTERESTING FROM A THEORETICAL PERSPECTIVE AS IT IS CONSISTENT IT IS SEL DOM USED IN PRACTICE AS IT RARELY LEADS TO BETTER ACCURACY AND IS MORE EXPENSIVE TO COMPUTE IFCRAMMERSINGER IS CHOSEN THE OPTIONS LOSS PENALTY AND DUAL WILL BE IGNORED
FITINTERCEPT BOOLEAN OPTIONAL DEFAULTTRUE WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO INTERCEPT WILL BE USED IN CALCULATIONS IE DATA IS EXPECTED TO

BE ALREADY CENTERED
INTERCEPTSCALING FLOAT OPTIONAL DEFAULT1 WHEN SELFFITINTERCEPT IS TRUE INSTANCE VECTOR
X BECOMESX SELFINTERCEPTSCALING IE A “SYNTHETIC” FEATURE WITH CONSTANT
VALUE EQUALS TO INTERCEPTSCALING IS APPENDED TO THE INSTANCE VECTOR THE INTERCEPT BECOMES
INTERCEPTSCALING SYNTHETIC FEATURE WEIGHT NOTE THE SYNTHETIC FEATURE WEIGHT IS SUBJECT TO
L1L2 REGULARIZATION AS ALL OTHER FEATURES TO LESSEN THE EFFECT OF REGULARIZATION ON SYNTHETIC
FEATURE WEIGHT AND THEREFORE ON THE INTERCEPT INTERCEPTSCALING HAS TO BE INCREASED
CLASSWEIGHT DICT ‘BALANCED’ OPTIONAL SET THE PARAMETER C OF CLASS I TO
CLASSWEIGHTI CFOR SVC IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT
ONE THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY
PROPORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES
NPBINCOUNTY
VERBOSE INT DEFAULT0 ENABLE VERBOSE OUTPUT NOTE THAT THIS SETTING TAKES ADVANTAGE OF A PER
PROCESS RUNTIME SETTING IN LIBLINEAR THAT IF ENABLED MAY NOT WORK PROPERLY IN A MULTITHREADED
CONTEXT
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA FOR THE DUAL COORDI
NATE DESCENT IF DUALTRUE WHENDUALFALSE THE UNDERLYING IMPLEMENTATION OF
LINEARSVC IS NOT RANDOM AND RANDOMSTATE HAS NO EFFECT ON THE RESULTS IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RAN
DOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE
RANDOMSTATE INSTANCE USED BY NPRANDOM
MAXITER INT DEFAULT1000 THE MAXIMUM NUMBER OF ITERATIONS TO BE RUN
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES IF NCLASSES 2 ELSE NCLASSES NFEATURES WEIGHTS AS
SIGNED TO THE FEATURES COEFFICIENTS IN THE PRIMAL PROBLEM THIS IS ONLY AVAILABLE IN THE CASE
OF A LINEAR KERNEL
COEF IS A READONLY PROPERTY DERIVED FROM RAWCOEF THAT FOLLOWS THE INTERNAL MEMORY
LAYOUT OF LIBLINEAR
INTERCEPT ARRAY SHAPE 1 IF NCLASSES 2 ELSE NCLASSES CONSTANTS IN DECISION FUNCTION
SEE ALSO
SVC IMPLEMENTATION OF SUPPORT VECTOR MACHINE CLASSIFIER USING LIBSVM THE KERNEL CAN BE NONLINEAR BUT ITS
SMO ALGORITHM DOES NOT SCALE TO LARGE NUMBER OF SAMPLES AS LINEARSVC DOES FURTHERMORE SVC MULTI
CLASS MODE IS IMPLEMENTED USING ONE VS ONE SCHEME WHILE LINEARSVC USES ONE VS THE REST IT IS POSSIBLE TO
IMPLEMENT ONE VS THE REST WITH SVC BY USING THE SKLEARNMULTICLASSONEVSRESTCLASSIFIER
WRAPPER FINALLY SVC CAN FIT DENSE DATA WITHOUT MEMORY COPY IF THE INPUT IS CCONTIGUOUS SPARSE DATA
WILL STILL INCUR MEMORY COPY THOUGH
SKLEARNLINEARMODELSGDCLASSIFIER SGDCLASSIFIER CAN OPTIMIZE THE SAME COST FUNCTION AS LIN
EARSVC BY ADJUSTING THE PENALTY AND LOSS PARAMETERS IN ADDITION IT REQUIRES LESS MEMORY ALLOWS INCRE
MENTAL ONLINE LEARNING AND IMPLEMENTS VARIOUS LOSS FUNCTIONS AND REGULARIZATION REGIMES
NOTES
THE UNDERLYING C IMPLEMENTATION USES A RANDOM NUMBER GENERATOR TO SELECT FEATURES WHEN FITTING THE MODEL
IT IS THUS NOT UNCOMMON TO HAVE SLIGHTLY DIFFERENT RESULTS FOR THE SAME INPUT DATA IF THAT HAPPENS TRY WITH A
SMALLERTOL PARAMETER

THE UNDERLYING IMPLEMENTATION LIBLINEAR USES A SPARSE INTERNAL REPRESENTATION FOR THE DATA THAT WILL INCUR A MEMORY COPY
PREDICT OUTPUT MAY NOT MATCH THAT OF STANDALONE LIBLINEAR IN CERTAIN CASES SEE DIFFERENCES FROM LIBLINEAR IN THE NARRATIVE DOCUMENTATION
REFERENCES
LIBLINEAR A LIBRARY FOR LARGE LINEAR CLASSIFICATION
EXAMPLES
FROM SKLEARNSVM IMPORT LINEARSVC
FROM SKLEARNDATASETS IMPORT MAKECLASSIFICATION
X Y MAKECLASSIFICATIONNFEATURES4 RANDOMSTATE0
CLF LINEARSVCRANDOMSTATE0 TOL1E5
CLFFITX Y
LINEARSVCC10 CLASSWEIGHTNONE DUALTRUE FITINTERCEPTTRUE
INTERCEPTSCALING1 LOSSSQUAREDHINGE MAXITER1000
MULTICLASSOVR PENALTYL2 RANDOMSTATE0 TOL1E05 VERBOSE0
PRINTCLFCOEF
0085 0394 0498 0375
PRINTCLFINTERCEPT
0284
PRINTCLFPREDICT0 0 0 0
1
METHODS
DECISIONFUNCTION SELF X PREDICT CONFIDENCE SCORES FOR SAMPLES
DENSIFY SELF CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
FITSELF X Y SAMPLEWEIGHT FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT CLASS LABELS FOR SAMPLES IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
SPARSIFY SELF CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
INIT SELFPENALTY'L2' LOSS'SQUAREDHINGE' DUALTRUE TOL00001 C10 MULTICLASS'OVR' FITINTERCEPTTRUE INTERCEPTSCALING1 CLASSWEIGHTNONE VERBOSE0 RAN DOMSTATENONE MAXITER1000
DECISIONFUNCTION SELFX
PREDICT CONFIDENCE SCORES FOR SAMPLES
THE CONFIDENCE SCORE FOR A SAMPLE IS THE SIGNED DISTANCE OF THAT SAMPLE TO THE HYPERPLANE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS

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ARRAY SHAPENSAMPLES IF NCLASSES 2 ELSE NSAMPLES NCLASSES CONFIDENCE
SCORES PER SAMPLE CLASS COMBINATION IN THE BINARY CASE CONFIDENCE SCORE FOR
SELFCLASSES1 WHERE 0 MEANS THIS CLASS WOULD BE PREDICTED
DENSIFYSELF
CONVERT COEFFICIENT MATRIX TO DENSE ARRAY FORMAT
CONVERTS THE COEF MEMBER BACK TO A NUMPYNDARRAY THIS IS THE DEFAULT FORMAT OF COEF AND IS
REQUIRED FOR FITTING SO CALLING THIS METHOD IS ONLY REQUIRED ON MODELS THAT HAVE PREVIOUSLY BEEN SPARSIFIED
OTHERWISE IT IS A NOOP
RETURNS
SELF ESTIMATOR
FITSELFXYSAMPLEWEIGHTNONE
FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE
NSAMPLES IN THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES TARGET VECTOR RELATIVE TO X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL ARRAY OF WEIGHTS THAT ARE AS
SIGNED TO INDIVIDUAL SAMPLES IF NOT PROVIDED THEN EACH SAMPLE IS GIVEN UNIT WEIGHT
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT CLASS LABELS FOR SAMPLES IN X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES PREDICTED CLASS LABEL PER SAMPLE
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X

SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT
RETURNS
SELF
SPARSIFY SELF
CONVERT COEFFICIENT MATRIX TO SPARSE FORMAT
CONVERTS THE COEF MEMBER TO A SCIPYSPARSE MATRIX WHICH FOR L1REGULARIZED MODELS CAN BE MUCH MORE MEMORY AND STORAGEEFFICIENT THAN THE USUAL NUMPYNDARRAY REPRESENTATION
THEINTERCEPT MEMBER IS NOT CONVERTED
RETURNS
SELF ESTIMATOR
NOTES
FOR NONSPARSE MODELS IE WHEN THERE ARE NOT MANY ZEROS IN COEF THIS MAY ACTUALLY INCREASE MEMORY USAGE SO USE THIS METHOD WITH CARE A RULE OF THUMB IS THAT THE NUMBER OF ZERO ELEMENTS WHICH CAN BE COMPUTED WITH COEF 0SUM MUST BE MORE THAN 50 FOR THIS TO PROVIDE SIGNIFICANT BENEFITS
AFTER CALLING THIS METHOD FURTHER FITTING WITH THE PARTIALFIT METHOD IF ANY WILL NOT WORK UNTIL YOU CALL DENSIFY
EXAMPLES USING SKLEARNSVMLINEARSVC
•EXPLICIT FEATURE MAP APPROXIMATION FOR RBF KERNELS
•COMPARISON OF CALIBRATION OF CLASSIFIERS
•PROBABILITY CALIBRATION CURVES
•SELECTING DIMENSIONALITY REDUCTION WITH PIPELINE AND GRIDSEARCHCV
•COLUMN TRANSFORMER WITH HETEROGENEOUS DATA SOURCES
•PIPELINE ANOVA SVM
•BALANCE MODEL COMPLEXITY AND CROSSVALIDATED SCORE
•PRECISIONRECALL
•FEATURE DISCRETIZATION
•PLOT DIFFERENT SVM CLASSIFIERS IN THE IRIS DATASET
•SCALING THE REGULARIZATION PARAMETER FOR SVCS
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES

SKLEARNSVM LINEARSVR
CLASSSKLEARNSVM LINEARSVR EPSILON00 TOL00001 C10 LOSS'EPSILONINSENSITIVE'
FITINTERCEPTTRUE INTERCEPTSCALING10 DUALTRUE VERBOSE0
RANDOMSTATENONE MAXITER1000
LINEAR SUPPORT VECTOR REGRESSION
SIMILAR TO SVR WITH PARAMETER KERNEL'LINEAR' BUT IMPLEMENTED IN TERMS OF LIBLINEAR RATHER THAN LIBSVM SO IT HAS MORE FLEXIBILITY IN THE CHOICE OF PENALTIES AND LOSS FUNCTIONS AND SHOULD SCALE BETTER TO LARGE NUMBERS OF SAMPLES
THIS CLASS SUPPORTS BOTH DENSE AND SPARSE INPUT
READ MORE IN THE USER GUIDE
PARAMETERS
EPSILON FLOAT OPTIONAL DEFAULT00 EPSILON PARAMETER IN THE EPSILONINSENSITIVE LOSS FUNCTION NOTE THAT THE VALUE OF THIS PARAMETER DEPENDS ON THE SCALE OF THE TARGET VARIABLE Y IF UNSURE SETEPSILON0
TOLFLOAT OPTIONAL DEFAULT1E4 TOLERANCE FOR STOPPING CRITERIA
CFLOAT OPTIONAL DEFAULT10 PENALTY PARAMETER C OF THE ERROR TERM THE PENALTY IS A SQUARED L2 PENALTY THE BIGGER THIS PARAMETER THE LESS REGULARIZATION IS USED
LOSS STRING OPTIONAL DEFAULT'EPSILONINSENSITIVE' SPECIFIES THE LOSS FUNCTION THE EPSILON INSENSITIVE LOSS STANDARD SVR IS THE L1 LOSS WHILE THE SQUARED EPSILONINSENSITIVE LOSS 'SQUAREDEPSILONINSENSITIVE' IS THE L2 LOSS
FITINTERCEPT BOOLEAN OPTIONAL DEFAULTTRUE WHETHER TO CALCULATE THE INTERCEPT FOR THIS MODEL IF SET TO FALSE NO INTERCEPT WILL BE USED IN CALCULATIONS IE DATA IS EXPECTED TO BE ALREADY CENTERED
INTERCEPTSCALING FLOAT OPTIONAL DEFAULT1 WHEN SELFFITINTERCEPT IS TRUE INSTANCE VEC TOR X BECOMES X SELFINTERCEPTSCALING IE A "SYNTHETIC" FEATURE WITH CONSTANT VALUE EQUALS TO INTERCEPTSCALING IS APPENDED TO THE INSTANCE VECTOR THE INTERCEPT BECOMES IN TERCEPTSCALING SYNTHETIC FEATURE WEIGHT NOTE THE SYNTHETIC FEATURE WEIGHT IS SUBJECT TO L1L2 REGULARIZATION AS ALL OTHER FEATURES TO LESSEN THE EFFECT OF REGULARIZATION ON SYNTHETIC FEATURE WEIGHT AND THEREFORE ON THE INTERCEPT INTERCEPTSCALING HAS TO BE INCREASED
DUAL BOOL DEFAULTTRUE SELECT THE ALGORITHM TO EITHER SOLVE THE DUAL OR PRIMAL OPTIMIZATION PROBLEM PREFER DUALFALSE WHEN NSAMPLES NFEATURES
VERBOSE INT DEFAULT0 ENABLE VERBOSE OUTPUT NOTE THAT THIS SETTING TAKES ADVANTAGE OF A PER PROCESS RUNTIME SETTING IN LIBLINEAR THAT IF ENABLED MAY NOT WORK PROPERLY IN A MULTITHREADED CONTEXT
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
MAXITER INT DEFAULT1000 THE MAXIMUM NUMBER OF ITERATIONS TO BE RUN
ATTRIBUTES
COEF ARRAY SHAPE NFEATURES IF NCLASSES 2 ELSE NCLASSES NFEATURES WEIGHTS AS SIGNED TO THE FEATURES COEFFICIENTS IN THE PRIMAL PROBLEM THIS IS ONLY AVAILABLE IN THE CASE OF A LINEAR KERNEL

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COEF IS A READONLY PROPERTY DERIVED FROM RAWCOEF THAT FOLLOWS THE INTERNAL MEMORY
LAYOUT OF LIBLINEAR
INTERCEPT ARRAY SHAPE 1 IF NCLASSES 2 ELSE NCLASSES CONSTANTS IN DECISION FUNCTION
SEE ALSO
LINEARSVC IMPLEMENTATION OF SUPPORT VECTOR MACHINE CLASSIFIER USING THE SAME LIBRARY AS THIS CLASS LIBLIN
EAR
SVR IMPLEMENTATION OF SUPPORT VECTOR MACHINE REGRESSION USING LIBSVM THE KERNEL CAN BE NONLINEAR BUT ITS
SMO ALGORITHM DOES NOT SCALE TO LARGE NUMBER OF SAMPLES AS LINEARSVC DOES
SKLEARNLINEARMODELSGDREGRESSOR SGDREGRESSOR CAN OPTIMIZE THE SAME COST FUNCTION AS LIN
EARSVR BY ADJUSTING THE PENALTY AND LOSS PARAMETERS IN ADDITION IT REQUIRES LESS MEMORY ALLOWS INCRE
MENTAL ONLINE LEARNING AND IMPLEMENTS VARIOUS LOSS FUNCTIONS AND REGULARIZATION REGIMES
EXAMPLES
 FROM SKLEARNSVM IMPORT LINEARSVR
 FROM SKLEARNDATASETS IMPORT MAKEREGRESSION
X Y MAKEREGRESSIONNFEATURES4 RANDOMSTATE0
REGR LINEARSVRRANDOMSTATE0 TOL1E5
REGRFITX Y
LINEARSVRC10 DUALTRUE EPSILON00 FITINTERCEPTTRUE
INTERCEPTSCALING10 LOSSEPSILONINSENSITIVE MAXITER1000
RANDOMSTATE0 TOL1E05 VERBOSE0
PRINTREGRCOEF
1635 2691 4230 6047
PRINTREGRINTERCEPT
429
PRINTREGRPREDICT0 0 0 0
429
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PREDICT USING THE LINEAR MODEL
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFEPSILON00 TOL00001 C10 LOSS’EPSILONINSENSITIVE’ FITINTERCEPTTRUE INTER
CEPTSCALING10 DUALTRUE VERBOSE0 RANDOMSTATENONE MAXITER1000
FITSELFXYSAMPLEWEIGHTNONE
FIT THE MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE
NSAMPLES IN THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAYLIKE SHAPE NSAMPLES TARGET VECTOR RELATIVE TO X

SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL ARRAY OF WEIGHTS THAT ARE AS
SIGNED TO INDIVIDUAL SAMPLES IF NOT PROVIDED THEN EACH SAMPLE IS GIVEN UNIT WEIGHT
RETURNS
SELF OBJECT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PREDICT USING THE LINEAR MODEL
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES SAMPLES
RETURNS
CARRAY SHAPE NSAMPLES RETURNS PREDICTED VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE

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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SKLEARNSVM NUSVC
CLASSSKLEARNSVM NUSVCNU05 KERNEL'RBF' DEGREE3 GAMMA'AUTODEPRECATED'
COEF000 SHRINKINGTRUE PROBABILITYFALSE TOL0001
CACHESIZE200 CLASSWEIGHTNONE VERBOSEFALSE MAXITER1 DECI
SIONFUNCTIONSHAPE'OVR' RANDOMSTATENONE
NUSUPPORT VECTOR CLASSIFICATION
SIMILAR TO SVC BUT USES A PARAMETER TO CONTROL THE NUMBER OF SUPPORT VECTORS
THE IMPLEMENTATION IS BASED ON LIBSVM
READ MORE IN THE USER GUIDE
PARAMETERS
NUFLOAT OPTIONAL DEFAULT05 AN UPPER BOUND ON THE FRACTION OF TRAINING ERRORS AND A LOWER
BOUND OF THE FRACTION OF SUPPORT VECTORS SHOULD BE IN THE INTERVAL 0 1
KERNEL STRING OPTIONAL DEFAULT'RBF' SPECIFIES THE KERNEL TYPE TO BE USED IN THE ALGORITHM
IT MUST BE ONE OF 'LINEAR' 'POLY' 'RBF' 'SIGMOID' 'PRECOMPUTED' OR A CALLABLE IF NONE IS
GIVEN 'RBF' WILL BE USED IF A CALLABLE IS GIVEN IT IS USED TO PRECOMPUTE THE KERNEL MATRIX
DEGREE INT OPTIONAL DEFAULT3 DEGREE OF THE POLYNOMIAL KERNEL FUNCTION 'POLY' IGNORED
BY ALL OTHER KERNELS
GAMMA FLOAT OPTIONAL DEFAULT'AUTO' KERNEL COEFFICIENT FOR 'RBF' 'POLY' AND 'SIGMOID'
CURRENT DEFAULT IS 'AUTO' WHICH USES 1 NFEATURES IF GAMMASCALE IS PASSED THEN IT
USES 1 NFEATURES XVAR AS VALUE OF GAMMA THE CURRENT DEFAULT OF GAMMA 'AUTO'
WILL CHANGE TO 'SCALE' IN VERSION 022 'AUTODEPRECATED' A DEPRECATED VERSION OF 'AUTO' IS
USED AS A DEFAULT INDICATING THAT NO EXPLICIT VALUE OF GAMMA WAS PASSED
COEF0 FLOAT OPTIONAL DEFAULT00 INDEPENDENT TERM IN KERNEL FUNCTION IT IS ONLY SIGNIFICANT
IN 'POLY' AND 'SIGMOID'
SHRINKING BOOLEAN OPTIONAL DEFAULTTRUE WHETHER TO USE THE SHRINKING HEURISTIC
PROBABILITY BOOLEAN OPTIONAL DEFAULTFALSE WHETHER TO ENABLE PROBABILITY ESTIMATES THIS
MUST BE ENABLED PRIOR TO CALLING FIT AND WILL SLOW DOWN THAT METHOD
TOLFLOAT OPTIONAL DEFAULT1E3 TOLERANCE FOR STOPPING CRITERION
CACHESIZE FLOAT OPTIONAL SPECIFY THE SIZE OF THE KERNEL CACHE IN MB
CLASSWEIGHT DICT 'BALANCED' OPTIONAL SET THE PARAMETER C OF CLASS I TO CLASSWEIGHTIC
FOR SVC IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT ONE THE "BALANCED" MODE
USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PROPORTIONAL TO CLASS FREQUEN
CIES ASNSAMPLES NCLASSES NPBINCOUNTY
637SKLEARNSVM SUPPORT VECTOR MACHINES 2307

VERBOSE BOOL DEFAULT FALSE ENABLE VERBOSE OUTPUT NOTE THAT THIS SETTING TAKES ADVANTAGE OF A PERPROCESS RUNTIME SETTING IN LIBSVM THAT IF ENABLED MAY NOT WORK PROPERLY IN A MULTITHREADED CONTEXT
MAXITER INT OPTIONAL DEFAULT1 HARD LIMIT ON ITERATIONS WITHIN SOLVER OR 1 FOR NO LIMIT
DECISIONFUNCTIONSHAPE ‘OVO’ ‘OVR’ DEFAULT’OVR’ WHETHER TO RETURN A ONEVSREST ‘OVR’ DECISION FUNCTION OF SHAPE NSAMPLES NCLASSES AS ALL OTHER CLASSIFIERS OR THE ORIGINAL ONEVSONE ‘OVO’ DECISION FUNCTION OF LIBSVM WHICH HAS SHAPE NSAMPLES NCLASSES NCLASSES 1 2
CHANGED IN VERSION 019 DECISIONFUNCTIONSHAPE IS ‘OVR’ BY DEFAULT
NEW IN VERSION 017 DECISIONFUNCTIONSHAPE’OVR’ IS RECOMMENDED
CHANGED IN VERSION 017 DEPRECATED DECISIONFUNCTIONSHAPE’OVO’ AND NONE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE PSEUDO RANDOM NUMBER GENERATOR USED WHEN SHUFFLING THE DATA FOR PROBABILITY ESTIMATES IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GEN ERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES
SUPPORT ARRAYLIKE SHAPE NSV INDICES OF SUPPORT VECTORS
SUPPORTVECTORS ARRAYLIKE SHAPE NSV NFEATURES SUPPORT VECTORS
NSUPPORT ARRAYLIKE DTYPEINT32 SHAPE NCLASS NUMBER OF SUPPORT VECTORS FOR EACH CLASS
DUALCOEF ARRAY SHAPE NCLASS1 NSV COEFFICIENTS OF THE SUPPORT VECTOR IN THE DECISION FUNCTION FOR MULTICLASS COEFFICIENT FOR ALL 1VS1 CLASSIFIERS THE LAYOUT OF THE COEFFICIENTS IN THE MULTICLASS CASE IS SOMEWHAT NONTRIVIAL SEE THE SECTION ABOUT MULTICLASS CLASSIFICA TION IN THE SVM SECTION OF THE USER GUIDE FOR DETAILS
COEF ARRAY SHAPE NCLASS NCLASS1 2 NFEATURES WEIGHTS ASSIGNED TO THE FEATURES COEFFICIENTS IN THE PRIMAL PROBLEM THIS IS ONLY AVAILABLE IN THE CASE OF A LINEAR KERNEL
COEF IS READONLY PROPERTY DERIVED FROM DUALCOEF ANDSUPPORTVECTORS
INTERCEPT ARRAY SHAPE NCLASS NCLASS1 2 CONSTANTS IN DECISION FUNCTION
SEE ALSO
SVC SUPPORT VECTOR MACHINE FOR CLASSIFICATION USING LIBSVM
LINEARSVC SCALABLE LINEAR SUPPORT VECTOR MACHINE FOR CLASSIFICATION USING LIBLINEAR
NOTES
REFERENCES LIBSVM A LIBRARY FOR SUPPORT VECTOR MACHINES
EXAMPLES
```
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 1 1 2 1
Y  NPARRAY1 1 2 2
 FROM SKLEARNSVM IMPORT NUSVC
```

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CLF NUSVCGAMMASCALE
CLFFITX Y
NUSVCCACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMASCALE KERNELRBF
MAXITER1 NU05 PROBABILITYFALSE RANDOMSTATENONE
SHRINKINGTRUE TOL0001 VERBOSEFALSE
PRINTCLFPREDICT08 1
1
METHODS
DECISIONFUNCTION SELF X EVALUATES THE DECISION FUNCTION FOR THE SAMPLES IN X
FITSELF X Y SAMPLEWEIGHT FIT THE SVM MODEL ACCORDING TO THE GIVEN TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PERFORM CLASSIFICATION ON SAMPLES IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNU05 KERNEL’RBF’ DEGREE3 GAMMA’AUTODEPRECATED’ COEF000 SHRINK
INGTRUE PROBABILITYFALSE TOL0001 CACHESIZE200 CLASSWEIGHTNONE VER
BOSEFALSE MAXITER1 DECISIONFUNCTIONSHAPE’OVR’ RANDOMSTATENONE
DECISIONFUNCTION SELFX
EVALUATES THE DECISION FUNCTION FOR THE SAMPLES IN X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
XARRAYLIKE SHAPE NSAMPLES NCLASSES NCLASSES1 2 RETURNS THE DECISION FUNC
TION OF THE SAMPLE FOR EACH CLASS IN THE MODEL IF DECISIONFUNCTIONSHAPE’OVR’ THE SHAPE
IS NSAMPLES NCLASSES
NOTES
IF DECISIONFUNCTIONSHAPE’OVO’ THE FUNCTION VALUES ARE PROPORTIONAL TO THE DISTANCE OF THE SAMPLES X TO
THE SEPARATING HYPERPLANE IF THE EXACT DISTANCES ARE REQUIRED DIVIDE THE FUNCTION VALUES BY THE NORM OF
THE WEIGHT VECTOR COEF SEE ALSO THIS QUESTION FOR FURTHER DETAILS IF DECISIONFUNCTIONSHAPE’OVR’
THE DECISION FUNCTION IS A MONOTONIC TRANSFORMATION OF OVO DECISION FUNCTION
FITSELFXYSAMPLEWEIGHTNONE
FIT THE SVM MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES FOR KER
NEL”PRECOMPUTED” THE EXPECTED SHAPE OF X IS NSAMPLES NSAMPLES
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUMBERS
IN REGRESSION
637SKLEARNSVM SUPPORT VECTOR MACHINES 2309

SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES PERSAMPLE WEIGHTS RESCALE C PER SAMPLE
HIGHER WEIGHTS FORCE THE CLASSIFIER TO PUT MORE EMPHASIS ON THESE POINTS
RETURNS
SELF OBJECT
NOTES
IF X AND Y ARE NOT CORDERED AND CONTIGUOUS ARRAYS OF NPFLOAT64 AND X IS NOT A SCIPYSPARSECSRMATRIX X
ANDOR Y MAY BE COPIED
IF X IS A DENSE ARRAY THEN THE OTHER METHODS WILL NOT SUPPORT SPARSE MATRICES AS INPUT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PERFORM CLASSIFICATION ON SAMPLES IN X
FOR AN ONECLASS MODEL 1 OR 1 IS RETURNED
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES FOR KERNEL”PRECOMPUTED”
THE EXPECTED SHAPE OF X IS NSAMPLESTEST NSAMPLESTRAIN
RETURNS
YPRED ARRAY SHAPE NSAMPLES CLASS LABELS FOR SAMPLES IN X
PREDICTLOGPROBA
COMPUTE LOG PROBABILITIES OF POSSIBLE OUTCOMES FOR SAMPLES IN X
THE MODEL NEED TO HAVE PROBABILITY INFORMATION COMPUTED AT TRAINING TIME FIT WITH ATTRIBUTE
PROBABILITY SET TO TRUE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES FOR KERNEL”PRECOMPUTED” THE EXPECTED
SHAPE OF X IS NSAMPLESTEST NSAMPLESTRAIN
RETURNS
TARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE LOGPROBABILITIES OF THE SAMPLE FOR
EACH CLASS IN THE MODEL THE COLUMNS CORRESPOND TO THE CLASSES IN SORTED ORDER AS THEY
APPEAR IN THE ATTRIBUTE CLASSES
NOTES
THE PROBABILITY MODEL IS CREATED USING CROSS VALIDATION SO THE RESULTS CAN BE SLIGHTLY DIFFERENT THAN THOSE
OBTAINED BY PREDICT ALSO IT WILL PRODUCE MEANINGLESS RESULTS ON VERY SMALL DATASETS

PREDICTPROBA
COMPUTE PROBABILITIES OF POSSIBLE OUTCOMES FOR SAMPLES IN X
THE MODEL NEED TO HAVE PROBABILITY INFORMATION COMPUTED AT TRAINING TIME FIT WITH ATTRIBUTE
PROBABILITY SET TO TRUE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES FOR KERNEL”PRECOMPUTED” THE EXPECTED
SHAPE OF X IS NSAMPLESTEST NSAMPLESTRAIN
RETURNS
TARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE PROBABILITY OF THE SAMPLE FOR EACH
CLASS IN THE MODEL THE COLUMNS CORRESPOND TO THE CLASSES IN SORTED ORDER AS THEY APPEAR
IN THE ATTRIBUTE CLASSES
NOTES
THE PROBABILITY MODEL IS CREATED USING CROSS VALIDATION SO THE RESULTS CAN BE SLIGHTLY DIFFERENT THAN THOSE
OBTAINED BY PREDICT ALSO IT WILL PRODUCE MEANINGLESS RESULTS ON VERY SMALL DATASETS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNSVMNUSVC
•NONLINEAR SVM

SCIKITLEARN USER GUIDE RELEASE 0213
SKLEARNSVM NUSVR
CLASSSKLEARNSVM NUSVRNU05 C10 KERNEL'RBF' DEGREE3 GAMMA'AUTODEPRECATED'
COEF000 SHRINKINGTRUE TOL0001 CACHESIZE200 VERBOSEFALSE
MAXITER1
NU SUPPORT VECTOR REGRESSION
SIMILAR TO NUSVC FOR REGRESSION USES A PARAMETER NU TO CONTROL THE NUMBER OF SUPPORT VECTORS HOWEVER
UNLIKE NUSVC WHERE NU REPLACES C HERE NU REPLACES THE PARAMETER EPSILON OF EPSILONSVR
THE IMPLEMENTATION IS BASED ON LIBSVM
READ MORE IN THE USER GUIDE
PARAMETERS
NUFLOAT OPTIONAL AN UPPER BOUND ON THE FRACTION OF TRAINING ERRORS AND A LOWER BOUND OF THE
FRACTION OF SUPPORT VECTORS SHOULD BE IN THE INTERVAL 0 1 BY DEFAULT 05 WILL BE TAKEN
CFLOAT OPTIONAL DEFAULT10 PENALTY PARAMETER C OF THE ERROR TERM
KERNEL STRING OPTIONAL DEFAULT'RBF' SPECIFIES THE KERNEL TYPE TO BE USED IN THE ALGORITHM
IT MUST BE ONE OF 'LINEAR' 'POLY' 'RBF' 'SIGMOID' 'PRECOMPUTED' OR A CALLABLE IF NONE IS
GIVEN 'RBF' WILL BE USED IF A CALLABLE IS GIVEN IT IS USED TO PRECOMPUTE THE KERNEL MATRIX
DEGREE INT OPTIONAL DEFAULT3 DEGREE OF THE POLYNOMIAL KERNEL FUNCTION 'POLY' IGNORED
BY ALL OTHER KERNELS
GAMMA FLOAT OPTIONAL DEFAULT'AUTO' KERNEL COEFFICIENT FOR 'RBF' 'POLY' AND 'SIGMOID'
CURRENT DEFAULT IS 'AUTO' WHICH USES 1 NFEATURES IF GAMMASCALE IS PASSED THEN IT
USES 1 NFEATURES XVAR AS VALUE OF GAMMA THE CURRENT DEFAULT OF GAMMA 'AUTO'
WILL CHANGE TO 'SCALE' IN VERSION 022 'AUTODEPRECATED' A DEPRECATED VERSION OF 'AUTO' IS
USED AS A DEFAULT INDICATING THAT NO EXPLICIT VALUE OF GAMMA WAS PASSED
COEF0 FLOAT OPTIONAL DEFAULT00 INDEPENDENT TERM IN KERNEL FUNCTION IT IS ONLY SIGNIFICANT
IN 'POLY' AND 'SIGMOID'
SHRINKING BOOLEAN OPTIONAL DEFAULTTRUE WHETHER TO USE THE SHRINKING HEURISTIC
TOLFLOAT OPTIONAL DEFAULT1E3 TOLERANCE FOR STOPPING CRITERION
CACHESIZE FLOAT OPTIONAL SPECIFY THE SIZE OF THE KERNEL CACHE IN MB
VERBOSE BOOL DEFAULT FALSE ENABLE VERBOSE OUTPUT NOTE THAT THIS SETTING TAKES ADVANTAGE
OF A PERPROCESS RUNTIME SETTING IN LIBSVM THAT IF ENABLED MAY NOT WORK PROPERLY IN A
MULTITHREADED CONTEXT
MAXITER INT OPTIONAL DEFAULT1 HARD LIMIT ON ITERATIONS WITHIN SOLVER OR 1 FOR NO LIMIT
ATTRIBUTES
SUPPORT ARRAYLIKE SHAPE NSV INDICES OF SUPPORT VECTORS
SUPPORTVECTORS ARRAYLIKE SHAPE NSV NFEATURES SUPPORT VECTORS
DUALCOEF ARRAY SHAPE 1 NSV COEFFICIENTS OF THE SUPPORT VECTOR IN THE DECISION FUNC
TION
COEF ARRAY SHAPE 1 NFEATURES WEIGHTS ASSIGNED TO THE FEATURES COEFFICIENTS IN THE PRIMAL
PROBLEM THIS IS ONLY AVAILABLE IN THE CASE OF A LINEAR KERNEL
COEF IS READONLY PROPERTY DERIVED FROM DUALCOEF ANDSUPPORTVECTORS
INTERCEPT ARRAY SHAPE 1 CONSTANTS IN DECISION FUNCTION

SEE ALSO
NUSVC SUPPORT VECTOR MACHINE FOR CLASSIFICATION IMPLEMENTED WITH LIBSVM WITH A PARAMETER TO CONTROL THE NUMBER OF SUPPORT VECTORS
SVR EPSILON SUPPORT VECTOR MACHINE FOR REGRESSION IMPLEMENTED WITH LIBSVM
NOTES
REFERENCES LIBSVM A LIBRARY FOR SUPPORT VECTOR MACHINES
EXAMPLES
```
 FROM SKLEARNSVM IMPORT NUSVR
 IMPORT NUMPY AS NP
NSAMPLES NFEATURES  10 5
NPRANDOMSEED0
Y  NPRANDOMRANDNNSAMPLES
X  NPRANDOMRANDNNSAMPLES NFEATURES
CLF  NUSVRGAMMASCALE C10 NU01
CLFFITX Y
NUSVRC10 CACHESIZE200 COEF000 DEGREE3 GAMMASCALE
KERNELRBF MAXITER1 NU01 SHRINKINGTRUE TOL0001
VERBOSEFALSE
```
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE SVM MODEL ACCORDING TO THE GIVEN TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PERFORM REGRESSION ON SAMPLES IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFNU05 C10 KERNEL’RBF’ DEGREE3 GAMMA’AUTODEPRECATED’ COEF000 SHRINK INGTRUE TOL0001 CACHESIZE200 VERBOSEFALSE MAXITER1
FITSELFXYSAMPLEWEIGHTNONE
FIT THE SVM MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES FOR KER NEL”PRECOMPUTED” THE EXPECTED SHAPE OF X IS NSAMPLES NSAMPLES
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUMBERS IN REGRESSION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES PERSAMPLE WEIGHTS RESCALE C PER SAMPLE HIGHER WEIGHTS FORCE THE CLASSIFIER TO PUT MORE EMPHASIS ON THESE POINTS
RETURNS

SCIKITLEARN USER GUIDE RELEASE 0213
SELF OBJECT
NOTES
IF X AND Y ARE NOT CORDERED AND CONTIGUOUS ARRAYS OF NPFLOAT64 AND X IS NOT A SCIPYSPARSECSRMATRIX X
ANDOR Y MAY BE COPIED
IF X IS A DENSE ARRAY THEN THE OTHER METHODS WILL NOT SUPPORT SPARSE MATRICES AS INPUT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PERFORM REGRESSION ON SAMPLES IN X
FOR AN ONECLASS MODEL 1 INLIER OR 1 OUTLIER IS RETURNED
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES FOR KERNEL”PRECOMPUTED”
THE EXPECTED SHAPE OF X IS NSAMPLESTEST NSAMPLESTRAIN
RETURNS
YPRED ARRAY SHAPE NSAMPLES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
2314 CHAPTER 6 API REFERENCE

TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES MULTIOUTPUTUNIFORMAVERAGE

SETPARAMS SELFPARAMS

SET THE PARAMETERS OF THIS ESTIMATOR

THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT OF A NESTED OBJECT

RETURNS

SELF

EXAMPLES USING SKLEARNSVMNUSVR

•MODEL COMPLEXITY INFLUENCE

SKLEARNSVM ONECLASSSVM

CLASSSKLEARNSVM ONECLASSSVM KERNEL'RBF' DEGREE3 GAMMA'AUTODEPRECATED' COEF000 TOL0001 NU05 SHRINKINGTRUE CACHESIZE200 VERBOSEFALSE MAXITER1 RANDOMSTATENONE

UNSUPERVISED OUTLIER DETECTION

ESTIMATE THE SUPPORT OF A HIGHDIMENSIONAL DISTRIBUTION

THE IMPLEMENTATION IS BASED ON LIBSVM

READ MORE IN THE USER GUIDE

PARAMETERS

KERNEL STRING OPTIONAL DEFAULT'RBF' SPECIFIES THE KERNEL TYPE TO BE USED IN THE ALGORITHM IT MUST BE ONE OF 'LINEAR' 'POLY' 'RBF' 'SIGMOID' 'PRECOMPUTED' OR A CALLABLE IF NONE IS GIVEN 'RBF' WILL BE USED IF A CALLABLE IS GIVEN IT IS USED TO PRECOMPUTE THE KERNEL MATRIX

DEGREE INT OPTIONAL DEFAULT3 DEGREE OF THE POLYNOMIAL KERNEL FUNCTION 'POLY' IGNORED BY ALL OTHER KERNELS

GAMMA FLOAT OPTIONAL DEFAULT'AUTO' KERNEL COEFFICIENT FOR 'RBF' 'POLY' AND 'SIGMOID' CURRENT DEFAULT IS 'AUTO' WHICH USES 1 NFEATURES IF GAMMASCALE IS PASSED THEN IT USES 1 NFEATURES XVAR AS VALUE OF GAMMA THE CURRENT DEFAULT OF GAMMA 'AUTO' WILL CHANGE TO 'SCALE' IN VERSION 022 'AUTODEPRECATED' A DEPRECATED VERSION OF 'AUTO' IS USED AS A DEFAULT INDICATING THAT NO EXPLICIT VALUE OF GAMMA WAS PASSED

COEF0 FLOAT OPTIONAL DEFAULT00 INDEPENDENT TERM IN KERNEL FUNCTION IT IS ONLY SIGNIFICANT IN 'POLY' AND 'SIGMOID'

TOLFLOAT OPTIONAL TOLERANCE FOR STOPPING CRITERION

NUFLOAT OPTIONAL AN UPPER BOUND ON THE FRACTION OF TRAINING ERRORS AND A LOWER BOUND OF THE FRACTION OF SUPPORT VECTORS SHOULD BE IN THE INTERVAL 0 1 BY DEFAULT 05 WILL BE TAKEN

SHRINKING BOOLEAN OPTIONAL WHETHER TO USE THE SHRINKING HEURISTIC

CACHESIZE FLOAT OPTIONAL SPECIFY THE SIZE OF THE KERNEL CACHE IN MB

VERBOSE BOOL DEFAULT FALSE ENABLE VERBOSE OUTPUT NOTE THAT THIS SETTING TAKES ADVANTAGE OF A PERPROCESS RUNTIME SETTING IN LIBSVM THAT IF ENABLED MAY NOT WORK PROPERLY IN A MULTITHREADED CONTEXT
MAXITER INT OPTIONAL DEFAULT1 HARD LIMIT ON ITERATIONS WITHIN SOLVER OR 1 FOR NO LIMIT
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IGNORED
DEPRECATED SINCE VERSION 020 RANDOMSTATE HAS BEEN DEPRECATED IN 020 AND WILL BE REMOVED IN 022
ATTRIBUTES
SUPPORT ARRAYLIKE SHAPE NSV INDICES OF SUPPORT VECTORS
SUPPORTVECTORS ARRAYLIKE SHAPE NSV NFEATURES SUPPORT VECTORS
DUALCOEF ARRAY SHAPE 1 NSV COEFFICIENTS OF THE SUPPORT VECTORS IN THE DECISION FUNC TION
COEF ARRAY SHAPE 1 NFEATURES WEIGHTS ASSIGNED TO THE FEATURES COEFFICIENTS IN THE PRIMAL PROBLEM THIS IS ONLY AVAILABLE IN THE CASE OF A LINEAR KERNEL
COEF IS READONLY PROPERTY DERIVED FROM DUALCOEF ANDSUPPORTVECTORS
INTERCEPT ARRAY SHAPE 1 CONSTANT IN THE DECISION FUNCTION
OFFSET FLOAT OFFSET USED TO DEFINE THE DECISION FUNCTION FROM THE RAW SCORES WE HAVE THE RELATION DECISIONFUNCTION SCORESAMPLES OFFSET THE OFFSET IS THE OPPOSITE OF INTERCEPT AND IS PROVIDED FOR CONSISTENCY WITH OTHER OUTLIER DETECTION ALGORITHMS
EXAMPLES
 FROM SKLEARNSVM IMPORT ONECLASSSVM
X 0 044 045 046 1
CLF ONECLASSSVMGAMMAAUTOFITX
CLFPREDICTX
ARRAY1 1 1 1 1
CLFSCORESAMPLESX
ARRAY17798 20547 20556 20561 17332
METHODS
DECISIONFUNCTION SELF X SIGNED DISTANCE TO THE SEPARATING HYPERPLANE
FITSELF X Y SAMPLEWEIGHT DETECTS THE SOFT BOUNDARY OF THE SET OF SAMPLES X
FITPREDICT SELF X Y PERFORMS FIT ON X AND RETURNS LABELS FOR X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PERFORM CLASSIFICATION ON SAMPLES IN X
SCORESAMPLES SELF X RAW SCORING FUNCTION OF THE SAMPLES
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFKERNEL’RBF’ DEGREE3 GAMMA’AUTODEPRECATED’ COEF000 TOL0001 NU05 SHRINKINGTRUE CACHESIZE200 VERBOSEFALSE MAXITER1 RANDOMSTATENONE
DECISIONFUNCTION SELFX
SIGNED DISTANCE TO THE SEPARATING HYPERPLANE

SIGNED DISTANCE IS POSITIVE FOR AN INLIER AND NEGATIVE FOR AN OUTLIER
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
DEC ARRAYLIKE SHAPE NSAMPLES RETURNS THE DECISION FUNCTION OF THE SAMPLES
FITSELFXYNONE SAMPLEWEIGHTNONE PARAMS
DETECTS THE SOFT BOUNDARY OF THE SET OF SAMPLES X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES SET OF SAMPLES WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES PERSAMPLE WEIGHTS RESCALE C PER SAMPLE
HIGHER WEIGHTS FORCE THE CLASSIFIER TO PUT MORE EMPHASIS ON THESE POINTS
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
SELF OBJECT
NOTES
IF X IS NOT A CORDERED CONTIGUOUS ARRAY IT IS COPIED
FITPREDICT SELFXYNONE
PERFORMS FIT ON X AND RETURNS LABELS FOR X
RETURNS 1 FOR OUTLIERS AND 1 FOR INLIERS
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES INPUT DATA
YIGNORED NOT USED PRESENT FOR API CONSISTENCY BY CONVENTION
RETURNS
YNDARRAY SHAPE NSAMPLES 1 FOR INLIERS 1 FOR OUTLIERS
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PERFORM CLASSIFICATION ON SAMPLES IN X
FOR A ONECLASS MODEL 1 OR 1 IS RETURNED
PARAMETERS

XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES FOR KERNEL”PRECOMPUTED”
THE EXPECTED SHAPE OF X IS NSAMPLESTEST NSAMPLESTRAIN
RETURNS
YPRED ARRAY SHAPE NSAMPLES CLASS LABELS FOR SAMPLES IN X
SCORESAMPLES SELFX
RAW SCORING FUNCTION OF THE SAMPLES
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
SCORESAMPLES ARRAYLIKE SHAPE NSAMPLES RETURNS THE UNSHIFTED SCORING FUNCTION OF
THE SAMPLES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNSVMONECLASSSVM
•COMPARING ANOMALY DETECTION ALGORITHMS FOR OUTLIER DETECTION ON TOY DATASETS
•OUTLIER DETECTION ON A REAL DATA SET
•SPECIES DISTRIBUTION MODELING
•LIBSVM GUI
•ONECLASS SVM WITH NONLINEAR KERNEL RBF
SKLEARNSVM SVC
CLASSSKLEARNSVM SVCC10 KERNEL’RBF’ DEGREE3 GAMMA’AUTODEPRECATED’ COEF000 SHRINK
INGTRUE PROBABILITYFALSE TOL0001 CACHESIZE200 CLASSWEIGHTNONE
VERBOSEFALSE MAXITER1 DECISIONFUNCTIONSHAPE’OVR’ RAN
DOMSTATENONE
CSUPPORT VECTOR CLASSIFICATION
THE IMPLEMENTATION IS BASED ON LIBSVM THE FIT TIME SCALES AT LEAST QUADRATICALLY WITH THE NUMBER OF SAMPLES
AND MAY BE IMPRACTICAL BEYOND TENS OF THOUSANDS OF SAMPLES FOR LARGE DATASETS CONSIDER USING SKLEARN
LINEARMODELLINEARSVC ORSKLEARNLINEARMODELSGDCLASSIFIER INSTEAD POSSIBLY AFTER
ASKLEARNKERNELAPPROXIMATIONNYSTROEM TRANSFORMER
THE MULTICLASS SUPPORT IS HANDLED ACCORDING TO A ONEVSONE SCHEME
FOR DETAILS ON THE PRECISE MATHEMATICAL FORMULATION OF THE PROVIDED KERNEL FUNCTIONS AND HOW GAMMA COEF0
ANDDEGREE AFFECT EACH OTHER SEE THE CORRESPONDING SECTION IN THE NARRATIVE DOCUMENTATION KERNEL FUNCTIONS
READ MORE IN THE USER GUIDE

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PARAMETERS
CFLOAT OPTIONAL DEFAULT10 PENALTY PARAMETER C OF THE ERROR TERM
KERNEL STRING OPTIONAL DEFAULT'RBF' SPECIFIES THE KERNEL TYPE TO BE USED IN THE ALGORITHM
IT MUST BE ONE OF 'LINEAR' 'POLY' 'RBF' 'SIGMOID' 'PRECOMPUTED' OR A CALLABLE IF NONE
IS GIVEN 'RBF' WILL BE USED IF A CALLABLE IS GIVEN IT IS USED TO PRECOMPUTE THE KER
NEL MATRIX FROM DATA MATRICES THAT MATRIX SHOULD BE AN ARRAY OF SHAPE NSAMPLES
NSAMPLES
DEGREE INT OPTIONAL DEFAULT3 DEGREE OF THE POLYNOMIAL KERNEL FUNCTION 'POLY' IGNORED
BY ALL OTHER KERNELS
GAMMA FLOAT OPTIONAL DEFAULT'AUTO' KERNEL COEFFICIENT FOR 'RBF' 'POLY' AND 'SIGMOID'
CURRENT DEFAULT IS 'AUTO' WHICH USES 1 NFEATURES IF GAMMASCALE IS PASSED THEN IT
USES 1 NFEATURES XVAR AS VALUE OF GAMMA THE CURRENT DEFAULT OF GAMMA 'AUTO'
WILL CHANGE TO 'SCALE' IN VERSION 022 'AUTODEPRECATED' A DEPRECATED VERSION OF 'AUTO' IS
USED AS A DEFAULT INDICATING THAT NO EXPLICIT VALUE OF GAMMA WAS PASSED
COEF0 FLOAT OPTIONAL DEFAULT00 INDEPENDENT TERM IN KERNEL FUNCTION IT IS ONLY SIGNIFICANT
IN 'POLY' AND 'SIGMOID'
SHRINKING BOOLEAN OPTIONAL DEFAULTTRUE WHETHER TO USE THE SHRINKING HEURISTIC
PROBABILITY BOOLEAN OPTIONAL DEFAULTFALSE WHETHER TO ENABLE PROBABILITY ESTIMATES THIS
MUST BE ENABLED PRIOR TO CALLING FIT AND WILL SLOW DOWN THAT METHOD
TOLFLOAT OPTIONAL DEFAULT1E3 TOLERANCE FOR STOPPING CRITERION
CACHESIZE FLOAT OPTIONAL SPECIFY THE SIZE OF THE KERNEL CACHE IN MB
CLASSWEIGHT DICT 'BALANCED' OPTIONAL SET THE PARAMETER C OF CLASS I TO CLASSWEIGHTIC
FOR SVC IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT ONE THE "BALANCED" MODE
USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PROPORTIONAL TO CLASS FREQUEN
CIES IN THE INPUT DATA AS NSAMPLES NCLASSES NPBINCOUNTY
VERBOSE BOOL DEFAULT FALSE ENABLE VERBOSE OUTPUT NOTE THAT THIS SETTING TAKES ADVANTAGE
OF A PERPROCESS RUNTIME SETTING IN LIBSVM THAT IF ENABLED MAY NOT WORK PROPERLY IN A
MULTITHREADED CONTEXT
MAXITER INT OPTIONAL DEFAULT1 HARD LIMIT ON ITERATIONS WITHIN SOLVER OR 1 FOR NO LIMIT
DECISIONFUNCTIONSHAPE 'OVO' 'OVR' DEFAULT'OVR' WHETHER TO RETURN A ONEVSREST 'OVR'
DECISION FUNCTION OF SHAPE NSAMPLES NCLASSES AS ALL OTHER CLASSIFIERS OR THE ORIGINAL
ONEVSONE 'OVO' DECISION FUNCTION OF LIBSVM WHICH HAS SHAPE NSAMPLES NCLASSES
NCLASSES 1 2 HOWEVER ONEVSONE 'OVO' IS ALWAYS USED AS MULTICLASS STRATEGY
CHANGED IN VERSION 019 DECISIONFUNCTIONSHAPE IS 'OVR' BY DEFAULT
NEW IN VERSION 017 DECISIONFUNCTIONSHAPE'OVR' IS RECOMMENDED
CHANGED IN VERSION 017 DEPRECATED DECISIONFUNCTIONSHAPE'OVO' AND NONE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR USED WHEN SHUFFLING THE DATA FOR PROBABILITY ESTIMATES
IF INT RANDOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE
INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GEN
ERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
ATTRIBUTES
SUPPORT ARRAYLIKE SHAPE NSV INDICES OF SUPPORT VECTORS

SUPPORTVECTORS ARRAYLIKE SHAPE NSV NFEATURES SUPPORT VECTORS
NSUPPORT ARRAYLIKE DTYPEINT32 SHAPE NCLASS NUMBER OF SUPPORT VECTORS FOR EACH
CLASS
DUALCOEF ARRAY SHAPE NCLASS1 NSV COEFFICIENTS OF THE SUPPORT VECTOR IN THE DECISION
FUNCTION FOR MULTICLASS COEFFICIENT FOR ALL 1VS1 CLASSIFIERS THE LAYOUT OF THE COEFFICIENTS
IN THE MULTICLASS CASE IS SOMEWHAT NONTRIVIAL SEE THE SECTION ABOUT MULTICLASS CLASSIFICA
TION IN THE SVM SECTION OF THE USER GUIDE FOR DETAILS
COEF ARRAY SHAPE NCLASS NCLASS1 2 NFEATURES WEIGHTS ASSIGNED TO THE FEATURES
COEFFICIENTS IN THE PRIMAL PROBLEM THIS IS ONLY AVAILABLE IN THE CASE OF A LINEAR KERNEL
COEF IS A READONLY PROPERTY DERIVED FROM DUALCOEF ANDSUPPORTVECTORS
INTERCEPT ARRAY SHAPE NCLASS NCLASS1 2 CONSTANTS IN DECISION FUNCTION
FITSTATUS INT 0 IF CORRECTLY FITTED 1 OTHERWISE WILL RAISE WARNING
PROBA ARRAY SHAPE NCLASS NCLASS1 2
PROBB ARRAY SHAPE NCLASS NCLASS1 2 IF PROBABILITYTRUE THE PARAMETERS
LEARNED IN PLATT SCALING TO PRODUCE PROBABILITY ESTIMATES FROM DECISION VALUES IF PROB
ABILITYFALSE AN EMPTY ARRAY PLATT SCALING USES THE LOGISTIC FUNCTION 1 1
EXPDECISIONVALUE PROBA PROBB WHEREPROBA ANDPROBB ARE
LEARNED FROM THE DATASET R20C70293EF722 FOR MORE INFORMATION ON THE MULTICLASS CASE
AND TRAINING PROCEDURE SEE SECTION 8 OF R20C70293EF721
SEE ALSO
SVR SUPPORT VECTOR MACHINE FOR REGRESSION IMPLEMENTED USING LIBSVM
LINEARSVC SCALABLE LINEAR SUPPORT VECTOR MACHINE FOR CLASSIFICATION IMPLEMENTED USING LIBLINEAR CHECK
THE SEE ALSO SECTION OF LINEARSVC FOR MORE COMPARISON ELEMENT
REFERENCES
R20C70293EF721 R20C70293EF722
EXAMPLES
```
 IMPORT NUMPY AS NP
X  NPARRAY1 1 2 1 1 1 2 1
Y  NPARRAY1 1 2 2
 FROM SKLEARNSVM IMPORT SVC
CLF  SVCGAMMAAUTO
CLFFITX Y
SVCC10 CACHESIZE200 CLASSWEIGHTNONE COEF000
DECISIONFUNCTIONSHAPEOVR DEGREE3 GAMMAAUTO KERNELRBF
MAXITER1 PROBABILITYFALSE RANDOMSTATENONE SHRINKINGTRUE
TOL0001 VERBOSEFALSE
PRINTCLFPREDICT08 1
1
```

METHODS
DECISIONFUNCTION SELF X EVALUATES THE DECISION FUNCTION FOR THE SAMPLES IN X
FITSELF X Y SAMPLEWEIGHT FIT THE SVM MODEL ACCORDING TO THE GIVEN TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PERFORM CLASSIFICATION ON SAMPLES IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFC10 KERNEL'RBF' DEGREE3 GAMMA'AUTODEPRECATED' COEF000 SHRINK
INGTRUE PROBABILITYFALSE TOL0001 CACHESIZE200 CLASSWEIGHTNONE VER
BOSEFALSE MAXITER1 DECISIONFUNCTIONSHAPE'OVR' RANDOMSTATENONE
DECISIONFUNCTION SELFX
EVALUATES THE DECISION FUNCTION FOR THE SAMPLES IN X
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES
RETURNS
XARRAYLIKE SHAPE NSAMPLES NCLASSES NCLASSES1 2 RETURNS THE DECISION FUNC
TION OF THE SAMPLE FOR EACH CLASS IN THE MODEL IF DECISIONFUNCTIONSHAPE'OVR' THE SHAPE
IS NSAMPLES NCLASSES
NOTES
IF DECISIONFUNCTIONSHAPE'OVO' THE FUNCTION VALUES ARE PROPORTIONAL TO THE DISTANCE OF THE SAMPLES X TO
THE SEPARATING HYPERPLANE IF THE EXACT DISTANCES ARE REQUIRED DIVIDE THE FUNCTION VALUES BY THE NORM OF
THE WEIGHT VECTOR COEF SEE ALSO THIS QUESTION FOR FURTHER DETAILS IF DECISIONFUNCTIONSHAPE'OVR'
THE DECISION FUNCTION IS A MONOTONIC TRANSFORMATION OF OVO DECISION FUNCTION
FITSELFXYSAMPLEWEIGHTNONE
FIT THE SVM MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES FOR KER
NEL"PRECOMPUTED" THE EXPECTED SHAPE OF X IS NSAMPLES NSAMPLES
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUMBERS
IN REGRESSION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES PERSAMPLE WEIGHTS RESCALE C PER SAMPLE
HIGHER WEIGHTS FORCE THE CLASSIFIER TO PUT MORE EMPHASIS ON THESE POINTS
RETURNS
SELF OBJECT
NOTES
IF X AND Y ARE NOT CORDERED AND CONTIGUOUS ARRAYS OF NPFLOAT64 AND X IS NOT A SCIPYSPARSECSRMATRIX X
ANDOR Y MAY BE COPIED

IF X IS A DENSE ARRAY THEN THE OTHER METHODS WILL NOT SUPPORT SPARSE MATRICES AS INPUT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFX
PERFORM CLASSIFICATION ON SAMPLES IN X
FOR AN ONECLASS MODEL 1 OR 1 IS RETURNED
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES FOR KERNEL”PRECOMPUTED”
THE EXPECTED SHAPE OF X IS NSAMPLESTEST NSAMPLESTRAIN
RETURNS
YPRED ARRAY SHAPE NSAMPLES CLASS LABELS FOR SAMPLES IN X
PREDICTLOGPROBA
COMPUTE LOG PROBABILITIES OF POSSIBLE OUTCOMES FOR SAMPLES IN X
THE MODEL NEED TO HAVE PROBABILITY INFORMATION COMPUTED AT TRAINING TIME FIT WITH ATTRIBUTE
PROBABILITY SET TO TRUE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES FOR KERNEL”PRECOMPUTED” THE EXPECTED
SHAPE OF X IS NSAMPLESTEST NSAMPLESTRAIN
RETURNS
TARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE LOGPROBABILITIES OF THE SAMPLE FOR
EACH CLASS IN THE MODEL THE COLUMNS CORRESPOND TO THE CLASSES IN SORTED ORDER AS THEY
APPEAR IN THE ATTRIBUTE CLASSES
NOTES
THE PROBABILITY MODEL IS CREATED USING CROSS VALIDATION SO THE RESULTS CAN BE SLIGHTLY DIFFERENT THAN THOSE
OBTAINED BY PREDICT ALSO IT WILL PRODUCE MEANINGLESS RESULTS ON VERY SMALL DATASETS
PREDICTPROBA
COMPUTE PROBABILITIES OF POSSIBLE OUTCOMES FOR SAMPLES IN X
THE MODEL NEED TO HAVE PROBABILITY INFORMATION COMPUTED AT TRAINING TIME FIT WITH ATTRIBUTE
PROBABILITY SET TO TRUE
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES FOR KERNEL”PRECOMPUTED” THE EXPECTED
SHAPE OF X IS NSAMPLESTEST NSAMPLESTRAIN
RETURNS

TARRAYLIKE SHAPE NSAMPLES NCLASSES RETURNS THE PROBABILITY OF THE SAMPLE FOR EACH
CLASS IN THE MODEL THE COLUMNS CORRESPOND TO THE CLASSES IN SORTED ORDER AS THEY APPEAR
IN THE ATTRIBUTE CLASSES
NOTES
THE PROBABILITY MODEL IS CREATED USING CROSS VALIDATION SO THE RESULTS CAN BE SLIGHTLY DIFFERENT THAN THOSE
OBTAINED BY PREDICT ALSO IT WILL PRODUCE MEANINGLESS RESULTS ON VERY SMALL DATASETS
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNSVMSVC
•MULTILABEL CLASSIFICATION
•EXPLICIT FEATURE MAP APPROXIMATION FOR RBF KERNELS
•FACES RECOGNITION EXAMPLE USING EIGENFACES AND SVMS
•LIBSVM GUI
•RECOGNIZING HANDWRITTEN DIGITS
•PLOT CLASSIFICATION PROBABILITY
•CLASSIFIER COMPARISON
•CONCATENATING MULTIPLE FEATURE EXTRACTION METHODS
•PLOT THE DECISION BOUNDARIES OF A VOTINGCLASSIFIER
•CROSSVALIDATION ON DIGITS DATASET EXERCISE
•SVM EXERCISE
•RECURSIVE FEATURE ELIMINATION

•RECURSIVE FEATURE ELIMINATION WITH CROSSVALIDATION
•TEST WITH PERMUTATIONS THE SIGNIFICANCE OF A CLASSIFICATION SCORE
•UNIVARIATE FEATURE SELECTION
•PLOTTING VALIDATION CURVES
•PARAMETER ESTIMATION USING GRID SEARCH WITH CROSSVALIDATION
•RECEIVER OPERATING CHARACTERISTIC ROC WITH CROSS VALIDATION
•NESTED VERSUS NONNESTED CROSSVALIDATION
•CONFUSION MATRIX
•RECEIVER OPERATING CHARACTERISTIC ROC
•PLOTTING LEARNING CURVES
•FEATURE DISCRETIZATION
•DECISION BOUNDARY OF LABEL PROPAGATION VERSUS SVM ON THE IRIS DATASET
•SVM MAXIMUM MARGIN SEPARATING HYPERPLANE
•SVM WITH CUSTOM KERNEL
•SVM WEIGHTED SAMPLES
•SVM SEPARATING HYPERPLANE FOR UNBALANCED CLASSES
•SVMKERNELS
•SVMANOVA SVM WITH UNIVARIATE FEATURE SELECTION
•SVM MARGINS EXAMPLE
•PLOT DIFFERENT SVM CLASSIFIERS IN THE IRIS DATASET
•RBF SVM PARAMETERS
SKLEARNSVM SVR
CLASSSKLEARNSVM SVRKERNEL’RBF’ DEGREE3 GAMMA’AUTODEPRECATED’ COEF000 TOL0001
C10 EPSILON01 SHRINKINGTRUE CACHESIZE200 VERBOSEFALSE
MAXITER1
EPSILONSUPPORT VECTOR REGRESSION
THE FREE PARAMETERS IN THE MODEL ARE C AND EPSILON
THE IMPLEMENTATION IS BASED ON LIBSVM THE FIT TIME COMPLEXITY IS MORE THAN QUADRATIC WITH THE NUMBER OF SAM
PLES WHICH MAKES IT HARD TO SCALE TO DATASETS WITH MORE THAN A COUPLE OF 10000 SAMPLES FOR LARGE DATASETS CON
SIDER USING SKLEARNLINEARMODELLINEARSVR ORSKLEARNLINEARMODELSGDREGRESSOR
INSTEAD POSSIBLY AFTER A SKLEARNKERNELAPPROXIMATIONNYSTROEM TRANSFORMER
READ MORE IN THE USER GUIDE
PARAMETERS
KERNEL STRING OPTIONAL DEFAULT’RBF’ SPECIFIES THE KERNEL TYPE TO BE USED IN THE ALGORITHM
IT MUST BE ONE OF ‘LINEAR’ ‘POLY’ ‘RBF’ ‘SIGMOID’ ‘PRECOMPUTED’ OR A CALLABLE IF NONE IS
GIVEN ‘RBF’ WILL BE USED IF A CALLABLE IS GIVEN IT IS USED TO PRECOMPUTE THE KERNEL MATRIX
DEGREE INT OPTIONAL DEFAULT3 DEGREE OF THE POLYNOMIAL KERNEL FUNCTION ‘POLY’ IGNORED
BY ALL OTHER KERNELS

GAMMA FLOAT OPTIONAL DEFAULT'AUTO' KERNEL COEFFICIENT FOR 'RBF' 'POLY' AND 'SIGMOID'
CURRENT DEFAULT IS 'AUTO' WHICH USES 1 NFEATURES IF GAMMASCALE IS PASSED THEN IT
USES 1 NFEATURES XVAR AS VALUE OF GAMMA THE CURRENT DEFAULT OF GAMMA 'AUTO'
WILL CHANGE TO 'SCALE' IN VERSION 022 'AUTODEPRECATED' A DEPRECATED VERSION OF 'AUTO' IS
USED AS A DEFAULT INDICATING THAT NO EXPLICIT VALUE OF GAMMA WAS PASSED
COEF0 FLOAT OPTIONAL DEFAULT00 INDEPENDENT TERM IN KERNEL FUNCTION IT IS ONLY SIGNIFICANT
IN 'POLY' AND 'SIGMOID'
TOLFLOAT OPTIONAL DEFAULT1E3 TOLERANCE FOR STOPPING CRITERION
CFLOAT OPTIONAL DEFAULT10 PENALTY PARAMETER C OF THE ERROR TERM
EPSILON FLOAT OPTIONAL DEFAULT01 EPSILON IN THE EPSILONSVR MODEL IT SPECIFIES THE
EPSILONTUBE WITHIN WHICH NO PENALTY IS ASSOCIATED IN THE TRAINING LOSS FUNCTION WITH POINTS
PREDICTED WITHIN A DISTANCE EPSILON FROM THE ACTUAL VALUE
SHRINKING BOOLEAN OPTIONAL DEFAULTTRUE WHETHER TO USE THE SHRINKING HEURISTIC
CACHESIZE FLOAT OPTIONAL SPECIFY THE SIZE OF THE KERNEL CACHE IN MB
VERBOSE BOOL DEFAULT FALSE ENABLE VERBOSE OUTPUT NOTE THAT THIS SETTING TAKES ADVANTAGE
OF A PERPROCESS RUNTIME SETTING IN LIBSVM THAT IF ENABLED MAY NOT WORK PROPERLY IN A
MULTITHREADED CONTEXT
MAXITER INT OPTIONAL DEFAULT1 HARD LIMIT ON ITERATIONS WITHIN SOLVER OR 1 FOR NO LIMIT
ATTRIBUTES
SUPPORT ARRAYLIKE SHAPE NSV INDICES OF SUPPORT VECTORS
SUPPORTVECTORS ARRAYLIKE SHAPE NSV NFEATURES SUPPORT VECTORS
DUALCOEF ARRAY SHAPE 1 NSV COEFFICIENTS OF THE SUPPORT VECTOR IN THE DECISION FUNC
TION
COEF ARRAY SHAPE 1 NFEATURES WEIGHTS ASSIGNED TO THE FEATURES COEFFICIENTS IN THE PRIMAL
PROBLEM THIS IS ONLY AVAILABLE IN THE CASE OF A LINEAR KERNEL
COEF IS READONLY PROPERTY DERIVED FROM DUALCOEF ANDSUPPORTVECTORS
INTERCEPT ARRAY SHAPE 1 CONSTANTS IN DECISION FUNCTION
SEE ALSO
NUSVR SUPPORT VECTOR MACHINE FOR REGRESSION IMPLEMENTED USING LIBSVM USING A PARAMETER TO CONTROL THE
NUMBER OF SUPPORT VECTORS
LINEARSVR SCALABLE LINEAR SUPPORT VECTOR MACHINE FOR REGRESSION IMPLEMENTED USING LIBLINEAR
NOTES
REFERENCES LIBSVM A LIBRARY FOR SUPPORT VECTOR MACHINES
EXAMPLES
```
 FROM SKLEARNSVM IMPORT SVR
 IMPORT NUMPY AS NP
NSAMPLES NFEATURES  10 5
RNG  NPRANDOMRANDOMSTATE0
```

Y RNGRANDNNSAMPLES
X RNGRANDNNSAMPLES NFEATURES
CLF SVRGAMMASCALE C10 EPSILON02
CLFFITX Y
SVRC10 CACHESIZE200 COEF000 DEGREE3 EPSILON02 GAMMASCALE
KERNELRBF MAXITER1 SHRINKINGTRUE TOL0001 VERBOSEFALSE
METHODS
FITSELF X Y SAMPLEWEIGHT FIT THE SVM MODEL ACCORDING TO THE GIVEN TRAINING DATA
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X PERFORM REGRESSION ON SAMPLES IN X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFKERNEL’RBF’ DEGREE3 GAMMA’AUTODEPRECATED’ COEF000 TOL0001 C10 EP
SILON01 SHRINKINGTRUE CACHESIZE200 VERBOSEFALSE MAXITER1
FITSELFXYSAMPLEWEIGHTNONE
FIT THE SVM MODEL ACCORDING TO THE GIVEN TRAINING DATA
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTORS WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES FOR KER
NEL”PRECOMPUTED” THE EXPECTED SHAPE OF X IS NSAMPLES NSAMPLES
YARRAYLIKE SHAPE NSAMPLES TARGET VALUES CLASS LABELS IN CLASSIFICATION REAL NUMBERS
IN REGRESSION
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES PERSAMPLE WEIGHTS RESCALE C PER SAMPLE
HIGHER WEIGHTS FORCE THE CLASSIFIER TO PUT MORE EMPHASIS ON THESE POINTS
RETURNS
SELF OBJECT
NOTES
IF X AND Y ARE NOT CORDERED AND CONTIGUOUS ARRAYS OF NPFLOAT64 AND X IS NOT A SCIPYSPARSECSRMATRIX X
ANDOR Y MAY BE COPIED
IF X IS A DENSE ARRAY THEN THE OTHER METHODS WILL NOT SUPPORT SPARSE MATRICES AS INPUT
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES

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PREDICTSELFX
PERFORM REGRESSION ON SAMPLES IN X
FOR AN ONECLASS MODEL 1 INLIER OR 1 OUTLIER IS RETURNED
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES FOR KERNEL”PRECOMPUTED”
THE EXPECTED SHAPE OF X IS NSAMPLESTEST NSAMPLESTRAIN
RETURNS
YPRED ARRAY SHAPE NSAMPLES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNSVMSVR
•COMPARISON OF KERNEL RIDGE REGRESSION AND SVR
•PREDICTION LATENCY
637SKLEARNSVM SUPPORT VECTOR MACHINES 2327

•SUPPORT VECTOR REGRESSION SVR USING LINEAR AND NONLINEAR KERNELS
SVML1MINC X Y LOSS FITINTERCEPT RETURN THE LOWEST BOUND FOR C SUCH THAT FOR C IN L1MINC
INFINITY THE MODEL IS GUARANTEED NOT TO BE EMPTY
SKLEARNSVM L1MINC
SKLEARNSVM L1MINC XYLOSS'SQUAREDHINGE' FITINTERCEPTTRUE INTERCEPTSCALING10
RETURN THE LOWEST BOUND FOR C SUCH THAT FOR C IN L1MINC INFINITY THE MODEL IS GUARANTEED NOT
TO BE EMPTY THIS APPLIES TO L1 PENALIZED CLASSIFIERS SUCH AS LINEARSVC WITH PENALTY'L1' AND LIN
EARMODELLOGISTICREGRESSION WITH PENALTY'L1'
THIS VALUE IS VALID IF CLASSWEIGHT PARAMETER IN FIT IS NOT SET
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES TRAINING VECTOR WHERE
NSAMPLES IN THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
YARRAY SHAPE NSAMPLES TARGET VECTOR RELATIVE TO X
LOSS 'SQUAREDHINGE' 'LOG' DEFAULT 'SQUAREDHINGE' SPECIFIES THE LOSS FUNCTION WITH
'SQUAREDHINGE' IT IS THE SQUARED HINGE LOSS AKA L2 LOSS WITH 'LOG' IT IS THE LOSS OF
LOGISTIC REGRESSION MODELS
FITINTERCEPT BOOL DEFAULT TRUE SPECIFIES IF THE INTERCEPT SHOULD BE FITTED BY THE MODEL IT
MUST MATCH THE FIT METHOD PARAMETER
INTERCEPTSCALING FLOAT DEFAULT 1 WHEN FITINTERCEPT IS TRUE INSTANCE VECTOR X BECOMES X
INTERCEPTSCALING IE A "SYNTHETIC" FEATURE WITH CONSTANT VALUE EQUALS TO INTERCEPTSCALING
IS APPENDED TO THE INSTANCE VECTOR IT MUST MATCH THE FIT METHOD PARAMETER
RETURNS
L1MINC FLOAT MINIMUM VALUE FOR C
EXAMPLES USING SKLEARNSVML1MINC
•REGULARIZATION PATH OF L1 LOGISTIC REGRESSION
6372 LOWLEVEL METHODS
SVMLIBSVMCROSSVALIDATION BINDING OF THE CROSSVALIDATION ROUTINE LOWLEVEL ROUTINE
SVMLIBSVMDECISIONFUNCTION PREDICT MARGIN LIBSVM NAME FOR THIS IS PREDICTVALUES
SVMLIBSVMFIT TRAIN THE MODEL USING LIBSVM LOWLEVEL METHOD
SVMLIBSVMPREDICT PREDICT TARGET VALUES OF X GIVEN A MODEL LOWLEVEL METHOD
SVMLIBSVMPREDICTPROBA PREDICT PROBABILITIES
SKLEARNSVMLIBSVM CROSSVALIDATION
SKLEARNSVMLIBSVM CROSSVALIDATION
BINDING OF THE CROSSVALIDATION ROUTINE LOWLEVEL ROUTINE
PARAMETERS

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XARRAYLIKE DTYPEFLOAT SIZENSAMPLES NFEATURES
YARRAY DTYPEFLOAT SIZENSAMPLES TARGET VECTOR
SVMTYPE 0 1 2 3 4 TYPE OF SVM C SVC NU SVC ONE CLASS EPSILON SVR NU SVR
KERNEL ‘LINEAR’ ‘RBF’ ‘POLY’ ‘SIGMOID’ ‘PRECOMPUTED’ KERNEL TO USE IN THE MODEL LINEAR
POLYNOMIAL RBF SIGMOID OR PRECOMPUTED
DEGREE INT DEGREE OF THE POLYNOMIAL KERNEL ONLY RELEVANT IF KERNEL IS SET TO POLYNOMIAL
GAMMA FLOAT GAMMA PARAMETER IN RBF POLY AND SIGMOID KERNELS IGNORED BY OTHER KERNELS
01 BY DEFAULT
COEF0 FLOAT INDEPENDENT PARAMETER IN POLYSIGMOID KERNEL
TOLFLOAT STOPPING CRITERIA
CFLOAT C PARAMETER IN CSUPPORT VECTOR CLASSIFICATION
NUFLOAT
CACHESIZE FLOAT
RANDOMSEED INT OPTIONAL SEED FOR THE RANDOM NUMBER GENERATOR USED FOR PROBABILITY ESTI
MATES 0 BY DEFAULT
RETURNS
TARGET ARRAY FLOAT
SKLEARNSVMLIBSVM DECISIONFUNCTION
SKLEARNSVMLIBSVM DECISIONFUNCTION
PREDICT MARGIN LIBSVM NAME FOR THIS IS PREDICTVALUES
WE HAVE TO RECONSTRUCT MODEL AND PARAMETERS TO MAKE SURE WE STAY IN SYNC WITH THE PYTHON OBJECT
SKLEARNSVMLIBSVM FIT
SKLEARNSVMLIBSVM FIT
TRAIN THE MODEL USING LIBSVM LOWLEVEL METHOD
PARAMETERS
XARRAYLIKE DTYPEFLOAT64 SIZENSAMPLES NFEATURES
YARRAY DTYPEFLOAT64 SIZENSAMPLES TARGET VECTOR
SVMTYPE 0 1 2 3 4 OPTIONAL TYPE OF SVM CSVC NUSVC ONECLASSSVM EP
SILONSVR OR NUSVR RESPECTIVELY 0 BY DEFAULT
KERNEL ‘LINEAR’ ‘RBF’ ‘POLY’ ‘SIGMOID’ ‘PRECOMPUTED’ OPTIONAL KERNEL TO USE IN THE MODEL
LINEAR POLYNOMIAL RBF SIGMOID OR PRECOMPUTED ‘RBF’ BY DEFAULT
DEGREE INT32 OPTIONAL DEGREE OF THE POLYNOMIAL KERNEL ONLY RELEVANT IF KERNEL IS SET TO POLY
NOMIAL 3 BY DEFAULT
GAMMA FLOAT64 OPTIONAL GAMMA PARAMETER IN RBF POLY AND SIGMOID KERNELS IGNORED BY
OTHER KERNELS 01 BY DEFAULT
COEF0 FLOAT64 OPTIONAL INDEPENDENT PARAMETER IN POLYSIGMOID KERNEL 0 BY DEFAULT
TOLFLOAT64 OPTIONAL NUMERIC STOPPING CRITERION WRITEME 1E3 BY DEFAULT
637SKLEARNSVM SUPPORT VECTOR MACHINES 2329

CFLOAT64 OPTIONAL C PARAMETER IN CSUPPORT VECTOR CLASSIFICATION 1 BY DEFAULT
NUFLOAT64 OPTIONAL 05 BY DEFAULT
EPSILON DOUBLE OPTIONAL 01 BY DEFAULT
CLASSWEIGHT ARRAY DTYPE FLOAT64 SHAPE NCLASSES OPTIONAL NPEMPTY0 BY DEFAULT
SAMPLEWEIGHT ARRAY DTYPE FLOAT64 SHAPE NSAMPLES OPTIONAL NPEMPTY0 BY DEFAULT
SHRINKING INT OPTIONAL 1 BY DEFAULT
PROBABILITY INT OPTIONAL 0 BY DEFAULT
CACHESIZE FLOAT64 OPTIONAL CACHE SIZE FOR GRAM MATRIX COLUMNS IN MEGABYTES 100 BY DEFAULT
MAXITER INT 1 FOR NO LIMIT OPTIONAL STOP SOLVER AFTER THIS MANY ITERATIONS REGARDLESS OF ACCURACY XXX CURRENTLY THERE IS NO API TO KNOW WHETHER THIS KICKED IN 1 BY DEFAULT
RANDOMSEED INT OPTIONAL SEED FOR THE RANDOM NUMBER GENERATOR USED FOR PROBABILITY ESTIMATES 0 BY DEFAULT
RETURNS
SUPPORT ARRAY SHAPENSUPPORT INDEX OF SUPPORT VECTORS
SUPPORTVECTORS ARRAY SHAPENSUPPORT NFEATURES SUPPORT VECTORS EQUIVALENT TO XSUPPORT WILL RETURN AN EMPTY ARRAY IN THE CASE OF PRECOMPUTED KERNEL
NCLASSSV ARRAY NUMBER OF SUPPORT VECTORS IN EACH CLASS
SVCOEF ARRAY COEFFICIENTS OF SUPPORT VECTORS IN DECISION FUNCTION
INTERCEPT ARRAY INTERCEPT IN DECISION FUNCTION
PROBA PROBB ARRAY PROBABILITY ESTIMATES EMPTY ARRAY FOR PROBABILITYFALSE
SKLEARNSVMLIBSVM PREDICT
SKLEARNSVMLIBSVM PREDICT
PREDICT TARGET VALUES OF X GIVEN A MODEL LOWLEVEL METHOD
PARAMETERS
XARRAYLIKE DTYPEFLOAT SIZENSAMPLES NFEATURES
SVMTYPE 0 1 2 3 4 TYPE OF SVM C SVC NU SVC ONE CLASS EPSILON SVR NU SVR
KERNEL ‘LINEAR’ ‘RBF’ ‘POLY’ ‘SIGMOID’ ‘PRECOMPUTED’ TYPE OF KERNEL
DEGREE INT DEGREE OF THE POLYNOMIAL KERNEL
GAMMA FLOAT GAMMA PARAMETER IN RBF POLY AND SIGMOID KERNELS IGNORED BY OTHER KERNELS 01 BY DEFAULT
COEF0 FLOAT INDEPENDENT PARAMETER IN POLYSIGMOID KERNEL
RETURNS
DECVALUES ARRAY PREDICTED VALUES

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SKLEARNSVMLIBSVM PREDICTPROBA
SKLEARNSVMLIBSVM PREDICTPROBA
PREDICT PROBABILITIES
SVMMODEL STORES ALL PARAMETERS NEEDED TO PREDICT A GIVEN VALUE
FOR SPEED ALL REAL WORK IS DONE AT THE C LEVEL IN FUNCTION COPYPREDICT LIBSVMHELPERC
WE HAVE TO RECONSTRUCT MODEL AND PARAMETERS TO MAKE SURE WE STAY IN SYNC WITH THE PYTHON OBJECT
SEE SKLEARNSVMPREDICT FOR A COMPLETE LIST OF PARAMETERS
PARAMETERS
XARRAYLIKE DTYPEFLOAT
KERNEL ‘LINEAR’ ‘RBF’ ‘POLY’ ‘SIGMOID’ ‘PRECOMPUTED’
RETURNS
DECVALUES ARRAY PREDICTED VALUES
638SKLEARNTREE DECISION TREES
THESKLEARNTREE MODULE INCLUDES DECISION TREEBASED MODELS FOR CLASSIFICATION AND REGRESSION
USER GUIDE SEE THE DECISION TREES SECTION FOR FURTHER DETAILS
TREEDECISIONTREECLASSIFIER CRITERION A DECISION TREE CLASSIFIER
TREEDECISIONTREEREGRESSOR CRITERION A DECISION TREE REGRESSOR
TREEEXTRATREECLASSIFIER CRITERION AN EXTREMELY RANDOMIZED TREE CLASSIFIER
TREEEXTRATREEREGRESSOR CRITERION AN EXTREMELY RANDOMIZED TREE REGRESSOR
6381SKLEARNTREE DECISIONTREECLASSIFIER
CLASSSKLEARNTREE DECISIONTREECLASSIFIER CRITERION’GINI’ SPLITTER’BEST’ MAXDEPTHNONE
MINSAMPLESSPLIT2 MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00
MAXFEATURESNONE RAN
DOMSTATENONE MAXLEAFNODESNONE
MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE CLASSWEIGHTNONE
PRESORTFALSE
A DECISION TREE CLASSIFIER
READ MORE IN THE USER GUIDE
PARAMETERS
CRITERION STRING OPTIONAL DEFAULT”GINI” THE FUNCTION TO MEASURE THE QUALITY OF A SPLIT SUP
PORTED CRITERIA ARE “GINI” FOR THE GINI IMPURITY AND “ENTROPY” FOR THE INFORMATION GAIN
SPLITTER STRING OPTIONAL DEFAULT”BEST” THE STRATEGY USED TO CHOOSE THE SPLIT AT EACH NODE
SUPPORTED STRATEGIES ARE “BEST” TO CHOOSE THE BEST SPLIT AND “RANDOM” TO CHOOSE THE BEST
RANDOM SPLIT
MAXDEPTH INT OR NONE OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF THE TREE IF NONE

THEN NODES ARE EXPANDED UNTIL ALL LEAVES ARE PURE OR UNTIL ALL LEAVES CONTAIN LESS THAN
MINSAMPLESSPLIT SAMPLES
MINSAMPLESSPLIT INT FLOAT OPTIONAL DEFAULT2 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST
MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY
HAVE THE EFFECT OF SMOOTHING THE MODEL ESPECIALLY IN REGRESSION
• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE
SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE
EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED
MAXFEATURES INT FLOAT STRING OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF FEATURES TO
CONSIDER WHEN LOOKING FOR THE BEST SPLIT
• IF INT THEN CONSIDER MAXFEATURES FEATURES AT EACH SPLIT
• IF FLOAT THEN MAXFEATURES IS A FRACTION AND INTMAXFEATURES
NFEATURES FEATURES ARE CONSIDERED AT EACH SPLIT
• IF “AUTO” THEN MAXFEATURESSQRTNFEATURES
• IF “SQRT” THEN MAXFEATURESSQRTNFEATURES
• IF “LOG2” THEN MAXFEATURESLOG2NFEATURES
• IF NONE THEN MAXFEATURESNFEATURES
NOTE THE SEARCH FOR A SPLIT DOES NOT STOP UNTIL AT LEAST ONE VALID PARTITION OF THE NODE SAMPLES
IS FOUND EVEN IF IT REQUIRES TO EFFECTIVELY INSPECT MORE THAN MAXFEATURES FEATURES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULTNONE GROW A TREE WITH MAXLEAFNODES
IN BESTFIRST FASHION BEST NODES ARE DEFINED AS RELATIVE REDUCTION IN IMPURITY IF NONE THEN
UNLIMITED NUMBER OF LEAF NODES
MINIMPURITYDECREASE FLOAT OPTIONAL DEFAULT0 A NODE WILL BE SPLIT IF THIS SPLIT INDUCES
A DECREASE OF THE IMPURITY GREATER THAN OR EQUAL TO THIS VALUE
THE WEIGHTED IMPURITY DECREASE EQUATION IS THE FOLLOWING
NT N IMPURITY NTR NT RIGHTIMPURITY
 NTL NT LEFTIMPURITY

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WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE
NTL IS THE NUMBER OF SAMPLES IN THE LEFT CHILD AND NTR IS THE NUMBER OF SAMPLES IN
THE RIGHT CHILD
NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED
NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE
WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
DEPRECATED SINCE VERSION 019 MINIMPURITYSPLIT HAS BEEN DEPRECATED IN FAVOR OF
MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT
WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE
MINIMPURITYDECREASE INSTEAD
CLASSWEIGHT DICT LIST OF DICTS “BALANCED” OR NONE DEFAULTNONE WEIGHTS ASSOCIATED WITH
CLASSES IN THE FORM CLASSLABEL WEIGHT IF NOT GIVEN ALL CLASSES ARE SUPPOSED
TO HAVE WEIGHT ONE FOR MULTIOUTPUT PROBLEMS A LIST OF DICTS CAN BE PROVIDED IN THE SAME
ORDER AS THE COLUMNS OF Y
NOTE THAT FOR MULTIOUTPUT INCLUDING MULTILABEL WEIGHTS SHOULD BE DEFINED FOR EACH CLASS OF
EVERY COLUMN IN ITS OWN DICT FOR EXAMPLE FOR FOURCLASS MULTILABEL CLASSIFICATION WEIGHTS
SHOULD BE 0 1 1 1 0 1 1 5 0 1 1 1 0 1 1 1 INSTEAD OF 11 25
31 41
THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP
BINCOUNTY
FOR MULTIOUTPUT THE WEIGHTS OF EACH COLUMN OF Y WILL BE MULTIPLIED
NOTE THAT THESE WEIGHTS WILL BE MULTIPLIED WITH SAMPLEWEIGHT PASSED THROUGH THE FIT
METHOD IF SAMPLEWEIGHT IS SPECIFIED
PRESORT BOOL OPTIONAL DEFAULTFALSE WHETHER TO PRESORT THE DATA TO SPEED UP THE FINDING OF
BEST SPLITS IN FITTING FOR THE DEFAULT SETTINGS OF A DECISION TREE ON LARGE DATASETS SETTING
THIS TO TRUE MAY SLOW DOWN THE TRAINING PROCESS WHEN USING EITHER A SMALLER DATASET OR A
RESTRICTED DEPTH THIS MAY SPEED UP THE TRAINING
ATTRIBUTES
CLASSES ARRAY OF SHAPE NCLASSES OR A LIST OF SUCH ARRAYS THE CLASSES LABELS SINGLE OUTPUT
PROBLEM OR A LIST OF ARRAYS OF CLASS LABELS MULTIOUTPUT PROBLEM
FEATUREIMPORTANCES ARRAY OF SHAPE NFEATURES RETURN THE FEATURE IMPORTANCES
MAXFEATURES INT THE INFERRED VALUE OF MAXFEATURES
NCLASSES INT OR LIST THE NUMBER OF CLASSES FOR SINGLE OUTPUT PROBLEMS OR A LIST CONTAINING
THE NUMBER OF CLASSES FOR EACH OUTPUT FOR MULTIOUTPUT PROBLEMS
NFEATURES INT THE NUMBER OF FEATURES WHEN FIT IS PERFORMED
NOUTPUTS INT THE NUMBER OF OUTPUTS WHEN FIT IS PERFORMED
TREE TREE OBJECT THE UNDERLYING TREE OBJECT PLEASE REFER TO HELPSKLEARNTREE
TREETREE FOR ATTRIBUTES OF TREE OBJECT AND UNDERSTANDING THE DECISION TREE STRUCTURE
FOR BASIC USAGE OF THESE ATTRIBUTES
SEE ALSO
DECISIONTREEREGRESSOR
638SKLEARNTREE DECISION TREES 2333

NOTES
THE DEFAULT VALUES FOR THE PARAMETERS CONTROLLING THE SIZE OF THE TREES EG MAXDEPTH
MINSAMPLESLEAF ETC LEAD TO FULLY GROWN AND UNPRUNED TREES WHICH CAN POTENTIALLY BE VERY LARGE ON
SOME DATA SETS TO REDUCE MEMORY CONSUMPTION THE COMPLEXITY AND SIZE OF THE TREES SHOULD BE CONTROLLED BY
SETTING THOSE PARAMETER VALUES
THE FEATURES ARE ALWAYS RANDOMLY PERMUTED AT EACH SPLIT THEREFORE THE BEST FOUND SPLIT MAY VARY EVEN WITH
THE SAME TRAINING DATA AND MAXFEATURESNFEATURES IF THE IMPROVEMENT OF THE CRITERION IS IDENTICAL FOR
SEVERAL SPLITS ENUMERATED DURING THE SEARCH OF THE BEST SPLIT TO OBTAIN A DETERMINISTIC BEHAVIOUR DURING FITTING
RANDOMSTATE HAS TO BE FIXED
REFERENCES
RB1EC977CD3071 RB1EC977CD3072 RB1EC977CD3073 RB1EC977CD3074
EXAMPLES
FROM SKLEARNDATASETS IMPORT LOADIRIS
FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
CLF DECISIONTREECLASSIFIERRANDOMSTATE0
IRIS LOADIRIS
CROSSVALSCORECLF IRISDATA IRISTARGET CV10

ARRAY 1 093 086 093 093
093 093 1 093 1
METHODS
APPLY SELF X CHECKINPUT RETURNS THE INDEX OF THE LEAF THAT EACH SAMPLE IS PRE
DICTED AS
DECISIONPATH SELF X CHECKINPUT RETURN THE DECISION PATH IN THE TREE
FITSELF X Y SAMPLEWEIGHT BUILD A DECISION TREE CLASSIFIER FROM THE TRAINING SET X
Y
GETDEPTH SELF RETURNS THE DEPTH OF THE DECISION TREE
GETNLEAVES SELF RETURNS THE NUMBER OF LEAVES OF THE DECISION TREE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X CHECKINPUT PREDICT CLASS OR REGRESSION VALUE FOR X
PREDICTLOGPROBA SELF X PREDICT CLASS LOGPROBABILITIES OF THE INPUT SAMPLES X
PREDICTPROBA SELF X CHECKINPUT PREDICT CLASS PROBABILITIES OF THE INPUT SAMPLES X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFCRITERION'GINI' SPLITTER'BEST' MAXDEPTHNONE MINSAMPLESSPLIT2
MINSAMPLESLEAF1 MINWEIGHTFRACTIONLEAF00 MAXFEATURESNONE
RANDOMSTATENONE MAXLEAFNODESNONE MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE CLASSWEIGHTNONE PRESORTFALSE

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APPLYSELFXCHECKINPUTTRUE
RETURNS THE INDEX OF THE LEAF THAT EACH SAMPLE IS PREDICTED AS
NEW IN VERSION 017
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES FOR EACH DATAPOINT X IN X RETURN THE INDEX OF
THE LEAF X ENDS UP IN LEAVES ARE NUMBERED WITHIN 0 SELFTREENODECOUNT
POSSIBLY WITH GAPS IN THE NUMBERING
DECISIONPATH SELFXCHECKINPUTTRUE
RETURN THE DECISION PATH IN THE TREE
NEW IN VERSION 018
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
INDICATOR SPARSE CSR ARRAY SHAPE NSAMPLES NNODES RETURN A NODE INDICATOR MATRIX
WHERE NON ZERO ELEMENTS INDICATES THAT THE SAMPLES GOES THROUGH THE NODES
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES
THE IMPORTANCE OF A FEATURE IS COMPUTED AS THE NORMALIZED TOTAL REDUCTION OF THE CRITERION BROUGHT BY THAT
FEATURE IT IS ALSO KNOWN AS THE GINI IMPORTANCE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES
FITSELFXYSAMPLEWEIGHTNONE CHECKINPUTTRUE XIDXSORTEDNONE
BUILD A DECISION TREE CLASSIFIER FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
INTERNALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED
TO A SPARSECSCMATRIX
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE TARGET VALUES CLASS LA
BELS AS INTEGERS OR STRINGS
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEGA
TIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE SPLITS ARE ALSO IGNORED IF
THEY WOULD RESULT IN ANY SINGLE CLASS CARRYING A NEGATIVE WEIGHT IN EITHER CHILD NODE
638SKLEARNTREE DECISION TREES 2335

CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
XIDXSORTED ARRAYLIKE SHAPE NSAMPLES NFEATURES OPTIONAL THE INDEXES OF THE
SORTED TRAINING INPUT SAMPLES IF MANY TREE ARE GROWN ON THE SAME DATASET THIS ALLOWS THE
ORDERING TO BE CACHED BETWEEN TREES IF NONE THE DATA WILL BE SORTED HERE DON’T USE THIS
PARAMETER UNLESS YOU KNOW WHAT TO DO
RETURNS
SELF OBJECT
GETDEPTH SELF
RETURNS THE DEPTH OF THE DECISION TREE
THE DEPTH OF A TREE IS THE MAXIMUM DISTANCE BETWEEN THE ROOT AND ANY LEAF
GETNLEAVES SELF
RETURNS THE NUMBER OF LEAVES OF THE DECISION TREE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXCHECKINPUTTRUE
PREDICT CLASS OR REGRESSION VALUE FOR X
FOR A CLASSIFICATION MODEL THE PREDICTED CLASS FOR EACH SAMPLE IN X IS RETURNED FOR A REGRESSION MODEL
THE PREDICTED VALUE BASED ON X IS RETURNED
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
YARRAY OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE PREDICTED CLASSES OR THE
PREDICT VALUES
PREDICTLOGPROBA SELFX
PREDICT CLASS LOGPROBABILITIES OF THE INPUT SAMPLES X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS

PARRAY OF SHAPE NSAMPLES NCLASSES OR A LIST OF NOUTPUTS SUCH ARRAYS IF NOUTPUTS
 1 THE CLASS LOGPROBABILITIES OF THE INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS
TO THAT IN THE ATTRIBUTE CLASSES
PREDICTPROBA SELFXCHECKINPUTTRUE
PREDICT CLASS PROBABILITIES OF THE INPUT SAMPLES X
THE PREDICTED CLASS PROBABILITY IS THE FRACTION OF SAMPLES OF THE SAME CLASS IN A LEAF
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE THIS PARAMETER
UNLESS YOU KNOW WHAT YOU DO
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOL RUN CHECKARRAY ON X
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES OR A LIST OF NOUTPUTS SUCH ARRAYS IF NOUTPUTS
 1 THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS TO
THAT IN THE ATTRIBUTE CLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNTREEDECISIONTREECLASSIFIER
•CLASSIFIER COMPARISON
•PLOT THE DECISION BOUNDARIES OF A VOTINGCLASSIFIER
•TWOCLASS ADABOOST
•MULTICLASS ADABOOSTED DECISION TREES

•DISCRETE VERSUS REAL ADABOOST
•PLOT THE DECISION SURFACES OF ENSEMBLES OF TREES ON THE IRIS DATASET
•DEMONSTRATION OF MULTIMETRIC EVALUATION ON CROSSVALSCORE AND GRIDSEARCHCV
•PLOT THE DECISION SURFACE OF A DECISION TREE ON THE IRIS DATASET
•UNDERSTANDING THE DECISION TREE STRUCTURE
6382SKLEARNTREE DECISIONTREEREGRESSOR
CLASSSKLEARNTREE DECISIONTREEREGRESSOR CRITERION'MSE' SPLITTER'BEST' MAXDEPTHNONE
MINSAMPLESSPLIT2 MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00 MAXFEATURESNONE
RANDOMSTATENONE MAXLEAFNODESNONE
MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE PRESORTFALSE
A DECISION TREE REGRESSOR
READ MORE IN THE USER GUIDE
PARAMETERS
CRITERION STRING OPTIONAL DEFAULT"MSE" THE FUNCTION TO MEASURE THE QUALITY OF A SPLIT SUP
PORTED CRITERIA ARE "MSE" FOR THE MEAN SQUARED ERROR WHICH IS EQUAL TO VARIANCE REDUCTION AS
FEATURE SELECTION CRITERION AND MINIMIZES THE L2 LOSS USING THE MEAN OF EACH TERMINAL NODE
"FRIEDMANMSE" WHICH USES MEAN SQUARED ERROR WITH FRIEDMAN'S IMPROVEMENT SCORE FOR
POTENTIAL SPLITS AND "MAE" FOR THE MEAN ABSOLUTE ERROR WHICH MINIMIZES THE L1 LOSS USING
THE MEDIAN OF EACH TERMINAL NODE
NEW IN VERSION 018 MEAN ABSOLUTE ERROR MAE CRITERION
SPLITTER STRING OPTIONAL DEFAULT"BEST" THE STRATEGY USED TO CHOOSE THE SPLIT AT EACH NODE
SUPPORTED STRATEGIES ARE "BEST" TO CHOOSE THE BEST SPLIT AND "RANDOM" TO CHOOSE THE BEST
RANDOM SPLIT
MAXDEPTH INT OR NONE OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF THE TREE IF NONE
THEN NODES ARE EXPANDED UNTIL ALL LEAVES ARE PURE OR UNTIL ALL LEAVES CONTAIN LESS THAN
MINSAMPLESSPLIT SAMPLES
MINSAMPLESSPLIT INT FLOAT OPTIONAL DEFAULT2 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST
MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY
HAVE THE EFFECT OF SMOOTHING THE MODEL ESPECIALLY IN REGRESSION
• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS

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MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED
MAXFEATURES INT FLOAT STRING OR NONE OPTIONAL DEFAULTNONE THE NUMBER OF FEATURES TO CONSIDER WHEN LOOKING FOR THE BEST SPLIT
• IF INT THEN CONSIDER MAXFEATURES FEATURES AT EACH SPLIT
• IF FLOAT THEN MAXFEATURES IS A FRACTION AND INTMAXFEATURES NFEATURES FEATURES ARE CONSIDERED AT EACH SPLIT
• IF “AUTO” THEN MAXFEATURESNFEATURES
• IF “SQRT” THEN MAXFEATURESSQRTNFEATURES
• IF “LOG2” THEN MAXFEATURESLOG2NFEATURES
• IF NONE THEN MAXFEATURESNFEATURES
NOTE THE SEARCH FOR A SPLIT DOES NOT STOP UNTIL AT LEAST ONE VALID PARTITION OF THE NODE SAMPLES IS FOUND EVEN IF IT REQUIRES TO EFFECTIVELY INSPECT MORE THAN MAXFEATURES FEATURES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE INSTANCE USED BY NPRANDOM
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULTNONE GROW A TREE WITH MAXLEAFNODES IN BESTFIRST FASHION BEST NODES ARE DEFINED AS RELATIVE REDUCTION IN IMPURITY IF NONE THEN UNLIMITED NUMBER OF LEAF NODES
MINIMPURITYDECREASE FLOAT OPTIONAL DEFAULT0 A NODE WILL BE SPLIT IF THIS SPLIT INDUCES A DECREASE OF THE IMPURITY GREATER THAN OR EQUAL TO THIS VALUE
THE WEIGHTED IMPURITY DECREASE EQUATION IS THE FOLLOWING
NT N IMPURITY NTR NT RIGHTIMPURITY
 NTL NT LEFTIMPURITY
WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE NTL IS THE NUMBER OF SAMPLES IN THE LEFT CHILD AND NTR IS THE NUMBER OF SAMPLES IN THE RIGHT CHILD
NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED
NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
DEPRECATED SINCE VERSION 019 MINIMPURITYSPLIT HAS BEEN DEPRECATED IN FAVOR OF MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE MINIMPURITYDECREASE INSTEAD
PRESORT BOOL OPTIONAL DEFAULTFALSE WHETHER TO PRESORT THE DATA TO SPEED UP THE FINDING OF BEST SPLITS IN FITTING FOR THE DEFAULT SETTINGS OF A DECISION TREE ON LARGE DATASETS SETTING THIS TO TRUE MAY SLOW DOWN THE TRAINING PROCESS WHEN USING EITHER A SMALLER DATASET OR A RESTRICTED DEPTH THIS MAY SPEED UP THE TRAINING
ATTRIBUTES
FEATUREIMPORTANCES ARRAY OF SHAPE NFEATURES RETURN THE FEATURE IMPORTANCES

MAXFEATURES INT THE INFERRED VALUE OF MAXFEATURES
NFEATURES INT THE NUMBER OF FEATURES WHEN FIT IS PERFORMED
NOUTPUTS INT THE NUMBER OF OUTPUTS WHEN FIT IS PERFORMED
TREE TREE OBJECT THE UNDERLYING TREE OBJECT PLEASE REFER TO HELPSKLEARNTREE
TREETREE FOR ATTRIBUTES OF TREE OBJECT AND UNDERSTANDING THE DECISION TREE STRUCTURE
FOR BASIC USAGE OF THESE ATTRIBUTES
SEE ALSO
DECISIONTREECLASSIFIER
NOTES
THE DEFAULT VALUES FOR THE PARAMETERS CONTROLLING THE SIZE OF THE TREES EG MAXDEPTH
MINSAMPLESLEAF ETC LEAD TO FULLY GROWN AND UNPRUNED TREES WHICH CAN POTENTIALLY BE VERY LARGE ON
SOME DATA SETS TO REDUCE MEMORY CONSUMPTION THE COMPLEXITY AND SIZE OF THE TREES SHOULD BE CONTROLLED BY
SETTING THOSE PARAMETER VALUES
THE FEATURES ARE ALWAYS RANDOMLY PERMUTED AT EACH SPLIT THEREFORE THE BEST FOUND SPLIT MAY VARY EVEN WITH
THE SAME TRAINING DATA AND MAXFEATURESNFEATURES IF THE IMPROVEMENT OF THE CRITERION IS IDENTICAL FOR
SEVERAL SPLITS ENUMERATED DURING THE SEARCH OF THE BEST SPLIT TO OBTAIN A DETERMINISTIC BEHAVIOUR DURING FITTING
RANDOMSTATE HAS TO BE FIXED
REFERENCES
RA37B7E3ADB191 RA37B7E3ADB192 RA37B7E3ADB193 RA37B7E3ADB194
EXAMPLES
FROM SKLEARNDATASETS IMPORT LOADBOSTON
FROM SKLEARNMODELSELECTION IMPORT CROSSVALSCORE
FROM SKLEARNTREE IMPORT DECISIONTREEREGRESSOR
BOSTON LOADBOSTON
REGRESSOR DECISIONTREEREGRESSORRANDOMSTATE0
CROSSVALSCOREREGRESSOR BOSTONDATA BOSTONTARGET CV10

ARRAY 061 057 034 041 075
007 029 033 142 177
METHODS
APPLY SELF X CHECKINPUT RETURNS THE INDEX OF THE LEAF THAT EACH SAMPLE IS PRE
DICTED AS
DECISIONPATH SELF X CHECKINPUT RETURN THE DECISION PATH IN THE TREE
FITSELF X Y SAMPLEWEIGHT BUILD A DECISION TREE REGRESSOR FROM THE TRAINING SET X
Y
GETDEPTH SELF RETURNS THE DEPTH OF THE DECISION TREE
CONTINUED ON NEXT PAGE

TABLE 6284 – CONTINUED FROM PREVIOUS PAGE
GETNLEAVES SELF RETURNS THE NUMBER OF LEAVES OF THE DECISION TREE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X CHECKINPUT PREDICT CLASS OR REGRESSION VALUE FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFCRITERION'MSE' SPLITTER'BEST' MAXDEPTHNONE MINSAMPLESSPLIT2
MINSAMPLESLEAF1 MINWEIGHTFRACTIONLEAF00 MAXFEATURESNONE
RANDOMSTATENONE MAXLEAFNODESNONE MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE PRESORTFALSE
APPLYSELFXCHECKINPUTTRUE
RETURNS THE INDEX OF THE LEAF THAT EACH SAMPLE IS PREDICTED AS
NEW IN VERSION 017
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON'T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES FOR EACH DATAPOINT X IN X RETURN THE INDEX OF
THE LEAF X ENDS UP IN LEAVES ARE NUMBERED WITHIN 0 SELFTREENODECOUNT
POSSIBLY WITH GAPS IN THE NUMBERING
DECISIONPATH SELFXCHECKINPUTTRUE
RETURN THE DECISION PATH IN THE TREE
NEW IN VERSION 018
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON'T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
INDICATOR SPARSE CSR ARRAY SHAPE NSAMPLES NNODES RETURN A NODE INDICATOR MATRIX
WHERE NON ZERO ELEMENTS INDICATES THAT THE SAMPLES GOES THROUGH THE NODES
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES
THE IMPORTANCE OF A FEATURE IS COMPUTED AS THE NORMALIZED TOTAL REDUCTION OF THE CRITERION BROUGHT BY THAT
FEATURE IT IS ALSO KNOWN AS THE GINI IMPORTANCE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES

FITSELFXYSAMPLEWEIGHTNONE CHECKINPUTTRUE XIDXSORTEDNONE
BUILD A DECISION TREE REGRESSOR FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
INTERNALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED
TO A SPARSECSCMATRIX
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE TARGET VALUES REAL NUM
BERS USEDTYPENPFLOAT64 ANDORDERC FOR MAXIMUM EFFICIENCY
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEGA
TIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
XIDXSORTED ARRAYLIKE SHAPE NSAMPLES NFEATURES OPTIONAL THE INDEXES OF THE
SORTED TRAINING INPUT SAMPLES IF MANY TREE ARE GROWN ON THE SAME DATASET THIS ALLOWS THE
ORDERING TO BE CACHED BETWEEN TREES IF NONE THE DATA WILL BE SORTED HERE DON’T USE THIS
PARAMETER UNLESS YOU KNOW WHAT TO DO
RETURNS
SELF OBJECT
GETDEPTH SELF
RETURNS THE DEPTH OF THE DECISION TREE
THE DEPTH OF A TREE IS THE MAXIMUM DISTANCE BETWEEN THE ROOT AND ANY LEAF
GETNLEAVES SELF
RETURNS THE NUMBER OF LEAVES OF THE DECISION TREE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXCHECKINPUTTRUE
PREDICT CLASS OR REGRESSION VALUE FOR X
FOR A CLASSIFICATION MODEL THE PREDICTED CLASS FOR EACH SAMPLE IN X IS RETURNED FOR A REGRESSION MODEL
THE PREDICTED VALUE BASED ON X IS RETURNED
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS

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YARRAY OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE PREDICTED CLASSES OR THE
PREDICT VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
EXAMPLES USING SKLEARNTREEDECISIONTREEREGRESSOR
•DECISION TREE REGRESSION WITH ADABOOST
•SINGLE ESTIMATOR VERSUS BAGGING BIASVARIANCE DECOMPOSITION
•IMPUTING MISSING VALUES WITH VARIANTS OF ITERATIVEIMPUTER
•USING KBINSDISCRETIZER TO DISCRETIZE CONTINUOUS FEATURES
•DECISION TREE REGRESSION
•MULTIOUTPUT DECISION TREE REGRESSION

6383SKLEARNTREE EXTRATREECLASSIFIER
CLASSSKLEARNTREE EXTRATREECLASSIFIER CRITERION'GINI' SPLITTER'RANDOM'
MAXDEPTHNONE MINSAMPLESSPLIT2
MINSAMPLESLEAF1 MINWEIGHTFRACTIONLEAF00
MAXFEATURES'AUTO' RANDOMSTATENONE
MAXLEAFNODESNONE MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE CLASSWEIGHTNONE
AN EXTREMELY RANDOMIZED TREE CLASSIFIER
EXTRATREES DIFFER FROM CLASSIC DECISION TREES IN THE WAY THEY ARE BUILT WHEN LOOKING FOR THE BEST SPLIT TO SEPARATE THE SAMPLES OF A NODE INTO TWO GROUPS RANDOM SPLITS ARE DRAWN FOR EACH OF THE MAXFEATURES RANDOMLY SELECTED FEATURES AND THE BEST SPLIT AMONG THOSE IS CHOSEN WHEN MAXFEATURES IS SET 1 THIS AMOUNTS TO BUILDING A TOTALLY RANDOM DECISION TREE
WARNING EXTRATREES SHOULD ONLY BE USED WITHIN ENSEMBLE METHODS
READ MORE IN THE USER GUIDE
PARAMETERS
CRITERION STRING OPTIONAL DEFAULT"GINI" THE FUNCTION TO MEASURE THE QUALITY OF A SPLIT SUPPORTED CRITERIA ARE "GINI" FOR THE GINI IMPURITY AND "ENTROPY" FOR THE INFORMATION GAIN
SPLITTER STRING OPTIONAL DEFAULT"RANDOM" THE STRATEGY USED TO CHOOSE THE SPLIT AT EACH NODE SUPPORTED STRATEGIES ARE "BEST" TO CHOOSE THE BEST SPLIT AND "RANDOM" TO CHOOSE THE BEST RANDOM SPLIT
MAXDEPTH INT OR NONE OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF THE TREE IF NONE THEN NODES ARE EXPANDED UNTIL ALL LEAVES ARE PURE OR UNTIL ALL LEAVES CONTAIN LESS THAN MINSAMPLESSPLIT SAMPLES
MINSAMPLESSPLIT INT FLOAT OPTIONAL DEFAULT2 THE MINIMUM NUMBER OF SAMPLES REQUIRED TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY HAVE THE EFFECT OF SMOOTHING THE MODEL ESPECIALLY IN REGRESSION
• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED
MAXFEATURES INT FLOAT STRING OR NONE OPTIONAL DEFAULT"AUTO" THE NUMBER OF FEATURES TO CONSIDER WHEN LOOKING FOR THE BEST SPLIT
• IF INT THEN CONSIDER MAXFEATURES FEATURES AT EACH SPLIT

• IF FLOAT THEN MAXFEATURES IS A FRACTION AND INTMAXFEATURES
NFEATURES FEATURES ARE CONSIDERED AT EACH SPLIT
• IF “AUTO” THEN MAXFEATURESSQRTNFEATURES
• IF “SQRT” THEN MAXFEATURESSQRTNFEATURES
• IF “LOG2” THEN MAXFEATURESLOG2NFEATURES
• IF NONE THEN MAXFEATURESNFEATURES
NOTE THE SEARCH FOR A SPLIT DOES NOT STOP UNTIL AT LEAST ONE VALID PARTITION OF THE NODE SAMPLES
IS FOUND EVEN IF IT REQUIRES TO EFFECTIVELY INSPECT MORE THAN MAXFEATURES FEATURES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULTNONE GROW A TREE WITH MAXLEAFNODES
IN BESTFIRST FASHION BEST NODES ARE DEFINED AS RELATIVE REDUCTION IN IMPURITY IF NONE THEN
UNLIMITED NUMBER OF LEAF NODES
MINIMPURITYDECREASE FLOAT OPTIONAL DEFAULT0 A NODE WILL BE SPLIT IF THIS SPLIT INDUCES
A DECREASE OF THE IMPURITY GREATER THAN OR EQUAL TO THIS VALUE
THE WEIGHTED IMPURITY DECREASE EQUATION IS THE FOLLOWING
NT N IMPURITY NTR NT RIGHTIMPURITY
 NTL NT LEFTIMPURITY
WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE
NTL IS THE NUMBER OF SAMPLES IN THE LEFT CHILD AND NTR IS THE NUMBER OF SAMPLES IN
THE RIGHT CHILD
NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED
NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE
WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
DEPRECATED SINCE VERSION 019 MINIMPURITYSPLIT HAS BEEN DEPRECATED IN FAVOR OF
MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT
WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE
MINIMPURITYDECREASE INSTEAD
CLASSWEIGHT DICT LIST OF DICTS “BALANCED” OR NONE DEFAULTNONE WEIGHTS ASSOCIATED WITH
CLASSES IN THE FORM CLASSLABEL WEIGHT IF NOT GIVEN ALL CLASSES ARE SUPPOSED
TO HAVE WEIGHT ONE FOR MULTIOUTPUT PROBLEMS A LIST OF DICTS CAN BE PROVIDED IN THE SAME
ORDER AS THE COLUMNS OF Y
NOTE THAT FOR MULTIOUTPUT INCLUDING MULTILABEL WEIGHTS SHOULD BE DEFINED FOR EACH CLASS OF
EVERY COLUMN IN ITS OWN DICT FOR EXAMPLE FOR FOURCLASS MULTILABEL CLASSIFICATION WEIGHTS
SHOULD BE 0 1 1 1 0 1 1 5 0 1 1 1 0 1 1 1 INSTEAD OF 11 25
31 41
THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES NP
BINCOUNTY
FOR MULTIOUTPUT THE WEIGHTS OF EACH COLUMN OF Y WILL BE MULTIPLIED

NOTE THAT THESE WEIGHTS WILL BE MULTIPLIED WITH SAMPLEWEIGHT PASSED THROUGH THE FIT
METHOD IF SAMPLEWEIGHT IS SPECIFIED
ATTRIBUTES
FEATUREIMPORTANCES RETURN THE FEATURE IMPORTANCES
SEE ALSO
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SKLEARNENSEMBLEEXTRATREESREGRESSOR
NOTES
THE DEFAULT VALUES FOR THE PARAMETERS CONTROLLING THE SIZE OF THE TREES EG MAXDEPTH
MINSAMPLESLEAF ETC LEAD TO FULLY GROWN AND UNPRUNED TREES WHICH CAN POTENTIALLY BE VERY LARGE ON
SOME DATA SETS TO REDUCE MEMORY CONSUMPTION THE COMPLEXITY AND SIZE OF THE TREES SHOULD BE CONTROLLED BY
SETTING THOSE PARAMETER VALUES
REFERENCES
RDD99A0224C6E1
METHODS
APPLY SELF X CHECKINPUT RETURNS THE INDEX OF THE LEAF THAT EACH SAMPLE IS PRE
DICTED AS
DECISIONPATH SELF X CHECKINPUT RETURN THE DECISION PATH IN THE TREE
FITSELF X Y SAMPLEWEIGHT BUILD A DECISION TREE CLASSIFIER FROM THE TRAINING SET X
Y
GETDEPTH SELF RETURNS THE DEPTH OF THE DECISION TREE
GETNLEAVES SELF RETURNS THE NUMBER OF LEAVES OF THE DECISION TREE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X CHECKINPUT PREDICT CLASS OR REGRESSION VALUE FOR X
PREDICTLOGPROBA SELF X PREDICT CLASS LOGPROBABILITIES OF THE INPUT SAMPLES X
PREDICTPROBA SELF X CHECKINPUT PREDICT CLASS PROBABILITIES OF THE INPUT SAMPLES X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND
LABELS
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFCRITERION’GINI’ SPLITTER’RANDOM’ MAXDEPTHNONE MINSAMPLESSPLIT2
MINSAMPLESLEAF1 MINWEIGHTFRACTIONLEAF00 MAXFEATURES’AUTO’
RANDOMSTATENONE MAXLEAFNODESNONE MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE CLASSWEIGHTNONE
APPLYSELFXCHECKINPUTTRUE
RETURNS THE INDEX OF THE LEAF THAT EACH SAMPLE IS PREDICTED AS
NEW IN VERSION 017
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER

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NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES FOR EACH DATAPOINT X IN X RETURN THE INDEX OF
THE LEAF X ENDS UP IN LEAVES ARE NUMBERED WITHIN 0 SELFTREENODECOUNT
POSSIBLY WITH GAPS IN THE NUMBERING
DECISIONPATH SELFXCHECKINPUTTRUE
RETURN THE DECISION PATH IN THE TREE
NEW IN VERSION 018
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
INDICATOR SPARSE CSR ARRAY SHAPE NSAMPLES NNODES RETURN A NODE INDICATOR MATRIX
WHERE NON ZERO ELEMENTS INDICATES THAT THE SAMPLES GOES THROUGH THE NODES
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES
THE IMPORTANCE OF A FEATURE IS COMPUTED AS THE NORMALIZED TOTAL REDUCTION OF THE CRITERION BROUGHT BY THAT
FEATURE IT IS ALSO KNOWN AS THE GINI IMPORTANCE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES
FITSELFXYSAMPLEWEIGHTNONE CHECKINPUTTRUE XIDXSORTEDNONE
BUILD A DECISION TREE CLASSIFIER FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
INTERNALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED
TO A SPARSECSCMATRIX
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE TARGET VALUES CLASS LA
BELS AS INTEGERS OR STRINGS
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEGA
TIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE SPLITS ARE ALSO IGNORED IF
THEY WOULD RESULT IN ANY SINGLE CLASS CARRYING A NEGATIVE WEIGHT IN EITHER CHILD NODE
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
XIDXSORTED ARRAYLIKE SHAPE NSAMPLES NFEATURES OPTIONAL THE INDEXES OF THE
SORTED TRAINING INPUT SAMPLES IF MANY TREE ARE GROWN ON THE SAME DATASET THIS ALLOWS THE

ORDERING TO BE CACHED BETWEEN TREES IF NONE THE DATA WILL BE SORTED HERE DON’T USE THIS
PARAMETER UNLESS YOU KNOW WHAT TO DO
RETURNS
SELF OBJECT
GETDEPTH SELF
RETURNS THE DEPTH OF THE DECISION TREE
THE DEPTH OF A TREE IS THE MAXIMUM DISTANCE BETWEEN THE ROOT AND ANY LEAF
GETNLEAVES SELF
RETURNS THE NUMBER OF LEAVES OF THE DECISION TREE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXCHECKINPUTTRUE
PREDICT CLASS OR REGRESSION VALUE FOR X
FOR A CLASSIFICATION MODEL THE PREDICTED CLASS FOR EACH SAMPLE IN X IS RETURNED FOR A REGRESSION MODEL
THE PREDICTED VALUE BASED ON X IS RETURNED
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
YARRAY OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE PREDICTED CLASSES OR THE
PREDICT VALUES
PREDICTLOGPROBA SELFX
PREDICT CLASS LOGPROBABILITIES OF THE INPUT SAMPLES X
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES OR A LIST OF NOUTPUTS SUCH ARRAYS IF NOUTPUTS
 1 THE CLASS LOGPROBABILITIES OF THE INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS
TO THAT IN THE ATTRIBUTE CLASSES
PREDICTPROBA SELFXCHECKINPUTTRUE
PREDICT CLASS PROBABILITIES OF THE INPUT SAMPLES X
THE PREDICTED CLASS PROBABILITY IS THE FRACTION OF SAMPLES OF THE SAME CLASS IN A LEAF

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CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE THIS PARAMETER
UNLESS YOU KNOW WHAT YOU DO
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOL RUN CHECKARRAY ON X
RETURNS
PARRAY OF SHAPE NSAMPLES NCLASSES OR A LIST OF NOUTPUTS SUCH ARRAYS IF NOUTPUTS
 1 THE CLASS PROBABILITIES OF THE INPUT SAMPLES THE ORDER OF THE CLASSES CORRESPONDS TO
THAT IN THE ATTRIBUTE CLASSES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE MEAN ACCURACY ON THE GIVEN TEST DATA AND LABELS
IN MULTILABEL CLASSIFICATION THIS IS THE SUBSET ACCURACY WHICH IS A HARSH METRIC SINCE YOU REQUIRE FOR EACH
SAMPLE THAT EACH LABEL SET BE CORRECTLY PREDICTED
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE LABELS FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT MEAN ACCURACY OF SELFPREDICTX WRT Y
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
6384SKLEARNTREE EXTRATREEREGRESSOR
CLASSSKLEARNTREE EXTRATREEREGRESSOR CRITERION’MSE’ SPLITTER’RANDOM’ MAXDEPTHNONE
MINSAMPLESSPLIT2 MINSAMPLESLEAF1
MINWEIGHTFRACTIONLEAF00 MAXFEATURES’AUTO’
RANDOMSTATENONE MINIMPURITYDECREASE00
MINIMPURITYSPLITNONE MAXLEAFNODESNONE
AN EXTREMELY RANDOMIZED TREE REGRESSOR
EXTRATREES DIFFER FROM CLASSIC DECISION TREES IN THE WAY THEY ARE BUILT WHEN LOOKING FOR THE BEST SPLIT TO SEPARATE
THE SAMPLES OF A NODE INTO TWO GROUPS RANDOM SPLITS ARE DRAWN FOR EACH OF THE MAXFEATURES RANDOMLY
SELECTED FEATURES AND THE BEST SPLIT AMONG THOSE IS CHOSEN WHEN MAXFEATURES IS SET 1 THIS AMOUNTS TO
BUILDING A TOTALLY RANDOM DECISION TREE
WARNING EXTRATREES SHOULD ONLY BE USED WITHIN ENSEMBLE METHODS

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PARAMETERS
CRITERION STRING OPTIONAL DEFAULT”MSE” THE FUNCTION TO MEASURE THE QUALITY OF A SPLIT SUP
PORTED CRITERIA ARE “MSE” FOR THE MEAN SQUARED ERROR WHICH IS EQUAL TO VARIANCE REDUCTION AS
FEATURE SELECTION CRITERION AND “MAE” FOR THE MEAN ABSOLUTE ERROR
NEW IN VERSION 018 MEAN ABSOLUTE ERROR MAE CRITERION
SPLITTER STRING OPTIONAL DEFAULT”RANDOM” THE STRATEGY USED TO CHOOSE THE SPLIT AT EACH NODE
SUPPORTED STRATEGIES ARE “BEST” TO CHOOSE THE BEST SPLIT AND “RANDOM” TO CHOOSE THE BEST
RANDOM SPLIT
MAXDEPTH INT OR NONE OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF THE TREE IF NONE
THEN NODES ARE EXPANDED UNTIL ALL LEAVES ARE PURE OR UNTIL ALL LEAVES CONTAIN LESS THAN
MINSAMPLESSPLIT SAMPLES
MINSAMPLESSPLIT INT FLOAT OPTIONAL DEFAULT2 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO SPLIT AN INTERNAL NODE
• IF INT THEN CONSIDER MINSAMPLESSPLIT AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESSPLIT IS A FRACTION AND CEILMINSAMPLESSPLIT
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH SPLIT
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINSAMPLESLEAF INT FLOAT OPTIONAL DEFAULT1 THE MINIMUM NUMBER OF SAMPLES REQUIRED
TO BE AT A LEAF NODE A SPLIT POINT AT ANY DEPTH WILL ONLY BE CONSIDERED IF IT LEAVES AT LEAST
MINSAMPLESLEAF TRAINING SAMPLES IN EACH OF THE LEFT AND RIGHT BRANCHES THIS MAY
HAVE THE EFFECT OF SMOOTHING THE MODEL ESPECIALLY IN REGRESSION
• IF INT THEN CONSIDER MINSAMPLESLEAF AS THE MINIMUM NUMBER
• IF FLOAT THEN MINSAMPLESLEAF IS A FRACTION AND CEILMINSAMPLESLEAF
NSAMPLES ARE THE MINIMUM NUMBER OF SAMPLES FOR EACH NODE
CHANGED IN VERSION 018 ADDED FLOAT VALUES FOR FRACTIONS
MINWEIGHTFRACTIONLEAF FLOAT OPTIONAL DEFAULT0 THE MINIMUM WEIGHTED FRACTION OF THE
SUM TOTAL OF WEIGHTS OF ALL THE INPUT SAMPLES REQUIRED TO BE AT A LEAF NODE SAMPLES HAVE
EQUAL WEIGHT WHEN SAMPLEWEIGHT IS NOT PROVIDED
MAXFEATURES INT FLOAT STRING OR NONE OPTIONAL DEFAULT”AUTO” THE NUMBER OF FEATURES TO
CONSIDER WHEN LOOKING FOR THE BEST SPLIT
• IF INT THEN CONSIDER MAXFEATURES FEATURES AT EACH SPLIT
• IF FLOAT THEN MAXFEATURES IS A FRACTION AND INTMAXFEATURES
NFEATURES FEATURES ARE CONSIDERED AT EACH SPLIT
• IF “AUTO” THEN MAXFEATURESNFEATURES
• IF “SQRT” THEN MAXFEATURESSQRTNFEATURES
• IF “LOG2” THEN MAXFEATURESLOG2NFEATURES
• IF NONE THEN MAXFEATURESNFEATURES
NOTE THE SEARCH FOR A SPLIT DOES NOT STOP UNTIL AT LEAST ONE VALID PARTITION OF THE NODE SAMPLES
IS FOUND EVEN IF IT REQUIRES TO EFFECTIVELY INSPECT MORE THAN MAXFEATURES FEATURES
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE

RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
MINIMPURITYDECREASE FLOAT OPTIONAL DEFAULT0 A NODE WILL BE SPLIT IF THIS SPLIT INDUCES
A DECREASE OF THE IMPURITY GREATER THAN OR EQUAL TO THIS VALUE
THE WEIGHTED IMPURITY DECREASE EQUATION IS THE FOLLOWING
NT N IMPURITY NTR NT RIGHTIMPURITY
 NTL NT LEFTIMPURITY
WHERENIS THE TOTAL NUMBER OF SAMPLES NT IS THE NUMBER OF SAMPLES AT THE CURRENT NODE
NTL IS THE NUMBER OF SAMPLES IN THE LEFT CHILD AND NTR IS THE NUMBER OF SAMPLES IN
THE RIGHT CHILD
NNTNTR ANDNTL ALL REFER TO THE WEIGHTED SUM IF SAMPLEWEIGHT IS PASSED
NEW IN VERSION 019
MINIMPURITYSPLIT FLOAT DEFAULT1E7 THRESHOLD FOR EARLY STOPPING IN TREE GROWTH A NODE
WILL SPLIT IF ITS IMPURITY IS ABOVE THE THRESHOLD OTHERWISE IT IS A LEAF
DEPRECATED SINCE VERSION 019 MINIMPURITYSPLIT HAS BEEN DEPRECATED IN FAVOR OF
MINIMPURITYDECREASE IN 019 THE DEFAULT VALUE OF MINIMPURITYSPLIT
WILL CHANGE FROM 1E7 TO 0 IN 023 AND IT WILL BE REMOVED IN 025 USE
MINIMPURITYDECREASE INSTEAD
MAXLEAFNODES INT OR NONE OPTIONAL DEFAULTNONE GROW A TREE WITH MAXLEAFNODES
IN BESTFIRST FASHION BEST NODES ARE DEFINED AS RELATIVE REDUCTION IN IMPURITY IF NONE THEN
UNLIMITED NUMBER OF LEAF NODES
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THE DEFAULT VALUES FOR THE PARAMETERS CONTROLLING THE SIZE OF THE TREES EG MAXDEPTH
MINSAMPLESLEAF ETC LEAD TO FULLY GROWN AND UNPRUNED TREES WHICH CAN POTENTIALLY BE VERY LARGE ON
SOME DATA SETS TO REDUCE MEMORY CONSUMPTION THE COMPLEXITY AND SIZE OF THE TREES SHOULD BE CONTROLLED BY
SETTING THOSE PARAMETER VALUES
REFERENCES
R4939D63D5A491
METHODS

APPLY SELF X CHECKINPUT RETURNS THE INDEX OF THE LEAF THAT EACH SAMPLE IS PRE
DICTED AS
DECISIONPATH SELF X CHECKINPUT RETURN THE DECISION PATH IN THE TREE
FITSELF X Y SAMPLEWEIGHT BUILD A DECISION TREE REGRESSOR FROM THE TRAINING SET X
Y
GETDEPTH SELF RETURNS THE DEPTH OF THE DECISION TREE
GETNLEAVES SELF RETURNS THE NUMBER OF LEAVES OF THE DECISION TREE
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
PREDICT SELF X CHECKINPUT PREDICT CLASS OR REGRESSION VALUE FOR X
SCORE SELF X Y SAMPLEWEIGHT RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PRE
DICTION
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT SELFCRITERION’MSE’ SPLITTER’RANDOM’ MAXDEPTHNONE MINSAMPLESSPLIT2
MINSAMPLESLEAF1 MINWEIGHTFRACTIONLEAF00 MAXFEATURES’AUTO’
RANDOMSTATENONE MINIMPURITYDECREASE00 MINIMPURITYSPLITNONE
MAXLEAFNODESNONE
APPLYSELFXCHECKINPUTTRUE
RETURNS THE INDEX OF THE LEAF THAT EACH SAMPLE IS PREDICTED AS
NEW IN VERSION 017
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
XLEAVES ARRAYLIKE SHAPE NSAMPLES FOR EACH DATAPOINT X IN X RETURN THE INDEX OF
THE LEAF X ENDS UP IN LEAVES ARE NUMBERED WITHIN 0 SELFTREENODECOUNT
POSSIBLY WITH GAPS IN THE NUMBERING
DECISIONPATH SELFXCHECKINPUTTRUE
RETURN THE DECISION PATH IN THE TREE
NEW IN VERSION 018
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
INDICATOR SPARSE CSR ARRAY SHAPE NSAMPLES NNODES RETURN A NODE INDICATOR MATRIX
WHERE NON ZERO ELEMENTS INDICATES THAT THE SAMPLES GOES THROUGH THE NODES
FEATUREIMPORTANCES
RETURN THE FEATURE IMPORTANCES

THE IMPORTANCE OF A FEATURE IS COMPUTED AS THE NORMALIZED TOTAL REDUCTION OF THE CRITERION BROUGHT BY THAT
FEATURE IT IS ALSO KNOWN AS THE GINI IMPORTANCE
RETURNS
FEATUREIMPORTANCES ARRAY SHAPE NFEATURES
FITSELFXYSAMPLEWEIGHTNONE CHECKINPUTTRUE XIDXSORTEDNONE
BUILD A DECISION TREE REGRESSOR FROM THE TRAINING SET X Y
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE TRAINING INPUT SAMPLES
INTERNALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED
TO A SPARSECSCMATRIX
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE TARGET VALUES REAL NUM
BERS USEDTYPENPFLOAT64 ANDORDERC FOR MAXIMUM EFFICIENCY
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OR NONE SAMPLE WEIGHTS IF NONE THEN
SAMPLES ARE EQUALLY WEIGHTED SPLITS THAT WOULD CREATE CHILD NODES WITH NET ZERO OR NEGA
TIVE WEIGHT ARE IGNORED WHILE SEARCHING FOR A SPLIT IN EACH NODE
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
XIDXSORTED ARRAYLIKE SHAPE NSAMPLES NFEATURES OPTIONAL THE INDEXES OF THE
SORTED TRAINING INPUT SAMPLES IF MANY TREE ARE GROWN ON THE SAME DATASET THIS ALLOWS THE
ORDERING TO BE CACHED BETWEEN TREES IF NONE THE DATA WILL BE SORTED HERE DON’T USE THIS
PARAMETER UNLESS YOU KNOW WHAT TO DO
RETURNS
SELF OBJECT
GETDEPTH SELF
RETURNS THE DEPTH OF THE DECISION TREE
THE DEPTH OF A TREE IS THE MAXIMUM DISTANCE BETWEEN THE ROOT AND ANY LEAF
GETNLEAVES SELF
RETURNS THE NUMBER OF LEAVES OF THE DECISION TREE
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
PREDICTSELFXCHECKINPUTTRUE
PREDICT CLASS OR REGRESSION VALUE FOR X
FOR A CLASSIFICATION MODEL THE PREDICTED CLASS FOR EACH SAMPLE IN X IS RETURNED FOR A REGRESSION MODEL
THE PREDICTED VALUE BASED ON X IS RETURNED
PARAMETERS

XARRAYLIKE OR SPARSE MATRIX OF SHAPE NSAMPLES NFEATURES THE INPUT SAMPLES INTER
NALLY IT WILL BE CONVERTED TO DTYPENPFLOAT32 AND IF A SPARSE MATRIX IS PROVIDED TO
A SPARSECSRMATRIX
CHECKINPUT BOOLEAN DEFAULTTRUE ALLOW TO BYPASS SEVERAL INPUT CHECKING DON’T USE
THIS PARAMETER UNLESS YOU KNOW WHAT YOU DO
RETURNS
YARRAY OF SHAPE NSAMPLES OR NSAMPLES NOUTPUTS THE PREDICTED CLASSES OR THE
PREDICT VALUES
SCORESELFXYSAMPLEWEIGHTNONE
RETURNS THE COEFFICIENT OF DETERMINATION R2 OF THE PREDICTION
THE COEFFICIENT R2 IS DEFINED AS 1 UV WHERE U IS THE RESIDUAL SUM OF SQUARES YTRUE YPRED
2SUM AND V IS THE TOTAL SUM OF SQUARES YTRUE YTRUEMEAN 2SUM THE BEST POSSIBLE SCORE
IS 10 AND IT CAN BE NEGATIVE BECAUSE THE MODEL CAN BE ARBITRARILY WORSE A CONSTANT MODEL THAT ALWAYS
PREDICTS THE EXPECTED VALUE OF Y DISREGARDING THE INPUT FEATURES WOULD GET A R2 SCORE OF 00
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES TEST SAMPLES FOR SOME ESTIMATORS THIS MAY
BE A PRECOMPUTED KERNEL MATRIX INSTEAD SHAPE NSAMPLES NSAMPLESFITTED WHERE
NSAMPLESFITTED IS THE NUMBER OF SAMPLES USED IN THE FITTING FOR THE ESTIMATOR
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS TRUE VALUES FOR X
SAMPLEWEIGHT ARRAYLIKE SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT R2 OF SELFPREDICTX WRT Y
NOTES
THE R2 SCORE USED WHEN CALLING SCORE ON A REGRESSOR WILL USE MULTIOUTPUTUNIFORMAVERAGE
FROM VERSION 023 TO KEEP CONSISTENT WITH METRICSR2SCORE THIS WILL INFLUENCE THE SCORE
METHOD OF ALL THE MULTIOUTPUT REGRESSORS EXCEPT FOR MULTIOUTPUTMULTIOUTPUTREGRESSOR
TO SPECIFY THE DEFAULT VALUE MANUALLY AND AVOID THE WARNING PLEASE EITHER CALL METRICSR2SCORE
DIRECTLY OR MAKE A CUSTOM SCORER WITH METRICSMAKESCORER THE BUILTIN SCORER R2 USES
MULTIOUTPUTUNIFORMAVERAGE
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TREEEXPORTGRAPHVIZ DECISIONTREE EXPORT A DECISION TREE IN DOT FORMAT
TREEPLOTTREE DECISIONTREE MAXDEPTH PLOT A DECISION TREE
TREEEXPORTTEXT DECISIONTREE BUILD A TEXT REPORT SHOWING THE RULES OF A DECISION TREE

6385SKLEARNTREE EXPORTGRAPHVIZ
SKLEARNTREE EXPORTGRAPHVIZ DECISIONTREE OUTFILENONE MAXDEPTHNONE FEA
TURENAMESNONE CLASSNAMESNONE LABEL'ALL' FILLEDFALSE
LEAVESPARALLELFALSE IMPURITYTRUE NODEIDSFALSE
PROPORTIONFALSE ROTATEFALSE ROUNDEDFALSE SPE
CIALCHARACTERSFALSE PRECISION3
EXPORT A DECISION TREE IN DOT FORMAT
THIS FUNCTION GENERATES A GRAPHVIZ REPRESENTATION OF THE DECISION TREE WHICH IS THEN WRITTEN INTO OUTFILE
ONCE EXPORTED GRAPHICAL RENDERINGS CAN BE GENERATED USING FOR EXAMPLE
 DOT TPS TREEDOT O TREEPS POSTSCRIPT FORMAT
 DOT TPNG TREEDOT O TREEPNG PNG FORMAT
THE SAMPLE COUNTS THAT ARE SHOWN ARE WEIGHTED WITH ANY SAMPLEWEIGHTS THAT MIGHT BE PRESENT
READ MORE IN THE USER GUIDE
PARAMETERS
DECISIONTREE DECISION TREE CLASSIFIER THE DECISION TREE TO BE EXPORTED TO GRAPHVIZ
OUTFILE FILE OBJECT OR STRING OPTIONAL DEFAULTNONE HANDLE OR NAME OF THE OUTPUT FILE IF
NONE THE RESULT IS RETURNED AS A STRING
CHANGED IN VERSION 020 DEFAULT OF OUTFILE CHANGED FROM "TREEDOT" TO NONE
MAXDEPTH INT OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF THE REPRESENTATION IF NONE
THE TREE IS FULLY GENERATED
FEATURENAMES LIST OF STRINGS OPTIONAL DEFAULTNONE NAMES OF EACH OF THE FEATURES
CLASSNAMES LIST OF STRINGS BOOL OR NONE OPTIONAL DEFAULTNONE NAMES OF EACH OF THE TARGET
CLASSES IN ASCENDING NUMERICAL ORDER ONLY RELEVANT FOR CLASSIFICATION AND NOT SUPPORTED FOR
MULTIOUTPUT IF TRUE SHOWS A SYMBOLIC REPRESENTATION OF THE CLASS NAME
LABEL 'ALL' 'ROOT' 'NONE' OPTIONAL DEFAULT'ALL' WHETHER TO SHOW INFORMATIVE LABELS FOR
IMPURITY ETC OPTIONS INCLUDE 'ALL' TO SHOW AT EVERY NODE 'ROOT' TO SHOW ONLY AT THE TOP ROOT
NODE OR 'NONE' TO NOT SHOW AT ANY NODE
FILLED BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE PAINT NODES TO INDICATE MAJORITY CLASS
FOR CLASSIFICATION EXTREMITY OF VALUES FOR REGRESSION OR PURITY OF NODE FOR MULTIOUTPUT
LEAVESPARALLEL BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE DRAW ALL LEAF NODES AT THE
BOTTOM OF THE TREE
IMPURITY BOOL OPTIONAL DEFAULTTRUE WHEN SET TO TRUE SHOW THE IMPURITY AT EACH NODE
NODEIDS BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE SHOW THE ID NUMBER ON EACH
NODE
PROPORTION BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE CHANGE THE DISPLAY OF 'VALUES'
ANDOR 'SAMPLES' TO BE PROPORTIONS AND PERCENTAGES RESPECTIVELY
ROTATE BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE ORIENT TREE LEFT TO RIGHT RATHER THAN
TOPDOWN
ROUNDED BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE DRAW NODE BOXES WITH ROUNDED
CORNERS AND USE HELVETICA FONTS INSTEAD OF TIMESROMAN
SPECIALCHARACTERS BOOL OPTIONAL DEFAULTFALSE WHEN SET TO FALSE IGNORE SPECIAL CHAR
ACTERS FOR POSTSCRIPT COMPATIBILITY

SCIKITLEARN USER GUIDE RELEASE 0213
PRECISION INT OPTIONAL DEFAULT3 NUMBER OF DIGITS OF PRECISION FOR FLOATING POINT IN THE VAL
UES OF IMPURITY THRESHOLD AND VALUE ATTRIBUTES OF EACH NODE
RETURNS
DOTDATA STRING STRING REPRESENTATION OF THE INPUT TREE IN GRAPHVIZ DOT FORMAT ONLY RETURNED
IFOUTFILE IS NONE
NEW IN VERSION 018
EXAMPLES
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARN IMPORT TREE
CLF TREEDECISIONTREECLASSIFIER
IRIS LOADIRIS
CLF CLFFITIRISDATA IRISTARGET
TREEEXPORTGRAPHVIZCLF
DIGRAPH TREE
6386SKLEARNTREE PLOTTREE
SKLEARNTREE PLOTTREE DECISIONTREE MAXDEPTHNONE FEATURENAMESNONE CLASSNAMESNONE
LABEL'ALL' FILLEDFALSE IMPURITYTRUE NODEIDSFALSE PROPOR
TIONFALSE ROTATEFALSE ROUNDEDFALSE PRECISION3 AXNONE FONT
SIZENONE
PLOT A DECISION TREE
THE SAMPLE COUNTS THAT ARE SHOWN ARE WEIGHTED WITH ANY SAMPLEWEIGHTS THAT MIGHT BE PRESENT THIS FUNCTION
REQUIRES MATPLOTLIB AND WORKS BEST WITH MATPLOTLIB 15
THE VISUALIZATION IS FIT AUTOMATICALLY TO THE SIZE OF THE AXIS USE THE FIGSIZE ORDPI ARGUMENTS OF PLT
FIGURE TO CONTROL THE SIZE OF THE RENDERING
READ MORE IN THE USER GUIDE
NEW IN VERSION 021
PARAMETERS
DECISIONTREE DECISION TREE REGRESSOR OR CLASSIFIER THE DECISION TREE TO BE EXPORTED TO
GRAPHVIZ
MAXDEPTH INT OPTIONAL DEFAULTNONE THE MAXIMUM DEPTH OF THE REPRESENTATION IF NONE
THE TREE IS FULLY GENERATED
FEATURENAMES LIST OF STRINGS OPTIONAL DEFAULTNONE NAMES OF EACH OF THE FEATURES
CLASSNAMES LIST OF STRINGS BOOL OR NONE OPTIONAL DEFAULTNONE NAMES OF EACH OF THE TARGET
CLASSES IN ASCENDING NUMERICAL ORDER ONLY RELEVANT FOR CLASSIFICATION AND NOT SUPPORTED FOR
MULTIOUTPUT IF TRUE SHOWS A SYMBOLIC REPRESENTATION OF THE CLASS NAME
LABEL 'ALL' 'ROOT' 'NONE' OPTIONAL DEFAULT'ALL' WHETHER TO SHOW INFORMATIVE LABELS FOR
IMPURITY ETC OPTIONS INCLUDE 'ALL' TO SHOW AT EVERY NODE 'ROOT' TO SHOW ONLY AT THE TOP ROOT
NODE OR 'NONE' TO NOT SHOW AT ANY NODE

FILLED BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE PAINT NODES TO INDICATE MAJORITY CLASS
FOR CLASSIFICATION EXTREMITY OF VALUES FOR REGRESSION OR PURITY OF NODE FOR MULTIOUTPUT
IMPURITY BOOL OPTIONAL DEFAULTTRUE WHEN SET TO TRUE SHOW THE IMPURITY AT EACH NODE
NODEIDS BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE SHOW THE ID NUMBER ON EACH
NODE
PROPORTION BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE CHANGE THE DISPLAY OF 'VALUES'
ANDOR 'SAMPLES' TO BE PROPORTIONS AND PERCENTAGES RESPECTIVELY
ROTATE BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE ORIENT TREE LEFT TO RIGHT RATHER THAN
TOPDOWN
ROUNDED BOOL OPTIONAL DEFAULTFALSE WHEN SET TO TRUE DRAW NODE BOXES WITH ROUNDED
CORNERS AND USE HELVETICA FONTS INSTEAD OF TIMESROMAN
PRECISION INT OPTIONAL DEFAULT3 NUMBER OF DIGITS OF PRECISION FOR FLOATING POINT IN THE VAL
UES OF IMPURITY THRESHOLD AND VALUE ATTRIBUTES OF EACH NODE
AXMATPLOTLIB AXIS OPTIONAL DEFAULTNONE AXES TO PLOT TO IF NONE USE CURRENT AXIS ANY
PREVIOUS CONTENT IS CLEARED
FONTSIZE INT OPTIONAL DEFAULTNONE SIZE OF TEXT FONT IF NONE DETERMINED AUTOMATICALLY TO
FIT FIGURE
RETURNS
ANNOTATIONS LIST OF ARTISTS LIST CONTAINING THE ARTISTS FOR THE ANNOTATION BOXES MAKING UP THE
TREE
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARN IMPORT TREE
CLF  TREEDECISIONTREECLASSIFIERRANDOMSTATE0
IRIS  LOADIRIS
CLF  CLFFITIRISDATA IRISTARGET
TREEPLOTTREECLF
TEXT2515345217X3  08
```
EXAMPLES USING SKLEARNTREEPLOTTREE
•PLOT THE DECISION SURFACE OF A DECISION TREE ON THE IRIS DATASET
6387SKLEARNTREE EXPORTTEXT
SKLEARNTREE EXPORTTEXT DECISIONTREE FEATURENAMESNONE MAXDEPTH10 SPACING3 DECI
MALS2 SHOWWEIGHTSFALSE
BUILD A TEXT REPORT SHOWING THE RULES OF A DECISION TREE
NOTE THAT BACKWARDS COMPATIBILITY MAY NOT BE SUPPORTED
PARAMETERS

SCIKITLEARN USER GUIDE RELEASE 0213
DECISIONTREE OBJECT THE DECISION TREE ESTIMATOR TO BE EXPORTED IT CAN BE AN INSTANCE OF
DECISIONTREECLASSIFIER OR DECISIONTREEREGRESSOR
FEATURENAMES LIST OPTIONAL DEFAULTNONE A LIST OF LENGTH NFEATURES CONTAINING THE FEATURE
NAMES IF NONE GENERIC NAMES WILL BE USED “FEATURE0” “FEATURE1”
MAXDEPTH INT OPTIONAL DEFAULT10 ONLY THE FIRST MAXDEPTH LEVELS OF THE TREE ARE EXPORTED
TRUNCATED BRANCHES WILL BE MARKED WITH “ ”
SPACING INT OPTIONAL DEFAULT3 NUMBER OF SPACES BETWEEN EDGES THE HIGHER IT IS THE WIDER
THE RESULT
DECIMALS INT OPTIONAL DEFAULT2 NUMBER OF DECIMAL DIGITS TO DISPLAY
SHOWWEIGHTS BOOL OPTIONAL DEFAULTFALSE IF TRUE THE CLASSIFICATION WEIGHTS WILL BE EXPORTED
ON EACH LEAF THE CLASSIFICATION WEIGHTS ARE THE NUMBER OF SAMPLES EACH CLASS
RETURNS
REPORT STRING TEXT SUMMARY OF ALL THE RULES IN THE DECISION TREE
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT LOADIRIS
 FROM SKLEARNTREE IMPORT DECISIONTREECLASSIFIER
 FROM SKLEARNTREEEXPORT IMPORT EXPORTTEXT
IRIS  LOADIRIS
X  IRISDATA
Y  IRISTARGET
DECISIONTREE  DECISIONTREECLASSIFIERRANDOMSTATE0 MAXDEPTH2
DECISIONTREE  DECISIONTREEFITX Y
R  EXPORTTEXTDECISIONTREE FEATURENAMESIRISFEATURENAMES
PRINTR
 PETAL WIDTH CM  080
  CLASS 0
 PETAL WIDTH CM  080
  PETAL WIDTH CM  175
   CLASS 1
  PETAL WIDTH CM  175
   CLASS 2
```

639SKLEARNUTILS UTILITIES
THESKLEARNUTILS MODULE INCLUDES VARIOUS UTILITIES
DEVELOPER GUIDE SEE THE UTILITIES FOR DEVELOPERS PAGE FOR FURTHER DETAILS
UTILSARRAYFUNCSCHOLESKYDELETE L
GOOUT
UTILSARRAYFUNCSMINPOS FIND THE MINIMUM VALUE OF AN ARRAY OVER POSITIVE VALUES
UTILSASFLOATARRAY X COPY FORCEALLFINITE CONVERTS AN ARRAYLIKE TO AN ARRAY OF FLOATS
UTILSASSERTALLFINITE X ALLOWNAN THROW A VALUEERROR IF X CONTAINS NAN OR INFINITY
UTILSCHECKXY X Y ACCEPTSPARSE INPUT VALIDATION FOR STANDARD ESTIMATORS
CONTINUED ON NEXT PAGE

TABLE 6288 – CONTINUED FROM PREVIOUS PAGE
UTILSCHECKARRAY ARRAY ACCEPTSPARSE INPUT VALIDATION ON AN ARRAY LIST SPARSE MATRIX OR SIMILAR
UTILSCHECKSCALAR X NAME TARGETTYPE VALIDATE SCALAR PARAMETERS TYPE AND VALUE
UTILSCHECKCONSISTENTLENGTH ARRAYS CHECK THAT ALL ARRAYS HAVE CONSISTENT FIRST DIMENSIONS
UTILSCHECKRANDOMSTATE SEED TURN SEED INTO A NPRANDOMRANDOMSTATE INSTANCE
UTILSCLASSWEIGHT
COMPUTECLASSWEIGHT ESTIMATE CLASS WEIGHTS FOR UNBALANCED DATASETS
UTILSCLASSWEIGHT
COMPUTESAMPLEWEIGHT ESTIMATE SAMPLE WEIGHTS BY CLASS FOR UNBALANCED DATASETS
UTILSDEPRECATED EXTRA DECORATOR TO MARK A FUNCTION OR CLASS AS DEPRECATED
UTILSESTIMATORCHECKS
CHECKESTIMATOR ESTIMATORCHECK IF ESTIMATOR ADHERES TO SCIKITLEARN CONVENTIONS
UTILSEXTMATHSAFESPARSEDOT A B DOT PRODUCT THAT HANDLE THE SPARSE MATRIX CASE CORRECTLY
UTILSEXTMATHRANDOMIZEDRANGEFINDER A
COMPUTES AN ORTHONORMAL MATRIX WHOSE RANGE APPROXI
MATES THE RANGE OF A
UTILSEXTMATHRANDOMIZEDSVD M
NCOMPONENTSCOMPUTES A TRUNCATED RANDOMIZED SVD
UTILSEXTMATHFASTLOGDET A COMPUTE LOGDETA FOR A SYMMETRIC
UTILSEXTMATHDENSITY W KWARGS COMPUTE DENSITY OF A SPARSE VECTOR
UTILSEXTMATHWEIGHTEDMODE A W AXIS RETURNS AN ARRAY OF THE WEIGHTED MODAL MOST COMMON
VALUE IN A
UTILSGENEVENSLICES N NPACKS NSAMPLES GENERATOR TO CREATE NPACKS SLICES GOING UP TO N
UTILSGRAPHSINGLESOURCESHORTESTPATHLENGTH RETURN THE SHORTEST PATH LENGTH FROM SOURCE TO ALL REACHABLE
NODES
UTILSGRAPHSHORTESTPATH
GRAPHSHORTESTPATH PERFORM A SHORTESTPATH GRAPH SEARCH ON A POSITIVE DIRECTED
OR UNDIRECTED GRAPH
UTILSINDEXABLE ITERABLES MAKE ARRAYS INDEXABLE FOR CROSSVALIDATION
UTILSMETAESTIMATORS
IFDELEGATEHASMETHOD CREATE A DECORATOR FOR METHODS THAT ARE DELEGATED TO A SUB
ESTIMATOR
UTILSMULTICLASSTYPEOFTARGET Y DETERMINE THE TYPE OF DATA INDICATED BY THE TARGET
UTILSMULTICLASSISMULTILABEL Y CHECK IF YIS IN A MULTILABEL FORMAT
UTILSMULTICLASSUNIQUELABELS YS EXTRACT AN ORDERED ARRAY OF UNIQUE LABELS
UTILSMURMURHASH332 COMPUTE THE 32BIT MURMURHASH3 OF KEY AT SEED
UTILSRESAMPLE ARRAYS OPTIONS RESAMPLE ARRAYS OR SPARSE MATRICES IN A CONSISTENT WAY
UTILSSAFEINDEXING X INDICES RETURN ITEMS OR ROWS FROM X USING INDICES
UTILSSAFEMASK X MASK RETURN A MASK WHICH IS SAFE TO USE ON X
UTILSSAFESQR X COPY ELEMENT WISE SQUARING OF ARRAYLIKES AND SPARSE MATRICES
UTILSSHUFFLE ARRAYS OPTIONS SHUFFLE ARRAYS OR SPARSE MATRICES IN A CONSISTENT WAY
UTILSSPARSEFUNCS
INCRMEANVARIANCEAXIS X COMPUTE INCREMENTAL MEAN AND VARIANCE ALONG AN AXIX ON
A CSR OR CSC MATRIX
UTILSSPARSEFUNCS
INPLACECOLUMNSCALE X SCALEINPLACE COLUMN SCALING OF A CSCCSR MATRIX
UTILSSPARSEFUNCSINPLACEROWSCALE X
SCALEINPLACE ROW SCALING OF A CSR OR CSC MATRIX
UTILSSPARSEFUNCSINPLACESWAPROW X M
NSWAPS TWO ROWS OF A CSCCSR MATRIX INPLACE
UTILSSPARSEFUNCS
INPLACESWAPCOLUMN X M NSWAPS TWO COLUMNS OF A CSCCSR MATRIX INPLACE
UTILSSPARSEFUNCSMEANVARIANCEAXIS X
AXISCOMPUTE MEAN AND VARIANCE ALONG AN AXIX ON A CSR OR
CSC MATRIX
UTILSSPARSEFUNCS
INPLACECSRCOLUMNSCALE X INPLACE COLUMN SCALING OF A CSR MATRIX
CONTINUED ON NEXT PAGE

TABLE 6288 – CONTINUED FROM PREVIOUS PAGE
UTILSSPARSEFUNCSFAST
INPLACECSRROWNORMALIZEL1 INPLACE ROW NORMALIZE USING THE L1 NORM
UTILSSPARSEFUNCSFAST
INPLACECSRROWNORMALIZEL2 INPLACE ROW NORMALIZE USING THE L2 NORM
UTILSRANDOMSAMPLEWITHOUTREPLACEMENT SAMPLE INTEGERS WITHOUT REPLACEMENT
UTILSVALIDATIONCHECKISFITTED ESTIMATOR
PERFORM ISFITTED VALIDATION FOR ESTIMATOR
UTILSVALIDATIONCHECKMEMORY MEMORY CHECK THAT MEMORY IS JOBLIBMEMORYLIKE
UTILSVALIDATIONCHECKSYMMETRIC ARRAY
MAKE SURE THAT ARRAY IS 2D SQUARE AND SYMMETRIC
UTILSVALIDATIONCOLUMNOR1D Y WARN RAVEL COLUMN OR 1D NUMPY ARRAY ELSE RAISES AN ERROR
UTILSVALIDATIONHASFITPARAMETER CHECKS WHETHER THE ESTIMATOR'S FIT METHOD SUPPORTS THE
GIVEN PARAMETER
UTILSTESTINGASSERTIN MEMBER CONTAINER
MSGJUST LIKE SELFASSERTTRUEA IN B BUT WITH A NICER DEFAULT
MESSAGE
UTILSTESTINGASSERTNOTIN MEMBER CON
TAINERJUST LIKE SELFASSERTTRUEA NOT IN B BUT WITH A NICER DEFAULT
MESSAGE
UTILSTESTINGASSERTRAISEMESSAGE HELPER FUNCTION TO TEST THE MESSAGE RAISED IN AN EXCEPTION
UTILSTESTINGALLESTIMATORS GET A LIST OF ALL ESTIMATORS FROM SKLEARN
6391SKLEARNUTILS ARRAYFUNCSCHOLESKYDELETE
6392SKLEARNUTILSARRAYFUNCS MINPOS
SKLEARNUTILSARRAYFUNCS MINPOS
FIND THE MINIMUM VALUE OF AN ARRAY OVER POSITIVE VALUES
RETURNS A HUGE VALUE IF NONE OF THE VALUES ARE POSITIVE
6393SKLEARNUTILS ASFLOATARRAY
SKLEARNUTILS ASFLOATARRAY XCOPYTRUE FORCEALLFINITETRUE
CONVERTS AN ARRAYLIKE TO AN ARRAY OF FLOATS
THE NEW DTYPE WILL BE NPFLOAT32 OR NPFLOAT64 DEPENDING ON THE ORIGINAL TYPE THE FUNCTION CAN CREATE A COPY
OR MODIFY THE ARGUMENT DEPENDING ON THE ARGUMENT COPY
PARAMETERS
XARRAYLIKE SPARSE MATRIX
COPY BOOL OPTIONAL IF TRUE A COPY OF X WILL BE CREATED IF FALSE A COPY MAY STILL BE RETURNED
IF X'S DTYPE IS NOT A FLOATING POINT TYPE
FORCEALLFINITE BOOLEAN OR 'ALLOWNAN' DEFAULTTRUE WHETHER TO RAISE AN ERROR ON NPINF
AND NPNAN IN X THE POSSIBILITIES ARE
• TRUE FORCE ALL VALUES OF X TO BE FINITE
• FALSE ACCEPT BOTH NPINF AND NPNAN IN X
• 'ALLOWNAN' ACCEPT ONLY NPNAN VALUES IN X VALUES CANNOT BE INFINITE
NEW IN VERSION 020 FORCEALLFINITE ACCEPTS THE STRING ALLOWNAN
RETURNS

XT ARRAY SPARSE MATRIX AN ARRAY OF TYPE NPFLOAT
6394SKLEARNUTILS ASSERTALLFINITE
SKLEARNUTILS ASSERTALLFINITE XALLOWNANFALSE
THROW A VALUEERROR IF X CONTAINS NAN OR INFINITY
PARAMETERS
XARRAY OR SPARSE MATRIX
ALLOWNAN BOOL
6395SKLEARNUTILS CHECKXY
SKLEARNUTILS CHECKXY XYACCEPTSPARSEFALSE ACCEPTLARGESPARSETRUE DTYPE'NUMERIC'
ORDERNONE COPYFALSE FORCEALLFINITETRUE ENSURE2DTRUE
ALLOWNDFALSE MULTIOUTPUTFALSE ENSUREMINSAMPLES1 EN
SUREMINFEATURES1 YNUMERICFALSE WARNONDTYPENONE ESTIMA
TORNONE
INPUT VALIDATION FOR STANDARD ESTIMATORS
CHECKS X AND Y FOR CONSISTENT LENGTH ENFORCES X TO BE 2D AND Y 1D BY DEFAULT X IS CHECKED TO BE NONEMPTY
AND CONTAINING ONLY FINITE VALUES STANDARD INPUT CHECKS ARE ALSO APPLIED TO Y SUCH AS CHECKING THAT Y DOES NOT
HAVE NPNAN OR NPINF TARGETS FOR MULTILABEL Y SET MULTIOUTPUTTRUE TO ALLOW 2D AND SPARSE Y IF THE DTYPE OF
X IS OBJECT ATTEMPT CONVERTING TO FLOAT RAISING ON FAILURE
PARAMETERS
XNDARRAY LIST OR SPARSE MATRIX INPUT DATA
YNDARRAY LIST OR SPARSE MATRIX LABELS
ACCEPTSPARSE STRING BOOLEAN OR LIST OF STRING DEFAULTFALSE STRINGS REPRESENTING ALLOWED
SPARSE MATRIX FORMATS SUCH AS 'CSC' 'CSR' ETC IF THE INPUT IS SPARSE BUT NOT IN THE ALLOWED
FORMAT IT WILL BE CONVERTED TO THE FIRST LISTED FORMAT TRUE ALLOWS THE INPUT TO BE ANY FORMAT
FALSE MEANS THAT A SPARSE MATRIX INPUT WILL RAISE AN ERROR
ACCEPTLARGESPARSE BOOL DEFAULTTRUE IF A CSR CSC COO OR BSR SPARSE MATRIX IS SUP
PLIED AND ACCEPTED BY ACCEPTSPARSE ACCEPTLARGESPARSE WILL CAUSE IT TO BE ACCEPTED ONLY
IF ITS INDICES ARE STORED WITH A 32BIT DTYPE
NEW IN VERSION 020
DTYPE STRING TYPE LIST OF TYPES OR NONE DEFAULT"NUMERIC" DATA TYPE OF RESULT IF NONE THE
DTYPE OF THE INPUT IS PRESERVED IF "NUMERIC" DTYPE IS PRESERVED UNLESS ARRAYDTYPE IS OBJECT
IF DTYPE IS A LIST OF TYPES CONVERSION ON THE FIRST TYPE IS ONLY PERFORMED IF THE DTYPE OF THE
INPUT IS NOT IN THE LIST
ORDER 'F' 'C' OR NONE DEFAULTNONE WHETHER AN ARRAY WILL BE FORCED TO BE FORTRAN OR CSTYLE
COPY BOOLEAN DEFAULTFALSE WHETHER A FORCED COPY WILL BE TRIGGERED IF COPYFALSE A COPY
MIGHT BE TRIGGERED BY A CONVERSION
FORCEALLFINITE BOOLEAN OR 'ALLOWNAN' DEFAULTTRUE WHETHER TO RAISE AN ERROR ON NPINF
AND NPNAN IN X THIS PARAMETER DOES NOT INFLUENCE WHETHER Y CAN HAVE NPINF OR NPNAN
VALUES THE POSSIBILITIES ARE
• TRUE FORCE ALL VALUES OF X TO BE FINITE

• FALSE ACCEPT BOTH NPINF AND NPNAN IN X
• ‘ALLOWNAN’ ACCEPT ONLY NPNAN VALUES IN X VALUES CANNOT BE INFINITE
NEW IN VERSION 020 FORCEALLFINITE ACCEPTS THE STRING ALLOWNAN
ENSURE2D BOOLEAN DEFAULTTRUE WHETHER TO RAISE A VALUE ERROR IF X IS NOT 2D
ALLOWND BOOLEAN DEFAULTFALSE WHETHER TO ALLOW XNDIM 2
MULTIOUTPUT BOOLEAN DEFAULTFALSE WHETHER TO ALLOW 2D Y ARRAY OR SPARSE MATRIX
IF FALSE Y WILL BE VALIDATED AS A VECTOR Y CANNOT HAVE NPNAN OR NPINF VALUES IF
MULTIOUTPUTTRUE
ENSUREMINSAMPLES INT DEFAULT1 MAKE SURE THAT X HAS A MINIMUM NUMBER OF SAMPLES IN
ITS FIRST AXIS ROWS FOR A 2D ARRAY
ENSUREMINFEATURES INT DEFAULT1 MAKE SURE THAT THE 2D ARRAY HAS SOME MINIMUM NUMBER
OF FEATURES COLUMNS THE DEFAULT VALUE OF 1 REJECTS EMPTY DATASETS THIS CHECK IS ONLY
ENFORCED WHEN X HAS EFFECTIVELY 2 DIMENSIONS OR IS ORIGINALLY 1D AND ENSURE2D IS TRUE
SETTING TO 0 DISABLES THIS CHECK
YNUMERIC BOOLEAN DEFAULTFALSE WHETHER TO ENSURE THAT Y HAS A NUMERIC TYPE IF DTYPE OF
Y IS OBJECT IT IS CONVERTED TO FLOAT64 SHOULD ONLY BE USED FOR REGRESSION ALGORITHMS
WARNONDTYPE BOOLEAN OR NONE OPTIONAL DEFAULTNONE RAISE DATACONVERSIONWARNING IF
THE DTYPE OF THE INPUT DATA STRUCTURE DOES NOT MATCH THE REQUESTED DTYPE CAUSING A MEMORY
COPY
DEPRECATED SINCE VERSION 021 WARNONDTYPE IS DEPRECATED IN VERSION 021 AND WILL BE
REMOVED IN 023
ESTIMATOR STR OR ESTIMATOR INSTANCE DEFAULTNONE IF PASSED INCLUDE THE NAME OF THE ESTIMATOR
IN WARNING MESSAGES
RETURNS
XCONVERTED OBJECT THE CONVERTED AND VALIDATED X
YCONVERTED OBJECT THE CONVERTED AND VALIDATED Y
6396SKLEARNUTILS CHECKARRAY
SKLEARNUTILS CHECKARRAY ARRAY ACCEPTSPARSEFALSE ACCEPTLARGESPARSETRUE
DTYPE’NUMERIC’ ORDERNONE COPYFALSE FORCEALLFINITETRUE
ENSURE2DTRUE ALLOWNDFALSE ENSUREMINSAMPLES1 EN
SUREMINFEATURES1 WARNONDTYPENONE ESTIMATORNONE
INPUT VALIDATION ON AN ARRAY LIST SPARSE MATRIX OR SIMILAR
BY DEFAULT THE INPUT IS CHECKED TO BE A NONEMPTY 2D ARRAY CONTAINING ONLY FINITE VALUES IF THE DTYPE OF THE
ARRAY IS OBJECT ATTEMPT CONVERTING TO FLOAT RAISING ON FAILURE
PARAMETERS
ARRAY OBJECT INPUT OBJECT TO CHECK CONVERT
ACCEPTSPARSE STRING BOOLEAN OR LISTTUPLE OF STRINGS DEFAULTFALSE STRINGS REPRESENTING
ALLOWED SPARSE MATRIX FORMATS SUCH AS ‘CSC’ ‘CSR’ ETC IF THE INPUT IS SPARSE BUT NOT IN THE
ALLOWED FORMAT IT WILL BE CONVERTED TO THE FIRST LISTED FORMAT TRUE ALLOWS THE INPUT TO BE ANY
FORMAT FALSE MEANS THAT A SPARSE MATRIX INPUT WILL RAISE AN ERROR

ACCEPTLARGESPARSE BOOL DEFAULTTRUE IF A CSR CSC COO OR BSR SPARSE MATRIX IS SUP
PLIED AND ACCEPTED BY ACCEPTSPARSE ACCEPTLARGESPARSEFALSE WILL CAUSE IT TO BE ACCEPTED
ONLY IF ITS INDICES ARE STORED WITH A 32BIT DTYPE
NEW IN VERSION 020
DTYPE STRING TYPE LIST OF TYPES OR NONE DEFAULT”NUMERIC” DATA TYPE OF RESULT IF NONE THE
DTYPE OF THE INPUT IS PRESERVED IF “NUMERIC” DTYPE IS PRESERVED UNLESS ARRAYDTYPE IS OBJECT
IF DTYPE IS A LIST OF TYPES CONVERSION ON THE FIRST TYPE IS ONLY PERFORMED IF THE DTYPE OF THE
INPUT IS NOT IN THE LIST
ORDER ‘F’ ‘C’ OR NONE DEFAULTNONE WHETHER AN ARRAY WILL BE FORCED TO BE FORTRAN OR CSTYLE
WHEN ORDER IS NONE DEFAULT THEN IF COPYFALSE NOTHING IS ENSURED ABOUT THE MEMORY
LAYOUT OF THE OUTPUT ARRAY OTHERWISE COPYTRUE THE MEMORY LAYOUT OF THE RETURNED ARRAY
IS KEPT AS CLOSE AS POSSIBLE TO THE ORIGINAL ARRAY
COPY BOOLEAN DEFAULTFALSE WHETHER A FORCED COPY WILL BE TRIGGERED IF COPYFALSE A COPY
MIGHT BE TRIGGERED BY A CONVERSION
FORCEALLFINITE BOOLEAN OR ‘ALLOWNAN’ DEFAULTTRUE WHETHER TO RAISE AN ERROR ON NPINF
AND NPNAN IN ARRAY THE POSSIBILITIES ARE
• TRUE FORCE ALL VALUES OF ARRAY TO BE FINITE
• FALSE ACCEPT BOTH NPINF AND NPNAN IN ARRAY
• ‘ALLOWNAN’ ACCEPT ONLY NPNAN VALUES IN ARRAY VALUES CANNOT BE INFINITE
FOR OBJECT DTYPED DATA ONLY NPNAN IS CHECKED AND NOT NPINF
NEW IN VERSION 020 FORCEALLFINITE ACCEPTS THE STRING ALLOWNAN
ENSURE2D BOOLEAN DEFAULTTRUE WHETHER TO RAISE A VALUE ERROR IF ARRAY IS NOT 2D
ALLOWND BOOLEAN DEFAULTFALSE WHETHER TO ALLOW ARRAYNDIM 2
ENSUREMINSAMPLES INT DEFAULT1 MAKE SURE THAT THE ARRAY HAS A MINIMUM NUMBER OF
SAMPLES IN ITS FIRST AXIS ROWS FOR A 2D ARRAY SETTING TO 0 DISABLES THIS CHECK
ENSUREMINFEATURES INT DEFAULT1 MAKE SURE THAT THE 2D ARRAY HAS SOME MINIMUM NUMBER
OF FEATURES COLUMNS THE DEFAULT VALUE OF 1 REJECTS EMPTY DATASETS THIS CHECK IS ONLY EN
FORCED WHEN THE INPUT DATA HAS EFFECTIVELY 2 DIMENSIONS OR IS ORIGINALLY 1D AND ENSURE2D
IS TRUE SETTING TO 0 DISABLES THIS CHECK
WARNONDTYPE BOOLEAN OR NONE OPTIONAL DEFAULTNONE RAISE DATACONVERSIONWARNING IF
THE DTYPE OF THE INPUT DATA STRUCTURE DOES NOT MATCH THE REQUESTED DTYPE CAUSING A MEMORY
COPY
DEPRECATED SINCE VERSION 021 WARNONDTYPE IS DEPRECATED IN VERSION 021 AND WILL BE
REMOVED IN 023
ESTIMATOR STR OR ESTIMATOR INSTANCE DEFAULTNONE IF PASSED INCLUDE THE NAME OF THE ESTIMATOR
IN WARNING MESSAGES
RETURNS
ARRAYCONVERTED OBJECT THE CONVERTED AND VALIDATED ARRAY
6397SKLEARNUTILS CHECKSCALAR
SKLEARNUTILS CHECKSCALAR XNAME TARGETTYPE MINVALNONE MAXVALNONE
VALIDATE SCALAR PARAMETERS TYPE AND VALUE

PARAMETERS
XOBJECT THE SCALAR PARAMETER TO VALIDATE
NAME STR THE NAME OF THE PARAMETER TO BE PRINTED IN ERROR MESSAGES
TARGETTYPE TYPE OR TUPLE ACCEPTABLE DATA TYPES FOR THE PARAMETER
MINVAL FLOAT OR INT OPTIONAL DEFAULTNONE THE MINIMUM VALID VALUE THE PARAMETER CAN
TAKE IF NONE DEFAULT IT IS IMPLIED THAT THE PARAMETER DOES NOT HAVE A LOWER BOUND
MAXVAL FLOAT OR INT OPTIONAL DEFAULTNONE THE MAXIMUM VALID VALUE THE PARAMETER CAN
TAKE IF NONE DEFAULT IT IS IMPLIED THAT THE PARAMETER DOES NOT HAVE AN UPPER BOUND
RAISES
TYPEERROR IF THE PARAMETER'S TYPE DOES NOT MATCH THE DESIRED TYPE
VALUEERROR IF THE PARAMETER'S VALUE VIOLATES THE GIVEN BOUNDS
6398SKLEARNUTILS CHECKCONSISTENTLENGTH
SKLEARNUTILS CHECKCONSISTENTLENGTH ARRAYS
CHECK THAT ALL ARRAYS HAVE CONSISTENT FIRST DIMENSIONS
CHECKS WHETHER ALL OBJECTS IN ARRAYS HAVE THE SAME SHAPE OR LENGTH
PARAMETERS
ARRAYS LIST OR TUPLE OF INPUT OBJECTS OBJECTS THAT WILL BE CHECKED FOR CONSISTENT LENGTH
6399SKLEARNUTILS CHECKRANDOMSTATE
SKLEARNUTILS CHECKRANDOMSTATE SEED
TURN SEED INTO A NPRANDOMRANDOMSTATE INSTANCE
PARAMETERS
SEED NONE INT INSTANCE OF RANDOMSTATE IF SEED IS NONE RETURN THE RANDOMSTATE SINGLETON
USED BY NPRANDOM IF SEED IS AN INT RETURN A NEW RANDOMSTATE INSTANCE SEEDED WITH SEED
IF SEED IS ALREADY A RANDOMSTATE INSTANCE RETURN IT OTHERWISE RAISE VALUEERROR
EXAMPLES USING SKLEARNUTILSCHECKRANDOMSTATE
•ISOTONIC REGRESSION
•FACE COMPLETION WITH A MULTIOUTPUT ESTIMATORS
•EMPIRICAL EVALUATION OF THE IMPACT OF KMEANS INITIALIZATION
•MNIST CLASSFIFICATION USING MULTINOMIAL LOGISTIC L1
•MANIFOLD LEARNING METHODS ON A SEVERED SPHERE
•SCALING THE REGULARIZATION PARAMETER FOR SVCS

63910SKLEARNUTILSCLASSWEIGHT COMPUTECLASSWEIGHT
SKLEARNUTILSCLASSWEIGHT COMPUTECLASSWEIGHT CLASSWEIGHT CLASSES Y
ESTIMATE CLASS WEIGHTS FOR UNBALANCED DATASETS
PARAMETERS
CLASSWEIGHT DICT ‘BALANCED’ OR NONE IF ‘BALANCED’ CLASS WEIGHTS WILL BE GIVEN BY
NSAMPLES NCLASSES NPBINCOUNTY IF A DICTIONARY IS GIVEN KEYS
ARE CLASSES AND VALUES ARE CORRESPONDING CLASS WEIGHTS IF NONE IS GIVEN THE CLASS WEIGHTS
WILL BE UNIFORM
CLASSES NDARRAY ARRAY OF THE CLASSES OCCURRING IN THE DATA AS GIVEN BY NPUNIQUEYORG
WITHYORG THE ORIGINAL CLASS LABELS
YARRAYLIKE SHAPE NSAMPLES ARRAY OF ORIGINAL CLASS LABELS PER SAMPLE
RETURNS
CLASSWEIGHTVECT NDARRAY SHAPE NCLASSES ARRAY WITH CLASSWEIGHTVECTI THE WEIGHT FOR
ITH CLASS
REFERENCES
THE “BALANCED” HEURISTIC IS INSPIRED BY LOGISTIC REGRESSION IN RARE EVENTS DATA KING ZEN 2001
63911SKLEARNUTILSCLASSWEIGHT COMPUTESAMPLEWEIGHT
SKLEARNUTILSCLASSWEIGHT COMPUTESAMPLEWEIGHT CLASSWEIGHT YINDICESNONE
ESTIMATE SAMPLE WEIGHTS BY CLASS FOR UNBALANCED DATASETS
PARAMETERS
CLASSWEIGHT DICT LIST OF DICTS “BALANCED” OR NONE OPTIONAL WEIGHTS ASSOCIATED WITH CLASSES
IN THE FORM CLASSLABEL WEIGHT IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE
WEIGHT ONE FOR MULTIOUTPUT PROBLEMS A LIST OF DICTS CAN BE PROVIDED IN THE SAME ORDER AS
THE COLUMNS OF Y
NOTE THAT FOR MULTIOUTPUT INCLUDING MULTILABEL WEIGHTS SHOULD BE DEFINED FOR EACH CLASS OF
EVERY COLUMN IN ITS OWN DICT FOR EXAMPLE FOR FOURCLASS MULTILABEL CLASSIFICATION WEIGHTS
SHOULD BE 0 1 1 1 0 1 1 5 0 1 1 1 0 1 1 1 INSTEAD OF 11 25
31 41
THE “BALANCED” MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA NSAMPLES NCLASSES NP
BINCOUNTY
FOR MULTIOUTPUT THE WEIGHTS OF EACH COLUMN OF Y WILL BE MULTIPLIED
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NOUTPUTS ARRAY OF ORIGINAL CLASS LABELS PER
SAMPLE
INDICES ARRAYLIKE SHAPE NSUBSAMPLE OR NONE ARRAY OF INDICES TO BE USED IN A SUBSAMPLE
CAN BE OF LENGTH LESS THAN NSAMPLES IN THE CASE OF A SUBSAMPLE OR EQUAL TO NSAMPLES IN
THE CASE OF A BOOTSTRAP SUBSAMPLE WITH REPEATED INDICES IF NONE THE SAMPLE WEIGHT WILL
BE CALCULATED OVER THE FULL SAMPLE ONLY “BALANCED” IS SUPPORTED FOR CLASSWEIGHT IF THIS IS
PROVIDED
RETURNS

SAMPLEWEIGHTVECT NDARRAY SHAPE NSAMPLES ARRAY WITH SAMPLE WEIGHTS AS APPLIED TO
THE ORIGINAL Y
63912SKLEARNUTILS DEPRECATED
SKLEARNUTILS DEPRECATED EXTRA‘‘
DECORATOR TO MARK A FUNCTION OR CLASS AS DEPRECATED
ISSUE A WARNING WHEN THE FUNCTION IS CALLEDTHE CLASS IS INSTANTIATED AND ADDS A WARNING TO THE DOCSTRING
THE OPTIONAL EXTRA ARGUMENT WILL BE APPENDED TO THE DEPRECATION MESSAGE AND THE DOCSTRING NOTE TO USE THIS
WITH THE DEFAULT VALUE FOR EXTRA PUT IN AN EMPTY OF PARENTHESES
FROM SKLEARNUTILS IMPORT DEPRECATED
DEPRECATED
SKLEARNUTILSDEPRECATIONDEPRECATED OBJECT AT
DEPRECATED
DEF SOMEFUNCTION PASS
PARAMETERS
EXTRA STRING TO BE ADDED TO THE DEPRECATION MESSAGES
63913SKLEARNUTILSESTIMATORCHECKS CHECKESTIMATOR
SKLEARNUTILSESTIMATORCHECKS CHECKESTIMATOR ESTIMATOR
CHECK IF ESTIMATOR ADHERES TO SCIKITLEARN CONVENTIONS
THIS ESTIMATOR WILL RUN AN EXTENSIVE TESTSUITE FOR INPUT VALIDATION SHAPES ETC ADDITIONAL TESTS FOR CLASSIFIERS
REGRESSORS CLUSTERING OR TRANSFORMERS WILL BE RUN IF THE ESTIMATOR CLASS INHERITS FROM THE CORRESPONDING MIXIN
FROM SKLEARNBASE
THIS TEST CAN BE APPLIED TO CLASSES OR INSTANCES CLASSES CURRENTLY HAVE SOME ADDITIONAL TESTS THAT RELATED TO
CONSTRUCTION WHILE PASSING INSTANCES ALLOWS THE TESTING OF MULTIPLE OPTIONS
PARAMETERS
ESTIMATOR ESTIMATOR OBJECT OR CLASS ESTIMATOR TO CHECK ESTIMATOR IS A CLASS OBJECT OR INSTANCE
63914SKLEARNUTILSEXTMATH SAFESPARSEDOT
SKLEARNUTILSEXTMATH SAFESPARSEDOT ABDENSEOUTPUTFALSE
DOT PRODUCT THAT HANDLE THE SPARSE MATRIX CASE CORRECTLY
USES BLAS GEMM AS REPLACEMENT FOR NUMPYDOT WHERE POSSIBLE TO AVOID UNNECESSARY COPIES
PARAMETERS
AARRAY OR SPARSE MATRIX
BARRAY OR SPARSE MATRIX
DENSEOUTPUT BOOLEAN DEFAULT FALSE WHEN FALSE EITHER AORBBEING SPARSE WILL YIELD SPARSE
OUTPUT WHEN TRUE OUTPUT WILL ALWAYS BE AN ARRAY
RETURNS

DOTPRODUCT ARRAY OR SPARSE MATRIX SPARSE IF AORBIS SPARSE AND DENSEOUTPUTFALSE
63915SKLEARNUTILSEXTMATH RANDOMIZEDRANGEFINDER
SKLEARNUTILSEXTMATH RANDOMIZEDRANGEFINDER A SIZE NITER
POWERITERATIONNORMALIZER'AUTO'
RANDOMSTATENONE
COMPUTES AN ORTHONORMAL MATRIX WHOSE RANGE APPROXIMATES THE RANGE OF A
PARAMETERS
A2D ARRAY THE INPUT DATA MATRIX
SIZE INTEGER SIZE OF THE RETURN ARRAY
NITER INTEGER NUMBER OF POWER ITERATIONS USED TO STABILIZE THE RESULT
POWERITERATIONNORMALIZER 'AUTO' DEFAULT 'QR' 'LU' 'NONE' WHETHER THE POWER ITER
ATIONS ARE NORMALIZED WITH STEPBYSTEP QR FACTORIZATION THE SLOWEST BUT MOST ACCURATE
'NONE' THE FASTEST BUT NUMERICALLY UNSTABLE WHEN NITER IS LARGE EG TYPICALLY 5 OR
LARGER OR 'LU' FACTORIZATION NUMERICALLY STABLE BUT CAN LOSE SLIGHTLY IN ACCURACY THE
'AUTO' MODE APPLIES NO NORMALIZATION IF NITER 2 AND SWITCHES TO LU OTHERWISE
NEW IN VERSION 018
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
RETURNS
Q2D ARRAY A SIZE X SIZE PROJECTION MATRIX THE RANGE OF WHICH APPROXIMATES WELL THE RANGE
OF THE INPUT MATRIX A
NOTES
FOLLOWS ALGORITHM 43 OF FINDING STRUCTURE WITH RANDOMNESS STOCHASTIC ALGORITHMS FOR CONSTRUCTING APPROXI
MATE MATRIX DECOMPOSITIONS HALKO ET AL 2009 ARXIV909 HTTPSARXIVORGPDF09094061PDF
AN IMPLEMENTATION OF A RANDOMIZED ALGORITHM FOR PRINCIPAL COMPONENT ANALYSIS A SZLAM ET AL 2014
63916SKLEARNUTILSEXTMATH RANDOMIZEDSVD
SKLEARNUTILSEXTMATH RANDOMIZEDSVD MNCOMPONENTS NOVERSAMPLES10 NITER'AUTO'
POWERITERATIONNORMALIZER'AUTO' TRANSPOSE'AUTO'
FLIPSIGNTRUE RANDOMSTATE0
COMPUTES A TRUNCATED RANDOMIZED SVD
PARAMETERS
MNDARRAY OR SPARSE MATRIX MATRIX TO DECOMPOSE
NCOMPONENTS INT NUMBER OF SINGULAR VALUES AND VECTORS TO EXTRACT
NOVERSAMPLES INT DEFAULT IS 10 ADDITIONAL NUMBER OF RANDOM VECTORS TO SAMPLE THE RANGE
OF M SO AS TO ENSURE PROPER CONDITIONING THE TOTAL NUMBER OF RANDOM VECTORS USED TO FIND

THE RANGE OF M IS NCOMPONENTS NOVERSAMPLES SMALLER NUMBER CAN IMPROVE SPEED BUT
CAN NEGATIVELY IMPACT THE QUALITY OF APPROXIMATION OF SINGULAR VECTORS AND SINGULAR VALUES
NITER INT OR ‘AUTO’ DEFAULT IS ‘AUTO’ NUMBER OF POWER ITERATIONS IT CAN BE USED TO DEAL
WITH VERY NOISY PROBLEMS WHEN ‘AUTO’ IT IS SET TO 4 UNLESS NCOMPONENTS IS SMALL
1 MINXSHAPE NITER IN WHICH CASE IS SET TO 7 THIS IMPROVES PRECISION WITH FEW
COMPONENTS
CHANGED IN VERSION 018
POWERITERATIONNORMALIZER ‘AUTO’ DEFAULT ‘QR’ ‘LU’ ‘NONE’ WHETHER THE POWER ITER
ATIONS ARE NORMALIZED WITH STEPBYSTEP QR FACTORIZATION THE SLOWEST BUT MOST ACCURATE
‘NONE’ THE FASTEST BUT NUMERICALLY UNSTABLE WHEN NITER IS LARGE EG TYPICALLY 5 OR
LARGER OR ‘LU’ FACTORIZATION NUMERICALLY STABLE BUT CAN LOSE SLIGHTLY IN ACCURACY THE
‘AUTO’ MODE APPLIES NO NORMALIZATION IF NITER 2 AND SWITCHES TO LU OTHERWISE
NEW IN VERSION 018
TRANSPOSE TRUE FALSE OR ‘AUTO’ DEFAULT WHETHER THE ALGORITHM SHOULD BE APPLIED TO MT
INSTEAD OF M THE RESULT SHOULD APPROXIMATELY BE THE SAME THE ‘AUTO’ MODE WILL TRIGGER
THE TRANSPOSITION IF MSHAPE1 MSHAPE0 SINCE THIS IMPLEMENTATION OF RANDOMIZED SVD
TEND TO BE A LITTLE FASTER IN THAT CASE
CHANGED IN VERSION 018
FLIPSIGN BOOLEAN TRUE BY DEFAULT THE OUTPUT OF A SINGULAR VALUE DECOMPOSITION IS ONLY
UNIQUE UP TO A PERMUTATION OF THE SIGNS OF THE SINGULAR VECTORS IF FLIPSIGN IS SET TO
TRUE THE SIGN AMBIGUITY IS RESOLVED BY MAKING THE LARGEST LOADINGS FOR EACH COMPONENT IN
THE LEFT SINGULAR VECTORS POSITIVE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
NOTES
THIS ALGORITHM FINDS A USUALLY VERY GOOD APPROXIMATE TRUNCATED SINGULAR VALUE DECOMPOSITION USING RANDOM
IZATION TO SPEED UP THE COMPUTATIONS IT IS PARTICULARLY FAST ON LARGE MATRICES ON WHICH YOU WISH TO EXTRACT ONLY
A SMALL NUMBER OF COMPONENTS IN ORDER TO OBTAIN FURTHER SPEED UP NITER CAN BE SET 2 AT THE COST OF LOSS
OF PRECISION
REFERENCES
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SITIONS HALKO ET AL 2009 HTTPSARXIVORGABS09094061
• A RANDOMIZED ALGORITHM FOR THE DECOMPOSITION OF MATRICES PERGUNNAR MARTINSSON VLADIMIR ROKHLIN AND
MARK TYGERT
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63917SKLEARNUTILSEXTMATH FASTLOGDET
SKLEARNUTILSEXTMATH FASTLOGDET A
COMPUTE LOGDETA FOR A SYMMETRIC
EQUIVALENT TO NPLOGNLDETA BUT MORE ROBUST IT RETURNS INF IF DETA IS NON POSITIVE OR IS NOT DEFINED
PARAMETERS
AARRAYLIKE THE MATRIX
63918SKLEARNUTILSEXTMATH DENSITY
SKLEARNUTILSEXTMATH DENSITYWKWARGS
COMPUTE DENSITY OF A SPARSE VECTOR
PARAMETERS
WARRAYLIKE THE SPARSE VECTOR
RETURNS
FLOAT THE DENSITY OF W BETWEEN 0 AND 1
EXAMPLES USING SKLEARNUTILSEXTMATHDENSITY
•CLASSIFICATION OF TEXT DOCUMENTS USING SPARSE FEATURES
63919SKLEARNUTILSEXTMATH WEIGHTEDMODE
SKLEARNUTILSEXTMATH WEIGHTEDMODE AWAXIS0
RETURNS AN ARRAY OF THE WEIGHTED MODAL MOST COMMON VALUE IN A
IF THERE IS MORE THAN ONE SUCH VALUE ONLY THE FIRST IS RETURNED THE BINCOUNT FOR THE MODAL BINS IS ALSO RETURNED
THIS IS AN EXTENSION OF THE ALGORITHM IN SCIPYSTATSMODE
PARAMETERS
AARRAYLIKE NDIMENSIONAL ARRAY OF WHICH TO FIND MODES
WARRAYLIKE NDIMENSIONAL ARRAY OF WEIGHTS FOR EACH VALUE
AXIS INT OPTIONAL AXIS ALONG WHICH TO OPERATE DEFAULT IS 0 IE THE FIRST AXIS
RETURNS
VALS NDARRAY ARRAY OF MODAL VALUES
SCORE NDARRAY ARRAY OF WEIGHTED COUNTS FOR EACH MODE
SEE ALSO
SCIPYSTATSMODE
EXAMPLES

SCIKITLEARN USER GUIDE RELEASE 0213
FROM SKLEARNUTILSEXTMATH IMPORT WEIGHTEDMODE
X 4 1 4 2 4 2
WEIGHTS 1 1 1 1 1 1
WEIGHTEDMODEX WEIGHTS
ARRAY4 ARRAY3
THE VALUE 4 APPEARS THREE TIMES WITH UNIFORM WEIGHTS THE RESULT IS SIMPLY THE MODE OF THE DISTRIBUTION
WEIGHTS 1 3 05 15 1 2 DEWEIGHT THE 4S
WEIGHTEDMODEX WEIGHTS
ARRAY2 ARRAY35
THE VALUE 2 HAS THE HIGHEST SCORE IT APPEARS TWICE WITH WEIGHTS OF 15 AND 2 THE SUM OF THESE IS 35
63920SKLEARNUTILS GENEVENSLICES
SKLEARNUTILS GENEVENSLICES NNPACKS NSAMPLESNONE
GENERATOR TO CREATE NPACKS SLICES GOING UP TO N
PARAMETERS
NINT
NPACKS INT NUMBER OF SLICES TO GENERATE
NSAMPLES INT OR NONE DEFAULT NONE NUMBER OF SAMPLES PASS NSAMPLES WHEN THE SLICES
ARE TO BE USED FOR SPARSE MATRIX INDEXING SLICING OFFTHEEND RAISES AN EXCEPTION WHILE IT
WORKS FOR NUMPY ARRAYS
YIELDS
SLICE
EXAMPLES
FROM SKLEARNUTILS IMPORT GENEVENSLICES
LISTGENEVENSLICES10 1
SLICE0 10 NONE
LISTGENEVENSLICES10 10
SLICE0 1 NONE SLICE1 2 NONE SLICE9 10 NONE
LISTGENEVENSLICES10 5
SLICE0 2 NONE SLICE2 4 NONE SLICE8 10 NONE
LISTGENEVENSLICES10 3
SLICE0 4 NONE SLICE4 7 NONE SLICE7 10 NONE
63921SKLEARNUTILSGRAPH SINGLESOURCESHORTESTPATHLENGTH
SKLEARNUTILSGRAPH SINGLESOURCESHORTESTPATHLENGTH GRAPH SOURCE CUT
OFFNONE
RETURN THE SHORTEST PATH LENGTH FROM SOURCE TO ALL REACHABLE NODES
RETURNS A DICTIONARY OF SHORTEST PATH LENGTHS KEYED BY TARGET
PARAMETERS
GRAPH SPARSE MATRIX OR 2D ARRAY PREFERABLY LIL MATRIX ADJACENCY MATRIX OF THE GRAPH

SOURCE INTEGER STARTING NODE FOR PATH
CUTOFF INTEGER OPTIONAL DEPTH TO STOP THE SEARCH ONLY PATHS OF LENGTH CUTOFF ARE RETURNED
EXAMPLES
 FROM SKLEARNUTILSGRAPH IMPORT SINGLESOURCESHORTESTPATHLENGTH
 IMPORT NUMPY AS NP
GRAPH NPARRAY 0 1 0 0
  1 0 1 0
  0 1 0 1
  0 0 1 0
LISTSORTEDSINGLESOURCESHORTESTPATHLENGTHGRAPH 0ITEMS
0 0 1 1 2 2 3 3
GRAPH NPONES6 6
LISTSORTEDSINGLESOURCESHORTESTPATHLENGTHGRAPH 2ITEMS
0 1 1 1 2 0 3 1 4 1 5 1
63922SKLEARNUTILSGRAPHSHORTESTPATH GRAPHSHORTESTPATH
SKLEARNUTILSGRAPHSHORTESTPATH GRAPHSHORTESTPATH
PERFORM A SHORTESTPATH GRAPH SEARCH ON A POSITIVE DIRECTED OR UNDIRECTED GRAPH
PARAMETERS
DISTMATRIX ARRAYLIKE OR SPARSE MATRIX SHAPE NN ARRAY OF POSITIVE DISTANCES IF VERTEX
I IS CONNECTED TO VERTEX J THEN DISTMATRIXIJ GIVES THE DISTANCE BETWEEN THE VERTICES IF
VERTEX I IS NOT CONNECTED TO VERTEX J THEN DISTMATRIXIJ 0
DIRECTED BOOLEAN IF TRUE THEN FIND THE SHORTEST PATH ON A DIRECTED GRAPH ONLY PROGRESS FROM
A POINT TO ITS NEIGHBORS NOT THE OTHER WAY AROUND IF FALSE THEN FIND THE SHORTEST PATH ON AN
UNDIRECTED GRAPH THE ALGORITHM CAN PROGRESS FROM A POINT TO ITS NEIGHBORS AND VICE VERSA
METHOD STRING ‘AUTO’’FW’’D’ METHOD TO USE OPTIONS ARE ‘AUTO’ ATTEMPT TO CHOOSE THE BEST
METHOD FOR THE CURRENT PROBLEM ‘FW’ FLOYDWARSHALL ALGORITHM ON3 ‘D’ DIJKSTRA’S
ALGORITHM WITH FIBONACCI STACKS OKLOGNN2
RETURNS
GNPNDARRAY FLOAT SHAPE NN GIJ GIVES THE SHORTEST DISTANCE FROM POINT I TO POINT J
ALONG THE GRAPH
NOTES
AS CURRENTLY IMPLEMENTED DIJKSTRA’S ALGORITHM DOES NOT WORK FOR GRAPHS WITH DIRECTIONDEPENDENT DISTANCES
WHEN DIRECTED FALSE IE IF DISTMATRIXIJ AND DISTMATRIXJI ARE NOT EQUAL AND BOTH ARE NONZERO
METHOD’D’ WILL NOT NECESSARILY YIELD THE CORRECT RESULT
ALSO THESE ROUTINES HAVE NOT BEEN TESTED FOR GRAPHS WITH NEGATIVE DISTANCES NEGATIVE DISTANCES CAN LEAD TO
INFINITE CYCLES THAT MUST BE HANDLED BY SPECIALIZED ALGORITHMS
63923SKLEARNUTILS INDEXABLE
SKLEARNUTILS INDEXABLE ITERABLES
MAKE ARRAYS INDEXABLE FOR CROSSVALIDATION

CHECKS CONSISTENT LENGTH PASSES THROUGH NONE AND ENSURES THAT EVERYTHING CAN BE INDEXED BY CONVERTING SPARSE MATRICES TO CSR AND CONVERTING NONINTERABLE OBJECTS TO ARRAYS
PARAMETERS
ITERABLES LISTS DATAFRAMES ARRAYS SPARSE MATRICES LIST OF OBJECTS TO ENSURE SLICEABILITY
63924SKLEARNUTILSMETAESTIMATORS IFDELEGATEHASMETHOD
SKLEARNUTILSMETAESTIMATORS IFDELEGATEHASMETHOD DELEGATE
CREATE A DECORATOR FOR METHODS THAT ARE DELEGATED TO A SUBESTIMATOR
THIS ENABLES DUCKTYPING BY HASATTR RETURNING TRUE ACCORDING TO THE SUBESTIMATOR
PARAMETERS
DELEGATE STRING LIST OF STRINGS OR TUPLE OF STRINGS NAME OF THE SUBESTIMATOR THAT CAN BE ACCESSED AS AN ATTRIBUTE OF THE BASE OBJECT IF A LIST OR A TUPLE OF NAMES ARE PROVIDED THE FIRST SUBESTIMATOR THAT IS AN ATTRIBUTE OF THE BASE OBJECT WILL BE USED
EXAMPLES USING SKLEARNUTILSMETAESTIMATORSIFDELEGATEHASMETHOD
•INDUCTIVE CLUSTERING
63925SKLEARNUTILSMULTICLASS TYPEOFTARGET
SKLEARNUTILSMULTICLASS TYPEOFTARGET Y
DETERMINE THE TYPE OF DATA INDICATED BY THE TARGET
NOTE THAT THIS TYPE IS THE MOST SPECIFIC TYPE THAT CAN BE INFERRED FOR EXAMPLE
•BINARY IS MORE SPECIFIC BUT COMPATIBLE WITH MULTICLASS
•MULTICLASS OF INTEGERS IS MORE SPECIFIC BUT COMPATIBLE WITH CONTINUOUS
•MULTILABELINDICATOR IS MORE SPECIFIC BUT COMPATIBLE WITH MULTICLASSMULTIOUTPUT
PARAMETERS
YARRAYLIKE
RETURNS
TARGETTYPE STRING ONE OF
• ‘CONTINUOUS’ YIS AN ARRAYLIKE OF FLOATS THAT ARE NOT ALL INTEGERS AND IS 1D OR A COLUMN VECTOR
• ‘CONTINUOUSMULTIOUTPUT’ YIS A 2D ARRAY OF FLOATS THAT ARE NOT ALL INTEGERS AND BOTH DIMENSIONS ARE OF SIZE 1
• ‘BINARY’ YCONTAINS 2 DISCRETE VALUES AND IS 1D OR A COLUMN VECTOR
• ‘MULTICLASS’ YCONTAINS MORE THAN TWO DISCRETE VALUES IS NOT A SEQUENCE OF SEQUENCES AND IS 1D OR A COLUMN VECTOR
• ‘MULTICLASSMULTIOUTPUT’ YIS A 2D ARRAY THAT CONTAINS MORE THAN TWO DISCRETE VALUES IS NOT A SEQUENCE OF SEQUENCES AND BOTH DIMENSIONS ARE OF SIZE 1
• ‘MULTILABELINDICATOR’ YIS A LABEL INDICATOR MATRIX AN ARRAY OF TWO DIMENSIONS WITH AT LEAST TWO COLUMNS AND AT MOST 2 UNIQUE VALUES

• ‘UNKNOWN’ YIS ARRAYLIKE BUT NONE OF THE ABOVE SUCH AS A 3D ARRAY SEQUENCE OF SE
QUENCES OR AN ARRAY OF NONSEQUENCE OBJECTS
EXAMPLES
```
 IMPORT NUMPY AS NP
TYPEOFTARGET01 06
CONTINUOUS
TYPEOFTARGET1 1 1 1
BINARY
TYPEOFTARGETA B A
BINARY
TYPEOFTARGET10 20
BINARY
TYPEOFTARGET1 0 2
MULTICLASS
TYPEOFTARGET10 00 30
MULTICLASS
TYPEOFTARGETA B C
MULTICLASS
TYPEOFTARGETNPARRAY1 2 3 1
MULTICLASSMULTIOUTPUT
TYPEOFTARGET1 2
MULTICLASSMULTIOUTPUT
TYPEOFTARGETNPARRAY15 20 30 16
CONTINUOUSMULTIOUTPUT
TYPEOFTARGETNPARRAY0 1 1 1
MULTILABELINDICATOR
```
63926SKLEARNUTILSMULTICLASS ISMULTILABEL
SKLEARNUTILSMULTICLASS ISMULTILABEL Y
CHECK IFYIS IN A MULTILABEL FORMAT
PARAMETERS
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
OUT BOOL RETURN TRUE IFYIS IN A MULTILABEL FORMAT ELSE FALSE
EXAMPLES
```
 IMPORT NUMPY AS NP
 FROM SKLEARNUTILSMULTICLASS IMPORT ISMULTILABEL
ISMULTILABEL0 1 0 1
FALSE
ISMULTILABEL1 0 2
FALSE
ISMULTILABELNPARRAY1 0 0 0
TRUE
ISMULTILABELNPARRAY1 0 0
FALSE
```

ISMULTILABELNPARRAY1 0 0
TRUE
63927SKLEARNUTILSMULTICLASS UNIQUELABELS
SKLEARNUTILSMULTICLASS UNIQUELABELS YS
EXTRACT AN ORDERED ARRAY OF UNIQUE LABELS
WE DON’T ALLOW
• MIX OF MULTILABEL AND MULTICLASS SINGLE LABEL TARGETS
• MIX OF LABEL INDICATOR MATRIX AND ANYTHING ELSE BECAUSE THERE ARE NO EXPLICIT LABELS
• MIX OF LABEL INDICATOR MATRICES OF DIFFERENT SIZES
• MIX OF STRING AND INTEGER LABELS
AT THE MOMENT WE ALSO DON’T ALLOW “MULTICLASSMULTIOUTPUT” INPUT TYPE
PARAMETERS
YS ARRAYLIKES
RETURNS
OUT NUMPY ARRAY OF SHAPE NUNIQUELABELS AN ORDERED ARRAY OF UNIQUE LABELS
EXAMPLES
FROM SKLEARNUTILSMULTICLASS IMPORT UNIQUELABELS
UNIQUELABELS3 5 5 5 7 7
ARRAY3 5 7
UNIQUELABELS1 2 3 4 2 2 3 4
ARRAY1 2 3 4
UNIQUELABELS1 2 10 5 11
ARRAY 1 2 5 10 11
EXAMPLES USING SKLEARNUTILSMULTICLASSUNIQUELABELS
•CONFUSION MATRIX
63928SKLEARNUTILS MURMURHASH332
SKLEARNUTILS MURMURHASH332
COMPUTE THE 32BIT MURMURHASH3 OF KEY AT SEED
THE UNDERLYING IMPLEMENTATION IS MURMURHASH3X8632 GENERATING LOW LATENCY 32BITS HASH SUITABLE FOR IM
PLEMENTING LOOKUP TABLES BLOOM FILTERS COUNT MIN SKETCH OR FEATURE HASHING
PARAMETERS
KEY INT32 BYTES UNICODE OR NDARRAY WITH DTYPE INT32 THE PHYSICAL OBJECT TO HASH
SEED INT OPTIONAL DEFAULT IS 0 INTEGER SEED FOR THE HASHING ALGORITHM
POSITIVE BOOLEAN OPTIONAL DEFAULT IS FALSE

TRUE THE RESULTS IS CASTED TO AN UNSIGNED INT FROM 0 TO 2 32 1
FALSE THE RESULTS IS CASTED TO A SIGNED INT FROM 2 31 TO 2 31 1
63929SKLEARNUTILS RESAMPLE
SKLEARNUTILS RESAMPLE ARRAYS OPTIONS
RESAMPLE ARRAYS OR SPARSE MATRICES IN A CONSISTENT WAY
THE DEFAULT STRATEGY IMPLEMENTS ONE STEP OF THE BOOTSTRAPPING PROCEDURE
PARAMETERS
ARRAYS SEQUENCE OF INDEXABLE DATASTRUCTURES INDEXABLE DATASTRUCTURES CAN BE ARRAYS LISTS
DATAFRAMES OR SCIPY SPARSE MATRICES WITH CONSISTENT FIRST DIMENSION
RETURNS
RESAMPLEDARRAYS SEQUENCE OF INDEXABLE DATASTRUCTURES SEQUENCE OF RESAMPLED COPIES OF
THE COLLECTIONS THE ORIGINAL ARRAYS ARE NOT IMPACTED
OTHER PARAMETERS
REPLACE BOOLEAN TRUE BY DEFAULT IMPLEMENTS RESAMPLING WITH REPLACEMENT IF FALSE THIS WILL
IMPLEMENT SLICED RANDOM PERMUTATIONS
NSAMPLES INT NONE BY DEFAULT NUMBER OF SAMPLES TO GENERATE IF LEFT TO NONE THIS IS AUTO
MATICALLY SET TO THE FIRST DIMENSION OF THE ARRAYS IF REPLACE IS FALSE IT SHOULD NOT BE LARGER
THAN THE LENGTH OF ARRAYS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
STRATIFY ARRAYLIKE OR NONE DEFAULTNONE IF NOT NONE DATA IS SPLIT IN A STRATIFIED FASHION
USING THIS AS THE CLASS LABELS
SEE ALSO
SKLEARNUTILSSHUFFLE
EXAMPLES
IT IS POSSIBLE TO MIX SPARSE AND DENSE ARRAYS IN THE SAME RUN
```
X  NPARRAY1 0 2 1 0 0
Y  NPARRAY0 1 2
 FROM SCIPYSPARSE IMPORT COOMATRIX
XSPARSE  COOMATRIXX
 FROM SKLEARNUTILS IMPORT RESAMPLE
X XSPARSE Y  RESAMPLEX XSPARSE Y RANDOMSTATE0
X
ARRAY1 0
2 1
1 0
```

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XSPARSE
3X2 SPARSE MATRIX OF TYPE NUMPYFLOAT64
WITH 4 STORED ELEMENTS IN COMPRESSED SPARSE ROW FORMAT
XSPARSETOARRAY
ARRAY1 0
2 1
1 0
Y
ARRAY0 1 0
RESAMPLEY NSAMPLES2 RANDOMSTATE0
ARRAY0 1
EXAMPLE USING STRATIFICATION
Y 0 0 1 1 1 1 1 1 1
RESAMPLEY NSAMPLES5 REPLACE FALSE STRATIFYY
 RANDOMSTATE0
1 1 1 0 1
63930SKLEARNUTILS SAFEINDEXING
SKLEARNUTILS SAFEINDEXING XINDICES
RETURN ITEMS OR ROWS FROM X USING INDICES
ALLOWS SIMPLE INDEXING OF LISTS OR ARRAYS
PARAMETERS
XARRAYLIKE SPARSEMATRIX LIST PANDASDATAFRAME PANDASSERIES DATA FROM WHICH TO SAM
PLE ROWS OR ITEMS
INDICES ARRAYLIKE OF INT INDICES ACCORDING TO WHICH X WILL BE SUBSAMPLED
RETURNS
SUBSET SUBSET OF X ON FIRST AXIS
NOTES
CSR CSC AND LIL SPARSE MATRICES ARE SUPPORTED COO SPARSE MATRICES ARE NOT SUPPORTED
63931SKLEARNUTILS SAFEMASK
SKLEARNUTILS SAFEMASK XMASK
RETURN A MASK WHICH IS SAFE TO USE ON X
PARAMETERS
XARRAYLIKE SPARSE MATRIX DATA ON WHICH TO APPLY MASK
MASK ARRAY MASK TO BE USED ON X
RETURNS

MASK
63932SKLEARNUTILS SAFESQR
SKLEARNUTILS SAFESQR XCOPYTRUE
ELEMENT WISE SQUARING OF ARRAYLIKES AND SPARSE MATRICES
PARAMETERS
XARRAY LIKE MATRIX SPARSE MATRIX
COPY BOOLEAN OPTIONAL DEFAULT TRUE WHETHER TO CREATE A COPY OF X AND OPERATE ON IT OR TO
PERFORM INPLACE COMPUTATION DEFAULT BEHAVIOUR
RETURNS
X 2 ELEMENT WISE SQUARE
63933SKLEARNUTILS SHUFFLE
SKLEARNUTILS SHUFFLEARRAYS OPTIONS
SHUFFLE ARRAYS OR SPARSE MATRICES IN A CONSISTENT WAY
THIS IS A CONVENIENCE ALIAS TO RESAMPLE ARRAYS REPLACEFALSE TO DO RANDOM PERMUTATIONS OF THE
COLLECTIONS
PARAMETERS
ARRAYS SEQUENCE OF INDEXABLE DATASTRUCTURES INDEXABLE DATASTRUCTURES CAN BE ARRAYS LISTS
DATAFRAMES OR SCIPY SPARSE MATRICES WITH CONSISTENT FIRST DIMENSION
RETURNS
SHUFFLEDARRAYS SEQUENCE OF INDEXABLE DATASTRUCTURES SEQUENCE OF SHUFFLED COPIES OF THE COL
LECTIONS THE ORIGINAL ARRAYS ARE NOT IMPACTED
OTHER PARAMETERS
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM
NSAMPLES INT NONE BY DEFAULT NUMBER OF SAMPLES TO GENERATE IF LEFT TO NONE THIS IS AUTO
MATICALLY SET TO THE FIRST DIMENSION OF THE ARRAYS
SEE ALSO
SKLEARNUTILSRESAMPLE
EXAMPLES
IT IS POSSIBLE TO MIX SPARSE AND DENSE ARRAYS IN THE SAME RUN

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X NPARRAY1 0 2 1 0 0
Y NPARRAY0 1 2
 FROM SCIPYSPARSE IMPORT COOMATRIX
XSPARSE COOMATRIXX
 FROM SKLEARNUTILS IMPORT SHUFFLE
X XSPARSE Y SHUFFLEX XSPARSE Y RANDOMSTATE0
X
ARRAY0 0
2 1
1 0
XSPARSE
3X2 SPARSE MATRIX OF TYPE NUMPYFLOAT64
WITH 3 STORED ELEMENTS IN COMPRESSED SPARSE ROW FORMAT
XSPARSETOARRAY
ARRAY0 0
2 1
1 0
Y
ARRAY2 1 0
SHUFFLEY NSAMPLES2 RANDOMSTATE0
ARRAY0 1
EXAMPLES USING SKLEARNUTILSSHUFFLE
•MODEL COMPLEXITY INFLUENCE
•PREDICTION LATENCY
•COLOR QUANTIZATION USING KMEANS
•EMPIRICAL EVALUATION OF THE IMPACT OF KMEANS INITIALIZATION
•GRADIENT BOOSTING REGRESSION
•EARLY STOPPING OF STOCHASTIC GRADIENT DESCENT
63934SKLEARNUTILSSPARSEFUNCS INCRMEANVARIANCEAXIS
SKLEARNUTILSSPARSEFUNCS INCRMEANVARIANCEAXIS XAXISLASTMEAN LASTVAR LASTN
COMPUTE INCREMENTAL MEAN AND VARIANCE ALONG AN AXIX ON A CSR OR CSC MATRIX
LASTMEAN LASTVAR ARE THE STATISTICS COMPUTED AT THE LAST STEP BY THIS FUNCTION BOTH MUST BE INITIALIZED TO 0
ARRAYS OF THE PROPER SIZE IE THE NUMBER OF FEATURES IN X LASTN IS THE NUMBER OF SAMPLES ENCOUNTERED UNTIL
NOW
PARAMETERS
XCSR OR CSC SPARSE MATRIX SHAPE NSAMPLES NFEATURES INPUT DATA
AXIS INT EITHER 0 OR 1 AXIS ALONG WHICH THE AXIS SHOULD BE COMPUTED
LASTMEAN FLOAT ARRAY WITH SHAPE NFEATURES ARRAY OF FEATUREWISE MEANS TO UPDATE WITH THE
NEW DATA X

LASTVAR FLOAT ARRAY WITH SHAPE NFEATURES ARRAY OF FEATUREWISE VAR TO UPDATE WITH THE NEW
DATA X
LASTN INT WITH SHAPE NFEATURES NUMBER OF SAMPLES SEEN SO FAR EXCLUDED X
RETURNS
MEANS FLOAT ARRAY WITH SHAPE NFEATURES UPDATED FEATUREWISE MEANS
VARIANCES FLOAT ARRAY WITH SHAPE NFEATURES UPDATED FEATUREWISE VARIANCES
NINT WITH SHAPE NFEATURES UPDATED NUMBER OF SEEN SAMPLES
NOTES
NANS ARE IGNORED IN THE ALGORITHM
63935SKLEARNUTILSSPARSEFUNCS INPLACECOLUMNSCALE
SKLEARNUTILSSPARSEFUNCS INPLACECOLUMNSCALE XSCALE
INPLACE COLUMN SCALING OF A CSCCSR MATRIX
SCALE EACH FEATURE OF THE DATA MATRIX BY MULTIPLYING WITH SPECIFIC SCALE PROVIDED BY THE CALLER ASSUMING A
NSAMPLES NFEATURES SHAPE
PARAMETERS
XCSC OR CSR MATRIX WITH SHAPE NSAMPLES NFEATURES MATRIX TO NORMALIZE USING THE VARI
ANCE OF THE FEATURES
SCALE FLOAT ARRAY WITH SHAPE NFEATURES ARRAY OF PRECOMPUTED FEATUREWISE VALUES TO USE FOR
SCALING
63936SKLEARNUTILSSPARSEFUNCS INPLACEROWSCALE
SKLEARNUTILSSPARSEFUNCS INPLACEROWSCALE XSCALE
INPLACE ROW SCALING OF A CSR OR CSC MATRIX
SCALE EACH ROW OF THE DATA MATRIX BY MULTIPLYING WITH SPECIFIC SCALE PROVIDED BY THE CALLER ASSUMING A
NSAMPLES NFEATURES SHAPE
PARAMETERS
XCSR OR CSC SPARSE MATRIX SHAPE NSAMPLES NFEATURES MATRIX TO BE SCALED
SCALE FLOAT ARRAY WITH SHAPE NFEATURES ARRAY OF PRECOMPUTED SAMPLEWISE VALUES TO USE FOR
SCALING
63937SKLEARNUTILSSPARSEFUNCS INPLACESWAPROW
SKLEARNUTILSSPARSEFUNCS INPLACESWAPROW XMN
SWAPS TWO ROWS OF A CSCCSR MATRIX INPLACE
PARAMETERS
XCSR OR CSC SPARSE MATRIX SHAPENSAMPLES NFEATURES MATRIX WHOSE TWO ROWS ARE TO
BE SWAPPED

MINT INDEX OF THE ROW OF X TO BE SWAPPED
NINT INDEX OF THE ROW OF X TO BE SWAPPED
63938SKLEARNUTILSSPARSEFUNCS INPLACESWAPCOLUMN
SKLEARNUTILSSPARSEFUNCS INPLACESWAPCOLUMN XMN
SWAPS TWO COLUMNS OF A CSCCSR MATRIX INPLACE
PARAMETERS
XCSR OR CSC SPARSE MATRIX SHAPENSAMPLES NFEATURES MATRIX WHOSE TWO COLUMNS ARE
TO BE SWAPPED
MINT INDEX OF THE COLUMN OF X TO BE SWAPPED
NINT INDEX OF THE COLUMN OF X TO BE SWAPPED
63939SKLEARNUTILSSPARSEFUNCS MEANVARIANCEAXIS
SKLEARNUTILSSPARSEFUNCS MEANVARIANCEAXIS XAXIS
COMPUTE MEAN AND VARIANCE ALONG AN AXIX ON A CSR OR CSC MATRIX
PARAMETERS
XCSR OR CSC SPARSE MATRIX SHAPE NSAMPLES NFEATURES INPUT DATA
AXIS INT EITHER 0 OR 1 AXIS ALONG WHICH THE AXIS SHOULD BE COMPUTED
RETURNS
MEANS FLOAT ARRAY WITH SHAPE NFEATURES FEATUREWISE MEANS
VARIANCES FLOAT ARRAY WITH SHAPE NFEATURES FEATUREWISE VARIANCES
63940SKLEARNUTILSSPARSEFUNCS INPLACECSRCOLUMNSCALE
SKLEARNUTILSSPARSEFUNCS INPLACECSRCOLUMNSCALE XSCALE
INPLACE COLUMN SCALING OF A CSR MATRIX
SCALE EACH FEATURE OF THE DATA MATRIX BY MULTIPLYING WITH SPECIFIC SCALE PROVIDED BY THE CALLER ASSUMING A
NSAMPLES NFEATURES SHAPE
PARAMETERS
XCSR MATRIX WITH SHAPE NSAMPLES NFEATURES MATRIX TO NORMALIZE USING THE VARIANCE OF
THE FEATURES
SCALE FLOAT ARRAY WITH SHAPE NFEATURES ARRAY OF PRECOMPUTED FEATUREWISE VALUES TO USE FOR
SCALING
63941SKLEARNUTILSSPARSEFUNCSFAST INPLACECSRROWNORMALIZEL1
SKLEARNUTILSSPARSEFUNCSFAST INPLACECSRROWNORMALIZEL1
INPLACE ROW NORMALIZE USING THE L1 NORM

63942SKLEARNUTILSSPARSEFUNCSFAST INPLACECSRROWNORMALIZEL2
SKLEARNUTILSSPARSEFUNCSFAST INPLACECSRROWNORMALIZEL2
INPLACE ROW NORMALIZE USING THE L2 NORM
63943SKLEARNUTILSRANDOM SAMPLEWITHOUTREPLACEMENT
SKLEARNUTILSRANDOM SAMPLEWITHOUTREPLACEMENT
SAMPLE INTEGERS WITHOUT REPLACEMENT
SELECT NSAMPLES INTEGERS FROM THE SET 0 NPOPULATION WITHOUT REPLACEMENT
PARAMETERS
NPOPULATION INT THE SIZE OF THE SET TO SAMPLE FROM
NSAMPLES INT THE NUMBER OF INTEGER TO SAMPLE
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULTNONE IF INT RAN
DOMSTATE IS THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE
RANDOMSTATE IS THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS
THE RANDOMSTATE INSTANCE USED BY NPRANDOM
METHOD “AUTO” “TRACKINGSELECTION” “RESERVOIRSAMPLING” OR “POOL” IF METHOD “AUTO”
THE RATIO OF NSAMPLES NPOPULATION IS USED TO DETERMINE WHICH ALGORITHM TO USE IF RA
TIO IS BETWEEN 0 AND 001 TRACKING SELECTION IS USED IF RATIO IS BETWEEN 001 AND 099
NUMPYRANDOMPERMUTATION IS USED IF RATIO IS GREATER THAN 099 RESERVOIR SAMPLING IS USED
THE ORDER OF THE SELECTED INTEGERS IS UNDEFINED IF A RANDOM ORDER IS DESIRED THE SELECTED
SUBSET SHOULD BE SHUFFLED
IF METHOD ”TRACKINGSELECTION” A SET BASED IMPLEMENTATION IS USED WHICH IS SUITABLE FOR
NSAMPLES NPOPULATION
IF METHOD “RESERVOIRSAMPLING” A RESERVOIR SAMPLING ALGORITHM IS USED WHICH IS SUITABLE
FOR HIGH MEMORY CONSTRAINT OR WHEN O NSAMPLES ONPOPULATION THE ORDER OF THE
SELECTED INTEGERS IS UNDEFINED IF A RANDOM ORDER IS DESIRED THE SELECTED SUBSET SHOULD BE
SHUFFLED
IF METHOD “POOL” A POOL BASED ALGORITHM IS PARTICULARLY FAST EVEN FASTER THAN THE TRACKING
SELECTION METHOD HOVEWER A VECTOR CONTAINING THE ENTIRE POPULATION HAS TO BE INITIALIZED
IF NSAMPLES NPOPULATION THE RESERVOIR SAMPLING METHOD IS FASTER
RETURNS
OUT ARRAY OF SIZE NSAMPLES THE SAMPLED SUBSETS OF INTEGER THE SUBSET OF SELECTED INTEGER
MIGHT NOT BE RANDOMIZED SEE THE METHOD ARGUMENT
63944SKLEARNUTILSVALIDATION CHECKISFITTED
SKLEARNUTILSVALIDATION CHECKISFITTED ESTIMATOR ATTRIBUTES MSGNONE
ALLORANYBUILTIN FUNCTION ALL
PERFORM ISFITTED VALIDATION FOR ESTIMATOR
CHECKS IF THE ESTIMATOR IS FITTED BY VERIFYING THE PRESENCE OF “ALLORANY” OF THE PASSED ATTRIBUTES AND RAISES A
NOTFITTEDERROR WITH THE GIVEN MESSAGE
PARAMETERS
ESTIMATOR ESTIMATOR INSTANCE ESTIMATOR INSTANCE FOR WHICH THE CHECK IS PERFORMED

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ATTRIBUTES ATTRIBUTE NAMES GIVEN AS STRING OR A LISTTUPLE OF STRINGS
EGCOEF ESTIMATOR COEF
MSG STRING THE DEFAULT ERROR MESSAGE IS “THIS NAMES INSTANCE IS NOT FITTED YET CALL ‘FIT’
WITH APPROPRIATE ARGUMENTS BEFORE USING THIS METHOD”
FOR CUSTOM MESSAGES IF “NAMES” IS PRESENT IN THE MESSAGE STRING IT IS SUBSTITUTED FOR THE
ESTIMATOR NAME
EG “ESTIMATOR NAMES MUST BE FITTED BEFORE SPARSIFYING”
ALLORANY CALLABLE ALL ANY DEFAULT ALL SPECIFY WHETHER ALL OR ANY OF THE GIVEN ATTRIBUTES
MUST EXIST
RETURNS
NONE
RAISES
NOTFITTEDERROR IF THE ATTRIBUTES ARE NOT FOUND
63945SKLEARNUTILSVALIDATION CHECKMEMORY
SKLEARNUTILSVALIDATION CHECKMEMORY MEMORY
CHECK THAT MEMORY IS JOBLIBMEMORYLIKE
JOBLIBMEMORYLIKE MEANS THAT MEMORY CAN BE CONVERTED INTO A JOBLIBMEMORY INSTANCE TYPICALLY A STR DENOTING
THELOCATION OR HAS THE SAME INTERFACE HAS A CACHE METHOD
PARAMETERS
MEMORY NONE STR OR OBJECT WITH THE JOBLIBMEMORY INTERFACE
RETURNS
MEMORY OBJECT WITH THE JOBLIBMEMORY INTERFACE
RAISES
VALUEERROR IFMEMORY IS NOT JOBLIBMEMORYLIKE
63946SKLEARNUTILSVALIDATION CHECKSYMMETRIC
SKLEARNUTILSVALIDATION CHECKSYMMETRIC ARRAY TOL1E10 RAISEWARNINGTRUE
RAISEEXCEPTIONFALSE
MAKE SURE THAT ARRAY IS 2D SQUARE AND SYMMETRIC
IF THE ARRAY IS NOT SYMMETRIC THEN A SYMMETRIZED VERSION IS RETURNED OPTIONALLY A WARNING OR EXCEPTION IS
RAISED IF THE MATRIX IS NOT SYMMETRIC
PARAMETERS
ARRAY NDARRAY OR SPARSE MATRIX INPUT OBJECT TO CHECK CONVERT MUST BE TWODIMENSIONAL AND
SQUARE OTHERWISE A VALUEERROR WILL BE RAISED
TOLFLOAT ABSOLUTE TOLERANCE FOR EQUIVALENCE OF ARRAYS DEFAULT 1E10
RAISEWARNING BOOLEAN DEFAULTTRUE IF TRUE THEN RAISE A WARNING IF CONVERSION IS REQUIRED
RAISEEXCEPTION BOOLEAN DEFAULTFALSE IF TRUE THEN RAISE AN EXCEPTION IF ARRAY IS NOT SYM
METRIC

RETURNS
ARRAYSYM NDARRAY OR SPARSE MATRIX SYMMETRIZED VERSION OF THE INPUT ARRAY IE THE AVERAGE
OF ARRAY AND ARRAYTRANSPOSE IF SPARSE THEN DUPLICATE ENTRIES ARE FIRST SUMMED AND ZEROS
ARE ELIMINATED
63947SKLEARNUTILSVALIDATION COLUMNOR1D
SKLEARNUTILSVALIDATION COLUMNOR1D YWARNFALSE
RAVEL COLUMN OR 1D NUMPY ARRAY ELSE RAISES AN ERROR
PARAMETERS
YARRAYLIKE
WARN BOOLEAN DEFAULT FALSE TO CONTROL DISPLAY OF WARNINGS
RETURNS
YARRAY
63948SKLEARNUTILSVALIDATION HASFITPARAMETER
SKLEARNUTILSVALIDATION HASFITPARAMETER ESTIMATOR PARAMETER
CHECKS WHETHER THE ESTIMATOR'S FIT METHOD SUPPORTS THE GIVEN PARAMETER
PARAMETERS
ESTIMATOR OBJECT AN ESTIMATOR TO INSPECT
PARAMETER STR THE SEARCHED PARAMETER
RETURNS
ISPARAMETER BOOL WHETHER THE PARAMETER WAS FOUND TO BE A NAMED PARAMETER OF THE ESTIMA
TOR'S FIT METHOD
EXAMPLES
FROM SKLEARNSVM IMPORT SVC
HASFITPARAMETERSVC SAMPLEWEIGHT
TRUE
63949SKLEARNUTILSTESTING ASSERTIN
SKLEARNUTILSTESTING ASSERTIN MEMBER CONTAINER MSGNONE
JUST LIKE SELFASSERTTRUEA IN B BUT WITH A NICER DEFAULT MESSAGE
63950SKLEARNUTILSTESTING ASSERTNOTIN
SKLEARNUTILSTESTING ASSERTNOTIN MEMBER CONTAINER MSGNONE
JUST LIKE SELFASSERTTRUEA NOT IN B BUT WITH A NICER DEFAULT MESSAGE
639SKLEARNUTILS UTILITIES 2383

63951SKLEARNUTILSTESTING ASSERTRAISEMESSAGE
SKLEARNUTILSTESTING ASSERTRAISEMESSAGE EXCEPTIONS MESSAGE FUNCTION ARGS
KWARGS
HELPER FUNCTION TO TEST THE MESSAGE RAISED IN AN EXCEPTION
GIVEN AN EXCEPTION A CALLABLE TO RAISE THE EXCEPTION AND A MESSAGE STRING TESTS THAT THE CORRECT EXCEPTION IS RAISED AND THAT THE MESSAGE IS A SUBSTRING OF THE ERROR THROWN USED TO TEST THAT THE SPECIFIC MESSAGE THROWN DURING AN EXCEPTION IS CORRECT
PARAMETERS
EXCEPTIONS EXCEPTION OR TUPLE OF EXCEPTION AN EXCEPTION OBJECT
MESSAGE STR THE ERROR MESSAGE OR A SUBSTRING OF THE ERROR MESSAGE
FUNCTION CALLABLE CALLABLE OBJECT TO RAISE ERROR
ARGS THE POSITIONAL ARGUMENTS TO FUNCTION
KWARGS THE KEYWORD ARGUMENTS TO FUNCTION
63952SKLEARNUTILSTESTING ALLESTIMATORS
SKLEARNUTILSTESTING ALLESTIMATORS INCLUDEMETAESTIMATORSNONE INCLUDEOTHERNONE TYPEFILTERNONE INCLUDEDONTTESTNONE
GET A LIST OF ALL ESTIMATORS FROM SKLEARN
THIS FUNCTION CRAWLS THE MODULE AND GETS ALL CLASSES THAT INHERIT FROM BASEESTIMATOR CLASSES THAT ARE DEFINED IN TESTMODULES ARE NOT INCLUDED BY DEFAULT METAESTIMATORS SUCH AS GRIDSEARCHCV ARE ALSO NOT INCLUDED
PARAMETERS
INCLUDEMETAESTIMATORS BOOLEAN DEFAULTFALSE DEPRECATED IGNORED DEPRECATED 021
INCLUDEMETAESTIMATORS HAS BEEN DEPRECATED AND HAS NO EFFECT IN 021 AND
WILL BE REMOVED IN 023
INCLUDEOTHER BOOLEAN DEFAULTFALSE DEPRECATED IGNORED DEPRECATED 021
INCLUDEOTHER HAS BEEN DEPRECATED AND HAS NOT EFFECT IN 021 AND WILL BE REMOVED
IN 023
TYPEFILTER STRING LIST OF STRING OR NONE DEFAULTNONE WHICH KIND OF ESTIMATORS SHOULD BE RETURNED IF NONE NO FILTER IS APPLIED AND ALL ESTIMATORS ARE RETURNED POSSIBLE VALUES ARE ‘CLASSIFIER’ ‘REGRESSOR’ ‘CLUSTER’ AND ‘TRANSFORMER’ TO GET ESTIMATORS ONLY OF THESE SPECIFIC TYPES OR A LIST OF THESE TO GET THE ESTIMATORS THAT FIT AT LEAST ONE OF THE TYPES
INCLUDEDONTTEST BOOLEAN DEFAULTFALSE DEPRECATED IGNORED DEPRECATED 021
INCLUDEDONTTEST HAS BEEN DEPRECATED AND HAS NO EFFECT IN 021 AND WILL BE
REMOVED IN 023
RETURNS
ESTIMATORS LIST OF TUPLES LIST OF NAME CLASS WHERE NAME IS THE CLASS NAME AS STRING AND CLASS IS THE ACTUALL TYPE OF THE CLASS
UTILITIES FROM JOBLIB

UTILSPARALLELBACKEND BACKEND NJOBS CHANGE THE DEFAULT BACKEND USED BY PARALLEL INSIDE A WITH
BLOCK
UTILSREGISTERPARALLELBACKEND NAME FAC
TORYREGISTER A NEW PARALLEL BACKEND FACTORY
63953SKLEARNUTILS PARALLELBACKEND
SKLEARNUTILS PARALLELBACKEND BACKEND NJOBS1 BACKENDPARAMS
CHANGE THE DEFAULT BACKEND USED BY PARALLEL INSIDE A WITH BLOCK
IFBACKEND IS A STRING IT MUST MATCH A PREVIOUSLY REGISTERED IMPLEMENTATION USING THE
REGISTERPARALLELBACKEND FUNCTION
BY DEFAULT THE FOLLOWING BACKENDS ARE AVAILABLE
• 'LOKY' SINGLEHOST PROCESSBASED PARALLELISM USED BY DEFAULT
• 'THREADING' SINGLEHOST THREADBASED PARALLELISM
• 'MULTIPROCESSING' LEGACY SINGLEHOST PROCESSBASED PARALLELISM
'LOKY' IS RECOMMENDED TO RUN FUNCTIONS THAT MANIPULATE PYTHON OBJECTS 'THREADING' IS A LOWOVERHEAD ALTERNATIVE
THAT IS MOST EFFICIENT FOR FUNCTIONS THAT RELEASE THE GLOBAL INTERPRETER LOCK EG IOBOUND CODE OR CPUBOUND
CODE IN A FEW CALLS TO NATIVE CODE THAT EXPLICITLY RELEASES THE GIL
IN ADDITION IF THE DASK ANDDISTRIBUTED PYTHON PACKAGES ARE INSTALLED IT IS POSSIBLE TO USE THE 'DASK'
BACKEND FOR BETTER SCHEDULING OF NESTED PARALLEL CALLS WITHOUT OVERSUBSCRIPTION AND POTENTIALLY DISTRIBUTE PARALLEL
CALLS OVER A NETWORKED CLUSTER OF SEVERAL HOSTS
ALTERNATIVELY THE BACKEND CAN BE PASSED DIRECTLY AS AN INSTANCE
BY DEFAULT ALL AVAILABLE WORKERS WILL BE USED NJOBS1 UNLESS THE CALLER PASSES AN EXPLICIT VALUE FOR THE
NJOBS PARAMETER
THIS IS AN ALTERNATIVE TO PASSING A BACKENDBACKENDNAME ARGUMENT TO THE PARALLEL CLASS CONSTRUC
TOR IT IS PARTICULARLY USEFUL WHEN CALLING INTO LIBRARY CODE THAT USES JOBLIB INTERNALLY BUT DOES NOT EXPOSE THE
BACKEND ARGUMENT IN ITS OWN API
```
 FROM OPERATOR IMPORT NEG
 WITH PARALLELBACKENDTHREADING
 PRINTPARALLELDELAYEDNEGI  1 FORIINRANGE5

1 2 3 4 5
```
WARNING THIS FUNCTION IS EXPERIMENTAL AND SUBJECT TO CHANGE IN A FUTURE VERSION OF JOBLIB
NEW IN VERSION 010
63954SKLEARNUTILS REGISTERPARALLELBACKEND
SKLEARNUTILS REGISTERPARALLELBACKEND NAME FACTORY MAKEDEFAULTFALSE
REGISTER A NEW PARALLEL BACKEND FACTORY
THE NEW BACKEND CAN THEN BE SELECTED BY PASSING ITS NAME AS THE BACKEND ARGUMENT TO THE PARALLEL CLASS
MOREOVER THE DEFAULT BACKEND CAN BE OVERWRITTEN GLOBALLY BY SETTING MAKEDEFAULTTRUE
THE FACTORY CAN BE ANY CALLABLE THAT TAKES NO ARGUMENT AND RETURN AN INSTANCE OF PARALLELBACKENDBASE
WARNING THIS FUNCTION IS EXPERIMENTAL AND SUBJECT TO CHANGE IN A FUTURE VERSION OF JOBLIB

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NEW IN VERSION 010
640 RECENTLY DEPRECATED
6401 TO BE REMOVED IN 023
UTILSMEMORY ARGS KWARGS
ATTRIBUTES
UTILSPARALLEL ARGS KWARGS
METHODS
SKLEARNUTILS MEMORY
WARNING DEPRECATED
CLASSSKLEARNUTILS MEMORYARGS KWARGS
ATTRIBUTES
CACHEDIR
METHODS
CACHE SELF FUNC IGNORE VERBOSE MMAPMODE DECORATES THE GIVEN FUNCTION FUNC TO ONLY COMPUTE ITS
RETURN VALUE FOR INPUT ARGUMENTS NOT CACHED ON DISK
CLEAR SELF WARN ERASE THE COMPLETE CACHE DIRECTORY
EVAL SELF FUNC ARGS KWARGS EVAL FUNCTION FUNC WITH ARGUMENTS ARGS AND
KWARGS IN THE CONTEXT OF THE MEMORY
FORMAT SELF OBJ INDENT RETURN THE FORMATTED REPRESENTATION OF THE OBJECT
REDUCESIZE SELF REMOVE CACHE ELEMENTS TO MAKE CACHE SIZE FIT IN
BYTESLIMIT
DEBUG
WARN
INIT ARGS KWARGS
DEPRECATED DEPRECATED IN VERSION 0201 TO BE REMOVED IN VERSION 023 PLEASE IMPORT THIS FUNCTION
ALITY DIRECTLY FROM JOBLIB WHICH CAN BE INSTALLED WITH PIP INSTALL JOBLIB
CACHESELFFUNCNONE IGNORENONE VERBOSENONE MMAPMODEFALSE
DECORATES THE GIVEN FUNCTION FUNC TO ONLY COMPUTE ITS RETURN VALUE FOR INPUT ARGUMENTS NOT CACHED ON DISK
PARAMETERS

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FUNC CALLABLE OPTIONAL THE FUNCTION TO BE DECORATED
IGNORE LIST OF STRINGS A LIST OF ARGUMENTS NAME TO IGNORE IN THE HASHING
VERBOSE INTEGER OPTIONAL THE VERBOSITY MODE OF THE FUNCTION BY DEFAULT THAT OF THE MEM
ORY OBJECT IS USED
MMAPMODE NONE ‘R’ ‘R’ ‘W’ ‘C’ OPTIONAL THE MEMMAPPING MODE USED WHEN
LOADING FROM CACHE NUMPY ARRAYS SEE NUMPYLOAD FOR THE MEANING OF THE ARGUMENTS
BY DEFAULT THAT OF THE MEMORY OBJECT IS USED
RETURNS
DECORATEDFUNC MEMORIZEDFUNC OBJECT THE RETURNED OBJECT IS A MEMORIZEDFUNC OBJECT
THAT IS CALLABLE BEHAVES LIKE A FUNCTION BUT OFFERS EXTRA METHODS FOR CACHE LOOKUP AND
MANAGEMENT SEE THE DOCUMENTATION FOR JOBLIBMEMORYMEMORIZEDFUNC
CLEARSELFWARNTRUE
ERASE THE COMPLETE CACHE DIRECTORY
EVALSELFFUNCARGS KWARGS
EVAL FUNCTION FUNC WITH ARGUMENTS ARGS ANDKWARGS IN THE CONTEXT OF THE MEMORY
THIS METHOD WORKS SIMILARLY TO THE BUILTIN APPLY EXCEPT THAT THE FUNCTION IS CALLED ONLY IF THE CACHE IS
NOT UP TO DATE
FORMATSELFOBJINDENT0
RETURN THE FORMATTED REPRESENTATION OF THE OBJECT
REDUCESIZE SELF
REMOVE CACHE ELEMENTS TO MAKE CACHE SIZE FIT IN BYTESLIMIT
SKLEARNUTILS PARALLEL
WARNING DEPRECATED
CLASSSKLEARNUTILS PARALLEL ARGS KWARGS
METHODS
CALL SELF ITERABLE
DISPATCHNEXT SELF DISPATCH MORE DATA FOR PARALLEL PROCESSING
DISPATCHONEBATCH SELF ITERATOR PREFETCH THE TASKS FOR THE NEXT BATCH AND DISPATCH THEM
FORMAT SELF OBJ INDENT RETURN THE FORMATTED REPRESENTATION OF THE OBJECT
PRINTPROGRESS SELF DISPLAY THE PROCESS OF THE PARALLEL EXECUTION ONLY A FRAC
TION OF TIME CONTROLLED BY SELFVERBOSE
DEBUG
RETRIEVE
WARN
INIT ARGS KWARGS
DEPRECATED DEPRECATED IN VERSION 0201 TO BE REMOVED IN VERSION 023 PLEASE IMPORT THIS FUNCTION
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ALITY DIRECTLY FROM JOBLIB WHICH CAN BE INSTALLED WITH PIP INSTALL JOBLIB
DISPATCHNEXT SELF
DISPATCH MORE DATA FOR PARALLEL PROCESSING
THIS METHOD IS MEANT TO BE CALLED CONCURRENTLY BY THE MULTIPROCESSING CALLBACK WE RELY ON THE THREAD
SAFETY OF DISPATCHONEBATCH TO PROTECT AGAINST CONCURRENT CONSUMPTION OF THE UNPROTECTED ITERATOR
DISPATCHONEBATCH SELFITERATOR
PREFETCH THE TASKS FOR THE NEXT BATCH AND DISPATCH THEM
THE EFFECTIVE SIZE OF THE BATCH IS COMPUTED HERE IF THERE ARE NO MORE JOBS TO DISPATCH RETURN FALSE ELSE
RETURN TRUE
THE ITERATOR CONSUMPTION AND DISPATCHING IS PROTECTED BY THE SAME LOCK SO CALLING THIS FUNCTION SHOULD BE
THREAD SAFE
FORMATSELFOBJINDENT0
RETURN THE FORMATTED REPRESENTATION OF THE OBJECT
PRINTPROGRESS SELF
DISPLAY THE PROCESS OF THE PARALLEL EXECUTION ONLY A FRACTION OF TIME CONTROLLED BY SELFVERBOSE
UTILSCPUCOUNT DEPRECATED DEPRECATED IN VERSION 0201 TO BE RE
MOVED IN VERSION 023
UTILSDELAYED FUNCTION CHECKPICKLE DEPRECATED DEPRECATED IN VERSION 0201 TO BE RE
MOVED IN VERSION 023
METRICSCALINSKIHARABAZSCORE X LABELS DEPRECATED FUNCTION ‘CALINSKIHARABAZSCORE’ HAS
BEEN RENAMED TO ‘CALINSKIHARABASZSCORE’ AND WILL BE RE
MOVED IN VERSION 023
METRICSJACCARDSIMILARITYSCORE YTRUE
YPREDJACCARD SIMILARITY COEFFICIENT SCORE
LINEARMODELLOGISTICREGRESSIONPATH X
YDEPRECATED LOGISTICREGRESSIONPATH WAS DEPRECATED
IN VERSION 021 AND WILL BE REMOVED IN VERSION 0230
SKLEARNUTILS CPUCOUNT
WARNING DEPRECATED
SKLEARNUTILS CPUCOUNT
DEPRECATED DEPRECATED IN VERSION 0201 TO BE REMOVED IN VERSION 023 PLEASE IMPORT THIS FUNCTIONALITY
DIRECTLY FROM JOBLIB WHICH CAN BE INSTALLED WITH PIP INSTALL JOBLIB
RETURN THE NUMBER OF CPUS
SKLEARNUTILS DELAYED
WARNING DEPRECATED
SKLEARNUTILS DELAYEDFUNCTION CHECKPICKLENONE
DEPRECATED DEPRECATED IN VERSION 0201 TO BE REMOVED IN VERSION 023 PLEASE IMPORT THIS FUNCTIONALITY
DIRECTLY FROM JOBLIB WHICH CAN BE INSTALLED WITH PIP INSTALL JOBLIB

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DECORATOR USED TO CAPTURE THE ARGUMENTS OF A FUNCTION
SKLEARNMETRICS CALINSKIHARABAZSCORE
WARNING DEPRECATED
SKLEARNMETRICS CALINSKIHARABAZSCORE XLABELS
DEPRECATED FUNCTION ‘CALINSKIHARABAZSCORE’ HAS BEEN RENAMED TO ‘CALINSKIHARABASZSCORE’ AND WILL BE REMOVED IN VERSION 023
SKLEARNMETRICS JACCARDSIMILARITYSCORE
WARNING DEPRECATED
SKLEARNMETRICS JACCARDSIMILARITYSCORE YTRUE YPRED NORMALIZETRUE SAM PLEWEIGHTNONE
JACCARD SIMILARITY COEFFICIENT SCORE
DEPRECATED SINCE VERSION 021 THIS IS DEPRECATED TO BE REMOVED IN 023 SINCE ITS HANDLING OF BINARY AND MULTICLASS INPUTS WAS BROKEN JACCARDSCORE HAS AN API THAT IS CONSISTENT WITH PRECISIONSCORE FSCORE ETC
READ MORE IN THE USER GUIDE
PARAMETERS
YTRUE 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX GROUND TRUTH CORRECT LABELS
YPRED 1D ARRAYLIKE OR LABEL INDICATOR ARRAY SPARSE MATRIX PREDICTED LABELS AS RETURNED BY A CLASSIFIER
NORMALIZE BOOL OPTIONAL DEFAULTTRUE IF FALSE RETURN THE SUM OF THE JACCARD SIMILARITY COEFFICIENT OVER THE SAMPLE SET OTHERWISE RETURN THE AVERAGE OF JACCARD SIMILARITY COEFFI CIENT
SAMPLEWEIGHT ARRAYLIKE OF SHAPE NSAMPLES OPTIONAL SAMPLE WEIGHTS
RETURNS
SCORE FLOAT IFNORMALIZE TRUE RETURN THE AVERAGE JACCARD SIMILARITY COEFFICIENT ELSE IT RETURNS THE SUM OF THE JACCARD SIMILARITY COEFFICIENT OVER THE SAMPLE SET
THE BEST PERFORMANCE IS 1 WITH NORMALIZE TRUE AND THE NUMBER OF SAMPLES WITH NORMALIZE FALSE
SEE ALSO
ACCURACYSCORE HAMMINGLOSS ZEROONELOSS
NOTES
IN BINARY AND MULTICLASS CLASSIFICATION THIS FUNCTION IS EQUIVALENT TO THE ACCURACYSCORE IT DIFFERS IN THE MULTILABEL CLASSIFICATION PROBLEM
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REFERENCES
1
SKLEARNLINEARMODEL LOGISTICREGRESSIONPATH
WARNING DEPRECATED
SKLEARNLINEARMODEL LOGISTICREGRESSIONPATH XY POSCLASSNONE CS10
FITINTERCEPTTRUE MAXITER100
TOL00001 VERBOSE0 SOLVER'LBFGS'
COEFNONE CLASSWEIGHTNONE
DUALFALSE PENALTY'L2' INTER
CEPTSCALING10 MULTICLASS'WARN'
RANDOMSTATENONE CHECKINPUTTRUE
MAXSQUAREDSUMNONE SAM
PLEWEIGHTNONE L1RATIONONE
DEPRECATED LOGISTICREGRESSIONPATH WAS DEPRECATED IN VERSION 021 AND WILL BE REMOVED IN VERSION 0230
COMPUTE A LOGISTIC REGRESSION MODEL FOR A LIST OF REGULARIZATION PARAMETERS
THIS IS AN IMPLEMENTATION THAT USES THE RESULT OF THE PREVIOUS MODEL TO SPEED UP COMPUTATIONS ALONG THE
SET OF SOLUTIONS MAKING IT FASTER THAN SEQUENTIALLY CALLING LOGISTICREGRESSION FOR THE DIFFERENT PARAMETERS
NOTE THAT THERE WILL BE NO SPEEDUP WITH LIBLINEAR SOLVER SINCE IT DOES NOT HANDLE WARMSTARTING
DEPRECATED SINCE VERSION 021 LOGISTICREGRESSIONPATH WAS DEPRECATED IN VERSION 021 AND
WILL BE REMOVED IN 023
READ MORE IN THE USER GUIDE
PARAMETERS
XARRAYLIKE OR SPARSE MATRIX SHAPE NSAMPLES NFEATURES
INPUT DATA
YARRAYLIKE SHAPE NSAMPLES OR NSAMPLES NTARGETS INPUT DATA TARGET VALUES
POSCLASS INT NONE THE CLASS WITH RESPECT TO WHICH WE PERFORM A ONEVSALL FIT IF NONE
THEN IT IS ASSUMED THAT THE GIVEN PROBLEM IS BINARY
CSINT ARRAYLIKE SHAPE NCS LIST OF VALUES FOR THE REGULARIZATION PARAMETER OR INTEGER
SPECIFYING THE NUMBER OF REGULARIZATION PARAMETERS THAT SHOULD BE USED IN THIS CASE THE
PARAMETERS WILL BE CHOSEN IN A LOGARITHMIC SCALE BETWEEN 1E4 AND 1E4
FITINTERCEPT BOOL WHETHER TO FIT AN INTERCEPT FOR THE MODEL IN THIS CASE THE SHAPE OF THE
RETURNED ARRAY IS NCS NFEATURES 1
MAXITER INT MAXIMUM NUMBER OF ITERATIONS FOR THE SOLVER
TOLFLOAT STOPPING CRITERION FOR THE NEWTONCG AND LBFGS SOLVERS THE ITERATION WILL STOP
WHENMAXGI I 1 N TOL WHEREGI IS THE ITH COMPONENT
OF THE GRADIENT
VERBOSE INT FOR THE LIBLINEAR AND LBFGS SOLVERS SET VERBOSE TO ANY POSITIVE NUMBER FOR
VERBOSITY
SOLVER 'LBFGS' 'NEWTONCG' 'LIBLINEAR' 'SAG' 'SAGA' NUMERICAL SOLVER TO USE

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COEF ARRAYLIKE SHAPE NFEATURES DEFAULT NONE INITIALIZATION VALUE FOR COEFFICIENTS OF
LOGISTIC REGRESSION USELESS FOR LIBLINEAR SOLVER
CLASSWEIGHT DICT OR 'BALANCED' OPTIONAL WEIGHTS ASSOCIATED WITH CLASSES IN THE FORM
CLASSLABEL WEIGHT IF NOT GIVEN ALL CLASSES ARE SUPPOSED TO HAVE WEIGHT
ONE
THE "BALANCED" MODE USES THE VALUES OF Y TO AUTOMATICALLY ADJUST WEIGHTS INVERSELY PRO
PORTIONAL TO CLASS FREQUENCIES IN THE INPUT DATA AS NSAMPLES NCLASSES
NPBINCOUNTY
NOTE THAT THESE WEIGHTS WILL BE MULTIPLIED WITH SAMPLEWEIGHT PASSED THROUGH THE FIT
METHOD IF SAMPLEWEIGHT IS SPECIFIED
DUAL BOOL DUAL OR PRIMAL FORMULATION DUAL FORMULATION IS ONLY IMPLEMENTED FOR L2
PENALTY WITH LIBLINEAR SOLVER PREFER DUALFALSE WHEN NSAMPLES NFEATURES
PENALTY STR 'L1' 'L2' OR 'ELASTICNET' USED TO SPECIFY THE NORM USED IN THE PENALIZATION
THE 'NEWTONCG' 'SAG' AND 'LBFGS' SOLVERS SUPPORT ONLY L2 PENALTIES 'ELASTICNET' IS ONLY
SUPPORTED BY THE 'SAGA' SOLVER
INTERCEPTSCALING FLOAT DEFAULT 1 USEFUL ONLY WHEN THE SOLVER 'LIBLINEAR' IS USED AND
SELFFITINTERCEPT IS SET TO TRUE IN THIS CASE X BECOMES X SELFINTERCEPTSCALING
IE A "SYNTHETIC" FEATURE WITH CONSTANT VALUE EQUAL TO INTERCEPTSCALING IS AP
PENDED TO THE INSTANCE VECTOR THE INTERCEPT BECOMES INTERCEPTSCALING
SYNTHETICFEATUREWEIGHT
NOTE THE SYNTHETIC FEATURE WEIGHT IS SUBJECT TO L1L2 REGULARIZATION AS ALL OTHER FEATURES
TO LESSEN THE EFFECT OF REGULARIZATION ON SYNTHETIC FEATURE WEIGHT AND THEREFORE ON THE
INTERCEPT INTERCEPTSCALING HAS TO BE INCREASED
MULTICLASS STR 'OVR' 'MULTINOMIAL' 'AUTO' DEFAULT 'OVR' IF THE OPTION CHOSEN IS 'OVR'
THEN A BINARY PROBLEM IS FIT FOR EACH LABEL FOR 'MULTINOMIAL' THE LOSS MINIMISED IS THE
MULTINOMIAL LOSS FIT ACROSS THE ENTIRE PROBABILITY DISTRIBUTION EVEN WHEN THE DATA IS BINARY
'MULTINOMIAL' IS UNAVAILABLE WHEN SOLVER'LIBLINEAR' 'AUTO' SELECTS 'OVR' IF THE DATA IS
BINARY OR IF SOLVER'LIBLINEAR' AND OTHERWISE SELECTS 'MULTINOMIAL'
NEW IN VERSION 018 STOCHASTIC AVERAGE GRADIENT DESCENT SOLVER FOR 'MULTINOMIAL' CASE
CHANGED IN VERSION 020 DEFAULT WILL CHANGE FROM 'OVR' TO 'AUTO' IN 022
RANDOMSTATE INT RANDOMSTATE INSTANCE OR NONE OPTIONAL DEFAULT NONE THE SEED OF THE
PSEUDO RANDOM NUMBER GENERATOR TO USE WHEN SHUFFLING THE DATA IF INT RANDOMSTATE IS
THE SEED USED BY THE RANDOM NUMBER GENERATOR IF RANDOMSTATE INSTANCE RANDOMSTATE IS
THE RANDOM NUMBER GENERATOR IF NONE THE RANDOM NUMBER GENERATOR IS THE RANDOMSTATE
INSTANCE USED BY NPRANDOM USED WHEN SOLVER 'SAG' OR 'LIBLINEAR'
CHECKINPUT BOOL DEFAULT TRUE IF FALSE THE INPUT ARRAYS X AND Y WILL NOT BE CHECKED
MAXSQUAREDSUM FLOAT DEFAULT NONE MAXIMUM SQUARED SUM OF X OVER SAMPLES USED
ONLY IN SAG SOLVER IF NONE IT WILL BE COMPUTED GOING THROUGH ALL THE SAMPLES THE
VALUE SHOULD BE PRECOMPUTED TO SPEED UP CROSS VALIDATION
SAMPLEWEIGHT ARRAYLIKE SHAPENSAMPLES OPTIONAL ARRAY OF WEIGHTS THAT ARE ASSIGNED
TO INDIVIDUAL SAMPLES IF NOT PROVIDED THEN EACH SAMPLE IS GIVEN UNIT WEIGHT
L1RATIO FLOAT OR NONE OPTIONAL DEFAULTNONE THE ELASTICNET MIXING PARAMETER
WITH0 L1RATIO 1 ONLY USED IF PENALTYELASTICNET SETTING
L1RATIO0 IS EQUIVALENT TO USING PENALTYL2 WHILE SETTING L1RATIO1 IS
EQUIVALENT TO USING PENALTYL1 FOR0 L1RATIO 1 THE PENALTY IS A COM
BINATION OF L1 AND L2
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RETURNS
COEFS NDARRAY SHAPE NCS NFEATURES OR NCS NFEATURES 1
LIST OF COEFFICIENTS FOR THE LOGISTIC REGRESSION MODEL IF FITINTERCEPT IS SET TO TRUE
THEN THE SECOND DIMENSION WILL BE NFEATURES 1 WHERE THE LAST ITEM REPRESENTS
THE INTERCEPT FOR MULTICLASSMULTINOMIAL THE SHAPE IS NCLASSES NCS
NFEATURES OR NCLASSES NCS NFEATURES 1
CSNDARRAY GRID OF CS USED FOR CROSSVALIDATION
NITER ARRAY SHAPE NCS ACTUAL NUMBER OF ITERATION FOR EACH CS
NOTES
YOU MIGHT GET SLIGHTLY DIFFERENT RESULTS WITH THE SOLVER LIBLINEAR THAN WITH THE OTHERS SINCE THIS USES LIBLINEAR
WHICH PENALIZES THE INTERCEPT
CHANGED IN VERSION 019 THE “COPY” PARAMETER WAS REMOVED
ENSEMBLEPARTIALDEPENDENCE
PARTIALDEPENDENCE   DEPRECATED THE FUNCTION ENSEM
BLEPARTIALDEPENDENCE HAS BEEN DEPRECATED IN FAVOUR
OF INSPECTIONPARTIALDEPENDENCE IN 021 AND WILL BE
REMOVED IN 023
ENSEMBLEPARTIALDEPENDENCE
PLOTPARTIALDEPENDENCE   DEPRECATED THE FUNCTION ENSEM
BLEPLOTPARTIALDEPENDENCE HAS BEEN DEPRECATED IN
FAVOUR OF SKLEARNINSPECTIONPLOTPARTIALDEPENDENCE IN
021 AND WILL BE REMOVED IN 023
SKLEARNENSEMBLEPARTIALDEPENDENCE PARTIALDEPENDENCE
SKLEARNENSEMBLEPARTIALDEPENDENCE PARTIALDEPENDENCE GBRT TARGETVARIABLES
GRIDNONE XNONE
PERCENTILES005 095
GRIDRESOLUTION100
DEPRECATED THE FUNCTION ENSEMBLEPARTIALDEPENDENCE HAS BEEN DEPRECATED IN FAVOUR OF INSPEC
TIONPARTIALDEPENDENCE IN 021 AND WILL BE REMOVED IN 023
PARTIAL DEPENDENCE OF TARGETVARIABLES
PARTIAL DEPENDENCE PLOTS SHOW THE DEPENDENCE BETWEEN THE JOINT VALUES OF THE
TARGETVARIABLES AND THE FUNCTION REPRESENTED BY THE GBRT
READ MORE IN THE USER GUIDE
DEPRECATED SINCE VERSION 021 THIS FUNCTION WAS DEPRECATED IN VERSION 021 IN FAVOR OF SKLEARN
INSPECTIONPARTIALDEPENDENCE AND WILL BE REMOVED IN 023
PARAMETERS
GBRT BASEGRADIENTBOOSTING
A FITTED GRADIENT BOOSTING MODEL
TARGETVARIABLES ARRAYLIKE DTYPEINT THE TARGET FEATURES FOR WHICH THE PARTIAL DEPEN
DENCY SHOULD BE COMPUTED SIZE SHOULD BE SMALLER THAN 3 FOR VISUAL RENDERINGS

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GRID ARRAYLIKE SHAPENPOINTS LENTARGETVARIABLES THE GRID OF
TARGETVARIABLES VALUES FOR WHICH THE PARTIAL DEPENDENCY SHOULD BE EVALU
ATED EITHER GRID ORXMUST BE SPECIFIED
XARRAYLIKE SHAPENSAMPLES NFEATURES THE DATA ON WHICH GBRT WAS TRAINED IT
IS USED TO GENERATE A GRID FOR THETARGETVARIABLES THEGRID COMPRISES
GRIDRESOLUTION EQUALLY SPACED POINTS BETWEEN THE TWO PERCENTILES
PERCENTILES LOW HIGH DEFAULT005 095 THE LOWER AND UPPER PERCENTILE USED CREATE
THE EXTREME VALUES FOR THE GRID ONLY IFXIS NOT NONE
GRIDRESOLUTION INT DEFAULT100 THE NUMBER OF EQUALLY SPACED POINTS ON THE GRID
RETURNS
PDP ARRAY SHAPENCLASSES NPOINTS
THE PARTIAL DEPENDENCE FUNCTION EVALUATED ON THE GRID FOR REGRESSION AND BINARY
CLASSIFICATION NCLASSES1
AXES SEQ OF NDARRAY OR NONE THE AXES WITH WHICH THE GRID HAS BEEN CREATED OR NONE IF THE
GRID HAS BEEN GIVEN
EXAMPLES
SAMPLES 0 0 2 1 0 0
LABELS 0 1
 FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGCLASSIFIER
GB GRADIENTBOOSTINGCLASSIFIERRANDOMSTATE0FITSAMPLES LABELS
KWARGS DICTXSAMPLES PERCENTILES0 1 GRIDRESOLUTION2
PARTIALDEPENDENCEGB 0 KWARGS
ARRAY452 452 ARRAY 0 1
SKLEARNENSEMBLEPARTIALDEPENDENCE PLOTPARTIALDEPENDENCE
SKLEARNENSEMBLEPARTIALDEPENDENCE PLOTPARTIALDEPENDENCE GBRTXFEATURES FEA
TURENAMESNONE
LABELNONE
NCOLS3
GRIDRESOLUTION100
PERCENTILES005
095 NJOBSNONE
VERBOSE0
AXNONE
LINEKWNONE
CONTOURKWNONE
FIGKW
DEPRECATED THE FUNCTION ENSEMBLEPLOTPARTIALDEPENDENCE HAS BEEN DEPRECATED IN FAVOUR OF
SKLEARNINSPECTIONPLOTPARTIALDEPENDENCE IN 021 AND WILL BE REMOVED IN 023
PARTIAL DEPENDENCE PLOTS FOR FEATURES
THELENFEATURES PLOTS ARE ARRANGED IN A GRID WITH NCOLS COLUMNS TWOWAY PARTIAL DEPEN
DENCE PLOTS ARE PLOTTED AS CONTOUR PLOTS
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DEPRECATED SINCE VERSION 021 THIS FUNCTION WAS DEPRECATED IN VERSION 021 IN FAVOR OF SKLEARN
INSPECTIONPLOTPARTIALDEPENDENCE AND WILL BE REMOVED IN 023
PARAMETERS
GBRT BASEGRADIENTBOOSTING
A FITTED GRADIENT BOOSTING MODEL
XARRAYLIKE SHAPENSAMPLES NFEATURES THE DATA ON WHICH GBRT WAS TRAINED
FEATURES SEQ OF INTS STRINGS OR TUPLES OF INTS OR STRINGS IF SEQI IS AN INT OR A TUPLE
WITH ONE INT VALUE A ONEWAY PDP IS CREATED IF SEQI IS A TUPLE OF TWO INTS A TWO
WAY PDP IS CREATED IF FEATURENAMES IS SPECIFIED AND SEQI IS AN INT SEQI MUST BE
LENFEATURENAMES IF SEQI IS A STRING FEATURENAMES MUST BE SPECIFIED AND SEQI MUST
BE IN FEATURENAMES
FEATURENAMES SEQ OF STR NAME OF EACH FEATURE FEATURENAMESI HOLDS THE NAME OF THE
FEATURE WITH INDEX I
LABEL OBJECT THE CLASS LABEL FOR WHICH THE PDPS SHOULD BE COMPUTED ONLY IF GBRT IS A
MULTICLASS MODEL MUST BE IN GBRTCLASSES
NCOLS INT THE NUMBER OF COLUMNS IN THE GRID PLOT DEFAULT 3
GRIDRESOLUTION INT DEFAULT100 THE NUMBER OF EQUALLY SPACED POINTS ON THE AXES
PERCENTILES LOW HIGH DEFAULT005 095 THE LOWER AND UPPER PERCENTILE USED TO CREATE
THE EXTREME VALUES FOR THE PDP AXES
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NONE MEANS 1 UNLESS IN A JOBLIB
PARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE GLOSSARY FOR MORE
DETAILS
VERBOSE INT VERBOSE OUTPUT DURING PD COMPUTATIONS DEFAULTS TO 0
AXMATPLOTLIB AXIS OBJECT DEFAULT NONE AN AXIS OBJECT ONTO WHICH THE PLOTS WILL BE DRAWN
LINEKW DICT DICT WITH KEYWORDS PASSED TO THE MATPLOTLIBPYPLOTPLOT CALL FOR
ONEWAY PARTIAL DEPENDENCE PLOTS
CONTOURKW DICT DICT WITH KEYWORDS PASSED TO THE MATPLOTLIBPYPLOTPLOT CALL
FOR TWOWAY PARTIAL DEPENDENCE PLOTS
FIGKW DICT DICT WITH KEYWORDS PASSED TO THE FIGURE CALL NOTE THAT ALL KEYWORDS NOT
RECOGNIZED ABOVE WILL BE AUTOMATICALLY INCLUDED HERE
RETURNS
FIGFIGURE
THE MATPLOTLIB FIGURE OBJECT
AXS SEQ OF AXIS OBJECTS A SEQ OF AXIS OBJECTS ONE FOR EACH SUBPLOT
EXAMPLES
```
 FROM SKLEARNDATASETS IMPORT MAKEFRIEDMAN1
 FROM SKLEARNENSEMBLE IMPORT GRADIENTBOOSTINGREGRESSOR
X Y  MAKEFRIEDMAN1
CLF  GRADIENTBOOSTINGREGRESSORNESTIMATORS10FITX Y
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FIG AXS PLOTPARTIALDEPENDENCECLF X 0 0 1

6402 TO BE REMOVED IN 022
COVARIANCEGRAPHLASSO ARGS KWARGS SPARSE INVERSE COVARIANCE ESTIMATION WITH AN L1PENALIZED ESTIMATOR
COVARIANCEGRAPHLASSOCV ARGS KWARGS SPARSE INVERSE COVARIANCE W CROSSVALIDATED CHOICE OF THE L1 PENALTY
PREPROCESSINGIMPUTER ARGS KWARGS IMPUTATION TRANSFORMER FOR COMPLETING MISSING VALUES
UTILSTESTINGMOCKMLDATAURLOPEN ARGS
   OBJECT THAT MOCKS THE URLOPEN FUNCTION TO FAKE REQUESTS TO MLDATA
SKLEARNCOVARIANCE GRAPHLASSO
WARNING DEPRECATED
CLASSSKLEARNCOVARIANCE GRAPHLASSO ARGS KWARGS
SPARSE INVERSE COVARIANCE ESTIMATION WITH AN L1PENALIZED ESTIMATOR
THIS CLASS IMPLEMENTS THE GRAPHICAL LASSO ALGORITHM
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHA POSITIVE FLOAT DEFAULT 001 THE REGULARIZATION PARAMETER THE HIGHER ALPHA THE MORE REGULARIZATION THE SPARSER THE INVERSE COVARIANCE
MODE ‘CD’ ‘LARS’ DEFAULT ‘CD’ THE LASSO SOLVER TO USE COORDINATE DESCENT OR LARS USE LARS FOR VERY SPARSE UNDERLYING GRAPHS WHERE P N ELSEWHERE PREFER CD WHICH IS MORE NUMERICALLY STABLE
TOLPOSITIVE FLOAT DEFAULT 1E4 THE TOLERANCE TO DECLARE CONVERGENCE IF THE DUAL GAP GOES BELOW THIS VALUE ITERATIONS ARE STOPPED
ENETTOL POSITIVE FLOAT OPTIONAL THE TOLERANCE FOR THE ELASTIC NET SOLVER USED TO CALCULATE THE DESCENT DIRECTION THIS PARAMETER CONTROLS THE ACCURACY OF THE SEARCH DIRECTION FOR A GIVEN COLUMN UPDATE NOT OF THE OVERALL PARAMETER ESTIMATE ONLY USED FOR MODE‘CD’
MAXITER INTEGER DEFAULT 100 THE MAXIMUM NUMBER OF ITERATIONS
VERBOSE BOOLEAN DEFAULT FALSE IF VERBOSE IS TRUE THE OBJECTIVE FUNCTION AND DUAL GAP ARE PLOTTED AT EACH ITERATION
ASSUMECENTERED BOOLEAN DEFAULT FALSE IF TRUE DATA ARE NOT CENTERED BEFORE COMPUTATION USEFUL WHEN WORKING WITH DATA WHOSE MEAN IS ALMOST BUT NOT EXACTLY ZERO IF FALSE DATA ARE CENTERED BEFORE COMPUTATION
ATTRIBUTES
COVARIANCE ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED COVARIANCE MATRIX
PRECISION ARRAYLIKE SHAPE NFEATURES NFEATURES ESTIMATED PSEUDO INVERSE MATRIX
NITER INT NUMBER OF ITERATIONS RUN
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SEE ALSO
GRAPHLASSO GRAPHLASSOCV
METHODS
ERRORNORM SELF COMPCOV NORM SCALING COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARI
ANCE ESTIMATORS
FITSELF X Y FITS THE GRAPHICALLASSO MODEL TO X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETPRECISION SELF GETTER FOR THE PRECISION MATRIX
MAHALANOBIS SELF X COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN
OBSERVATIONS
SCORE SELF XTEST Y COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH
SELFCOVARIANCE AS AN ESTIMATOR OF ITS COVARI
ANCE MATRIX
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT ARGS KWARGS
DEPRECATED THE ‘GRAPHLASSO’ WAS RENAMED TO ‘GRAPHICALLASSO’ IN VERSION 020 AND WILL BE REMOVED
IN 022
ERRORNORM SELFCOMPCOV NORM’FROBENIUS’ SCALINGTRUE SQUAREDTRUE
COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARIANCE ESTIMATORS IN THE SENSE OF THE FROBENIUS
NORM
PARAMETERS
COMPCOV ARRAYLIKE SHAPE NFEATURES NFEATURES THE COVARIANCE TO COMPARE WITH
NORM STR THE TYPE OF NORM USED TO COMPUTE THE ERROR AVAILABLE ERROR TYPES ‘FROBENIUS’
DEFAULT SQRTTRATA ‘SPECTRAL’ SQRTMAXEIGENVALUESATA WHERE A IS THE ERROR
COMPCOV SELFCOVARIANCE
SCALING BOOL IF TRUE DEFAULT THE SQUARED ERROR NORM IS DIVIDED BY NFEATURES IF FALSE
THE SQUARED ERROR NORM IS NOT RESCALED
SQUARED BOOL WHETHER TO COMPUTE THE SQUARED ERROR NORM OR THE ERROR NORM IF TRUE
DEFAULT THE SQUARED ERROR NORM IS RETURNED IF FALSE THE ERROR NORM IS RETURNED
RETURNS
THE MEAN SQUARED ERROR IN THE SENSE OF THE FROBENIUS NORM BETWEEN
SELF ANDCOMPCOV COVARIANCE ESTIMATORS
FITSELFXYNONE
FITS THE GRAPHICALLASSO MODEL TO X
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES DATA FROM WHICH TO COMPUTE THE COVARIANCE ES
TIMATE
YIGNORED
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR

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PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETPRECISION SELF
GETTER FOR THE PRECISION MATRIX
RETURNS
PRECISION ARRAYLIKE THE PRECISION MATRIX ASSOCIATED TO THE CURRENT COVARIANCE OBJECT
MAHALANOBIS SELFX
COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN OBSERVATIONS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE OBSERVATIONS THE MAHALANOBIS DISTANCES
OF THE WHICH WE COMPUTE OBSERVATIONS ARE ASSUMED TO BE DRAWN FROM THE SAME DISTRIBU
TION THAN THE DATA USED IN FIT
RETURNS
DIST ARRAY SHAPE NSAMPLES SQUARED MAHALANOBIS DISTANCES OF THE OBSERVATIONS
SCORESELFXTEST YNONE
COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
COVARIANCE MATRIX
PARAMETERS
XTEST ARRAYLIKE SHAPE NSAMPLES NFEATURES TEST DATA OF WHICH WE COMPUTE THE
LIKELIHOOD WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF
FEATURES XTEST IS ASSUMED TO BE DRAWN FROM THE SAME DISTRIBUTION THAN THE DATA USED IN
FIT INCLUDING CENTERING
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS
RESFLOAT THE LIKELIHOOD OF THE DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
COVARIANCE MATRIX
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT’S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SKLEARNCOVARIANCE GRAPHLASSOCV
WARNING DEPRECATED
640 RECENTLY DEPRECATED 2397

CLASSSKLEARNCOVARIANCE GRAPHLASSOCV ARGS KWARGS
SPARSE INVERSE COVARIANCE W CROSSVALIDATED CHOICE OF THE L1 PENALTY
SEE GLOSSARY ENTRY FOR CROSSVALIDATION ESTIMATOR
THIS CLASS IMPLEMENTS THE GRAPHICAL LASSO ALGORITHM
READ MORE IN THE USER GUIDE
PARAMETERS
ALPHAS INTEGER OR LIST POSITIVE FLOAT OPTIONAL IF AN INTEGER IS GIVEN IT FIXES THE NUMBER OF POINTS
ON THE GRIDS OF ALPHA TO BE USED IF A LIST IS GIVEN IT GIVES THE GRID TO BE USED SEE THE NOTES
IN THE CLASS DOCSTRING FOR MORE DETAILS
NREFINEMENTS STRICTLY POSITIVE INTEGER THE NUMBER OF TIMES THE GRID IS REFINED NOT USED IF
EXPLICIT VALUES OF ALPHAS ARE PASSED
CVINT CROSSVALIDATION GENERATOR OR AN ITERABLE OPTIONAL DETERMINES THE CROSSVALIDATION SPLIT
TING STRATEGY POSSIBLE INPUTS FOR CV ARE
• NONE TO USE THE DEFAULT 3FOLD CROSSVALIDATION
• INTEGER TO SPECIFY THE NUMBER OF FOLDS
•CV SPLITTER
• AN ITERABLE YIELDING TRAIN TEST SPLITS AS ARRAYS OF INDICES
FOR INTEGERNONE INPUTS KFOLD IS USED
REFER USER GUIDE FOR THE VARIOUS CROSSVALIDATION STRATEGIES THAT CAN BE USED HERE
CHANGED IN VERSION 020 CVDEFAULT VALUE IF NONE WILL CHANGE FROM 3FOLD TO 5FOLD IN
V022
TOLPOSITIVE FLOAT OPTIONAL THE TOLERANCE TO DECLARE CONVERGENCE IF THE DUAL GAP GOES BELOW
THIS VALUE ITERATIONS ARE STOPPED
ENETTOL POSITIVE FLOAT OPTIONAL THE TOLERANCE FOR THE ELASTIC NET SOLVER USED TO CALCULATE THE
DESCENT DIRECTION THIS PARAMETER CONTROLS THE ACCURACY OF THE SEARCH DIRECTION FOR A GIVEN
COLUMN UPDATE NOT OF THE OVERALL PARAMETER ESTIMATE ONLY USED FOR MODE'CD'
MAXITER INTEGER OPTIONAL MAXIMUM NUMBER OF ITERATIONS
MODE 'CD' 'LARS' THE LASSO SOLVER TO USE COORDINATE DESCENT OR LARS USE LARS FOR
VERY SPARSE UNDERLYING GRAPHS WHERE NUMBER OF FEATURES IS GREATER THAN NUMBER OF SAMPLES
ELSEWHERE PREFER CD WHICH IS MORE NUMERICALLY STABLE
NJOBS INT OR NONE OPTIONAL DEFAULTNONE NUMBER OF JOBS TO RUN IN PARALLEL NONE MEANS 1
UNLESS IN A JOBLIBPARALLELBACKEND CONTEXT1MEANS USING ALL PROCESSORS SEE
GLOSSARY FOR MORE DETAILS
VERBOSE BOOLEAN OPTIONAL IF VERBOSE IS TRUE THE OBJECTIVE FUNCTION AND DUALITY GAP ARE PRINTED
AT EACH ITERATION
ASSUMECENTERED BOOLEAN IF TRUE DATA ARE NOT CENTERED BEFORE COMPUTATION USEFUL WHEN
WORKING WITH DATA WHOSE MEAN IS ALMOST BUT NOT EXACTLY ZERO IF FALSE DATA ARE CENTERED
BEFORE COMPUTATION
ATTRIBUTES
COVARIANCE NUMPYNDARRAY SHAPE NFEATURES NFEATURES ESTIMATED COVARIANCE MATRIX
PRECISION NUMPYNDARRAY SHAPE NFEATURES NFEATURES ESTIMATED PRECISION MATRIX INVERSE
COVARIANCE

ALPHA FLOAT PENALIZATION PARAMETER SELECTED
CVALPHAS LIST OF FLOAT ALL PENALIZATION PARAMETERS EXPLORED
GRIDSCORES 2D NUMPYNDARRAY NALPHAS NFOLDS LOGLIKELIHOOD SCORE ON LEFTOUT DATA
ACROSS FOLDS
NITER INT NUMBER OF ITERATIONS RUN FOR THE OPTIMAL ALPHA
SEE ALSO
GRAPHLASSO GRAPHLASSO
NOTES
THE SEARCH FOR THE OPTIMAL PENALIZATION PARAMETER ALPHA IS DONE ON AN ITERATIVELY REFINED GRID FIRST THE CROSS
VALIDATED SCORES ON A GRID ARE COMPUTED THEN A NEW REFINED GRID IS CENTERED AROUND THE MAXIMUM AND SO ON
ONE OF THE CHALLENGES WHICH IS FACED HERE IS THAT THE SOLVERS CAN FAIL TO CONVERGE TO A WELLCONDITIONED ESTIMATE
THE CORRESPONDING VALUES OF ALPHA THEN COME OUT AS MISSING VALUES BUT THE OPTIMUM MAY BE CLOSE TO THESE
MISSING VALUES
METHODS
ERRORNORM SELF COMPCOV NORM SCALING COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARI
ANCE ESTIMATORS
FITSELF X Y FITS THE GRAPHICALLASSO COVARIANCE MODEL TO X
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
GETPRECISION SELF GETTER FOR THE PRECISION MATRIX
MAHALANOBIS SELF X COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN
OBSERVATIONS
SCORE SELF XTEST Y COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH
SELFCOVARIANCE AS AN ESTIMATOR OF ITS COVARI
ANCE MATRIX
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
INIT ARGS KWARGS
DEPRECATED THE ‘GRAPHLASSOCV’ WAS RENAMED TO ‘GRAPHICALLASSOCV’ IN VERSION 020 AND WILL BE
REMOVED IN 022
ERRORNORM SELFCOMPCOV NORM’FROBENIUS’ SCALINGTRUE SQUAREDTRUE
COMPUTES THE MEAN SQUARED ERROR BETWEEN TWO COVARIANCE ESTIMATORS IN THE SENSE OF THE FROBENIUS
NORM
PARAMETERS
COMPCOV ARRAYLIKE SHAPE NFEATURES NFEATURES THE COVARIANCE TO COMPARE WITH
NORM STR THE TYPE OF NORM USED TO COMPUTE THE ERROR AVAILABLE ERROR TYPES ‘FROBENIUS’
DEFAULT SQRTTRATA ‘SPECTRAL’ SQRTMAXEIGENVALUESATA WHERE A IS THE ERROR
COMPCOV SELFCOVARIANCE
SCALING BOOL IF TRUE DEFAULT THE SQUARED ERROR NORM IS DIVIDED BY NFEATURES IF FALSE
THE SQUARED ERROR NORM IS NOT RESCALED
SQUARED BOOL WHETHER TO COMPUTE THE SQUARED ERROR NORM OR THE ERROR NORM IF TRUE

DEFAULT THE SQUARED ERROR NORM IS RETURNED IF FALSE THE ERROR NORM IS RETURNED
RETURNS
THE MEAN SQUARED ERROR IN THE SENSE OF THE FROBENIUS NORM BETWEEN
SELF ANDCOMPCOV COVARIANCE ESTIMATORS
FITSELFXYNONE
FITS THE GRAPHICALLASSO COVARIANCE MODEL TO X
PARAMETERS
XNDARRAY SHAPE NSAMPLES NFEATURES DATA FROM WHICH TO COMPUTE THE COVARIANCE ES
TIMATE
YIGNORED
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED
SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
GETPRECISION SELF
GETTER FOR THE PRECISION MATRIX
RETURNS
PRECISION ARRAYLIKE THE PRECISION MATRIX ASSOCIATED TO THE CURRENT COVARIANCE OBJECT
MAHALANOBIS SELFX
COMPUTES THE SQUARED MAHALANOBIS DISTANCES OF GIVEN OBSERVATIONS
PARAMETERS
XARRAYLIKE SHAPE NSAMPLES NFEATURES THE OBSERVATIONS THE MAHALANOBIS DISTANCES
OF THE WHICH WE COMPUTE OBSERVATIONS ARE ASSUMED TO BE DRAWN FROM THE SAME DISTRIBU
TION THAN THE DATA USED IN FIT
RETURNS
DIST ARRAY SHAPE NSAMPLES SQUARED MAHALANOBIS DISTANCES OF THE OBSERVATIONS
SCORESELFXTEST YNONE
COMPUTES THE LOGLIKELIHOOD OF A GAUSSIAN DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
COVARIANCE MATRIX
PARAMETERS
XTEST ARRAYLIKE SHAPE NSAMPLES NFEATURES TEST DATA OF WHICH WE COMPUTE THE
LIKELIHOOD WHERE NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF
FEATURES XTEST IS ASSUMED TO BE DRAWN FROM THE SAME DISTRIBUTION THAN THE DATA USED IN
FIT INCLUDING CENTERING
YNOT USED PRESENT FOR API CONSISTENCE PURPOSE
RETURNS
RESFLOAT THE LIKELIHOOD OF THE DATA SET WITH SELFCOVARIANCE AS AN ESTIMATOR OF ITS
COVARIANCE MATRIX

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SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR
THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
SKLEARNPREPROCESSING IMPUTER
WARNING DEPRECATED
CLASSSKLEARNPREPROCESSING IMPUTERARGS KWARGS
IMPUTATION TRANSFORMER FOR COMPLETING MISSING VALUES
READ MORE IN THE USER GUIDE
PARAMETERS
MISSINGVALUES INTEGER OR "NAN" OPTIONAL DEFAULT"NAN" THE PLACEHOLDER FOR THE MISS
ING VALUES ALL OCCURRENCES OF MISSINGVALUES WILL BE IMPUTED FOR MISSING VALUES
ENCODED AS NPNAN USE THE STRING VALUE "NAN"
STRATEGY STRING OPTIONAL DEFAULT"MEAN" THE IMPUTATION STRATEGY
• IF "MEAN" THEN REPLACE MISSING VALUES USING THE MEAN ALONG THE AXIS
• IF "MEDIAN" THEN REPLACE MISSING VALUES USING THE MEDIAN ALONG THE AXIS
• IF "MOSTFREQUENT" THEN REPLACE MISSING USING THE MOST FREQUENT VALUE ALONG THE AXIS
AXIS INTEGER OPTIONAL DEFAULT0 THE AXIS ALONG WHICH TO IMPUTE
• IFAXIS0 THEN IMPUTE ALONG COLUMNS
• IFAXIS1 THEN IMPUTE ALONG ROWS
VERBOSE INTEGER OPTIONAL DEFAULT0 CONTROLS THE VERBOSITY OF THE IMPUTER
COPY BOOLEAN OPTIONAL DEFAULTTRUE IF TRUE A COPY OF X WILL BE CREATED IF FALSE IMPUTATION
WILL BE DONE INPLACE WHENEVER POSSIBLE NOTE THAT IN THE FOLLOWING CASES A NEW COPY WILL
ALWAYS BE MADE EVEN IF COPYFALSE
• IF X IS NOT AN ARRAY OF FLOATING VALUES
• IF X IS SPARSE AND MISSINGVALUES0
• IFAXIS0 AND X IS ENCODED AS A CSR MATRIX
• IFAXIS1 AND X IS ENCODED AS A CSC MATRIX
ATTRIBUTES
STATISTICS ARRAY OF SHAPE NFEATURES THE IMPUTATION FILL VALUE FOR EACH FEATURE IF AXIS 0
640 RECENTLY DEPRECATED 2401

NOTES
• WHENAXIS0 COLUMNS WHICH ONLY CONTAINED MISSING VALUES AT FIT ARE DISCARDED UPON TRANSFORM
• WHENAXIS1 AN EXCEPTION IS RAISED IF THERE ARE ROWS FOR WHICH IT IS NOT POSSIBLE TO FILL IN THE MISSING VALUES EG BECAUSE THEY ONLY CONTAIN MISSING VALUES
METHODS
FITSELF X Y FIT THE IMPUTER ON X
FITTRANSFORM SELF X Y FIT TO DATA THEN TRANSFORM IT
GETPARAMS SELF DEEP GET PARAMETERS FOR THIS ESTIMATOR
SETPARAMS SELF PARAMS SET THE PARAMETERS OF THIS ESTIMATOR
TRANSFORM SELF X IMPUTE ALL MISSING VALUES IN X
INIT ARGS KWARGS
DEPRECATED IMPUTER WAS DEPRECATED IN VERSION 020 AND WILL BE REMOVED IN 022 IMPORT IM
PUTESIMPLEIMPUTER FROM SKLEARN INSTEAD
FITSELFXYNONE
FIT THE IMPUTER ON X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES INPUT DATA WHERE
NSAMPLES IS THE NUMBER OF SAMPLES AND NFEATURES IS THE NUMBER OF FEATURES
RETURNS
SELF IMPUTER
FITTRANSFORM SELFXYNONE FITPARAMS
FIT TO DATA THEN TRANSFORM IT
FITS TRANSFORMER TO X AND Y WITH OPTIONAL PARAMETERS FITPARAMS AND RETURNS A TRANSFORMED VERSION OF X
PARAMETERS
XNUMPY ARRAY OF SHAPE NSAMPLES NFEATURES TRAINING SET
YNUMPY ARRAY OF SHAPE NSAMPLES TARGET VALUES
RETURNS
XNEW NUMPY ARRAY OF SHAPE NSAMPLES NFEATURESNEW TRANSFORMED ARRAY
GETPARAMS SELFDEEPTRUE
GET PARAMETERS FOR THIS ESTIMATOR
PARAMETERS
DEEP BOOLEAN OPTIONAL IF TRUE WILL RETURN THE PARAMETERS FOR THIS ESTIMATOR AND CONTAINED SUBOBJECTS THAT ARE ESTIMATORS
RETURNS
PARAMS MAPPING OF STRING TO ANY PARAMETER NAMES MAPPED TO THEIR VALUES
SETPARAMS SELFPARAMS
SET THE PARAMETERS OF THIS ESTIMATOR

THE METHOD WORKS ON SIMPLE ESTIMATORS AS WELL AS ON NESTED OBJECTS SUCH AS PIPELINES THE LATTER HAVE
PARAMETERS OF THE FORM COMPONENTPARAMETER SO THAT IT'S POSSIBLE TO UPDATE EACH COMPONENT
OF A NESTED OBJECT
RETURNS
SELF
TRANSFORM SELFX
IMPUTE ALL MISSING VALUES IN X
PARAMETERS
XARRAYLIKE SPARSE MATRIX SHAPE NSAMPLES NFEATURES THE INPUT DATA TO COMPLETE
SKLEARNUTILSTESTING MOCKMLDATAURLOPEN
WARNING DEPRECATED
CLASSSKLEARNUTILSTESTING MOCKMLDATAURLOPEN ARGS KWARGS
OBJECT THAT MOCKS THE URLOPEN FUNCTION TO FAKE REQUESTS TO MLDATA
WHEN REQUESTING A DATASET WITH A NAME THAT IS IN MOCKDATASETS THIS OBJECT CREATES A FAKE DATASET IN A STRINGIO
OBJECT AND RETURNS IT OTHERWISE IT RAISES AN HTTPERROR
DEPRECATED SINCE VERSION 020 WILL BE REMOVED IN VERSION 022
PARAMETERS
MOCKDATASETS DICT A DICTIONARY OF DATASETNAME DATADICT OR DATASETNAME DATADICT
ORDERING DATADICT ITSELF IS A DICTIONARY OF COLUMNNAME DATAARRAY AND
ORDERING IS A LIST OF COLUMNNAMES TO DETERMINE THE ORDERING IN THE DATA SET SEE
FAKEMLDATA FOR DETAILS
METHODS
CALL SELF URLNAME
PARAMETERS
INIT ARGS KWARGS
DEPRECATED DEPRECATED IN VERSION 020 TO BE REMOVED IN VERSION 022
COVARIANCEGRAPHLASSO EMPCOV ALPHA DEPRECATED THE 'GRAPHLASSO' WAS RENAMED TO
'GRAPHICALLASSO' IN VERSION 020 AND WILL BE REMOVED IN
022
DATASETSFETCHMLDATA DATANAME DEPRECATED FETCHMLDATA WAS DEPRECATED IN VERSION
020 AND WILL BE REMOVED IN VERSION 022
DATASETSMLDATAFILENAME DATANAME DEPRECATED MLDATAFILENAME WAS DEPRECATED IN VER
SION 020 AND WILL BE REMOVED IN VERSION 022

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SKLEARNCOVARIANCE GRAPHLASSO
WARNING DEPRECATED
SKLEARNCOVARIANCE GRAPHLASSO EMPCOV ALPHA COVINITNONE MODE'CD' TOL00001
ENETTOL00001 MAXITER100 VERBOSEFALSE RE
TURNCOSTSFALSE EPS2220446049250313E16 RE
TURNNITERFALSE
DEPRECATED THE 'GRAPHLASSO' WAS RENAMED TO 'GRAPHICALLASSO' IN VERSION 020 AND WILL BE REMOVED IN
022
L1PENALIZED COVARIANCE ESTIMATOR
READ MORE IN THE USER GUIDE
PARAMETERS
EMPCOV 2D NDARRAY SHAPE NFEATURES NFEATURES
EMPIRICAL COVARIANCE FROM WHICH TO COMPUTE THE COVARIANCE ESTIMATE
ALPHA POSITIVE FLOAT THE REGULARIZATION PARAMETER THE HIGHER ALPHA THE MORE REGULARIZA
TION THE SPARSER THE INVERSE COVARIANCE
COVINIT 2D ARRAY NFEATURES NFEATURES OPTIONAL THE INITIAL GUESS FOR THE COVARIANCE
MODE 'CD' 'LARS' THE LASSO SOLVER TO USE COORDINATE DESCENT OR LARS USE LARS
FOR VERY SPARSE UNDERLYING GRAPHS WHERE P N ELSEWHERE PREFER CD WHICH IS MORE
NUMERICALLY STABLE
TOLPOSITIVE FLOAT OPTIONAL THE TOLERANCE TO DECLARE CONVERGENCE IF THE DUAL GAP GOES
BELOW THIS VALUE ITERATIONS ARE STOPPED
ENETTOL POSITIVE FLOAT OPTIONAL THE TOLERANCE FOR THE ELASTIC NET SOLVER USED TO CALCULATE
THE DESCENT DIRECTION THIS PARAMETER CONTROLS THE ACCURACY OF THE SEARCH DIRECTION FOR A
GIVEN COLUMN UPDATE NOT OF THE OVERALL PARAMETER ESTIMATE ONLY USED FOR MODE'CD'
MAXITER INTEGER OPTIONAL THE MAXIMUM NUMBER OF ITERATIONS
VERBOSE BOOLEAN OPTIONAL IF VERBOSE IS TRUE THE OBJECTIVE FUNCTION AND DUAL GAP ARE
PRINTED AT EACH ITERATION
RETURNCOSTS BOOLEAN OPTIONAL IF RETURNCOSTS IS TRUE THE OBJECTIVE FUNCTION AND DUAL
GAP AT EACH ITERATION ARE RETURNED
EPS FLOAT OPTIONAL THE MACHINEPRECISION REGULARIZATION IN THE COMPUTATION OF THE
CHOLESKY DIAGONAL FACTORS INCREASE THIS FOR VERY ILLCONDITIONED SYSTEMS
RETURNNITER BOOL OPTIONAL WHETHER OR NOT TO RETURN THE NUMBER OF ITERATIONS
RETURNS
COVARIANCE 2D NDARRAY SHAPE NFEATURES NFEATURES
THE ESTIMATED COVARIANCE MATRIX
PRECISION 2D NDARRAY SHAPE NFEATURES NFEATURES THE ESTIMATED SPARSE PRECISION
MATRIX

COSTS LIST OF OBJECTIVE DUALGAP PAIRS THE LIST OF VALUES OF THE OBJECTIVE FUNCTION AND THE
DUAL GAP AT EACH ITERATION RETURNED ONLY IF RETURNCOSTS IS TRUE
NITER INT NUMBER OF ITERATIONS RETURNED ONLY IF RETURNNITER IS SET TO TRUE
NOTES
THE ALGORITHM EMPLOYED TO SOLVE THIS PROBLEM IS THE GLASSO ALGORITHM FROM THE FRIEDMAN 2008 BIOSTATISTICS
PAPER IT IS THE SAME ALGORITHM AS IN THE R GLASSO PACKAGE
ONE POSSIBLE DIFFERENCE WITH THE GLASSO R PACKAGE IS THAT THE DIAGONAL COEFFICIENTS ARE NOT PENALIZED
SKLEARNDATASETS FETCHMLDATA
WARNING DEPRECATED
SKLEARNDATASETS FETCHMLDATA DATANAME TARGETNAME’LABEL’ DATANAME’DATA’ TRANS
POSEDATATRUE DATAHOMENONE
DEPRECATED FETCHMLDATA WAS DEPRECATED IN VERSION 020 AND WILL BE REMOVED IN VERSION 022 PLEASE USE
FETCHOPENML
FETCH AN MLDATAORG DATA SET
MLDATAORG IS NO LONGER OPERATIONAL
IF THE FILE DOES NOT EXIST YET IT IS DOWNLOADED FROM MLDATAORG
MLDATAORG DOES NOT HAVE AN ENFORCED CONVENTION FOR STORING DATA OR NAMING THE COLUMNS IN A DATA
SET THE DEFAULT BEHAVIOR OF THIS FUNCTION WORKS WELL WITH THE MOST COMMON CASES
1 DATA VALUES ARE STORED IN THE COLUMN ‘DATA’ AND TARGET VALUES IN THE COLUMN ‘LABEL’
2 ALTERNATIVELY THE FIRST COLUMN STORES TARGET VALUES AND THE SECOND DATA VALUES
3 THE DATA ARRAY IS STORED AS NFEATURES X NSAMPLES AND THUS NEEDS TO BE TRANSPOSED TO
MATCH THESKLEARN STANDARD
KEYWORD ARGUMENTS ALLOW TO ADAPT THESE DEFAULTS TO SPECIFIC DATA SETS SEE PARAMETERS
TARGETNAME DATANAME TRANSPOSEDATA AND THE EXAMPLES BELOW
MLDATAORG DATA SETS MAY HAVE MULTIPLE COLUMNS WHICH ARE STORED IN THE BUNCH OBJECT WITH THEIR
ORIGINAL NAME
DEPRECATED SINCE VERSION 020 WILL BE REMOVED IN VERSION 022
PARAMETERS
DATANAME STR
NAME OF THE DATA SET ON MLDATAORG EG “LEUKEMIA” “WHISTLER DAILY SNOWFALL” ETC
THE RAW NAME IS AUTOMATICALLY CONVERTED TO A MLDATAORG URL
TARGETNAME OPTIONAL DEFAULT ‘LABEL’ NAME OR INDEX OF THE COLUMN CONTAINING THE TARGET
VALUES
DATANAME OPTIONAL DEFAULT ‘DATA’ NAME OR INDEX OF THE COLUMN CONTAINING THE DATA
TRANSPOSEDATA OPTIONAL DEFAULT TRUE IF TRUE TRANSPOSE THE DOWNLOADED DATA ARRAY

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DATAHOME OPTIONAL DEFAULT NONE SPECIFY ANOTHER DOWNLOAD AND CACHE FOLDER FOR THE
DATA SETS BY DEFAULT ALL SCIKITLEARN DATA IS STORED IN ‘SCIKITLEARNDATA’ SUBFOLDERS
RETURNS
DATA BUNCH DICTIONARYLIKE OBJECT THE INTERESTING ATTRIBUTES ARE ‘DATA’ THE DATA TO LEARN
‘TARGET’ THE CLASSIFICATION LABELS ‘DESCR’ THE FULL DESCRIPTION OF THE DATASET AND
‘COLNAMES’ THE ORIGINAL NAMES OF THE DATASET COLUMNS
SKLEARNDATASETS MLDATAFILENAME
WARNING DEPRECATED
SKLEARNDATASETS MLDATAFILENAME DATANAME
DEPRECATED MLDATAFILENAME WAS DEPRECATED IN VERSION 020 AND WILL BE REMOVED IN VERSION 022 PLEASE
USE FETCHOPENML
CONVERT A RAW NAME FOR A DATA SET IN A MLDATAORG FILENAME
DEPRECATED SINCE VERSION 020 WILL BE REMOVED IN VERSION 022
PARAMETERS
DATANAME STR NAME OF DATASET
RETURNS
FNAME STR THE CONVERTED DATANAME

CHAPTER
SEVEN
DEVELOPER’S GUIDE
71 CONTRIBUTING
THIS PROJECT IS A COMMUNITY EFFORT AND EVERYONE IS WELCOME TO CONTRIBUTE
THE PROJECT IS HOSTED ON HTTPSGITHUBCOMSCIKITLEARNSCIKITLEARN
THE DECISION MAKING PROCESS AND GOVERNANCE STRUCTURE OF SCIKITLEARN IS LAID OUT IN THE GOVERNANCE DOCUMENT SCIKIT LEARN GOVERNANCE AND DECISIONMAKING
SCIKITLEARN IS SOMEWHAT SELECTIVE WHEN IT COMES TO ADDING NEW ALGORITHMS AND THE BEST WAY TO CONTRIBUTE AND TO HELP THE PROJECT IS TO START WORKING ON KNOWN ISSUES SEE ISSUES FOR NEW CONTRIBUTORS TO GET STARTED
OUR COMMUNITY OUR VALUES
WE ARE A COMMUNITY BASED ON OPENNESS AND FRIENDLY DIDACTIC DISCUSSIONS
WE ASPIRE TO TREAT EVERYBODY EQUALLY AND VALUE THEIR CONTRIBUTIONS
DECISIONS ARE MADE BASED ON TECHNICAL MERIT AND CONSENSUS
CODE IS NOT THE ONLY WAY TO HELP THE PROJECT REVIEWING PULL REQUESTS ANSWERING QUESTIONS TO HELP OTHERS ON MAILING LISTS OR ISSUES ORGANIZING AND TEACHING TUTORIALS WORKING ON THE WEBSITE IMPROVING THE DOCUMENTATION ARE ALL PRICELESS CONTRIBUTIONS
WE ABIDE BY THE PRINCIPLES OF OPENNESS RESPECT AND CONSIDERATION OF OTHERS OF THE PYTHON SOFTWARE FOUNDATION HTTPSWWWPYTHONORGPSFCODEOFCONDUCT
IN CASE YOU EXPERIENCE ISSUES USING THIS PACKAGE DO NOT HESITATE TO SUBMIT A TICKET TO THE GITHUB ISSUE TRACKER YOU ARE ALSO WELCOME TO POST FEATURE REQUESTS OR PULL REQUESTS
711 WAYS TO CONTRIBUTE
THERE ARE MANY WAYS TO CONTRIBUTE TO SCIKITLEARN WITH THE MOST COMMON ONES BEING CONTRIBUTION OF CODE OR DOCU MENTATION TO THE PROJECT IMPROVING THE DOCUMENTATION IS NO LESS IMPORTANT THAN IMPROVING THE LIBRARY ITSELF IF YOU FIND A TYPO IN THE DOCUMENTATION OR HAVE MADE IMPROVEMENTS DO NOT HESITATE TO SEND AN EMAIL TO THE MAILING LIST OR PREFERABLY SUBMIT A GITHUB PULL REQUEST FULL DOCUMENTATION CAN BE FOUND UNDER THE DOC DIRECTORY
BUT THERE ARE MANY OTHER WAYS TO HELP IN PARTICULAR ANSWERING QUERIES ON THE ISSUE TRACKER INVESTIGATING BUGS ANDREVIEWING OTHER DEVELOPERS’ PULL REQUESTS ARE VERY VALUABLE CONTRIBUTIONS THAT DECREASE THE BURDEN ON THE PROJECT MAINTAINERS

ANOTHER WAY TO CONTRIBUTE IS TO REPORT ISSUES YOU’RE FACING AND GIVE A “THUMBS UP” ON ISSUES THAT OTHERS REPORTED AND THAT ARE RELEVANT TO YOU IT ALSO HELPS US IF YOU SPREAD THE WORD REFERENCE THE PROJECT FROM YOUR BLOG AND ARTICLES LINK TO IT FROM YOUR WEBSITE OR SIMPLY STAR TO SAY “I USE IT”

IN CASE A CONTRIBUTIONISSUE INVOLVES CHANGES TO THE API PRINCIPLES OR CHANGES TO DEPENDENCIES OR SUPPORTED VERSIONS IT MUST BE BACKED BY A ENHANCEMENT PROPOSALS SLEPS WHERE A SLEP MUST BE SUBMITTED AS A PULLREQUEST TO ENHANCEMENT PROPOSALS USING THE SLEP TEMPLATE AND FOLLOWS THE DECISIONMAKING PROCESS OUTLINED IN SCIKITLEARN GOVERNANCE AND DECISIONMAKING

CONTRIBUTING TO RELATED PROJECTS

SCIKITLEARN THRIVES IN AN ECOSYSTEM OF SEVERAL RELATED PROJECTS WHICH ALSO MAY HAVE RELEVANT ISSUES TO WORK ON INCLUDING SMALLER PROJECTS SUCH AS

- SCIKITLEARNCONTRIB
- JOBLIB
- SPHINXGALLERY
- NUMPYDOC
- LIACARFF

AND LARGER PROJECTS

- NUMPY
- SCIPY
- MATPLOTLIB
- AND SO ON

LOOK FOR ISSUES MARKED “HELP WANTED” OR SIMILAR HELPING THESE PROJECTS MAY HELP SCIKITLEARN TOO SEE ALSO RELATED PROJECTS

712 SUBMITTING A BUG REPORT OR A FEATURE REQUEST

WE USE GITHUB ISSUES TO TRACK ALL BUGS AND FEATURE REQUESTS FEEL FREE TO OPEN AN ISSUE IF YOU HAVE FOUND A BUG OR WISH TO SEE A FEATURE IMPLEMENTED

IN CASE YOU EXPERIENCE ISSUES USING THIS PACKAGE DO NOT HESITATE TO SUBMIT A TICKET TO THE BUG TRACKER YOU ARE ALSO WELCOME TO POST FEATURE REQUESTS OR PULL REQUESTS

IT IS RECOMMENDED TO CHECK THAT YOUR ISSUE COMPLIES WITH THE FOLLOWING RULES BEFORE SUBMITTING

- VERIFY THAT YOUR ISSUE IS NOT BEING CURRENTLY ADDRESSED BY OTHER ISSUES OR PULL REQUESTS
- IF YOU ARE SUBMITTING AN ALGORITHM OR FEATURE REQUEST PLEASE VERIFY THAT THE ALGORITHM FULFILLS OUR NEW ALGORITHM REQUIREMENTS
- IF YOU ARE SUBMITTING A BUG REPORT WE STRONGLY ENCOURAGE YOU TO FOLLOW THE GUIDELINES IN HOW TO MAKE A GOOD BUG REPORT

HOW TO MAKE A GOOD BUG REPORT

WHEN YOU SUBMIT AN ISSUE TO GITHUB PLEASE DO YOUR BEST TO FOLLOW THESE GUIDELINES THIS WILL MAKE IT A LOT EASIER TO PROVIDE YOU WITH GOOD FEEDBACK

• THE IDEAL BUG REPORT CONTAINS A SHORT REPRODUCIBLE CODE SNIPPET THIS WAY ANYONE CAN TRY TO REPRODUCE THE BUG EASILY SEE THIS FOR MORE DETAILS IF YOUR SNIPPET IS LONGER THAN AROUND 50 LINES PLEASE LINK TO A GIST OR A GITHUB REPO
• IF NOT FEASIBLE TO INCLUDE A REPRODUCIBLE SNIPPET PLEASE BE SPECIFIC ABOUT WHAT ESTIMATORS ANDOR FUNCTIONS ARE INVOLVED AND THE SHAPE OF THE DATA
• IF AN EXCEPTION IS RAISED PLEASE PROVIDE THE FULL TRACEBACK
• PLEASE INCLUDE YOUR OPERATING SYSTEM TYPE AND VERSION NUMBER AS WELL AS YOUR PYTHON SCIKITLEARN NUMPY AND SCIPY VERSIONS THIS INFORMATION CAN BE FOUND BY RUNNING THE FOLLOWING CODE SNIPPET

```
IMPORT SKLEARN
SKLEARNSHOWVERSIONS
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NOTE THIS UTILITY FUNCTION IS ONLY AVAILABLE IN SCIKITLEARN V020 FOR PREVIOUS VERSIONS ONE HAS TO EXPLICITLY RUN

```
IMPORT PLATFORM  PRINTPLATFORMPLATFORM
IMPORT SYS  PRINTPYTHON SYSVERSION
IMPORT NUMPY  PRINTNUMPY NUMPYVERSION
IMPORT SCIPY  PRINTSCIPY SCIPYVERSION
IMPORT SKLEARN  PRINTSCIKITLEARN SKLEARNVERSION
```

• PLEASE ENSURE ALL CODE SNIPPETS AND ERROR MESSAGES ARE FORMATTED IN APPROPRIATE CODE BLOCKS SEE CREATING AND HIGHLIGHTING CODE BLOCKS FOR MORE DETAILS

713 CONTRIBUTING CODE

NOTE TO AVOID DUPLICATING WORK IT IS HIGHLY ADVISED THAT YOU SEARCH THROUGH THE ISSUE TRACKER AND THE PR LIST IF IN DOUBT ABOUT DUPLICATED WORK OR IF YOU WANT TO WORK ON A NONTRIVIAL FEATURE IT’S RECOMMENDED TO FIRST OPEN AN ISSUE IN THE ISSUE TRACKER TO GET SOME FEEDBACKS FROM CORE DEVELOPERS

HOW TO CONTRIBUTE

THE PREFERRED WAY TO CONTRIBUTE TO SCIKITLEARN IS TO FORK THE MAIN REPOSITORY ON GITHUB THEN SUBMIT A “PULL REQUEST” PR

1 CREATE AN ACCOUNT ON GITHUB IF YOU DO NOT ALREADY HAVE ONE
2 FORK THE PROJECT REPOSITORY CLICK ON THE ‘FORK’ BUTTON NEAR THE TOP OF THE PAGE THIS CREATES A COPY OF THE CODE UNDER YOUR ACCOUNT ON THE GITHUB USER ACCOUNT FOR MORE DETAILS ON HOW TO FORK A REPOSITORY SEE THIS GUIDE
3 CLONE YOUR FORK OF THE SCIKITLEARN REPO FROM YOUR GITHUB ACCOUNT TO YOUR LOCAL DISK

```
GIT CLONE GITGITHUBCOMYOURLOGINSCIKITLEARNGIT
CD SCIKITLEARN
```

4 INSTALL THE DEVELOPMENT DEPENDENCIES

```
PIP INSTALL CYTHON PYTEST FLAKE8
```

5 INSTALL SCIKITLEARN IN EDITABLE MODE

```
 PIP INSTALL EDITABLE
```

FOR MORE DETAILS ABOUT ADVANCED INSTALLATION SEE THE BUILDING FROM SOURCE SECTION

6 ADD THE UPSTREAM REMOTE THIS SAVES A REFERENCE TO THE MAIN SCIKITLEARN REPOSITORY WHICH YOU CAN USE TO KEEP YOUR REPOSITORY SYNCHRONIZED WITH THE LATEST CHANGES

```
 GIT REMOTE ADD UPSTREAM HTTPSGITHUBCOMSCIKITLEARNSCIKITLEARNGIT
```

7 FETCH THE UPSTREAM AND THEN CREATE A BRANCH TO HOLD YOUR DEVELOPMENT CHANGES

```
 GIT FETCH UPSTREAM
 GIT CHECKOUT B MYFEATURE UPSTREAMMASTER
```

AND START MAKING CHANGES ALWAYS USE A FEATURE BRANCH IT’S GOOD PRACTICE TO NEVER WORK ON THE MASTER BRANCH

8 DEVELOP THE FEATURE ON YOUR FEATURE BRANCH ON YOUR COMPUTER USING GIT TO DO THE VERSION CONTROL WHEN YOU’RE DONE EDITING ADD CHANGED FILES USING GIT ADD AND THENGIT COMMIT FILES

```
 GIT ADD MODIFIEDFILES
 GIT COMMIT
```

TO RECORD YOUR CHANGES IN GIT THEN PUSH THE CHANGES TO YOUR GITHUB ACCOUNT WITH

```
 GIT PUSH U ORIGIN MYFEATURE
```

9 FOLLOW THESE INSTRUCTIONS TO CREATE A PULL REQUEST FROM YOUR FORK THIS WILL SEND AN EMAIL TO THE COMMITTERS YOU MAY WANT TO CONSIDER SENDING AN EMAIL TO THE MAILING LIST FOR MORE VISIBILITY

NOTE IF YOU ARE MODIFYING A CYTHON MODULE YOU HAVE TO RERUN STEP 5 AFTER MODIFICATIONS AND BEFORE TESTING THEM

IT IS OFTEN HELPFUL TO KEEP YOUR LOCAL BRANCH SYNCHRONIZED WITH THE LATEST CHANGES OF THE MAIN SCIKITLEARN REPOSITORY

```
 GIT FETCH UPSTREAM
 GIT MERGE UPSTREAMMASTER
```

SUBSEQUENTLY YOU MIGHT NEED TO SOLVE THE CONFLICTS YOU CAN REFER TO THE GIT DOCUMENTATION RELATED TO RESOLVING MERGE CONFLICT USING THE COMMAND LINE

LEARNING GIT

THE GIT DOCUMENTATION AND HTTPTRYGITHUBIO ARE EXCELLENT RESOURCES TO GET STARTED WITH GIT AND UNDERSTANDING ALL OF THE COMMANDS SHOWN HERE

PULL REQUEST CHECKLIST

BEFORE A PR CAN BE MERGED IT NEEDS TO BE APPROVED BY TWO CORE DEVELOPERS PLEASE PREFIX THE TITLE OF YOUR PULL REQUEST WITHMRG IF THE CONTRIBUTION IS COMPLETE AND SHOULD BE SUBJECTED TO A DETAILED REVIEW AN INCOMPLETE CONTRIBUTION – WHERE YOU EXPECT TO DO MORE WORK BEFORE RECEIVING A FULL REVIEW – SHOULD BE PREFIXED WIP TO INDICATE A WORK IN PROGRESS AND CHANGED TO MRG WHEN IT MATURES WIPS MAY BE USEFUL TO INDICATE YOU ARE WORKING ON SOMETHING TO AVOID DUPLICATED WORK REQUEST BROAD REVIEW OF FUNCTIONALITY OR API OR SEEK COLLABORATORS WIPS OFTEN BENEFIT FROM THE INCLUSION OF A TASK LIST IN THE PR DESCRIPTION

IN ORDER TO EASE THE REVIEWING PROCESS WE RECOMMEND THAT YOUR CONTRIBUTION COMPLIES WITH THE FOLLOWING RULES BEFORE MARKING A PR AS MRG THE BOLDED ONES ARE ESPECIALLY IMPORTANT
1GIVE YOUR PULL REQUEST A HELPFUL TITLE THAT SUMMARISES WHAT YOUR CONTRIBUTION DOES THIS TITLE WILL OFTEN BECOME THE COMMIT MESSAGE ONCE MERGED SO IT SHOULD SUMMARISE YOUR CONTRIBUTION FOR POSTERITY IN SOME CASES “FIX ISSUE TITLE” IS ENOUGH “FIX ISSUE NUMBER” IS NEVER A GOOD TITLE
2MAKE SURE YOUR CODE PASSES THE TESTS THE WHOLE TEST SUITE CAN BE RUN WITH PYTEST BUT IT IS USUALLY NOT RECOMMENDED SINCE IT TAKES A LONG TIME IT IS OFTEN ENOUGH TO ONLY RUN THE TEST RELATED TO YOUR CHANGES FOR EXAMPLE IF YOU CHANGED SOMETHING IN SKLEARNLINEARMODELLOGISTICPY RUNNING THE FOLLOWING COMMANDS WILL USUALLY BE ENOUGH
•PYTEST SKLEARNLINEARMODELLOGISTICPY TO MAKE SURE THE DOCTEST EXAMPLES ARE CORRECT
•PYTEST SKLEARNLINEARMODELTESTSTESTLOGISTICPY TO RUN THE TESTS SPECIFIC TO THE FILE
•PYTEST SKLEARNLINEARMODEL TO TEST THE WHOLE GENERALIZED LINEAR MODELS MODULE
•PYTEST SKLEARNDOCLINEARMODELRST TO MAKE SURE THE USER GUIDE EXAMPLES ARE CORRECT
•PYTEST SKLEARNTESTSTESTCOMMONPY K LOGISTICREGRESSION TO RUN ALL OUR ESTI MATOR CHECKS SPECIFICALLY FOR LOGISTICREGRESSION IF THAT’S THE ESTIMATOR YOU CHANGED
THERE MAY BE OTHER FAILING TESTS BUT THEY WILL BE CAUGHT BY THE CI SO YOU DON’T NEED TO RUN THE WHOLE TEST SUITE LOCALLY YOU CAN READ MORE IN TESTING AND IMPROVING TEST COVERAGE
3MAKE SURE YOUR CODE IS PROPERLY COMMENTED AND DOCUMENTED AND MAKE SURE THE DOCUMENTATION RENDERS PROPERLY TO BUILD THE DOCUMENTATION PLEASE REFER TO OUR DOCUMENTATION GUIDELINES THE CI WILL ALSO BUILD THE DOCS PLEASE REFER TO GENERATED DOCUMENTATION ON CIRCLECI
4TESTS ARE NECESSARY FOR ENHANCEMENTS TO BE ACCEPTED BUGFIXES OR NEW FEATURES SHOULD BE PROVIDED WITH NON REGRESSION TESTS THESE TESTS VERIFY THE CORRECT BEHAVIOR OF THE FIX OR FEATURE IN THIS MANNER FURTHER MODIFICATIONS ON THE CODE BASE ARE GRANTED TO BE CONSISTENT WITH THE DESIRED BEHAVIOR IN THE CASE OF BUG FIXES AT THE TIME OF THE PR THE NONREGRESSION TESTS SHOULD FAIL FOR THE CODE BASE IN THE MASTER BRANCH AND PASS FOR THE PR CODE
5MAKE SURE THAT YOUR PR DOES NOT ADD PEP8 VIOLATIONS ON A UNIXLIKE SYSTEM YOU CAN RUN MAKE FLAKE8DIFF FLAKE8 PATHTOFILE WOULD WORK FOR ANY SYSTEM BUT PLEASE AVOID REFORMATTING PARTS OF THE FILE THAT YOUR PULL REQUEST DOESN’T CHANGE AS IT DISTRACTS FROM CODE REVIEW
6 FOLLOW THE CODINGGUIDELINES SEE BELOW
7 WHEN APPLICABLE USE THE VALIDATION TOOLS AND SCRIPTS IN THE SKLEARNUTILS SUBMODULE A LIST OF UTILITY ROUTINES AVAILABLE FOR DEVELOPERS CAN BE FOUND IN THE UTILITIES FOR DEVELOPERS PAGE
8 OFTEN PULL REQUESTS RESOLVE ONE OR MORE OTHER ISSUES OR PULL REQUESTS IF MERGING YOUR PULL REQUEST MEANS THAT SOME OTHER ISSUESPRS SHOULD BE CLOSED YOU SHOULD USE KEYWORDS TO CREATE LINK TO THEM EG FIXES 1234 MULTIPLE ISSUESPRS ARE ALLOWED AS LONG AS EACH ONE IS PRECEDED BY A KEYWORD UPON MERGING THOSE ISSUESPRS WILL AUTOMATICALLY BE CLOSED BY GITHUB IF YOUR PULL REQUEST IS SIMPLY RELATED TO SOME OTHER ISSUESPRS CREATE A LINK TO THEM WITHOUT USING THE KEYWORDS EG SEE ALSO 1234
9 PRS SHOULD OFTEN SUBSTANTIATE THE CHANGE THROUGH BENCHMARKS OF PERFORMANCE AND EFFICIENCY OR THROUGH EXAM PLES OF USAGE EXAMPLES ALSO ILLUSTRATE THE FEATURES AND INTRICACIES OF THE LIBRARY TO USERS HAVE A LOOK AT OTHER EXAMPLES IN THE EXAMPLES DIRECTORY FOR REFERENCE EXAMPLES SHOULD DEMONSTRATE WHY THE NEW FUNCTIONALITY IS USEFUL IN PRACTICE AND IF POSSIBLE COMPARE IT TO OTHER METHODS AVAILABLE IN SCIKITLEARN
10 NEW FEATURES OFTEN NEED TO BE ILLUSTRATED WITH NARRATIVE DOCUMENTATION IN THE USER GUIDE WITH SMALL CODE SNIPETS IF RELEVANT PLEASE ALSO ADD REFERENCES IN THE LITERATURE WITH PDF LINKS WHEN POSSIBLE
11 THE USER GUIDE SHOULD ALSO INCLUDE EXPECTED TIME AND SPACE COMPLEXITY OF THE ALGORITHM AND SCALABILITY EG “THIS ALGORITHM CAN SCALE TO A LARGE NUMBER OF SAMPLES 100000 BUT DOES NOT SCALE IN DIMENSIONALITY NFEATURES IS EXPECTED TO BE LOWER THAN 100”

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YOU CAN ALSO CHECK OUR CODE REVIEW GUIDELINES TO GET AN IDEA OF WHAT REVIEWERS WILL EXPECT
YOU CAN CHECK FOR COMMON PROGRAMMING ERRORS WITH THE FOLLOWING TOOLS
• CODE WITH A GOOD UNITTEST COVERAGE AT LEAST 80 BETTER 100 CHECK WITH
PIP INSTALL PYTEST PYTESTCOV
PYTEST COV SKLEARN PATHTOTESTSFORPACKAGE
SEE ALSO TESTING AND IMPROVING TEST COVERAGE
BONUS POINTS FOR CONTRIBUTIONS THAT INCLUDE A PERFORMANCE ANALYSIS WITH A BENCHMARK SCRIPT AND PROFILING OUTPUT PLEASE REPORT ON THE MAILING LIST OR ON THE GITHUB ISSUE
ALSO CHECK OUT THE HOW TO OPTIMIZE FOR SPEED GUIDE FOR MORE DETAILS ON PROFILING AND CYTHON OPTIMIZATIONS
NOTE THE CURRENT STATE OF THE SCIKITLEARN CODE BASE IS NOT COMPLIANT WITH ALL OF THOSE GUIDELINES BUT WE EXPECT THAT ENFORCING THOSE CONSTRAINTS ON ALL NEW CONTRIBUTIONS WILL GET THE OVERALL CODE BASE QUALITY IN THE RIGHT DIRECTION
NOTE FOR TWO VERY WELL DOCUMENTED AND MORE DETAILED GUIDES ON DEVELOPMENT WORKFLOW PLEASE PAY A VISIT TO THE SCIPY DEVELOPMENT WORKFLOW AND THE ASTROPY WORKFLOW FOR DEVELOPERS SECTIONS
CONTINUOUS INTEGRATION CI
• AZURE PIPELINES ARE USED FOR TESTING SCIKITLEARN ON LINUX MAC AND WINDOWS WITH DIFFERENT DEPENDENCIES AND SETTINGS
• CIRCLECI IS USED TO BUILD THE DOCS FOR VIEWING FOR LINTING WITH FLAKE8 AND FOR TESTING WITH PYPY ON LINUX
PLEASE NOTE THAT IF ONE OF THE FOLLOWING MARKERS APPEAR IN THE LATEST COMMIT MESSAGE THE FOLLOWING ACTIONS ARE TAKEN
COMMIT MESSAGE
MARKERACTION TAKEN BY CI
SCIPYDEV ADD A TRAVIS BUILD WITH OUR DEPENDENCIES NUMPY SCIPY ETC DEVELOP
MENT BUILDS
CI SKIP CI IS SKIPPED COMPLETELY
DOC SKIP DOCS ARE NOT BUILT
DOC QUICK DOCS BUILT BUT EXCLUDES EXAMPLE GALLERY PLOTS
DOC BUILD DOCS BUILT INCLUDING EXAMPLE GALLERY PLOTS
STALLED PULL REQUESTS
AS CONTRIBUTING A FEATURE CAN BE A LENGTHY PROCESS SOME PULL REQUESTS APPEAR INACTIVE BUT UNFINISHED IN SUCH A CASE TAKING THEM OVER IS A GREAT SERVICE FOR THE PROJECT
A GOOD ETIQUETTE TO TAKE OVER IS
•DETERMINE IF A PR IS STALLED
–A PULL REQUEST MAY HAVE THE LABEL “STALLED” OR “HELP WANTED” IF WE HAVE ALREADY IDENTIFIED IT AS A CANDIDATE FOR OTHER CONTRIBUTORS

–TO DECIDE WHETHER AN INACTIVE PR IS STALLED ASK THE CONTRIBUTOR IF SHEHE PLANS TO CONTINUE WORKING ON THE PR IN THE NEAR FUTURE FAILURE TO RESPOND WITHIN 2 WEEKS WITH AN ACTIVITY THAT MOVES THE PR FORWARD SUGGESTS THAT THE PR IS STALLED AND WILL RESULT IN TAGGING THAT PR WITH “HELP WANTED”
NOTE THAT IF A PR HAS RECEIVED EARLIER COMMENTS ON THE CONTRIBUTION THAT HAVE HAD NO REPLY IN A MONTH IT IS SAFE TO ASSUME THAT THE PR IS STALLED AND TO SHORTEN THE WAIT TIME TO ONE DAY
AFTER A SPRINT FOLLOWUP FOR UNMERGED PRS OPENED DURING SPRINT WILL BE COMMUNICATED TO PARTICIPANTS AT THE SPRINT AND THOSE PRS WILL BE TAGGED “SPRINT” PRS TAGGED WITH “SPRINT” CAN BE REASSIGNED OR DECLARED STALLED BY SPRINT LEADERS
•TAKING OVER A STALLED PR TO TAKE OVER A PR IT IS IMPORTANT TO COMMENT ON THE STALLED PR THAT YOU ARE TAKING OVER AND TO LINK FROM THE NEW PR TO THE OLD ONE THE NEW PR SHOULD BE CREATED BY PULLING FROM THE OLD ONE
ISSUES FOR NEW CONTRIBUTORS
NEW CONTRIBUTORS SHOULD LOOK FOR THE FOLLOWING TAGS WHEN LOOKING FOR ISSUES WE STRONGLY RECOMMEND THAT NEW CONTRIBUTORS TACKLE “EASY” ISSUES FIRST THIS HELPS THE CONTRIBUTOR BECOME FAMILIAR WITH THE CONTRIBUTION WORKFLOW AND FOR THE CORE DEVS TO BECOME ACQUAINTED WITH THE CONTRIBUTOR BESIDES WHICH WE FREQUENTLY UNDERESTIMATE HOW EASY AN ISSUE IS TO SOLVE
GOOD FIRST ISSUE TAG
A GREAT WAY TO START CONTRIBUTING TO SCIKITLEARN IS TO PICK AN ITEM FROM THE LIST OF GOOD FIRST ISSUES IN THE ISSUE TRACKER RESOLVING THESE ISSUES ALLOW YOU TO START CONTRIBUTING TO THE PROJECT WITHOUT MUCH PRIOR KNOWLEDGE IF YOU HAVE ALREADY CONTRIBUTED TO SCIKITLEARN YOU SHOULD LOOK AT EASY ISSUES INSTEAD
EASY TAG
IF YOU HAVE ALREADY CONTRIBUTED TO SCIKITLEARN ANOTHER GREAT WAY TO CONTRIBUTE TO SCIKITLEARN IS TO PICK AN ITEM FROM THE LIST OF EASY ISSUES IN THE ISSUE TRACKER YOUR ASSISTANCE IN THIS AREA WILL BE GREATLY APPRECIATED BY THE MORE EXPERIENCED DEVELOPERS AS IT HELPS FREE UP THEIR TIME TO CONCENTRATE ON OTHER ISSUES
HELP WANTED TAG
WE OFTEN USE THE HELP WANTED TAG TO MARK ISSUES REGARDLESS OF DIFFICULTY ADDITIONALLY WE USE THE HELP WANTED TAG TO MARK PULL REQUESTS WHICH HAVE BEEN ABANDONED BY THEIR ORIGINAL CONTRIBUTOR AND ARE AVAILABLE FOR SOMEONE TO PICK UP WHERE THE ORIGINAL CONTRIBUTOR LEFT OFF THE LIST OF ISSUES WITH THE HELP WANTED TAG CAN BE FOUND HERE
NOTE THAT NOT ALL ISSUES WHICH NEED CONTRIBUTORS WILL HAVE THIS TAG
714 DOCUMENTATION
WE ARE GLAD TO ACCEPT ANY SORT OF DOCUMENTATION FUNCTION DOCSTRINGS RESTRUCTUREDTEXT DOCUMENTS LIKE THIS ONE TUTORIALS ETC RESTRUCTUREDTEXT DOCUMENTS LIVE IN THE SOURCE CODE REPOSITORY UNDER THE DOC DIRECTORY
YOU CAN EDIT THE DOCUMENTATION USING ANY TEXT EDITOR AND THEN GENERATE THE HTML OUTPUT BY TYPING MAKE FROM THEDOC DIRECTORY ALTERNATIVELY MAKE HTML MAY BE USED TO GENERATE THE DOCUMENTATION WITH THE EXAMPLE GALLERY WHICH TAKES QUITE SOME TIME THE RESULTING HTML FILES WILL BE PLACED IN BUILDHTMLSTABLE AND ARE VIEWABLE IN A WEB BROWSER

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BUILDING THE DOCUMENTATION
FIRST MAKE SURE YOU HAVE PROPERLY INSTALLED THE DEVELOPMENT VERSION
BUILDING THE DOCUMENTATION REQUIRES INSTALLING SOME ADDITIONAL PACKAGES
PIP INSTALL SPHINX SPHINXGALLERY NUMPYDOC MATPLOTLIB PILLOW PANDAS SCIKITIMAGE
TO BUILD THE DOCUMENTATION YOU NEED TO BE IN THE DOC FOLDER
CD DOC
IN THE VAST MAJORITY OF CASES YOU ONLY NEED TO GENERATE THE FULL WEB SITE WITHOUT THE EXAMPLE GALLERY
MAKE
THE DOCUMENTATION WILL BE GENERATED IN THE BUILDHTMLSTABLE DIRECTORY TO ALSO GENERATE THE EXAMPLE GALLERY
YOU CAN USE
MAKE HTML
THIS WILL RUN ALL THE EXAMPLES WHICH TAKES A WHILE IF YOU ONLY WANT TO GENERATE A FEW EXAMPLES YOU CAN USE
EXAMPLESPATTERNYOURREGEXGOESHERE MAKE HTML
THIS IS PARTICULARLY USEFUL IF YOU ARE MODIFYING A FEW EXAMPLES
SET THE ENVIRONMENT VARIABLE NOMATHJAX1 IF YOU INTEND TO VIEW THE DOCUMENTATION IN AN OFFLINE SETTING
TO BUILD THE PDF MANUAL RUN
MAKE LATEXPDF
WARNING SPHINX VERSION
WHILE WE DO OUR BEST TO HAVE THE DOCUMENTATION BUILD UNDER AS MANY VERSIONS OF SPHINX AS POSSIBLE THE DIFFERENT VERSIONS TEND TO BEHAVE SLIGHTLY DIFFERENTLY TO GET THE BEST RESULTS YOU SHOULD USE THE SAME VERSION AS THE ONE WE USED ON CIRCLECI LOOK AT THIS GITHUB SEARCH TO KNOW THE EXACT VERSION
GUIDELINES FOR WRITING DOCUMENTATION
IT IS IMPORTANT TO KEEP A GOOD COMPROMISE BETWEEN MATHEMATICAL AND ALGORITHMIC DETAILS AND GIVE INTUITION TO THE READER ON WHAT THE ALGORITHM DOES
BASICALLY TO ELABORATE ON THE ABOVE IT IS BEST TO ALWAYS START WITH A SMALL PARAGRAPH WITH A HANDWAVING EXPLANATION OF WHAT THE METHOD DOES TO THE DATA THEN IT IS VERY HELPFUL TO POINT OUT WHY THE FEATURE IS USEFUL AND WHEN IT SHOULD BE USED THE LATTER ALSO INCLUDING “BIG O” □□□ COMPLEXITIES OF THE ALGORITHM AS OPPOSED TO JUST RULES OF THUMB AS THE LATTER CAN BE VERY MACHINEDEPENDENT IF THOSE COMPLEXITIES ARE NOT AVAILABLE THEN RULES OF THUMB MAY BE PROVIDED INSTEAD
SECONDLY A GENERATED FIGURE FROM AN EXAMPLE AS MENTIONED IN THE PREVIOUS PARAGRAPH SHOULD THEN BE INCLUDED TO FURTHER PROVIDE SOME INTUITION
NEXT ONE OR TWO SMALL CODE EXAMPLES TO SHOW ITS USE CAN BE ADDED

NEXT ANY MATH AND EQUATIONS FOLLOWED BY REFERENCES CAN BE ADDED TO FURTHER THE DOCUMENTATION NOT STARTING THE DOCUMENTATION WITH THE MATHS MAKES IT MORE FRIENDLY TOWARDS USERS THAT ARE JUST INTERESTED IN WHAT THE FEATURE WILL DO AS OPPOSED TO HOW IT WORKS “UNDER THE HOOD”
FINALLY FOLLOW THE FORMATTING RULES BELOW TO MAKE IT CONSISTENTLY GOOD
• ADD “SEE ALSO” IN DOCSTRINGS FOR RELATED CLASSESFUNCTIONS
• “SEE ALSO” IN DOCSTRINGS SHOULD BE ONE LINE PER REFERENCE WITH A COLON AND AN EXPLANATION FOR EXAMPLE
SEE ALSO

SELECTKBEST SELECT FEATURES BASED ON THE K HIGHEST SCORES
SELECTFPR SELECT FEATURES BASED ON A FALSE POSITIVE RATE TEST
• FOR UNWRITTEN FORMATTING RULES TRY TO FOLLOW EXISTING GOOD WORKS
–FOR “REFERENCES” IN DOCSTRINGS SEE THE SILHOUETTE COEFFICIENT SKLEARNMETRICS
SILHOUETTESCORE
• WHEN EDITING RESTRUCTUREDTEXT RST FILES TRY TO KEEP LINE LENGTH UNDER 80 CHARACTERS WHEN POSSIBLE EXCEP
TIONS INCLUDE LINKS AND TABLES
GENERATED DOCUMENTATION ON CIRCLECI
WHEN YOU CHANGE THE DOCUMENTATION IN A PULL REQUEST CIRCLECI AUTOMATICALLY BUILDS IT TO VIEW THE DOCUMENTATION GENERATED BY CIRCLECI
• NAVIGATE TO THE BOTTOM OF YOUR PULL REQUEST PAGE TO SEE THE CI STATUSES YOU MAY NEED TO CLICK ON “SHOW ALL CHECKS” TO SEE ALL THE CI STATUSES
• CLICK ON THE CIRCLECI STATUS WITH “DOC” IN THE TITLE
• ADDARTIFACTS AT THE END OF THE URL NOTE YOU NEED TO WAIT FOR THE CIRCLECI BUILD TO FINISH BEFORE BEING ABLE TO LOOK AT THE ARTIFACTS
• ONCE THE ARTIFACTS ARE VISIBLE NAVIGATE TO DOCCHANGEDHTML TO SEE A LIST OF DOCUMENTATION PAGES THAT ARE LIKELY TO BE AFFECTED BY YOUR PULL REQUEST NAVIGATE TO DOCINDEXHTML TO SEE THE FULL GENERATED HTML DOCUMENTATION
IF YOU OFTEN NEED TO LOOK AT THE DOCUMENTATION GENERATED BY CIRCLECI EG WHEN REVIEWING PULL REQUESTS YOU MAY FIND THIS TIP VERY HANDY
715 TESTING AND IMPROVING TEST COVERAGE
HIGHQUALITY UNIT TESTING IS A CORNERSTONE OF THE SCIKITLEARN DEVELOPMENT PROCESS FOR THIS PURPOSE WE USE THE PYTEST PACKAGE THE TESTS ARE FUNCTIONS APPROPRIATELY NAMED LOCATED IN TESTS SUBDIRECTORIES THAT CHECK THE VALIDITY OF THE ALGORITHMS AND THE DIFFERENT OPTIONS OF THE CODE
THE FULL SCIKITLEARN TESTS CAN BE RUN USING ‘MAKE’ IN THE ROOT FOLDER ALTERNATIVELY RUNNING ‘PYTEST’ IN A FOLDER WILL RUN ALL THE TESTS OF THE CORRESPONDING SUBPACKAGES
WE EXPECT CODE COVERAGE OF NEW FEATURES TO BE AT LEAST AROUND 90
FOR GUIDELINES ON HOW TO USE PYTEST EFFICIENTLY SEE THE USEFUL PYTEST ALIASES AND FLAGS

WRITING MATPLOTLIB RELATED TESTS
TEST FIXTURES ENSURE THAT A SET OF TESTS WILL BE EXECUTING WITH THE APPROPRIATE INITIALIZATION AND CLEANUP THE SCIKITLEARN TEST SUITE IMPLEMENTS A FIXTURE WHICH CAN BE USED WITH MATPLOTLIB
PYPLOT THEPYPLOT FIXTURE SHOULD BE USED WHEN A TEST FUNCTION IS DEALING WITH MATPLOTLIB MATPLOTLIB IS A SOFT DEPENDENCY AND IS NOT REQUIRED THIS FIXTURE IS IN CHARGE OF SKIPPING THE TESTS IF MATPLOTLIB IS NOT INSTALLED IN ADDITION FIGURES CREATED DURING THE TESTS WILL BE AUTOMATICALLY CLOSED ONCE THE TEST FUNCTION HAS BEEN EXECUTED
TO USE THIS FIXTURE IN A TEST FUNCTION ONE NEEDS TO PASS IT AS AN ARGUMENT
DEFTESTREQUIRINGMPLFIXTUREPYPLOT
YOU CAN NOW SAFELY USE MATPLOTLIB
WORKFLOW TO IMPROVE TEST COVERAGE
TO TEST CODE COVERAGE YOU NEED TO INSTALL THE COVERAGE PACKAGE IN ADDITION TO PYTEST
1RUN ‘MAKE TESTCOVERAGE’ THE OUTPUT LISTS FOR EACH FILE THE LINE NUMBERS THAT ARE NOT TESTED
2FIND A LOW HANGING FRUIT LOOKING AT WHICH LINES ARE NOT TESTED WRITE OR ADAPT A TEST SPECIFICALLY FOR THESE LINES
3 LOOP
ISSUE TRACKER TAGS
ALL ISSUES AND PULL REQUESTS ON THE GITHUB ISSUE TRACKER SHOULD HAVE AT LEAST ONE OF THE FOLLOWING TAGS
BUG CRASH SOMETHING IS HAPPENING THAT CLEARLY SHOULDN’T HAPPEN WRONG RESULTS AS WELL AS UNEXPECTED ERRORS FROM ESTIMATORS GO HERE
CLEANUP ENHANCEMENT IMPROVING PERFORMANCE USABILITY CONSISTENCY
DOCUMENTATION MISSING INCORRECT OR SUBSTANDARD DOCUMENTATIONS AND EXAMPLES
NEW FEATURE FEATURE REQUESTS AND PULL REQUESTS IMPLEMENTING A NEW FEATURE
THERE ARE FOUR OTHER TAGS TO HELP NEW CONTRIBUTORS
GOOD FIRST ISSUE THIS ISSUE IS IDEAL FOR A FIRST CONTRIBUTION TO SCIKITLEARN ASK FOR HELP IF THE FORMULATION IS UNCLEAR IF YOU HAVE ALREADY CONTRIBUTED TO SCIKITLEARN LOOK AT EASY ISSUES INSTEAD
EASY THIS ISSUE CAN BE TACKLED WITHOUT MUCH PRIOR EXPERIENCE
MODERATE MIGHT NEED SOME KNOWLEDGE OF MACHINE LEARNING OR THE PACKAGE BUT IS STILL APPROACHABLE FOR SOMEONE NEW TO THE PROJECT
HELP WANTED THIS TAG MARKS AN ISSUE WHICH CURRENTLY LACKS A CONTRIBUTOR OR A PR THAT NEEDS ANOTHER CONTRIBUTOR TO TAKE OVER THE WORK THESE ISSUES CAN RANGE IN DIFFICULTY AND MAY NOT BE APPROACHABLE FOR NEW CONTRIBUTORS NOTE THAT NOT ALL ISSUES WHICH NEED CONTRIBUTORS WILL HAVE THIS TAG
716 CODING GUIDELINES
THE FOLLOWING ARE SOME GUIDELINES ON HOW NEW CODE SHOULD BE WRITTEN OF COURSE THERE ARE SPECIAL CASES AND THERE WILL BE EXCEPTIONS TO THESE RULES HOWEVER FOLLOWING THESE RULES WHEN SUBMITTING NEW CODE MAKES THE REVIEW EASIER SO NEW CODE CAN BE INTEGRATED IN LESS TIME

UNIFORMLY FORMATTED CODE MAKES IT EASIER TO SHARE CODE OWNERSHIP THE SCIKITLEARN PROJECT TRIES TO CLOSELY FOLLOW THE OFFICIAL PYTHON GUIDELINES DETAILED IN PEP8 THAT DETAIL HOW CODE SHOULD BE FORMATTED AND INDENTED PLEASE READ IT AND FOLLOW IT

IN ADDITION WE ADD THE FOLLOWING GUIDELINES

• USE UNDERSCORES TO SEPARATE WORDS IN NON CLASS NAMES NSAMPLES RATHER THAN NSAMPLES

• AVOID MULTIPLE STATEMENTS ON ONE LINE PREFER A LINE RETURN AFTER A CONTROL FLOW STATEMENT IFFOR

• USE RELATIVE IMPORTS FOR REFERENCES INSIDE SCIKITLEARN

• UNIT TESTS ARE AN EXCEPTION TO THE PREVIOUS RULE THEY SHOULD USE ABSOLUTE IMPORTS EXACTLY AS CLIENT CODE WOULD A COROLLARY IS THAT IF SKLEARNFOO EXPORTS A CLASS OR FUNCTION THAT IS IMPLEMENTED IN SKLEARNFOOBAR BAZ THE TEST SHOULD IMPORT IT FROM SKLEARNFOO

•PLEASE DON’T USE IMPORTIN ANY CASE IT IS CONSIDERED HARMFUL BY THE OFFICIAL PYTHON RECOMMENDATIONS IT MAKES THE CODE HARDER TO READ AS THE ORIGIN OF SYMBOLS IS NO LONGER EXPLICITLY REFERENCED BUT MOST IMPORTANT IT PREVENTS USING A STATIC ANALYSIS TOOL LIKE PYFLAKES TO AUTOMATICALLY FIND BUGS IN SCIKITLEARN

• USE THE NUMPY DOCSTRING STANDARD IN ALL YOUR DOCSTRINGS

A GOOD EXAMPLE OF CODE THAT WE LIKE CAN BE FOUND HERE

INPUT VALIDATION

THE MODULE SKLEARNUTILS CONTAINS VARIOUS FUNCTIONS FOR DOING INPUT VALIDATION AND CONVERSION SOMETIMES NPASARRAY SUFFICES FOR VALIDATION DO NOTUSENPASANYARRAY ORNPATLEAST2D SINCE THOSE LET NUMPY’S NPMATRIX THROUGH WHICH HAS A DIFFERENT API EG MEANS DOT PRODUCT ON NPMATRIX BUT HADAMARD PRODUCT ONNPNDARRAY

IN OTHER CASES BE SURE TO CALL CHECKARRAY ON ANY ARRAYLIKE ARGUMENT PASSED TO A SCIKITLEARN API FUNCTION THE EXACT PARAMETERS TO USE DEPENDS MAINLY ON WHETHER AND WHICH SCIPYSPARSE MATRICES MUST BE ACCEPTED

FOR MORE INFORMATION REFER TO THE UTILITIES FOR DEVELOPERS PAGE

RANDOM NUMBERS

IF YOUR CODE DEPENDS ON A RANDOM NUMBER GENERATOR DO NOT USE NUMPYRANDOMRANDOM OR SIMILAR ROUTINES TO ENSURE REPEATABILITY IN ERROR CHECKING THE ROUTINE SHOULD ACCEPT A KEYWORD RANDOMSTATE AND USE THIS TO CON STRUCT ANUMPYRANDOMRANDOMSTATE OBJECT SEE SKLEARNUTILSCHECKRANDOMSTATE INUTILITIES

FOR DEVELOPERS

HERE’S A SIMPLE EXAMPLE OF CODE USING SOME OF THE ABOVE GUIDELINES

```
FROM SKLEARNUTILS IMPORT CHECKARRAY CHECKRANDOMSTATE
DEFCHOOSERANDOMSAMPLEX RANDOMSTATE0

CHOOSE A RANDOM POINT FROM X
PARAMETERS

X  ARRAYLIKE SHAPE NSAMPLES NFEATURES
ARRAY REPRESENTING THE DATA
RANDOMSTATE  RANDOMSTATE OR AN INT SEED 0 BY DEFAULT
A RANDOM NUMBER GENERATOR INSTANCE TO DEFINE THE STATE OF THE
RANDOM PERMUTATIONS GENERATOR
```

RETURNS

X NUMPY ARRAY SHAPE NFEATURES
A RANDOM POINT SELECTED FROM X

X CHECKARRAYX
RANDOMSTATE CHECKRANDOMSTATERANDOMSTATE
I RANDOMSTATERANDINTXSHAPE0
RETURNXI
IF YOU USE RANDOMNESS IN AN ESTIMATOR INSTEAD OF A FREESTANDING FUNCTION SOME ADDITIONAL GUIDELINES APPLY
FIRST OFF THE ESTIMATOR SHOULD TAKE A RANDOMSTATE ARGUMENT TO ITS INIT WITH A DEFAULT VALUE OF
NONE IT SHOULD STORE THAT ARGUMENT'S VALUE UNMODIFIED IN AN ATTRIBUTE RANDOMSTATE FIT CAN CALL
CHECKRANDOMSTATE ON THAT ATTRIBUTE TO GET AN ACTUAL RANDOM NUMBER GENERATOR IF FOR SOME REASON RAN
DOMNESS IS NEEDED AFTER FIT THE RNG SHOULD BE STORED IN AN ATTRIBUTE RANDOMSTATE THE FOLLOWING EXAMPLE
SHOULD MAKE THIS CLEAR
CLASS GAUSSIANNOISE BASEESTIMATOR TRANSFORMERMIXIN
THIS ESTIMATOR IGNORES ITS INPUT AND RETURNS RANDOM GAUSSIAN NOISE
IT ALSO DOES NOT ADHERE TO ALL SCIKITLEARN CONVENTIONS
BUT SHOWCASES HOW TO HANDLE RANDOMNESS

DEFINITSELF NCOMPONENTS100 RANDOMSTATE NONE
SELFRANDOMSTATE RANDOMSTATE
 THE ARGUMENTS ARE IGNORED ANYWAY SO WE MAKE THEM OPTIONAL
DEFFITSELF X NONE YNONE
SELFRANDOMSTATE CHECKRANDOMSTATESELFRANDOMSTATE
DEFTRANSFORMSELF X
NSAMPLES XSHAPE0
RETURNSELFRANDOMSTATERANDNNSAMPLES NCOMPONENTS
THE REASON FOR THIS SETUP IS REPRODUCIBILITY WHEN AN ESTIMATOR IS FIT TWICE TO THE SAME DATA IT SHOULD PRODUCE AN
IDENTICAL MODEL BOTH TIMES HENCE THE VALIDATION IN FIT NOTINIT
DEPRECATION
IF ANY PUBLICLY ACCESSIBLE METHOD FUNCTION ATTRIBUTE OR PARAMETER IS RENAMED WE STILL SUPPORT THE OLD ONE FOR TWO
RELEASES AND ISSUE A DEPRECATION WARNING WHEN IT IS CALLEDPASSEDACCESSED EG IF THE FUNCTION ZEROONE IS RE
NAMED TOZEROONELOSS WE ADD THE DECORATOR DEPRECATED FROMSKLEARNUTILS TOZEROONE AND CALL
ZEROONELOSS FROM THAT FUNCTION
FROM UTILS IMPORT DEPRECATED
DEFZEROONELOSSYTRUE YPRED NORMALIZE TRUE
 ACTUAL IMPLEMENTATION
PASS
DEPRECATED FUNCTION ZEROONE WAS RENAMED TO ZEROONELOSS
IN VERSION 013 AND WILL BE REMOVED IN RELEASE 015
DEFAULT BEHAVIOR IS CHANGED FROM NORMALIZEFALSE TO
NORMALIZETRUE

DEFZEROONEYTRUE YPRED NORMALIZE FALSE
RETURNZEROONELOSSYTRUE YPRED NORMALIZE
IF AN ATTRIBUTE IS TO BE DEPRECATED USE THE DECORATOR DEPRECATED ON A PROPERTY PLEASE NOTE THAT THE PROPERTY DECORATOR SHOULD BE PLACED BEFORE THE DEPRECATED DECORATOR FOR THE DOCSTRINGS TO BE RENDERED PROPERLY EG RENAMING AN ATTRIBUTE LABELS TOCLASSES CAN BE DONE AS
DEPRECATED ATTRIBUTE LABELS WAS DEPRECATED IN VERSION 013 AND
WILL BE REMOVED IN 015 USE CLASSES INSTEAD
PROPERTY
DEFLABELSSELF
RETURNSELFCLASSES
IF A PARAMETER HAS TO BE DEPRECATED USE DEPRECATIONWARNING APPROPRIATELY IN THE FOLLOWING EXAMPLE K IS DEPRECATED AND RENAMED TO NCLUSTERS
IMPORT WARNINGS
DEFEXAMPLEFUNCTIONNCLUSTERS8 KNOTUSED
IFK NOTUSED
WARNINGSWARNK WAS RENAMED TO NCLUSTERS IN VERSION 013 AND
WILL BE REMOVED IN 015 DEPRECATIONWARNING
NCLUSTERS K
WHEN THE CHANGE IS IN A CLASS WE VALIDATE AND RAISE WARNING IN FIT
IMPORT WARNINGS
CLASS EXAMPLEESTIMATOR BASEESTIMATOR
DEFINITSELF NCLUSTERS8 KNOTUSED
SELFNCLUSTERS NCLUSTERS
SELFK K
DEFFITSELF X Y
IFSELFK NOTUSED
WARNINGSWARNK WAS RENAMED TO NCLUSTERS IN VERSION 013 AND
WILL BE REMOVED IN 015 DEPRECATIONWARNING
SELFNCLUSTERS SELFK
ELSE
SELFNCLUSTERS SELFNCLUSTERS
AS IN THESE EXAMPLES THE WARNING MESSAGE SHOULD ALWAYS GIVE BOTH THE VERSION IN WHICH THE DEPRECATION HAPPENED AND THE VERSION IN WHICH THE OLD BEHAVIOR WILL BE REMOVED IF THE DEPRECATION HAPPENED IN VERSION 0XDEV THE MESSAGE SHOULD SAY DEPRECATION OCCURRED IN VERSION 0X AND THE REMOVAL WILL BE IN 0X2 SO THAT USERS WILL HAVE ENOUGH TIME TO ADAPT THEIR CODE TO THE NEW BEHAVIOUR FOR EXAMPLE IF THE DEPRECATION HAPPENED IN VERSION 018DEV THE MESSAGE SHOULD SAY IT HAPPENED IN VERSION 018 AND THE OLD BEHAVIOR WILL BE REMOVED IN VERSION 020
IN ADDITION A DEPRECATION NOTE SHOULD BE ADDED IN THE DOCSTRING RECALLING THE SAME INFORMATION AS THE DEPRECATION WARNING AS EXPLAINED ABOVE USE THE DEPRECATED DIRECTIVE
 DEPRECATED 013
K WAS RENAMED TO NCLUSTERS IN VERSION 013 AND WILL BE REMOVED
IN 015
WHAT’S MORE A DEPRECATION REQUIRES A TEST WHICH ENSURES THAT THE WARNING IS RAISED IN RELEVANT CASES BUT NOT IN OTHER CASES THE WARNING SHOULD BE CAUGHT IN ALL OTHER TESTS USING EG PYTESTMARKFILTERWARNINGS AND THERE SHOULD BE NO WARNING IN THE EXAMPLES

CHANGE THE DEFAULT VALUE OF A PARAMETER
IF THE DEFAULT VALUE OF A PARAMETER NEEDS TO BE CHANGED PLEASE REPLACE THE DEFAULT VALUE WITH A SPECIFIC VALUE EG WARN AND RAISEFUTUREWARNING WHEN USERS ARE USING THE DEFAULT VALUE IN THE FOLLOWING EXAMPLE WE CHANGE THE DEFAULT VALUE OF NCLUSTERS FROM 5 TO 10 CURRENT VERSION IS 020

```
IMPORT WARNINGS
DEFEXAMPLEFUNCTIONNCLUSTERSWARN
IFNCLUSTERS  WARN
WARNINGSWARNTHE DEFAULT VALUE OF NCLUSTERS WILL CHANGE FROM
5 TO 10 IN 022 FUTUREWARNING
NCLUSTERS  5
```

WHEN THE CHANGE IS IN A CLASS WE VALIDATE AND RAISE WARNING IN FIT

```
IMPORT WARNINGS
CLASS EXAMPLEESTIMATOR
DEFINITSELF NCLUSTERSWARN
SELFNCLUSTERS  NCLUSTERS
DEFFITSELF X Y
IFSELFNCLUSTERS  WARN
WARNINGSWARNTHE DEFAULT VALUE OF NCLUSTERS WILL CHANGE FROM
5 TO 10 IN 022 FUTUREWARNING
SELFNCLUSTERS  5
```

SIMILAR TO DEPRECATIONS THE WARNING MESSAGE SHOULD ALWAYS GIVE BOTH THE VERSION IN WHICH THE CHANGE HAPPENED AND THE VERSION IN WHICH THE OLD BEHAVIOR WILL BE REMOVED THE DOCSTRING NEEDS TO BE UPDATED ACCORDINGLY WE NEED A TEST WHICH ENSURES THAT THE WARNING IS RAISED IN RELEVANT CASES BUT NOT IN OTHER CASES THE WARNING SHOULD BE CAUGHT IN ALL OTHER TESTS USING EG PYTESTMARKFILTERWARNINGS AND THERE SHOULD BE NO WARNING IN THE EXAMPLES

PYTHON VERSIONS SUPPORTED

SINCE SCIKITLEARN 021 ONLY PYTHON 35 AND NEWER IS SUPPORTED

717 CODE REVIEW GUIDELINES

REVIEWING CODE CONTRIBUTED TO THE PROJECT AS PRS IS A CRUCIAL COMPONENT OF SCIKITLEARN DEVELOPMENT WE ENCOURAGE ANYONE TO START REVIEWING CODE OF OTHER DEVELOPERS THE CODE REVIEW PROCESS IS OFTEN HIGHLY EDUCATIONAL FOR EVERYBODY INVOLVED THIS IS PARTICULARLY APPROPRIATE IF IT IS A FEATURE YOU WOULD LIKE TO USE AND SO CAN RESPOND CRITICALLY ABOUT WHETHER THE PR MEETS YOUR NEEDS WHILE EACH PULL REQUEST NEEDS TO BE SIGNED OFF BY TWO CORE DEVELOPERS YOU CAN SPEED UP THIS PROCESS BY PROVIDING YOUR FEEDBACK

HERE ARE A FEW IMPORTANT ASPECTS THAT NEED TO BE COVERED IN ANY CODE REVIEW FROM HIGHLEVEL QUESTIONS TO A MORE DETAILED CHECKLIST

- DO WE WANT THIS IN THE LIBRARY IS IT LIKELY TO BE USED DO YOU AS A SCIKITLEARN USER LIKE THE CHANGE AND INTEND TO USE IT IS IT IN THE SCOPE OF SCIKITLEARN WILL THE COST OF MAINTAINING A NEW FEATURE BE WORTH ITS BENEFITS
- IS THE CODE CONSISTENT WITH THE API OF SCIKITLEARN ARE PUBLIC FUNCTIONSCLASSESPARAMETERS WELL NAMED AND INTUITIVELY DESIGNED
- ARE ALL PUBLIC FUNCTIONSCLASSES AND THEIR PARAMETERS RETURN TYPES AND STORED ATTRIBUTES NAMED ACCORDING TO SCIKITLEARN CONVENTIONS AND DOCUMENTED CLEARLY

• IS ANY NEW FUNCTIONALITY DESCRIBED IN THE USERGUIDE AND ILLUSTRATED WITH EXAMPLES
• IS EVERY PUBLIC FUNCTIONCLASS TESTED ARE A REASONABLE SET OF PARAMETERS THEIR VALUES VALUE TYPES AND COMBI NATIONS TESTED DO THE TESTS VALIDATE THAT THE CODE IS CORRECT IE DOING WHAT THE DOCUMENTATION SAYS IT DOES IF THE CHANGE IS A BUGFIX IS A NONREGRESSION TEST INCLUDED LOOK AT THIS TO GET STARTED WITH TESTING IN PYTHON
• DO THE TESTS PASS IN THE CONTINUOUS INTEGRATION BUILD IF APPROPRIATE HELP THE CONTRIBUTOR UNDERSTAND WHY TESTS FAILED
• DO THE TESTS COVER EVERY LINE OF CODE SEE THE COVERAGE REPORT IN THE BUILD LOG IF NOT ARE THE LINES MISSING COVERAGE GOOD EXCEPTIONS
• IS THE CODE EASY TO READ AND LOW ON REDUNDANCY SHOULD VARIABLE NAMES BE IMPROVED FOR CLARITY OR CONSISTENCY SHOULD COMMENTS BE ADDED SHOULD COMMENTS BE REMOVED AS UNHELPFUL OR EXTRANEOUS
• COULD THE CODE EASILY BE REWRITTEN TO RUN MUCH MORE EFFICIENTLY FOR RELEVANT SETTINGS
• IS THE CODE BACKWARDS COMPATIBLE WITH PREVIOUS VERSIONS OR IS A DEPRECATION CYCLE NECESSARY
• WILL THE NEW CODE ADD ANY DEPENDENCIES ON OTHER LIBRARIES THIS IS UNLIKELY TO BE ACCEPTED
• DOES THE DOCUMENTATION RENDER PROPERLY SEE THE DOCUMENTATION SECTION FOR MORE DETAILS AND ARE THE PLOTS INSTRUCTIVE

STANDARD REPLIES FOR REVIEWING INCLUDES SOME FREQUENT COMMENTS THAT REVIEWERS MAY MAKE

718 APIS OF SCIKITLEARN OBJECTS

TO HAVE A UNIFORM API WE TRY TO HAVE A COMMON BASIC API FOR ALL THE OBJECTS IN ADDITION TO AVOID THE PROLIFERATION OF FRAMEWORK CODE WE TRY TO ADOPT SIMPLE CONVENTIONS AND LIMIT TO A MINIMUM THE NUMBER OF METHODS AN OBJECT MUST IMPLEMENT

ELEMENTS OF THE SCIKITLEARN API ARE DESCRIBED MORE DEFINITIVELY IN THE GLOSSARY OF COMMON TERMS AND API ELEMENTS

DIFFERENT OBJECTS

THE MAIN OBJECTS IN SCIKITLEARN ARE ONE CLASS CAN IMPLEMENT MULTIPLE INTERFACES

ESTIMATOR THE BASE OBJECT IMPLEMENTS A FIT METHOD TO LEARN FROM DATA EITHER
ESTIMATOR ESTIMATORFITDATA TARGETS
OR
ESTIMATOR ESTIMATORFITDATA

PREDICTOR FOR SUPERVISED LEARNING OR SOME UNSUPERVISED PROBLEMS IMPLEMENTS
PREDICTION PREDICTORPREDICTDATA

CLASSIFICATION ALGORITHMS USUALLY ALSO OFFER A WAY TO QUANTIFY CERTAINTY OF A PREDICTION EITHER USING DECISIONFUNCTION ORPREDICTPROBA
PROBABILITY PREDICTORPREDICTPROBADATA

TRANSFORMER FOR FILTERING OR MODIFYING THE DATA IN A SUPERVISED OR UNSUPERVISED WAY IMPLEMENTS
NEWDATA TRANSFORMERTRANSFORMDATA

WHEN FITTING AND TRANSFORMING CAN BE PERFORMED MUCH MORE EFFICIENTLY TOGETHER THAN SEPARATELY
IMPLEMENTS
NEWDATA TRANSFORMERFITTRANSFORMDATA
MODEL A MODEL THAT CAN GIVE A GOODNESS OF FIT MEASURE OR A LIKELIHOOD OF UNSEEN DATA IMPLEMENTS HIGHER
IS BETTER
SCORE MODELSCOREDATA
ESTIMATORS
THE API HAS ONE PREDOMINANT OBJECT THE ESTIMATOR A ESTIMATOR IS AN OBJECT THAT FITS A MODEL BASED ON SOME TRAINING
DATA AND IS CAPABLE OF INFERRING SOME PROPERTIES ON NEW DATA IT CAN BE FOR INSTANCE A CLASSIFIER OR A REGRESSOR ALL
ESTIMATORS IMPLEMENT THE FIT METHOD
ESTIMATORFITX Y
ALL BUILTIN ESTIMATORS ALSO HAVE A SETPARAMS METHOD WHICH SETS DATAINDEPENDENT PARAMETERS OVERRIDING PREVI
OUS PARAMETER VALUES PASSED TO INIT
ALL ESTIMATORS IN THE MAIN SCIKITLEARN CODEBASE SHOULD INHERIT FROM SKLEARNBASEBASEESTIMATOR
INSTANTIATION
THIS CONCERNS THE CREATION OF AN OBJECT THE OBJECT'S INIT METHOD MIGHT ACCEPT CONSTANTS AS ARGUMENTS THAT
DETERMINE THE ESTIMATOR'S BEHAVIOR LIKE THE C CONSTANT IN SVMS IT SHOULD NOT HOWEVER TAKE THE ACTUAL TRAINING DATA
AS AN ARGUMENT AS THIS IS LEFT TO THE FIT METHOD
CLF2 SVCC23
CLF3 SVC1 2 2 3 1 1 WRONG
THE ARGUMENTS ACCEPTED BY INIT SHOULD ALL BE KEYWORD ARGUMENTS WITH A DEFAULT VALUE IN OTHER WORDS A USER
SHOULD BE ABLE TO INSTANTIATE AN ESTIMATOR WITHOUT PASSING ANY ARGUMENTS TO IT THE ARGUMENTS SHOULD ALL CORRESPOND TO
HYPERPARAMETERS DESCRIBING THE MODEL OR THE OPTIMISATION PROBLEM THE ESTIMATOR TRIES TO SOLVE THESE INITIAL ARGUMENTS
OR PARAMETERS ARE ALWAYS REMEMBERED BY THE ESTIMATOR ALSO NOTE THAT THEY SHOULD NOT BE DOCUMENTED UNDER THE
"ATTRIBUTES" SECTION BUT RATHER UNDER THE "PARAMETERS" SECTION FOR THAT ESTIMATOR
IN ADDITION EVERY KEYWORD ARGUMENT ACCEPTED BY INIT SHOULD CORRESPOND TO AN ATTRIBUTE ON THE INSTANCE
SCIKITLEARN RELIES ON THIS TO FIND THE RELEVANT ATTRIBUTES TO SET ON AN ESTIMATOR WHEN DOING MODEL SELECTION
TO SUMMARIZE AN INIT SHOULD LOOK LIKE
DEFINITSELF PARAM11 PARAM22
SELFPARAM1 PARAM1
SELFPARAM2 PARAM2
THERE SHOULD BE NO LOGIC NOT EVEN INPUT VALIDATION AND THE PARAMETERS SHOULD NOT BE CHANGED THE CORRESPONDING
LOGIC SHOULD BE PUT WHERE THE PARAMETERS ARE USED TYPICALLY IN FIT THE FOLLOWING IS WRONG
DEFINITSELF PARAM11 PARAM22 PARAM33
 WRONG PARAMETERS SHOULD NOT BE MODIFIED
IFPARAM1 1
PARAM2 1
SELFPARAM1 PARAM1

WRONG THE OBJECTS ATTRIBUTES SHOULD HAVE EXACTLY THE NAME OF
THE ARGUMENT IN THE CONSTRUCTOR
SELFPARAM3 PARAM2
THE REASON FOR POSTPONING THE VALIDATION IS THAT THE SAME VALIDATION WOULD HAVE TO BE PERFORMED IN SETPARAMS
WHICH IS USED IN ALGORITHMS LIKE GRIDSEARCHCV
FITTING
THE NEXT THING YOU WILL PROBABLY WANT TO DO IS TO ESTIMATE SOME PARAMETERS IN THE MODEL THIS IS IMPLEMENTED IN THE
FIT METHOD
THEFIT METHOD TAKES THE TRAINING DATA AS ARGUMENTS WHICH CAN BE ONE ARRAY IN THE CASE OF UNSUPERVISED LEARNING
OR TWO ARRAYS IN THE CASE OF SUPERVISED LEARNING
NOTE THAT THE MODEL IS FITTED USING X AND Y BUT THE OBJECT HOLDS NO REFERENCE TO X AND Y THERE ARE HOWEVER SOME
EXCEPTIONS TO THIS AS IN THE CASE OF PRECOMPUTED KERNELS WHERE THIS DATA MUST BE STORED FOR USE BY THE PREDICT METHOD
PARAMETERS
X ARRAYLIKE SHAPE NSAMPLES NFEATURES
Y ARRAY SHAPE NSAMPLES
KWARGS OPTIONAL DATADEPENDENT PARAMETERS
XSHAPE0 SHOULD BE THE SAME AS YSHAPE0 IF THIS REQUISITE IS NOT MET AN EXCEPTION OF TYPE VALUEERROR
SHOULD BE RAISED
YMIGHT BE IGNORED IN THE CASE OF UNSUPERVISED LEARNING HOWEVER TO MAKE IT POSSIBLE TO USE THE ESTIMATOR AS PART OF
A PIPELINE THAT CAN MIX BOTH SUPERVISED AND UNSUPERVISED TRANSFORMERS EVEN UNSUPERVISED ESTIMATORS NEED TO ACCEPT
AYNONE KEYWORD ARGUMENT IN THE SECOND POSITION THAT IS JUST IGNORED BY THE ESTIMATOR FOR THE SAME REASON
FITPREDICT FITTRANSFORM SCORE ANDPARTIALFIT METHODS NEED TO ACCEPT A YARGUMENT IN THE SECOND
PLACE IF THEY ARE IMPLEMENTED
THE METHOD SHOULD RETURN THE OBJECT SELF THIS PATTERN IS USEFUL TO BE ABLE TO IMPLEMENT QUICK ONE LINERS IN AN
IPYTHON SESSION SUCH AS
YPREDICTED SVCC100FITXTRAIN YTRAINPREDICTXTEST
DEPENDING ON THE NATURE OF THE ALGORITHM FIT CAN SOMETIMES ALSO ACCEPT ADDITIONAL KEYWORDS ARGUMENTS HOWEVER
ANY PARAMETER THAT CAN HAVE A VALUE ASSIGNED PRIOR TO HAVING ACCESS TO THE DATA SHOULD BE AN INIT KEYWORD
ARGUMENT FIT PARAMETERS SHOULD BE RESTRICTED TO DIRECTLY DATA DEPENDENT VARIABLES FOR INSTANCE A GRAM MATRIX
OR AN AFFINITY MATRIX WHICH ARE PRECOMPUTED FROM THE DATA MATRIX XARE DATA DEPENDENT A TOLERANCE STOPPING CRITERION
TOL IS NOT DIRECTLY DATA DEPENDENT ALTHOUGH THE OPTIMAL VALUE ACCORDING TO SOME SCORING FUNCTION PROBABLY IS
WHENFIT IS CALLED ANY PREVIOUS CALL TO FIT SHOULD BE IGNORED IN GENERAL CALLING ESTIMATORFITX1 AND
THENESTIMATORFITX2 SHOULD BE THE SAME AS ONLY CALLING ESTIMATORFITX2 HOWEVER THIS MAY NOT
BE TRUE IN PRACTICE WHEN FIT DEPENDS ON SOME RANDOM PROCESS SEE RANDOMSTATE ANOTHER EXCEPTION TO THIS RULE IS
WHEN THE HYPERPARAMETER WARMSTART IS SET TOTRUE FOR ESTIMATORS THAT SUPPORT IT WARMSTARTTRUE MEANS
THAT THE PREVIOUS STATE OF THE TRAINABLE PARAMETERS OF THE ESTIMATOR ARE REUSED INSTEAD OF USING THE DEFAULT INITIALIZATION
STRATEGY
ESTIMATED ATTRIBUTES
ATTRIBUTES THAT HAVE BEEN ESTIMATED FROM THE DATA MUST ALWAYS HAVE A NAME ENDING WITH TRAILING UNDERSCORE FOR
EXAMPLE THE COEFFICIENTS OF SOME REGRESSION ESTIMATOR WOULD BE STORED IN A COEF ATTRIBUTE AFTER FIT HAS BEEN CALLED

THE ESTIMATED ATTRIBUTES ARE EXPECTED TO BE OVERRIDDEN WHEN YOU CALL FIT A SECOND TIME
OPTIONAL ARGUMENTS
IN ITERATIVE ALGORITHMS THE NUMBER OF ITERATIONS SHOULD BE SPECIFIED BY AN INTEGER CALLED NITER
PAIRWISE ATTRIBUTES
AN ESTIMATOR THAT ACCEPT XOF SHAPENSAMPLES NSAMPLES AND DEFINES A PAIRWISE PROPERTY EQUAL TO TRUE
ALLOWS FOR CROSSVALIDATION OF THE DATASET EG WHEN XIS A PRECOMPUTED KERNEL MATRIX SPECIFICALLY THE PAIRWISE
PROPERTY IS USED BY UTILSMETAESTIMATORSSAFESPLIT TO SLICE ROWS AND COLUMNS
719 ROLLING YOUR OWN ESTIMATOR
IF YOU WANT TO IMPLEMENT A NEW ESTIMATOR THAT IS SCIKITLEARNCOMPATIBLE WHETHER IT IS JUST FOR YOU OR FOR CONTRIBUTING IT
TO SCIKITLEARN THERE ARE SEVERAL INTERNALS OF SCIKITLEARN THAT YOU SHOULD BE AWARE OF IN ADDITION TO THE SCIKITLEARN API
OUTLINED ABOVE YOU CAN CHECK WHETHER YOUR ESTIMATOR ADHERES TO THE SCIKITLEARN INTERFACE AND STANDARDS BY RUNNING
UTILSESTIMATORCHECKSCHECKESTIMATOR ON THE CLASS

```
 FROM SKLEARNUTILSESTIMATORCHECKS IMPORT CHECKESTIMATOR
 FROM SKLEARNSVM IMPORT LINEARSVC
CHECKESTIMATORLINEARSVC  PASSES
```

THE MAIN MOTIVATION TO MAKE A CLASS COMPATIBLE TO THE SCIKITLEARN ESTIMATOR INTERFACE MIGHT BE THAT YOU WANT
TO USE IT TOGETHER WITH MODEL EVALUATION AND SELECTION TOOLS SUCH AS MODELSELECTIONGRIDSEARCHCV AND
PIPELINEPIPELINE
BEFORE DETAILING THE REQUIRED INTERFACE BELOW WE DESCRIBE TWO WAYS TO ACHIEVE THE CORRECT INTERFACE MORE EASILY
PROJECT TEMPLATE
WE PROVIDE A PROJECT TEMPLATE WHICH HELPS IN THE CREATION OF PYTHON PACKAGES CONTAINING SCIKITLEARN COMPATIBLE
ESTIMATORS IT PROVIDES
• AN INITIAL GIT REPOSITORY WITH PYTHON PACKAGE DIRECTORY STRUCTURE
• A TEMPLATE OF A SCIKITLEARN ESTIMATOR
• AN INITIAL TEST SUITE INCLUDING USE OF CHECKESTIMATOR
• DIRECTORY STRUCTURES AND SCRIPTS TO COMPILE DOCUMENTATION AND EXAMPLE GALLERIES
• SCRIPTS TO MANAGE CONTINUOUS INTEGRATION TESTING ON LINUX AND WINDOWS
• INSTRUCTIONS FROM GETTING STARTED TO PUBLISHING ON PYPI
BASEESTIMATOR AND MIXINS
WE TEND TO USE “DUCK TYPING” SO BUILDING AN ESTIMATOR WHICH FOLLOWS THE API SUFFICES FOR COMPATIBILITY WITHOUT
NEEDING TO INHERIT FROM OR EVEN IMPORT ANY SCIKITLEARN CLASSES

HOWEVER IF A DEPENDENCY ON SCIKITLEARN IS ACCEPTABLE IN YOUR CODE YOU CAN PREVENT A LOT OF BOILERPLATE CODE BY DERIVING A CLASS FROM BASEESTIMATOR AND OPTIONALLY THE MIXIN CLASSES IN SKLEARNBASE FOR EXAMPLE BELOW IS A CUSTOM CLASSIFIER WITH MORE EXAMPLES INCLUDED IN THE SCIKITLEARNCONTRIB PROJECT TEMPLATE

```
IMPORT NUMPY AS NP
FROM SKLEARNBASE IMPORT BASEESTIMATOR CLASSIFIERMIXIN
FROM SKLEARNUTILSVALIDATION IMPORT CHECKXY CHECKARRAY CHECKISFITTED
FROM SKLEARNUTILSMULTICLASS IMPORT UNIQUELABELS
FROM SKLEARNMETRICS IMPORT EUCLIDEANDISTANCES
CLASS TEMPLATECLASSIFIER BASEESTIMATOR CLASSIFIERMIXIN

DEF INITSELF DEMOPARAMDEMO
SELFDEMOPARAM  DEMOPARAM

DEF FITSELF X Y

 CHECK THAT X AND Y HAVE CORRECT SHAPE
X Y  CHECKXYX Y
 STORE THE CLASSES SEEN DURING FIT
SELFCLASSES  UNIQUELABELSY

SELFX  X
SELFY  Y
 RETURN THE CLASSIFIER
RETURN SELF

DEF PREDICTSELF X

 CHECK IS FIT HAD BEEN CALLED
CHECKISFITTEDSELF X Y

 INPUT VALIDATION
X  CHECKARRAYX

CLOSEST  NPARGMINEUCLIDEANDISTANCESX SELFX AXIS1
RETURN SELFYCLOSEST
```

GETPARAMS AND SETPARAMS

ALL SCIKITLEARN ESTIMATORS HAVE GETPARAMS ANDSETPARAMS FUNCTIONS THE GETPARAMS FUNCTION TAKES NO ARGUMENTS AND RETURNS A DICT OF THE INIT PARAMETERS OF THE ESTIMATOR TOGETHER WITH THEIR VALUES IT MUST TAKE ONE KEYWORD ARGUMENT DEEP WHICH RECEIVES A BOOLEAN VALUE THAT DETERMINES WHETHER THE METHOD SHOULD RETURN THE PARAMETERS OF SUBESTIMATORS FOR MOST ESTIMATORS THIS CAN BE IGNORED THE DEFAULT VALUE FOR DEEP SHOULD BE TRUE THESETPARAMS ON THE OTHER HAND TAKES AS INPUT A DICT OF THE FORM PARAMETER VALUE AND SETS THE PARAMETER OF THE ESTIMATOR USING THIS DICT RETURN VALUE MUST BE ESTIMATOR ITSELF

WHILE THEGETPARAMS MECHANISM IS NOT ESSENTIAL SEE CLONING BELOW THE SETPARAMS FUNCTION IS NECESSARY AS IT IS USED TO SET PARAMETERS DURING GRID SEARCHES

THE EASIEST WAY TO IMPLEMENT THESE FUNCTIONS AND TO GET A SENSIBLE REPR METHOD IS TO INHERIT FROM SKLEARN BASEBASEESTIMATOR IF YOU DO NOT WANT TO MAKE YOUR CODE DEPENDENT ON SCIKITLEARN THE EASIEST WAY TO IMPLEMENT THE INTERFACE IS

```
DEFGETPARAMSSELF DEEP TRUE
 SUPPOSE THIS ESTIMATOR HAS PARAMETERS ALPHA AND RECURSIVE
RETURNALPHA SELFALPHA RECURSIVE SELFRECURSIVE
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SCIKITLEARN USER GUIDE RELEASE 0213
DEFSETPARAMSSELF PARAMETERS
FORPARAMETER VALUE INPARAMETERSITEMS
SETATTRSELF PARAMETER VALUE
RETURNSELF
PARAMETERS AND INIT
ASMODELSELECTIONGRIDSEARCHCV USESSETPARAMS TO APPLY PARAMETER SETTING TO ESTIMATORS IT IS ESSEN
TIAL THAT CALLING SETPARAMS HAS THE SAME EFFECT AS SETTING PARAMETERS USING THE INIT METHOD THE EASIEST
AND RECOMMENDED WAY TO ACCOMPLISH THIS IS TO NOT DO ANY PARAMETER VALIDATION IN INIT ALL LOGIC BEHIND
ESTIMATOR PARAMETERS LIKE TRANSLATING STRING ARGUMENTS INTO FUNCTIONS SHOULD BE DONE IN FIT
ALSO IT IS EXPECTED THAT PARAMETERS WITH TRAILING ARENOT TO BE SET INSIDE THE INIT METHOD ALL AND ONLY THE
PUBLIC ATTRIBUTES SET BY FIT HAVE A TRAILING AS A RESULT THE EXISTENCE OF PARAMETERS WITH TRAILING IS USED TO CHECK IF
THE ESTIMATOR HAS BEEN FITTED
CLONING
FOR USE WITH THE MODELSELECTION MODULE AN ESTIMATOR MUST SUPPORT THE BASECLONE FUNCTION TO REPLI
CATE AN ESTIMATOR THIS CAN BE DONE BY PROVIDING A GETPARAMS METHOD IF GETPARAMS IS PRESENT THEN
CLONEESTIMATOR WILL BE AN INSTANCE OF TYPEESTIMATOR ON WHICHSETPARAMS HAS BEEN CALLED WITH
CLONES OF THE RESULT OF ESTIMATORGETPARAMS
OBJECTS THAT DO NOT PROVIDE THIS METHOD WILL BE DEEPCOPIED USING THE PYTHON STANDARD FUNCTION COPYDEEPCOPY
IFSAFEFALSE IS PASSED TO CLONE
PIPELINE COMPATIBILITY
FOR AN ESTIMATOR TO BE USABLE TOGETHER WITH PIPELINEPIPELINE IN ANY BUT THE LAST STEP IT NEEDS TO PROVIDE A FIT
ORFITTRANSFORM FUNCTION TO BE ABLE TO EVALUATE THE PIPELINE ON ANY DATA BUT THE TRAINING SET IT ALSO NEEDS TO
PROVIDE ATRANSFORM FUNCTION THERE ARE NO SPECIAL REQUIREMENTS FOR THE LAST STEP IN A PIPELINE EXCEPT THAT IT HAS A
FIT FUNCTION ALL FIT ANDFITTRANSFORM FUNCTIONS MUST TAKE ARGUMENTS X Y EVEN IF Y IS NOT USED SIMILARLY
FORSCORE TO BE USABLE THE LAST STEP OF THE PIPELINE NEEDS TO HAVE A SCORE FUNCTION THAT ACCEPTS AN OPTIONAL Y
ESTIMATOR TYPES
SOME COMMON FUNCTIONALITY DEPENDS ON THE KIND OF ESTIMATOR PASSED FOR EXAMPLE CROSSVALIDATION IN
MODELSELECTIONGRIDSEARCHCV ANDMODELSELECTIONCROSSVALSCORE DEFAULTS TO BEING STRAT
IFIED WHEN USED ON A CLASSIFIER BUT NOT OTHERWISE SIMILARLY SCORERS FOR AVERAGE PRECISION THAT TAKE A CONTINUOUS
PREDICTION NEED TO CALL DECISIONFUNCTION FOR CLASSIFIERS BUT PREDICT FOR REGRESSORS THIS DISTINCTION BE
TWEEN CLASSIFIERS AND REGRESSORS IS IMPLEMENTED USING THE ESTIMATORTYPE ATTRIBUTE WHICH TAKES A STRING VALUE
IT SHOULD BE CLASSIFIER FOR CLASSIFIERS AND REGRESSOR FOR REGRESSORS AND CLUSTERER FOR CLUSTERING
METHODS TO WORK AS EXPECTED INHERITING FROM CLASSIFIERMIXIN REGRESSORMIXIN ORCLUSTERMIXIN WILL
SET THE ATTRIBUTE AUTOMATICALLY WHEN A METAESTIMATOR NEEDS TO DISTINGUISH AMONG ESTIMATOR TYPES INSTEAD OF CHECKING
ESTIMATORTYPE DIRECTLY HELPERS LIKE BASEISCLASSIFIER SHOULD BE USED
SPECIFIC MODELS
CLASSIFIERS SHOULD ACCEPT YTARGET ARGUMENTS TO FIT THAT ARE SEQUENCES LISTS ARRAYS OF EITHER STRINGS OR INTEGERS
THEY SHOULD NOT ASSUME THAT THE CLASS LABELS ARE A CONTIGUOUS RANGE OF INTEGERS INSTEAD THEY SHOULD STORE A LIST OF

CLASSES IN A CLASSES ATTRIBUTE OR PROPERTY THE ORDER OF CLASS LABELS IN THIS ATTRIBUTE SHOULD MATCH THE ORDER IN WHICH PREDICTPROBA PREDICTLOGPROBA ANDDECISIONFUNCTION RETURN THEIR VALUES THE EASIEST WAY TO
ACHIEVE THIS IS TO PUT
SELFCLASSES Y NPUNIQUEY RETURNINVERSE TRUE
INFIT THIS RETURNS A NEW YTHAT CONTAINS CLASS INDEXES RATHER THAN LABELS IN THE RANGE 0 NCLASSES
A CLASSIFIER'S PREDICT METHOD SHOULD RETURN ARRAYS CONTAINING CLASS LABELS FROM CLASSES IN A CLASSIFIER THAT IMPLEMENTS DECISIONFUNCTION THIS CAN BE ACHIEVED WITH
DEFPREDICTSELF X
D SELFDECISIONFUNCTIONX
RETURNSELFCLASSESNPARGMAXD AXIS1
IN LINEAR MODELS COEFFICIENTS ARE STORED IN AN ARRAY CALLED COEF AND THE INDEPENDENT TERM IS STORED IN INTERCEPT
SKLEARNLINEARMODELBASE CONTAINS A FEW BASE CLASSES AND MIXINS THAT IMPLEMENT COMMON LINEAR MODEL PATTERNS
THESKLEARNUTILSMULTICLASS MODULE CONTAINS USEFUL FUNCTIONS FOR WORKING WITH MULTICLASS AND MULTILABEL PROBLEMS
ESTIMATOR TAGS
WARNING THE ESTIMATOR TAGS ARE EXPERIMENTAL AND THE API IS SUBJECT TO CHANGE
SCIKITLEARN INTRODUCED ESTIMATOR TAGS IN VERSION 021 THESE ARE ANNOTATIONS OF ESTIMATORS THAT ALLOW PROGRAMMATIC INSPECTION OF THEIR CAPABILITIES SUCH AS SPARSE MATRIX SUPPORT SUPPORTED OUTPUT TYPES AND SUPPORTED METHODS THE ESTIMATOR TAGS ARE A DICTIONARY RETURNED BY THE METHOD GETTAGS THESE TAGS ARE USED BY THE COMMON TESTS AND THESKLEARNUTILSESTIMATORCHECKSCHECKESTIMATOR FUNCTION TO DECIDE WHAT TESTS TO RUN AND WHAT INPUT DATA IS APPROPRIATE TAGS CAN DEPEND ON ESTIMATOR PARAMETERS OR EVEN SYSTEM ARCHITECTURE AND CAN IN GENERAL ONLY BE DETERMINED AT RUNTIME
THE DEFAULT VALUE OF ALL TAGS EXCEPT FOR XTYPES ISFALSE THESE ARE DEFINED IN THE BASEESTIMATOR CLASS
THE CURRENT SET OF ESTIMATOR TAGS ARE
NONDETERMINISTIC WHETHER THE ESTIMATOR IS NOT DETERMINISTIC GIVEN A FIXED RANDOMSTATE
REQUIRESPOSITIVEDATA UNUSED FOR NOW WHETHER THE ESTIMATOR REQUIRES POSITIVE X
NOVALIDATION WHETHER THE ESTIMATOR SKIPS INPUTVALIDATION THIS IS ONLY MEANT FOR STATELESS AND DUMMY TRANSFORMERS
MULTIOUTPUT UNUSED FOR NOW WHETHER A REGRESSOR SUPPORTS MULTITARGET OUTPUTS OR A CLASSIFIER SUPPORTS MULTICLASS MULTIOUTPUT
MULTILABEL WHETHER THE ESTIMATOR SUPPORTS MULTILABEL OUTPUT
STATELESS WHETHER THE ESTIMATOR NEEDS ACCESS TO DATA FOR FITTING EVEN THOUGH AN ESTIMATOR IS STATELESS IT MIGHT STILL NEED A CALL TO FIT FOR INITIALIZATION
ALLOWNAN WHETHER THE ESTIMATOR SUPPORTS DATA WITH MISSING VALUES ENCODED AS NPNAN
POORSCORE WHETHER THE ESTIMATOR FAILS TO PROVIDE A "REASONABLE" TESTSET SCORE WHICH CURRENTLY FOR REGRESSION IS AN R2 OF 05 ON A SUBSET OF THE BOSTON HOUSING DATASET AND FOR CLASSIFICATION AN ACCURACY OF 083 ON MAKEBLOBSNSAMPLES300 RANDOMSTATE0 THESE DATASETS AND VALUES ARE BASED ON CURRENT ESTIMATORS IN SKLEARN AND MIGHT BE REPLACED BY SOMETHING MORE SYSTEMATIC
MULTIOUTPUTONLY WHETHER ESTIMATOR SUPPORTS ONLY MULTIOUTPUT CLASSIFICATION OR REGRESSION

SKIPTEST WHETHER TO SKIP COMMON TESTS ENTIRELY DON’T USE THIS UNLESS YOU HAVE A VERY GOOD REASON
XTYPES SUPPORTED INPUT TYPES FOR X AS LIST OF STRINGS TESTS ARE CURRENTLY ONLY RUN IF ‘2DARRAY’ IS CONTAINED IN THE LIST SIGNIFYING THAT THE ESTIMATOR TAKES CONTINUOUS 2D NUMPY ARRAYS AS INPUT THE DEFAULT VALUE IS ‘2DARRAY’ OTHER POSSIBLE TYPES ARE STRING SPARSE CATEGORICAL DICT 1DLABELS AND2DLABELS
THE GOAL IS THAT IN THE FUTURE THE SUPPORTED INPUT TYPE WILL DETERMINE THE DATA USED DURING TESTING IN PARTICULAR FORSTRING SPARSE ANDCATEGORICAL DATA FOR NOW THE TEST FOR SPARSE DATA DO NOT MAKE USE OF THESPARSE TAG
TO OVERRIDE THE TAGS OF A CHILD CLASS ONE MUST DEFINE THE MORETAGS METHOD AND RETURN A DICT WITH THE DESIRED TAGS EG
CLASS MYMULTIOUTPUTESTIMATOR BASEESTIMATOR
DEFMORETAGSSELF
RETURNMULTIOUTPUTONLY TRUE
NONDETERMINISTIC TRUE
IN ADDITION TO THE TAGS ESTIMATORS ALSO NEED TO DECLARE ANY NONOPTIONAL PARAMETERS TO INIT IN THE REQUIREDPARAMETERS CLASS ATTRIBUTE WHICH IS A LIST OR TUPLE IF REQUIREDPARAMETERS IS ONLY ESTIMATOR ORBASEESTIMATOR THEN THE ESTIMATOR WILL BE INSTANTIATED WITH AN INSTANCE OF LINEARDISCRIMINANTANALYSIS ORRIDGEREGRESSION IF THE ESTIMATOR IS A REGRESSOR IN THE TESTS THE CHOICE OF THESE TWO MODELS IS SOMEWHAT IDIOSYNCRATIC BUT BOTH SHOULD PROVIDE ROBUST CLOSEDFORM SOLUTIONS

7110 READING THE EXISTING CODE BASE

READING AND DIGESTING AN EXISTING CODE BASE IS ALWAYS A DIFFICULT EXERCISE THAT TAKES TIME AND EXPERIENCE TO MASTER EVEN THOUGH WE TRY TO WRITE SIMPLE CODE IN GENERAL UNDERSTANDING THE CODE CAN SEEM OVERWHELMING AT FIRST GIVEN THE SHEER SIZE OF THE PROJECT HERE IS A LIST OF TIPS THAT MAY HELP MAKE THIS TASK EASIER AND FASTER IN NO PARTICULAR ORDER

• GET ACQUAINTED WITH THE APIS OF SCIKITLEARN OBJECTS UNDERSTAND WHAT FITPREDICT TRANSFORM ETC ARE USED FOR
• BEFORE DIVING INTO READING THE CODE OF A FUNCTION CLASS GO THROUGH THE DOCSTRINGS FIRST AND TRY TO GET AN IDEA OF WHAT EACH PARAMETER ATTRIBUTE IS DOING IT MAY ALSO HELP TO STOP A MINUTE AND THINK HOW WOULD I DO THIS MYSELF IF I HAD TO
• THE TRICKIEST THING IS OFTEN TO IDENTIFY WHICH PORTIONS OF THE CODE ARE RELEVANT AND WHICH ARE NOT IN SCIKIT LEARN A LOT OF INPUT CHECKING IS PERFORMED ESPECIALLY AT THE BEGINNING OF THE FITMETHODS SOMETIMES ONLY A VERY SMALL PORTION OF THE CODE IS DOING THE ACTUAL JOB FOR EXAMPLE LOOKING AT THE FIT METHOD OFSKLEARNLINEARMODELLINEARREGRESSION WHAT YOU’RE LOOKING FOR MIGHT JUST BE THE CALL THE SCIPYLINALGLSTSQ BUT IT IS BURIED INTO MULTIPLE LINES OF INPUT CHECKING AND THE HANDLING OF DIFFERENT KINDS OF PARAMETERS
• DUE TO THE USE OF INHERITANCE SOME METHODS MAY BE IMPLEMENTED IN PARENT CLASSES ALL ESTIMATORS INHERIT AT LEAST FROM BASEESTIMATOR AND FROM A MIXIN CLASS EG CLASSIFIERMIXIN THAT ENABLES DEFAULT BEHAVIOUR DEPENDING ON THE NATURE OF THE ESTIMATOR CLASSIFIER REGRESSOR TRANSFORMER ETC
• SOMETIMES READING THE TESTS FOR A GIVEN FUNCTION WILL GIVE YOU AN IDEA OF WHAT ITS INTENDED PURPOSE IS YOU CAN USEGIT GREP SEE BELOW TO FIND ALL THE TESTS WRITTEN FOR A FUNCTION MOST TESTS FOR A SPECIFIC FUNCTIONCLASS ARE PLACED UNDER THE TESTS FOLDER OF THE MODULE
• YOU’LL OFTEN SEE CODE LOOKING LIKE THIS OUT PARALLEL DELAYEDSOMEFUNCTIONPARAM FOR PARAM IN SOMEITERABLE THIS RUNS SOMEFUNCTION IN PARALLEL USING JOBLIB OUT IS THEN AN ITERABLE CONTAINING THE VALUES RETURNED BY SOMEFUNCTION FOR EACH CALL
• WE USE CYTHON TO WRITE FAST CODE CYTHON CODE IS LOCATED IN PYX ANDPXD FILES CYTHON CODE HAS A MORE CLIKE FLAVOR WE USE POINTERS PERFORM MANUAL MEMORY ALLOCATION ETC HAVING SOME MINIMAL EXPERIENCE IN C

SCIKITLEARN USER GUIDE RELEASE 0213
C IS PRETTY MUCH MANDATORY HERE
• MASTER YOUR TOOLS
–WITH SUCH A BIG PROJECT BEING EFFICIENT WITH YOUR FAVORITE EDITOR OR IDE GOES A LONG WAY TOWARDS DIGESTING THE CODE BASE BEING ABLE TO QUICKLY JUMP OR PEEK TO A FUNCTIONCLASSATTRIBUTE DEFINITION HELPS A LOT SO DOES BEING ABLE TO QUICKLY SEE WHERE A GIVEN NAME IS USED IN A FILE
–GIT ALSO HAS SOME BUILTIN KILLER FEATURES IT IS OFTEN USEFUL TO UNDERSTAND HOW A FILE CHANGED OVER TIME USING EGGIT BLAME MANUAL THIS CAN ALSO BE DONE DIRECTLY ON GITHUB GIT GREP EXAMPLES IS ALSO EXTREMELY USEFUL TO SEE EVERY OCCURRENCE OF A PATTERN EG A FUNCTION CALL OR A VARIABLE IN THE CODE BASE
72 DEVELOPERS' TIPS AND TRICKS
721 PRODUCTIVITY AND SANITYPRESERVING TIPS
IN THIS SECTION WE GATHER SOME USEFUL ADVICE AND TOOLS THAT MAY INCREASE YOUR QUALITYOFLIFE WHEN REVIEWING PULL REQUESTS RUNNING UNIT TESTS AND SO FORTH SOME OF THESE TRICKS CONSIST OF USERSCRIPTS THAT REQUIRE A BROWSER EXTENSION SUCH AS TAMPERMONKEY OR GREASEMONKEY TO SET UP USERSCRIPTS YOU MUST HAVE ONE OF THESE EXTENSIONS INSTALLED ENABLED AND RUNNING WE PROVIDE USERSCRIPTS AS GITHUB GISTS TO INSTALL THEM CLICK ON THE "RAW" BUTTON ON THE GIST PAGE
VIEWING THE RENDERED HTML DOCUMENTATION FOR A PULL REQUEST
WE USE CIRCLECI TO BUILD THE HTML DOCUMENTATION FOR EVERY PULL REQUEST TO ACCESS THAT DOCUMENTATION INSTRUCTIONS ARE PROVIDED IN THE DOCUMENTATION SECTION OF THE CONTRIBUTOR GUIDE TO SAVE YOU A FEW CLICKS WE PROVIDE A USERSCRIPT THAT ADDS A BUTTON TO EVERY PR AFTER INSTALLING THE USERSCRIPT NAVIGATE TO ANY GITHUB PR A NEW BUTTON LABELED "SEE CIRCLECI DOC FOR THIS PR" SHOULD APPEAR IN THE TOPRIGHT AREA
FOLDING AND UNFOLDING OUTDATED DIFFS ON PULL REQUESTS
GITHUB HIDES DISCUSSIONS ON PRS WHEN THE CORRESPONDING LINES OF CODE HAVE BEEN CHANGED IN THE MEAN WHILE THIS USERSCRIPT PROVIDES A SHORTCUT CONTROLALTP AT THE TIME OF WRITING BUT LOOK AT THE CODE TO BE SURE TO UNFOLD ALL SUCH HIDDEN DISCUSSIONS AT ONCE SO YOU CAN CATCH UP
CHECKING OUT PULL REQUESTS AS REMOTETRACKING BRANCHES
IN YOUR LOCAL FORK ADD TO YOUR GITCONFIG UNDER THEREMOTE UPSTREAM HEADING THE LINE
FETCH REFSPULL HEADREFSREMOTESUPSTREAMPR
YOU MAY THEN USE GIT CHECKOUT PRPRNUMBER TO NAVIGATE TO THE CODE OF THE PULLREQUEST WITH THE GIVEN NUMBER READ MORE IN THIS GIST
DISPLAY CODE COVERAGE IN PULL REQUESTS
TO OVERLAY THE CODE COVERAGE REPORTS GENERATED BY THE CODECOV CONTINUOUS INTEGRATION CONSIDER THIS BROWSER EXTEN SION THE COVERAGE OF EACH LINE WILL BE DISPLAYED AS A COLOR BACKGROUND BEHIND THE LINE NUMBER

USEFUL PYTEST ALIASES AND FLAGS
THE FULL TEST SUITE TAKES FAIRLY LONG TO RUN FOR FASTER ITERATIONS IT IS POSSIBLY TO SELECT A SUBSET OF TESTS USING PYTEST
SELECTORS IN PARTICULAR ONE CAN RUN A SINGLE TEST BASED ON ITS NODE ID
PYTEST V SKLEARNLINEARMODELTESTSTESTLOGISTICPYTESTSPARSIFY
OR USE THE K PYTEST PARAMETER TO SELECT TESTS BASED ON THEIR NAME FOR INSTANCE
PYTEST SKLEARNTESTSTESTCOMMONPY V K LOGISTICREGRESSION
WILL RUN ALL COMMON TESTS FOR THELOGISTICREGRESSION ESTIMATOR
WHEN A UNIT TEST FAILS THE FOLLOWING TRICKS CAN MAKE DEBUGGING EASIER
1 THE COMMAND LINE ARGUMENT PYTEST L INSTRUCTS PYTEST TO PRINT THE LOCAL VARIABLES WHEN A FAILURE OCCURS
2 THE ARGUMENT PYTEST PDB DROPS INTO THE PYTHON DEBUGGER ON FAILURE TO INSTEAD DROP INTO THE RICH IPYTHON
DEBUGGERIPDB YOU MAY SET UP A SHELL ALIAS TO
PYTEST PDBCLSIPYTHONTERMINALDEBUGGERTERMINALPDB CAPTURE NO
OTHERPYTEST OPTIONS THAT MAY BECOME USEFUL INCLUDE
•XWHICH EXITS ON THE FIRST FAILED TEST
•LF TO RERUN THE TESTS THAT FAILED ON THE PREVIOUS RUN
•FF TO RERUN ALL PREVIOUS TESTS RUNNING THE ONES THAT FAILED FIRST
•SSO THAT PYTEST DOES NOT CAPTURE THE OUTPUT OF PRINT STATEMENTS
•TBSHORT ORTBLINE TO CONTROL THE LENGTH OF THE LOGS
SINCE OUR CONTINUOUS INTEGRATION TESTS WILL ERROR IF DEPRECATIONWARNING ORFUTUREWARNING AREN’T PROP
ERLY CAUGHT IT IS ALSO RECOMMENDED TO RUN PYTEST ALONG WITH THE WERRORDEPRECATIONWARNING AND
WERRORFUTUREWARNING FLAGS
STANDARD REPLIES FOR REVIEWING
IT MAY BE HELPFUL TO STORE SOME OF THESE IN GITHUB’S SAVED REPLIES FOR REVIEWING
ISSUE USAGE QUESTIONS
YOURE ASKING A USAGE QUESTION THE ISSUE TRACKER IS MAINLY FOR BUGS AND NEW
‹→FEATURES FOR USAGE QUESTIONS IT IS RECOMMENDED TO TRY STACK OVERFLOWHTTPS
‹→STACKOVERFLOWCOMQUESTIONSTAGGEDSCIKITLEARN OR THE MAILING LISTHTTPS
‹→MAILPYTHONORGMAILMANLISTINFOSCIKITLEARN
ISSUE YOU’RE WELCOME TO UPDATE THE DOCS
PLEASE FEEL FREE TO OFFER A PULL REQUEST UPDATING THE DOCUMENTATION IF YOU FEEL
‹→IT COULD BE IMPROVED
ISSUE SELFCONTAINED EXAMPLE FOR BUG
PLEASE PROVIDE SELFCONTAINED EXAMPLE CODEHTTPSSTACKOVERFLOWCOMHELPMCVE
‹→INCLUDING IMPORTS AND DATA IF POSSIBLE SO THAT OTHER CONTRIBUTORS CAN JUST
‹→RUN IT AND REPRODUCE YOUR ISSUE IDEALLY YOUR EXAMPLE CODE SHOULD BE MINIMAL

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ISSUE SOFTWARE VERSIONS
TO HELP DIAGNOSE YOUR ISSUE PLEASE PASTE THE OUTPUT OF
PY
IMPORT SKLEARN SKLEARNSHOWVERSIONS

THANKS
ISSUE CODE BLOCKS
READABILITY CAN BE GREATLY IMPROVED IF YOU FORMATHTTPSHELPGITHUBCOM
‹→ARTICLESCREATINGANDHIGHLIGHTINGCODEBLOCKS YOUR CODE SNIPPETS AND
‹→COMPLETE ERROR MESSAGES APPROPRIATELY FOR EXAMPLE
PYTHON
PRINTSOMETHING

GENERATES
PYTHON
PRINTSOMETHING

AND
PYTB
TRACEBACK MOST RECENT CALL LAST
FILE STDIN LINE 1 IN MODULE
IMPORTERROR NO MODULE NAMED HELLO

GENERATES
PYTB
TRACEBACK MOST RECENT CALL LAST
FILE STDIN LINE 1 IN MODULE
IMPORTERROR NO MODULE NAMED HELLO

YOU CAN EDIT YOUR ISSUE DESCRIPTIONS AND COMMENTS AT ANY TIME TO IMPROVE
‹→READABILITY THIS HELPS MAINTAINERS A LOT THANKS
ISSUECOMMENT LINKING TO CODE
FRIENDLY ADVICE FOR CLARITYS SAKE YOU CAN LINK TO CODE LIKE THISHTTPS
‹→HELPGITHUBCOMARTICLESCREATINGAPERMANENTLINKTOACODESNIPPET
ISSUECOMMENT LINKING TO COMMENTS
PLEASE USE LINKS TO COMMENTS WHICH MAKE IT A LOT EASIER TO SEE WHAT YOU ARE
‹→REFERRING TO RATHER THAN JUST LINKING TO THE ISSUE SEE THISHTTPS
‹→STACKOVERFLOWCOMQUESTIONS25163598HOWDOIREFERENCEASPECIFICISSUE
‹→COMMENTONGITHUB FOR MORE DETAILS
PRNEW BETTER DESCRIPTION
THANKS FOR THE PULL REQUEST PLEASE MAKE THE TITLE OF THE PR DESCRIPTIVE SO THAT
‹→WE CAN EASILY RECALL THE ISSUE IT IS RESOLVING YOU SHOULD STATE WHAT ISSUE OR
‹→PR IT FIXESRESOLVES IN THE DESCRIPTION SEE HEREHTTPSCIKITLEARNORG
‹→DEVDEVELOPERSCONTRIBUTINGHTMLCONTRIBUTINGPULLREQUESTS
PRNEW FIX

PLEASE USE FIX ISSUENUMBER IN YOUR PR DESCRIPTION AND YOU CAN DO IT MORE THAN
‹→ONCE THIS WAY THE ASSOCIATED ISSUE GETS CLOSED AUTOMATICALLY WHEN THE PR IS
‹→MERGED FOR MORE DETAILS LOOK AT THISHTTPSGITHUBCOMBLOG1506CLOSING
‹→ISSUESVIAPULLREQUESTS
PRNEW OR ISSUE MAINTENANCE COST
EVERY FEATURE WE INCLUDE HAS A MAINTENANCE COSTHTTPSCIKITLEARNORGDEVFAQ
‹→HTMLWHYAREYOUSOSELECTIVEONWHATALGORITHMSYOUINCLUDEINSCIKITLEARN
‹→OUR MAINTAINERS ARE MOSTLY VOLUNTEERS FOR A NEW FEATURE TO BE INCLUDED WE
‹→NEED EVIDENCE THAT IT IS OFTEN USEFUL AND IDEALLY WELLESTABLISHEDHTTP
‹→SCIKITLEARNORGDEVFAQHTMLWHATARETHEINCLUSIONCRITERIAFORNEW
‹→ALGORITHMS IN THE LITERATURE OR IN PRACTICE THAT DOESNT STOP YOU
‹→IMPLEMENTING IT FOR YOURSELF AND PUBLISHING IT IN A SEPARATE REPOSITORY OR
‹→EVEN SCIKITLEARNCONTRIBHTTPSSCIKITLEARNCONTRIBGITHUBIO
PRWIP WHAT’S NEEDED BEFORE MERGE
PLEASE CLARIFY PERHAPS AS A TODO LIST IN THE PR DESCRIPTION WHAT WORK YOU
‹→BELIEVE STILL NEEDS TO BE DONE BEFORE IT CAN BE REVIEWED FOR MERGE WHEN IT IS
‹→READY PLEASE PREFIX THE PR TITLE WITH MRG
PRWIP REGRESSION TEST NEEDED
PLEASE ADD A NONREGRESSION TESTHTTPSENWIKIPEDIAORGWIKINONREGRESSION
‹→TESTING THAT WOULD FAIL AT MASTER BUT PASS IN THIS PR
PRWIP PEP8
YOU HAVE SOME PEP8HTTPSWWWPYTHONORGDEVPEPSPEP0008 VIOLATIONS WHOSE
‹→DETAILS YOU CAN SEE IN THE CIRCLE CI LINT JOB IT MIGHT BE WORTH CONFIGURING
‹→YOUR CODE EDITOR TO CHECK FOR SUCH ERRORS ON THE FLY SO YOU CAN CATCH THEM
‹→BEFORE COMMITTING
PRMRG PATIENCE
BEFORE MERGING WE GENERALLY REQUIRE TWO CORE DEVELOPERS TO AGREE THAT YOUR PULL
‹→REQUEST IS DESIRABLE AND READY PLEASE BE PATIENTHTTPSCIKITLEARNORGDEV
‹→FAQHTMLWHYISMYPULLREQUESTNOTGETTINGANYATTENTION AS WE MOSTLY RELY
‹→ON VOLUNTEERED TIME FROM BUSY CORE DEVELOPERS YOU ARE ALSO WELCOME TO HELP US
‹→OUT WITH REVIEWING OTHER PRSHTTPSCIKITLEARNORGDEVDEVELOPERS
‹→CONTRIBUTINGHTMLCODEREVIEWGUIDELINES
PRMRG ADD TO WHAT’S NEW
PLEASE ADD AN ENTRY TO THE CHANGE LOG AT DOCWHATSNEWV RST LIKE THE OTHER
‹→ENTRIES THERE PLEASE REFERENCE THIS PULL REQUEST WITH PR AND CREDIT
‹→YOURSELF AND OTHER CONTRIBUTORS IF APPLICABLE WITH USER
PR DON’T CHANGE UNRELATED
PLEASE DO NOT CHANGE UNRELATED LINES IT MAKES YOUR CONTRIBUTION HARDER TO REVIEW
‹→AND MAY INTRODUCE MERGE CONFLICTS TO OTHER PULL REQUESTS

722 DEBUGGING MEMORY ERRORS IN CYTHON WITH VALGRIND

WHILE PYTHONNUMPY'S BUILTIN MEMORY MANAGEMENT IS RELATIVELY ROBUST IT CAN LEAD TO PERFORMANCE PENALTIES FOR SOME ROUTINES FOR THIS REASON MUCH OF THE HIGHPERFORMANCE CODE IN SCIKITLEARN IN WRITTEN IN CYTHON THIS PERFORMANCE GAIN COMES WITH A TRADEOFF HOWEVER IT IS VERY EASY FOR MEMORY BUGS TO CROP UP IN CYTHON CODE ESPECIALLY IN SITUATIONS WHERE THAT CODE RELIES HEAVILY ON POINTER ARITHMETIC

MEMORY ERRORS CAN MANIFEST THEMSELVES A NUMBER OF WAYS THE EASIEST ONES TO DEBUG ARE OFTEN SEGMENTATION FAULTS AND RELATED GLIBC ERRORS UNINITIALIZED VARIABLES CAN LEAD TO UNEXPECTED BEHAVIOR THAT IS DIFFICULT TO TRACK DOWN A VERY USEFUL TOOL WHEN DEBUGGING THESE SORTS OF ERRORS IS VALGRIND

VALGRIND IS A COMMANDLINE TOOL THAT CAN TRACE MEMORY ERRORS IN A VARIETY OF CODE FOLLOW THESE STEPS

1 INSTALL VALGRIND ON YOUR SYSTEM

2 DOWNLOAD THE PYTHON VALGRIND SUPPRESSION FILE VALGRINDPYTHONSUPP

3 FOLLOW THE DIRECTIONS IN THE READMEVALGRIND FILE TO CUSTOMIZE YOUR PYTHON SUPPRESSIONS IF YOU DON'T YOU WILL HAVE SPURIOUS OUTPUT COMING RELATED TO THE PYTHON INTERPRETER INSTEAD OF YOUR OWN CODE

4 RUN VALGRIND AS FOLLOWS

VALGRIND V SUPPRESSIONSVALGRINDPYTHONSUPP PYTHON MYTESTSCRIPTPY

THE RESULT WILL BE A LIST OF ALL THE MEMORYRELATED ERRORS WHICH REFERENCE LINES IN THE CCODE GENERATED BY CYTHON FROM YOUR PYX FILE IF YOU EXAMINE THE REFERENCED LINES IN THE C FILE YOU WILL SEE COMMENTS WHICH INDICATE THE CORRESPONDING LOCATION IN YOUR PYX SOURCE FILE HOPEFULLY THE OUTPUT WILL GIVE YOU CLUES AS TO THE SOURCE OF YOUR MEMORY ERROR

FOR MORE INFORMATION ON VALGRIND AND THE ARRAY OF OPTIONS IT HAS SEE THE TUTORIALS AND DOCUMENTATION ON THE VALGRIND WEB SITE

73 UTILITIES FOR DEVELOPERS

SCIKITLEARN CONTAINS A NUMBER OF UTILITIES TO HELP WITH DEVELOPMENT THESE ARE LOCATED IN SKLEARNUTILS AND INCLUDE TOOLS IN A NUMBER OF CATEGORIES ALL THE FOLLOWING FUNCTIONS AND CLASSES ARE IN THE MODULE SKLEARNUTILS WARNING THESE UTILITIES ARE MEANT TO BE USED INTERNALLY WITHIN THE SCIKITLEARN PACKAGE THEY ARE NOT GUAR ANTEED TO BE STABLE BETWEEN VERSIONS OF SCIKITLEARN BACKPORTS IN PARTICULAR WILL BE REMOVED AS THE SCIKITLEARN DEPENDENCIES EVOLVE

731 VALIDATION TOOLS

THESE ARE TOOLS USED TO CHECK AND VALIDATE INPUT WHEN YOU WRITE A FUNCTION WHICH ACCEPTS ARRAYS MATRICES OR SPARSE MATRICES AS ARGUMENTS THE FOLLOWING SHOULD BE USED WHEN APPLICABLE

•ASSERTALLFINITE THROW AN ERROR IF ARRAY CONTAINS NANS OR INFS

•ASFLOATARRAY CONVERT INPUT TO AN ARRAY OF FLOATS IF A SPARSE MATRIX IS PASSED A SPARSE MATRIX WILL BE RETURNED

•CHECKARRAY CHECK THAT INPUT IS A 2D ARRAY RAISE ERROR ON SPARSE MATRICES ALLOWED SPARSE MATRIX FORMATS CAN BE GIVEN OPTIONALLY AS WELL AS ALLOWING 1D OR NDIMENSIONAL ARRAYS CALLS ASSERTALLFINITE BY DEFAULT

•CHECKXY CHECK THAT X AND Y HAVE CONSISTENT LENGTH CALLS CHECKARRAY ON X AND COLUMNOR1D ON Y FOR MULTILABEL CLASSIFICATION OR MULTITARGET REGRESSION SPECIFY MULTIOUTPUTTRUE IN WHICH CASE CHECKARRAY WILL BE CALLED ON Y
•INDEXABLE CHECK THAT ALL INPUT ARRAYS HAVE CONSISTENT LENGTH AND CAN BE SLICED OR INDEXED USING SAFEINDEX THIS IS USED TO VALIDATE INPUT FOR CROSSVALIDATION
•VALIDATIONCHECKMEMORY CHECKS THAT INPUT IS JOBLIBMEMORY LIKE WHICH MEANS THAT IT CAN BE CONVERTED INTO A SKLEARNUTILSMEMORY INSTANCE TYPICALLY A STR DENOTING THE CACHEDIR OR HAS THE SAME INTERFACE
IF YOUR CODE RELIES ON A RANDOM NUMBER GENERATOR IT SHOULD NEVER USE FUNCTIONS LIKE NUMPYRANDOMRANDOM ORNUMPYRANDOMNORMAL THIS APPROACH CAN LEAD TO REPEATABILITY ISSUES IN UNIT TESTS INSTEAD A NUMPY RANDOMRANDOMSTATE OBJECT SHOULD BE USED WHICH IS BUILT FROM A RANDOMSTATE ARGUMENT PASSED TO THE CLASS OR FUNCTION THE FUNCTION CHECKRANDOMSTATE BELOW CAN THEN BE USED TO CREATE A RANDOM NUMBER GENERATOR OBJECT
•CHECKRANDOMSTATE CREATE ANPRANDOMRANDOMSTATE OBJECT FROM A PARAMETER RANDOMSTATE
–IFRANDOMSTATE ISNONE ORNPRANDOM THEN A RANDOMLYINITIALIZED RANDOMSTATE OBJECT IS RE TURNED
–IFRANDOMSTATE IS AN INTEGER THEN IT IS USED TO SEED A NEW RANDOMSTATE OBJECT
–IFRANDOMSTATE IS ARANDOMSTATE OBJECT THEN IT IS PASSED THROUGH
FOR EXAMPLE
```
 FROM SKLEARNUTILS IMPORT CHECKRANDOMSTATE
RANDOMSTATE  0
RANDOMSTATE  CHECKRANDOMSTATERANDOMSTATE
RANDOMSTATERAND4
ARRAY05488135  071518937 060276338 054488318
```
WHEN DEVELOPING YOUR OWN SCIKITLEARN COMPATIBLE ESTIMATOR THE FOLLOWING HELPERS ARE AVAILABLE
•VALIDATIONCHECKISFITTED CHECK THAT THE ESTIMATOR HAS BEEN FITTED BEFORE CALLING TRANSFORM PREDICT OR SIMILAR METHODS THIS HELPER ALLOWS TO RAISE A STANDARDIZED ERROR MESSAGE ACROSS ESTIMATOR
•VALIDATIONHASFITPARAMETER CHECK THAT A GIVEN PARAMETER IS SUPPORTED IN THE FIT METHOD OF A GIVEN ESTIMATOR
732 EFFICIENT LINEAR ALGEBRA ARRAY OPERATIONS
•EXTMATHRANDOMIZEDRANGEFINDER CONSTRUCT AN ORTHONORMAL MATRIX WHOSE RANGE APPROXIMATES THE RANGE OF THE INPUT THIS IS USED IN EXTMATHRANDOMIZEDSVD BELOW
•EXTMATHRANDOMIZEDSVD COMPUTE THE KTRUNCATED RANDOMIZED SVD THIS ALGORITHM FINDS THE EXACT TRUNCATED SINGULAR VALUES DECOMPOSITION USING RANDOMIZATION TO SPEED UP THE COMPUTATIONS IT IS PARTICULARLY FAST ON LARGE MATRICES ON WHICH YOU WISH TO EXTRACT ONLY A SMALL NUMBER OF COMPONENTS
•ARRAYFUNCSCHOLESKYDELETE USED INSKLEARNLINEARMODELLARSPATH REMOVE AN ITEM FROM A CHOLESKY FACTORIZATION
•ARRAYFUNCSMINPOS USED INSKLEARNLINEARMODELLEASTANGLE FIND THE MINIMUM OF THE POSITIVE VALUES WITHIN AN ARRAY
•EXTMATHFASTLOGDET EFFICIENTLY COMPUTE THE LOG OF THE DETERMINANT OF A MATRIX
•EXTMATHDENSITY EFFICIENTLY COMPUTE THE DENSITY OF A SPARSE VECTOR

•EXTMATHSAFESPARSEDOT DOT PRODUCT WHICH WILL CORRECTLY HANDLE SCIPYSPARSE INPUTS IF THE INPUTS ARE DENSE IT IS EQUIVALENT TO NUMPYDOT
•EXTMATHWEIGHTEDMODE AN EXTENSION OF SCIPYSTATSMODE WHICH ALLOWS EACH ITEM TO HAVE A REAL VALUED WEIGHT
•RESAMPLE RESAMPLE ARRAYS OR SPARSE MATRICES IN A CONSISTENT WAY USED IN SHUFFLE BELOW
•SHUFFLE SHUFFLE ARRAYS OR SPARSE MATRICES IN A CONSISTENT WAY USED IN SKLEARNCLUSTERKMEANS

733 EFFICIENT RANDOM SAMPLING

•RANDOMSAMPLEWITHOUTREPLACEMENT IMPLEMENTS EFFICIENT ALGORITHMS FOR SAMPLING NSAMPLES INTEGERS FROM A POPULATION OF SIZE NPOPULATION WITHOUT REPLACEMENT

734 EFFICIENT ROUTINES FOR SPARSE MATRICES

THESKLEARNUTILSSPARSEFUNCS CYTHON MODULE HOSTS COMPILED EXTENSIONS TO EFFICIENTLY PROCESS SCIPY SPARSE DATA
•SPARSEFUNCSMEANVARIANCEAXIS COMPUTE THE MEANS AND VARIANCES ALONG A SPECIFIED AXIS OF A CSR MATRIX USED FOR NORMALIZING THE TOLERANCE STOPPING CRITERION IN SKLEARNCLUSTERKMEANS
•SPARSEFUNCSFASTINPLACECSRROWNORMALIZEL1 ANDSPARSEFUNCSFAST INPLACECSRROWNORMALIZEL2 CAN BE USED TO NORMALIZE INDIVIDUAL SPARSE SAMPLES TO UNIT L1 OR L2 NORM AS DONE IN SKLEARNPREPROCESSINGNORMALIZER
•SPARSEFUNCSINPLACECSRCOLUMNSCALE CAN BE USED TO MULTIPLY THE COLUMNS OF A CSR MATRIX BY A CONSTANT SCALE ONE SCALE PER COLUMN USED FOR SCALING FEATURES TO UNIT STANDARD DEVIATION IN SKLEARN PREPROCESSINGSTANDARDSCALER

735 GRAPH ROUTINES

•GRAPHSINGLESOURCESHORTESTPATHLENGTH NOT CURRENTLY USED IN SCIKITLEARN RETURN THE SHORTEST PATH FROM A SINGLE SOURCE TO ALL CONNECTED NODES ON A GRAPH CODE IS ADAPTED FROM NETWORKX IF THIS IS EVER NEEDED AGAIN IT WOULD BE FAR FASTER TO USE A SINGLE ITERATION OF DIJKSTRA'S ALGORITHM FROM GRAPHSHORTESTPATH
•GRAPHSHORTESTPATHGRAPHSHORTESTPATH USED INSKLEARNMANIFOLDISOMAP RETURN THE SHORTEST PATH BETWEEN ALL PAIRS OF CONNECTED POINTS ON A DIRECTED OR UNDIRECTED GRAPH BOTH THE FLOYD WARSHALL ALGORITHM AND DIJKSTRA'S ALGORITHM ARE AVAILABLE THE ALGORITHM IS MOST EFFICIENT WHEN THE CONNECTIVITY MATRIX IS ASCIPYSPARSECSRMATRIX

736 TESTING FUNCTIONS

•TESTINGASSERTIN TESTINGASSERTNOTIN ASSERTIONS FOR CONTAINER MEMBERSHIP DESIGNED FOR FORWARD COMPATIBILITY WITH NOSE 10
•TESTINGASSERTRAISEMESSAGE ASSERTIONS FOR CHECKING THE ERROR RAISE MESSAGE
•TESTINGMOCKMLDATAURLOPEN MOCKS THE URLOPEN FUNCTION TO FAKE REQUESTS TO MLDATAORG USED IN TESTS OFSKLEARNDATASETS
•TESTINGALLESTIMATORS RETURNS A LIST OF ALL ESTIMATORS IN SCIKITLEARN TO TEST FOR CONSISTENT BEHAVIOR AND INTERFACES

737 MULTICLASS AND MULTILABEL UTILITY FUNCTION
•MULTICLASSISMULTILABEL HELPER FUNCTION TO CHECK IF THE TASK IS A MULTILABEL CLASSIFICATION ONE
•MULTICLASSUNIQUELABELS HELPER FUNCTION TO EXTRACT AN ORDERED ARRAY OF UNIQUE LABELS FROM DIFFERENT FORMATS OF TARGET
738 HELPER FUNCTIONS
•GENEVENSLICES GENERATOR TO CREATE NPACKS OF SLICES GOING UP TO N USED IN SKLEARN DECOMPOSITIONDICTLEARNING ANDSKLEARNCLUSTERKMEANS
•SAFEMASK HELPER FUNCTION TO CONVERT A MASK TO THE FORMAT EXPECTED BY THE NUMPY ARRAY OR SCIPY SPARSE MATRIX ON WHICH TO USE IT SPARSE MATRICES SUPPORT INTEGER INDICES ONLY WHILE NUMPY ARRAYS SUPPORT BOTH BOOLEAN MASKS AND INTEGER INDICES
•SAFESQR HELPER FUNCTION FOR UNIFIED SQUARING 2 OF ARRAYLIKES MATRICES AND SPARSE MATRICES
739 HASH FUNCTIONS
•MURMURHASH332 PROVIDES A PYTHON WRAPPER FOR THE MURMURHASH3X8632 C NON CRYPTOGRAPHIC HASH FUNCTION THIS HASH FUNCTION IS SUITABLE FOR IMPLEMENTING LOOKUP TABLES BLOOM FILTERS COUNT MIN SKETCH FEATURE HASHING AND IMPLICITLY DEFINED SPARSE RANDOM PROJECTIONS

```
 FROM SKLEARNUTILS IMPORT MURMURHASH332
MURMURHASH332SOME FEATURE SEED0  384616559
TRUE
MURMURHASH332SOME FEATURE SEED0 POSITIVE TRUE  3910350737
TRUE
```

THESKLEARNUTILSMURMURHASH MODULE CAN ALSO BE “CIMPORTED” FROM OTHER CYTHON MODULES SO AS TO BENEFIT FROM THE HIGH PERFORMANCE OF MURMURHASH WHILE SKIPPING THE OVERHEAD OF THE PYTHON INTERPRETER
7310 WARNINGS AND EXCEPTIONS
•DEPRECATED DECORATOR TO MARK A FUNCTION OR CLASS AS DEPRECATED
•SKLEARNEXCEPTIONSCONVERGENCEWARNING CUSTOM WARNING TO CATCH CONVERGENCE PROBLEMS USED INSKLEARNCOVARIANCEGRAPHICALLASSO
74 HOW TO OPTIMIZE FOR SPEED
THE FOLLOWING GIVES SOME PRACTICAL GUIDELINES TO HELP YOU WRITE EFFICIENT CODE FOR THE SCIKITLEARN PROJECT
NOTE WHILE IT IS ALWAYS USEFUL TO PROFILE YOUR CODE SO AS TO CHECK PERFORMANCE ASSUMPTIONS IT IS ALSO HIGHLY RECOMMENDED TO REVIEW THE LITERATURE TO ENSURE THAT THE IMPLEMENTED ALGORITHM IS THE STATE OF THE ART FOR THE TASK BEFORE INVESTING INTO COSTLY IMPLEMENTATION OPTIMIZATION
TIMES AND TIMES HOURS OF EFFORTS INVESTED IN OPTIMIZING COMPLICATED IMPLEMENTATION DETAILS HAVE BEEN RENDERED IRRELEVANT BY THE SUBSEQUENT DISCOVERY OF SIMPLE ALGORITHMIC TRICKS OR BY USING ANOTHER ALGORITHM ALTOGETHER THAT IS BETTER SUITED TO THE PROBLEM

THE SECTION A SIMPLE ALGORITHMIC TRICK WARM RESTARTS GIVES AN EXAMPLE OF SUCH A TRICK

741 PYTHON CYTHON OR CC

IN GENERAL THE SCIKITLEARN PROJECT EMPHASIZES THE READABILITY OF THE SOURCE CODE TO MAKE IT EASY FOR THE PROJECT USERS TO DIVE INTO THE SOURCE CODE SO AS TO UNDERSTAND HOW THE ALGORITHM BEHAVES ON THEIR DATA BUT ALSO FOR EASE OF MAINTAINABILITY BY THE DEVELOPERS

WHEN IMPLEMENTING A NEW ALGORITHM IS THUS RECOMMENDED TO START IMPLEMENTING IT IN PYTHON USING NUMPY AND SCIPY BY TAKING CARE OF AVOIDING LOOPING CODE USING THE VECTORIZED IDIOMS OF THOSE LIBRARIES IN PRACTICE THIS MEANS TRYING TO REPLACE ANY NESTED FOR LOOPS BY CALLS TO EQUIVALENT NUMPY ARRAY METHODS THE GOAL IS TO AVOID THE CPU WASTING TIME IN THE PYTHON INTERPRETER RATHER THAN CRUNCHING NUMBERS TO FIT YOUR STATISTICAL MODEL IT'S GENERALLY A GOOD IDEA TO CONSIDER NUMPY AND SCIPY PERFORMANCE TIPS HTTPSSCIPYGITHUBIOOLDWIKIPAGESPERFORMANCETIPS

SOMETIMES HOWEVER AN ALGORITHM CANNOT BE EXPRESSED EFFICIENTLY IN SIMPLE VECTORIZED NUMPY CODE IN THIS CASE THE RECOMMENDED STRATEGY IS THE FOLLOWING

1PROFILE THE PYTHON IMPLEMENTATION TO FIND THE MAIN BOTTLENECK AND ISOLATE IT IN A DEDICATED MODULE LEVEL FUNC TION THIS FUNCTION WILL BE REIMPLEMENTED AS A COMPILED EXTENSION MODULE

2 IF THERE EXISTS A WELL MAINTAINED BSD OR MIT CC IMPLEMENTATION OF THE SAME ALGORITHM THAT IS NOT TOO BIG YOU CAN WRITE A CYTHON WRAPPER FOR IT AND INCLUDE A COPY OF THE SOURCE CODE OF THE LIBRARY IN THE SCIKIT LEARN SOURCE TREE THIS STRATEGY IS USED FOR THE CLASSES SVMLINEARSVC SVMSVC ANDLINEARMODEL LOGISTICREGRESSION WRAPPERS FOR LIBLINEAR AND LIBSVM

3 OTHERWISE WRITE AN OPTIMIZED VERSION OF YOUR PYTHON FUNCTION USING CYTHON DIRECTLY THIS STRATEGY IS USED FOR THELINEARMODELELASTICNET ANDLINEARMODELSGDCLASSIFIER CLASSES FOR INSTANCE

4MOVE THE PYTHON VERSION OF THE FUNCTION IN THE TESTS AND USE IT TO CHECK THAT THE RESULTS OF THE COMPILED EXTENSION ARE CONSISTENT WITH THE GOLD STANDARD EASY TO DEBUG PYTHON VERSION

5 ONCE THE CODE IS OPTIMIZED NOT SIMPLE BOTTLENECK SPOTTABLE BY PROFILING CHECK WHETHER IT IS POSSIBLE TO HAVE COARSE GRAINED PARALLELISM THAT IS AMENABLE TO MULTIPROCESSING BY USING THE JOBLIBPARALLEL CLASS

WHEN USING CYTHON USE EITHER

```
 PYTHON SETUPPY BUILDEXT I  PYTHON SETUPPY INSTALL
```

TO GENERATE C FILES YOU ARE RESPONSIBLE FOR ADDING CCPP EXTENSIONS ALONG WITH BUILD PARAMETERS IN EACH SUBMODULE SETUPPY

CC GENERATED FILES ARE EMBEDDED IN DISTRIBUTED STABLE PACKAGES THE GOAL IS TO MAKE IT POSSIBLE TO INSTALL SCIKITLEARN STABLE VERSION ON ANY MACHINE WITH PYTHON NUMPY SCIPY AND CC COMPILER

742 PROFILING PYTHON CODE

IN ORDER TO PROFILE PYTHON CODE WE RECOMMEND TO WRITE A SCRIPT THAT LOADS AND PREPARE YOU DATA AND THEN USE THE IPYTHON INTEGRATED PROFILER FOR INTERACTIVELY EXPLORING THE RELEVANT PART FOR THE CODE

SUPPOSE WE WANT TO PROFILE THE NON NEGATIVE MATRIX FACTORIZATION MODULE OF SCIKITLEARN LET US SETUP A NEW IPYTHON SESSION AND LOAD THE DIGITS DATASET AND AS IN THE RECOGNIZING HANDWRITTEN DIGITS EXAMPLE

```
IN 1 FROM SKLEARNDECOMPOSITION IMPORT NMF
IN 2 FROM SKLEARNDATASETS IMPORT LOADDIGITS
IN 3 X  LOADDIGITSDATA
```

BEFORE STARTING THE PROFILING SESSION AND ENGAGING IN TENTATIVE OPTIMIZATION ITERATIONS IT IS IMPORTANT TO MEASURE THE TOTAL EXECUTION TIME OF THE FUNCTION WE WANT TO OPTIMIZE WITHOUT ANY KIND OF PROFILER OVERHEAD AND SAVE IT SOMEWHERE FOR LATER REFERENCE

```
IN 4 TIMEIT NMFNCOMPONENTS16 TOL1E2FITX
1 LOOPS BEST OF 3 17 S PER LOOP
```

TO HAVE A LOOK AT THE OVERALL PERFORMANCE PROFILE USING THE PRUN MAGIC COMMAND

```
IN 5 PRUN L NMFPY NMFNCOMPONENTS16 TOL1E2FITX
14496 FUNCTION CALLS IN1682 CPU SECONDS
ORDERED BY INTERNAL TIME
LIST REDUCED FROM90 TO 9 DUE TO RESTRICTION NMFPY
NCALLS TOTTIME PERCALL CUMTIME PERCALL FILENAMELINENOFUNCTION
36 0609 0017 1499 0042 NMFPY151NLSSUBPROBLEM
1263 0157 0000 0157 0000 NMFPY18POS
1 0053 0053 1681 1681 NMFPY352FITTRANSFORM
673 0008 0000 0057 0000 NMFPY28NORM
1 0006 0006 0047 0047 NMFPY42INITIALIZENMF
36 0001 0000 0010 0000 NMFPY36SPARSENESS
30 0001 0000 0001 0000 NMFPY23NEG
1 0000 0000 0000 0000 NMFPY337INIT
1 0000 0000 1681 1681 NMFPY461FIT
```

THETOTTIME COLUMN IS THE MOST INTERESTING IT GIVES TO TOTAL TIME SPENT EXECUTING THE CODE OF A GIVEN FUNCTION IGNORING THE TIME SPENT IN EXECUTING THE SUBFUNCTIONS THE REAL TOTAL TIME LOCAL CODE SUBFUNCTION CALLS IS GIVEN BY THECUMTIME COLUMN

NOTE THE USE OF THE L NMFPY THAT RESTRICTS THE OUTPUT TO LINES THAT CONTAINS THE “NMFPY” STRING THIS IS USEFUL TO HAVE A QUICK LOOK AT THE HOTSPOT OF THE NMF PYTHON MODULE ITSELF IGNORING ANYTHING ELSE

HERE IS THE BEGINNING OF THE OUTPUT OF THE SAME COMMAND WITHOUT THE L NMFPY FILTER

```
IN 5 PRUN NMFNCOMPONENTS16 TOL1E2FITX
16159 FUNCTION CALLS IN1840 CPU SECONDS
ORDERED BY INTERNAL TIME
NCALLS TOTTIME PERCALL CUMTIME PERCALL FILENAMELINENOFUNCTION
2833 0653 0000 0653 0000 NUMPYCOREDOTBLASDOT
46 0651 0014 1636 0036 NMFPY151NLSSUBPROBLEM
1397 0171 0000 0171 0000 NMFPY18POS
2780 0167 0000 0167 0000 METHOD SUM OF NUMPYNDARRAY
‹→OBJECTS
1 0064 0064 1840 1840 NMFPY352FITTRANSFORM
1542 0043 0000 0043 0000 METHOD FLATTEN OF NUMPYNDARRAY
‹→OBJECTS
337 0019 0000 0019 0000 METHOD ALL OF NUMPYNDARRAY
‹→OBJECTS
2734 0011 0000 0181 0000 FROMNUMERICPY1185SUM
2 0010 0005 0010 0005 NUMPYLINALGLAPACKLITEDGESDD
748 0009 0000 0065 0000 NMFPY28NORM
```

THE ABOVE RESULTS SHOW THAT THE EXECUTION IS LARGELY DOMINATED BY DOT PRODUCTS OPERATIONS DELEGATED TO BLAS HENCE THERE IS PROBABLY NO HUGE GAIN TO EXPECT BY REWRITING THIS CODE IN CYTHON OR CC IN THIS CASE OUT OF THE 17S TOTAL EXECUTION TIME ALMOST 07S ARE SPENT IN COMPILED CODE WE CAN CONSIDER OPTIMAL BY REWRITING THE REST OF THE PYTHON

CODE AND ASSUMING WE COULD ACHIEVE A 1000 BOOST ON THIS PORTION WHICH IS HIGHLY UNLIKELY GIVEN THE SHALLOWNESS
OF THE PYTHON LOOPS WE WOULD NOT GAIN MORE THAN A 24X SPEEDUP GLOBALLY
HENCE MAJOR IMPROVEMENTS CAN ONLY BE ACHIEVED BY ALGORITHMIC IMPROVEMENTS IN THIS PARTICULAR EXAMPLE EG
TRYING TO FIND OPERATION THAT ARE BOTH COSTLY AND USELESS TO AVOID COMPUTING THEN RATHER THAN TRYING TO OPTIMIZE THEIR
IMPLEMENTATION
IT IS HOWEVER STILL INTERESTING TO CHECK WHAT'S HAPPENING INSIDE THE NLSSUBPROBLEM FUNCTION WHICH IS THE HOTSPOT
IF WE ONLY CONSIDER PYTHON CODE IT TAKES AROUND 100 OF THE ACCUMULATED TIME OF THE MODULE IN ORDER TO BETTER
UNDERSTAND THE PROFILE OF THIS SPECIFIC FUNCTION LET US INSTALL LINEPROFILER AND WIRE IT TO IPYTHON
PIP INSTALL LINEPROFILER
•UNDER IPYTHON 013 FIRST CREATE A CONFIGURATION PROFILE
IPYTHON PROFILE CREATE
THEN REGISTER THE LINEPROFILER EXTENSION IN IPYTHONPROFILEDEFAULTIPYTHONCONFIGPY
CTERMINALIPYTHONAPPEXTENSIONSAPPENDLINEPROFILER
CINTERACTIVESHELLAPPEXTENSIONSAPPENDLINEPROFILER
THIS WILL REGISTER THE LPRUN MAGIC COMMAND IN THE IPYTHON TERMINAL APPLICATION AND THE OTHER FRONTENDS SUCH
AS QTCONSOLE AND NOTEBOOK
NOW RESTART IPYTHON AND LET US USE THIS NEW TOY
IN 1 FROM SKLEARNDATASETS IMPORT LOADDIGITS
IN 2 FROM SKLEARNDECOMPOSITIONNMF IMPORT NLSSUBPROBLEM NMF
IN 3 X LOADDIGITSDATA
IN 4 LPRUN F NLSSUBPROBLEM NMFNCOMPONENTS16 TOL1E2FITX
TIMER UNIT 1E06 S
FILE SKLEARNDECOMPOSITIONNMFPY
FUNCTION NLSSUBPROBLEM AT LINE 137
TOTAL TIME 173153 S
LINE HITS TIME PER HIT TIME LINE CONTENTS

137 DEFNLSSUBPROBLEMV W HINIT
‹→TOL MAXITER
138 NONNEGATIVE LEAST SQUARE
‹→SOLVER

170
171 48 5863 1221 03 IFHINIT 0ANY
172 RAISEVALUEERRORNEGATIVE
‹→VALUES IN HINIT PASSED TO NLS SOLVER
173
174 48 139 29 00 H HINIT
175 48 112141 23363 58 WTV NPDOTWT V
176 48 16144 3363 08 WTW NPDOTWT W
177
178 VALUES JUSTIFIED IN THE PAPER
179 48 144 30 00 ALPHA 1
180 48 113 24 00 BETA 01

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181 638 1880 29 01 FORNITERINRANGE1 MAXITER
‘→ 1
182 638 195133 3059 102 GRAD NPDOTWTW H WTV
183 638 495761 7771 259 PROJGRADIENT NORMGRADNP
‘→LOGICALORGRAD 0 H 0
184 638 2449 38 01 IFPROJGRADIENT TOL
185 48 130 27 00 BREAK
186
187 1474 4474 30 02 FORINNERITER INRANGE1
‘→20
188 1474 83833 569 44 HN H ALPHA GRAD
189 HN NPWHEREHN 0
‘→HN 0
190 1474 194239 1318 101 HN POSHN
191 1474 48858 331 25 D HN H
192 1474 150407 1020 78 GRADD NPSUMGRAD D
193 1474 515390 3497 269 DQD NPSUMNPDOTWTW
‘→DD

BY LOOKING AT THE TOP VALUES OF THE TIME COLUMN IT IS REALLY EASY TO PINPOINT THE MOST EXPENSIVE EXPRESSIONS THAT WOULD DESERVE ADDITIONAL CARE
743 MEMORY USAGE PROFILING
YOU CAN ANALYZE IN DETAIL THE MEMORY USAGE OF ANY PYTHON CODE WITH THE HELP OF MEMORYPROFILER FIRST INSTALL THE LATEST VERSION
 PIP INSTALL U MEMORYPROFILER
THEN SETUP THE MAGICS IN A MANNER SIMILAR TO LINEPROFILER
•UNDER IPYTHON 011 FIRST CREATE A CONFIGURATION PROFILE
 IPYTHON PROFILE CREATE
THEN REGISTER THE EXTENSION IN IPYTHONPROFILEDEFAULTIPYTHONCONFIGPY ALONGSIDE THE LINE PROFILER
CTERMINALIPYTHONAPPEXTENSIONSAPPENDMEMORYPROFILER
CINTERACTIVESHELLAPPEXTENSIONSAPPENDMEMORYPROFILER
THIS WILL REGISTER THE MEMIT ANDMPRUN MAGIC COMMANDS IN THE IPYTHON TERMINAL APPLICATION AND THE OTHER FRONTENDS SUCH AS QTCONSOLE AND NOTEBOOK
MPRUN IS USEFUL TO EXAMINE LINEBYLINE THE MEMORY USAGE OF KEY FUNCTIONS IN YOUR PROGRAM IT IS VERY SIMILAR TO LPRUN DISCUSSED IN THE PREVIOUS SECTION FOR EXAMPLE FROM THE MEMORYPROFILEREXAMPLES DIRECTORY
IN 1FROM EXAMPLE IMPORT MYFUNC
IN 2 MPRUN F MYFUNC MYFUNC
FILENAME EXAMPLEPY
LINE MEM USAGE INCREMENT LINE CONTENTS

3 PROFILE
4 597 MB 000 MB DEFMYFUNC

5 1361 MB 764 MB A 1 106
6 16620 MB 15259 MB B 2 2107
7 1361 MB 15259 MB DELB
8 1361 MB 000 MB RETURNA
ANOTHER USEFUL MAGIC THAT MEMORYPROFILER DEFINES ISMEMIT WHICH IS ANALOGOUS TO TIMEIT IT CAN BE USED
AS FOLLOWS
IN 1 IMPORT NUMPY AS NP
IN 2 MEMIT NPZEROS1E7
MAXIMUM OF 3 76402344 MB PER LOOP
FOR MORE DETAILS SEE THE DOCSTRINGS OF THE MAGICS USING MEMIT ANDMPRUN
744 PERFORMANCE TIPS FOR THE CYTHON DEVELOPER
IF PROFILING OF THE PYTHON CODE REVEALS THAT THE PYTHON INTERPRETER OVERHEAD IS LARGER BY ONE ORDER OF MAGNITUDE OR MORE THAN THE COST OF THE ACTUAL NUMERICAL COMPUTATION EG FOR LOOPS OVER VECTOR COMPONENTS NESTED EVALUATION OF CONDITIONAL EXPRESSION SCALAR ARITHMETIC IT IS PROBABLY ADEQUATE TO EXTRACT THE HOTSPOT PORTION OF THE CODE AS A STANDALONE FUNCTION IN A PYX FILE ADD STATIC TYPE DECLARATIONS AND THEN USE CYTHON TO GENERATE A C PROGRAM SUITABLE TO BE COMPILED AS A PYTHON EXTENSION MODULE
THE OFFICIAL DOCUMENTATION AVAILABLE AT HTTPDOCSCYTHONORG CONTAINS A TUTORIAL AND REFERENCE GUIDE FOR DEVELOPING SUCH A MODULE IN THE FOLLOWING WE WILL JUST HIGHLIGHT A COUPLE OF TRICKS THAT WE FOUND IMPORTANT IN PRACTICE ON THE EXISTING CYTHON CODEBASE IN THE SCIKITLEARN PROJECT
TODO HTML REPORT TYPE DECLARATIONS BOUND CHECKS DIVISION BY ZERO CHECKS MEMORY ALIGNMENT DIRECT BLAS CALLS
• HTTPSWWWYOUTUBECOMWATCHVGMVKIQGOW8
• HTTPCONFERENCESCIPYORGPROCEEDINGSSCIPY2009PAPER1
• HTTPCONFERENCESCIPYORGPROCEEDINGSSCIPY2009PAPER2
USING OPENMP
SINCE SCIKITLEARN CAN BE BUILT WITHOUT OPENMP SUPPORT IT’S NECESSARY TO PROTECT EACH DIRECT CALL TO OPENMP THIS CAN BE DONE USING THE FOLLOWING SYNTAX
 IMPORTING OPENMP
IF SKLEARNOPENMPSUPPORTED
CIMPORT OPENMP
 CALLING OPENMP
IF SKLEARNOPENMPSUPPORTED
MAXTHREADS OPENMPOMPGETMAXTHREADS
ELSE
MAXTHREADS 1
NOTE PROTECTING THE PARALLEL LOOP PRANGE IS ALREADY DONE BY CYTHON

745 PROFILING COMPILED EXTENSIONS
WHEN WORKING WITH COMPILED EXTENSIONS WRITTEN IN CC WITH A WRAPPER OR DIRECTLY AS CYTHON EXTENSION THE DEFAULT PYTHON PROFILER IS USELESS WE NEED A DEDICATED TOOL TO INTROSPECT WHAT'S HAPPENING INSIDE THE COMPILED EXTENSION IT SELF
USING YEP AND GPERFTOOLS
EASY PROFILING WITHOUT SPECIAL COMPILATION OPTIONS USE YEP
• HTTPSPYPIORGPROJECTYEP
• HTTPFABIANPNETBLOG2011APROFILERFORPYTHONEXTENSIONS
USING GPROF
IN ORDER TO PROFILE COMPILED PYTHON EXTENSIONS ONE COULD USE GPROF AFTER HAVING RECOMPILED THE PROJECT WITH GCC PG AND USING THE PYTHONDBG VARIANT OF THE INTERPRETER ON DEBIAN UBUNTU HOWEVER THIS APPROACH REQUIRES TO ALSO HAVENUMPY ANDSCIPY RECOMPILED WITH PG WHICH IS RATHER COMPLICATED TO GET WORKING
FORTUNATELY THERE EXIST TWO ALTERNATIVE PROFILERS THAT DON'T REQUIRE YOU TO RECOMPILE EVERYTHING
USING VALGRIND CALLGRIND KCACHEGRIND
KCACHEGRIND
YEP CAN BE USED TO CREATE A PROFILING REPORT KCACHEGRIND PROVIDES A GRAPHICAL ENVIRONMENT TO VISUALIZE THIS REPORT
 RUN YEP TO PROFILE SOME PYTHON SCRIPT
PYTHON M YEP C MYFILEPY
 OPEN MYFILEPYCALLGRIN WITH KCACHEGRIND
KCACHEGRIND MYFILEPYPROF
NOTEYEP CAN BE EXECUTED WITH THE ARGUMENT LINES ORLTO COMPILE A PROFILING REPORT 'LINE BY LINE'
746 MULTICORE PARALLELISM USING JOBLIBPARALLEL
TODO GIVE A SIMPLE TEASER EXAMPLE HERE
CHECKOUT THE OFFICIAL JOBLIB DOCUMENTATION
• HTTPSJOBLIBREADTHEDOCSIO
747 A SIMPLE ALGORITHMIC TRICK WARM RESTARTS
SEE THE GLOSSARY ENTRY FOR WARMSTART

75 ADVANCED INSTALLATION INSTRUCTIONS

THERE ARE DIFFERENT WAYS TO GET SCIKITLEARN INSTALLED

•INSTALL AN OFFICIAL RELEASE THIS IS THE BEST APPROACH FOR MOST USERS IT WILL PROVIDE A STABLE VERSION AND PREBUILD PACKAGES ARE AVAILABLE FOR MOST PLATFORMS

• INSTALL THE VERSION OF SCIKITLEARN PROVIDED BY YOUR OPERATING SYSTEM OR PYTHON DISTRIBUTION THIS IS A QUICK OPTION FOR THOSE WHO HAVE OPERATING SYSTEMS THAT DISTRIBUTE SCIKITLEARN IT MIGHT NOT PROVIDE THE LATEST RELEASE VERSION

•BUILDING THE PACKAGE FROM SOURCE THIS IS BEST FOR USERS WHO WANT THE LATESTANDGREATEST FEATURES AND AREN'T AFRAID OF RUNNING BRANDNEW CODE THIS DOCUMENT DESCRIBES HOW TO BUILD FROM SOURCE

NOTE IF YOU WISH TO CONTRIBUTE TO THE PROJECT YOU NEED TO INSTALL THE LATEST DEVELOPMENT VERSION

751 INSTALLING NIGHTLY BUILDS

THE CONTINUOUS INTEGRATION SERVERS OF THE SCIKITLEARN PROJECT BUILD TEST AND UPLOAD WHEEL PACKAGES FOR THE MOST RECENT PYTHON VERSION ON A NIGHTLY BASIS TO HELP USERS TEST BLEEDING EDGE FEATURES OR BUG FIXES

PIP INSTALL PRE F HTTPSSKLEARNNIGHTLYSCDN8SECURERAXCDNCOM SCIKITLEARN

752 BUILDING FROM SOURCE

IN THE VAST MAJORITY OF CASES BUILDING SCIKITLEARN FOR DEVELOPMENT PURPOSES CAN BE DONE WITH

PIP INSTALL CYTHON PYTEST FLAKE8

THEN IN THE MAIN REPOSITORY

PIP INSTALL EDITABLE

PLEASE READ BELOW FOR DETAILS AND MORE ADVANCED INSTRUCTIONS

DEPENDENCIES

SCIKITLEARN REQUIRES

• PYTHON 35
• NUMPY 111
• SCIPY 017
• JOBLIB 011

NOTE FOR INSTALLING ON PYPY PYPY3V510 NUMPY 1140 AND SCIPY 110 ARE REQUIRED FOR PYPY ONLY INSTALLA TION INSTRUCTIONS WITH PIP APPLY

BUILDING SCIKITLEARN ALSO REQUIRES

• CYTHON 0285

• OPENMP
NOTE IT IS POSSIBLE TO BUILD SCIKITLEARN WITHOUT OPENMP SUPPORT BY SETTING THE SKLEARNNOOPENMP ENVIRON
MENT VARIABLE BEFORE CYTHONIZATION THIS IS NOT RECOMMENDED SINCE IT WILL FORCE SOME ESTIMATORS TO RUN IN SEQUENTIAL
MODE AND THEIR NJOBS PARAMETER WILL BE IGNORED
RUNNING TESTS REQUIRES
• PYTEST 330
SOME TESTS ALSO REQUIRE PANDAS
RETRIEVING THE LATEST CODE
WE USE GIT FOR VERSION CONTROL AND GITHUB FOR HOSTING OUR MAIN REPOSITORY
YOU CAN CHECK OUT THE LATEST SOURCES WITH THE COMMAND
GIT CLONE GITGITHUBCOMSCIKITLEARNSCIKITLEARNGIT
IF YOU WANT TO BUILD A STABLE VERSION YOU CAN GIT CHECKOUT VERSION TO GET THE CODE FOR THAT PARTICULAR
VERSION OR DOWNLOAD AN ZIP ARCHIVE OF THE VERSION FROM GITHUB
ONCE YOU HAVE ALL THE BUILD REQUIREMENTS INSTALLED SEE BELOW FOR DETAILS YOU CAN BUILD AND INSTALL THE PACKAGE IN THE
FOLLOWING WAY
IF YOU RUN THE DEVELOPMENT VERSION IT IS CUMBERSOME TO REINSTALL THE PACKAGE EACH TIME YOU UPDATE THE SOURCES
THEREFORE IT’S RECOMMENDED THAT YOU INSTALL IN EDITABLE MODE WHICH ALLOWS YOU TO EDIT THE CODE INPLACE THIS BUILDS
THE EXTENSION IN PLACE AND CREATES A LINK TO THE DEVELOPMENT DIRECTORY SEE THE PIP DOCS
PIP INSTALL EDITABLE
NOTE THIS IS FUNDAMENTALLY SIMILAR TO USING THE COMMAND PYTHON SETUPPY DEVELOP SEE THE SETUPTOOL
DOCS IT IS HOWEVER PREFERRED TO USE PIP
NOTE YOU WILL HAVE TO RERUN
PIP INSTALL EDITABLE
EVERY TIME THE SOURCE CODE OF A COMPILED EXTENSION IS CHANGED FOR INSTANCE WHEN SWITCHING BRANCHES OR PULLING
CHANGES FROM UPSTREAM COMPILED EXTENSIONS ARE CYTHON FILES ENDING IN PYX ORPXD
ON UNIXLIKE SYSTEMS YOU CAN EQUIVALENTLY TYPE MAKE IN FROM THE TOPLEVEL FOLDER HAVE A LOOK AT THE MAKEFILE
FOR ADDITIONAL UTILITIES
MAC OSX
THE DEFAULT C COMPILER APPLECLANG ON MAC OSX DOES NOT DIRECTLY SUPPORT OPENMP THE FIRST SOLUTION TO BUILD
SCIKITLEARN IS TO INSTALL ANOTHER C COMPILER SUCH AS GCC OR LLVMCLANG ANOTHER SOLUTION IS TO ENABLE OPENMP SUPPORT
ON THE DEFAULT APPLECLANG IN THE FOLLOWING WE PRESENT HOW TO CONFIGURE THIS SECOND OPTION
YOU FIRST NEED TO INSTALL THE OPENMP LIBRARY

BREW INSTALL LIBOMP
THEN YOU NEED TO SET THE FOLLOWING ENVIRONMENT VARIABLES
EXPORT CCUSRBINCLANG
EXPORT CXXUSRBINCLANG
EXPORT CPPFLAGSCPPFLAGS XPREPROCESSOR FOPENMP
EXPORT CFLAGSCFLAGS IUSRLOCALOPTLIBOMPINCLUDE
EXPORT CXXFLAGSCXXFLAGS IUSRLOCALOPTLIBOMPINCLUDE
EXPORT LDFLAGSLDFLAGS LUSRLOCALOPTLIBOMPLIB LOMP
EXPORT DYLDLIBRARYPATHUSRLOCALOPTLIBOMPLIB
FINALLY YOU CAN BUILD THE PACKAGE USING THE STANDARD COMMAND
FREEBSD
THE CLANG COMPILER INCLUDED IN FREEBSD 120 AND 112 BASE SYSTEMS DOES NOT INCLUDE OPENMP SUPPORT YOU NEED TO INSTALL THEOPENMP LIBRARY FROM PACKAGES OR PORTS
SUDO PKG INSTALL OPENMP
THIS WILL INSTALL HEADER FILES IN USRLOCALINCLUDE AND LIBS INUSRLOCALLIB SINCE THESE DIRECTORIES ARE NOT SEARCHED BY DEFAULT YOU CAN SET THE ENVIRONMENT VARIABLES TO THESE LOCATIONS
EXPORT CFLAGSCFLAGS IUSRLOCALINCLUDE
EXPORT CXXFLAGSCXXFLAGS IUSRLOCALINCLUDE
EXPORT LDFLAGSLDFLAGS LUSRLOCALLIB LOMP
EXPORT DYLDLIBRARYPATHUSRLOCALLIB
FINALLY YOU CAN BUILD THE PACKAGE USING THE STANDARD COMMAND
FOR THE UPCOMMING FREEBSD 121 AND 113 VERSIONS OPENMP WILL BE INCLUDED IN THE BASE SYSTEM AND THESE STEPS WILL NOT BE NECESSARY
753 INSTALLING BUILD DEPENDENCIES
LINUX
INSTALLING FROM SOURCE WITHOUT CONDA REQUIRES YOU TO HAVE INSTALLED THE SCIKITLEARN RUNTIME DEPENDENCIES PYTHON DEVELOPMENT HEADERS AND A WORKING CC COMPILER UNDER DEBIANBASED OPERATING SYSTEMS WHICH INCLUDE UBUNTU
SUDO APTGET INSTALL BUILDESSENTIAL PYTHON3DEV PYTHON3SETUPTOOLS
PYTHON3PIP
AND THEN
PIP3 INSTALL NUMPY SCIPY CYTHON
NOTE IN ORDER TO BUILD THE DOCUMENTATION AND RUN THE EXAMPLE CODE CONTAINS IN THIS DOCUMENTATION YOU WILL NEED MATPLOTLIB
PIP3 INSTALL MATPLOTLIB

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WHEN PRECOMPILED WHEELS ARE NOT AVALAIBLE FOR YOUR ARCHITECTURE YOU CAN INSTALL THE SYSTEM VERSIONS
SUDO APTGET INSTALL CYTHON3 PYTHON3NUMPY PYTHON3SCIPY PYTHON3MATPLOTLIB
ON RED HAT AND CLONES EG CENTOS INSTALL THE DEPENDENCIES USING
SUDO YUM Y INSTALL GCC GCCC PYTHONDEVEL NUMPY SCIPY
NOTE TO USE A HIGH PERFORMANCE BLAS LIBRARY EG OPENBLAS SEE SCIPY INSTALLATION INSTRUCTIONS
WINDOWS
TO BUILD SCIKITLEARN ON WINDOWS YOU NEED A WORKING CC COMPILER IN ADDITION TO NUMPY SCIPY AND SETUPTOOLS
THE BUILDING COMMAND DEPENDS ON THE ARCHITECTURE OF THE PYTHON INTERPRETER 32BIT OR 64BIT YOU CAN CHECK THE ARCHITECTURE BY RUNNING THE FOLLOWING IN CMD ORPOWERSHELL CONSOLE
PYTHON C IMPORT STRUCT PRINTSTRUCTCALCSIZEP 8
THE ABOVE COMMANDS ASSUME THAT YOU HAVE THE PYTHON INSTALLATION FOLDER IN YOUR PATH ENVIRONMENT VARIABLE
YOU WILL NEED BUILD TOOLS FOR VISUAL STUDIO 2017
FOR 64BIT PYTHON CONFIGURE THE BUILD ENVIRONMENT WITH
SET DISTUTILSUSESDK1
CPROGRAM FILES X86MICROSOFT VISUAL
‘→STUDIO2017BUILDTOOLSVCAUXILIARYBUILD VCVARSALLBAT X64
AND BUILD SCIKITLEARN FROM THIS ENVIRONMENT
PYTHON SETUPPY INSTALL
REPLACEX64 BYX86 TO BUILD FOR 32BIT PYTHON
BUILDING BINARY PACKAGES AND INSTALLERS
THEWHL PACKAGE AND EXE INSTALLERS CAN BE BUILT WITH
PIP INSTALL WHEEL
PYTHON SETUPPY BDISTWHEEL BDISTWININST B DOCLOGOSSCIKITLEARNLOGOBMP
THE RESULTING PACKAGES ARE GENERATED IN THE DIST FOLDER
USING AN ALTERNATIVE COMPILER
IT IS POSSIBLE TO USE MINGW A PORT OF GCC TO WINDOWS OS AS AN ALTERNATIVE TO MSVC FOR 32BIT PYTHON NOT THAT EXTENSIONS BUILT WITH MINGW32 CAN BE REDISTRIBUTED AS REUSABLE PACKAGES AS THEY DEPEND ON GCC RUNTIME LIBRARIES TYPICALLY NOT INSTALLED ON ENDUSERS ENVIRONMENT
TO FORCE THE USE OF A PARTICULAR COMPILER PASS THE COMPILER FLAG TO THE BUILD STEP

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PYTHON SETUPPY BUILD COMPILERMYCOMPILER INSTALL
WHEREMYCOMPILER SHOULD BE ONE OF MINGW32 ORMSVC
76 MAINTAINER COREDEVELOPER INFORMATION
761 BEFORE A RELEASE
1 UPDATE AUTHORS TABLE
 CD BUILDTOOLS MAKE AUTHORS CD
AND COMMIT
2 CONFIRM ANY BLOCKERS TAGGED FOR THE MILESTONE ARE RESOLVED AND THAT OTHER ISSUES TAGGED FOR THE MILESTONE CAN BE POSTPONED
3 ENSURE THE CHANGE LOG AND COMMITS CORRESPOND WITHIN REASON AND THAT THE CHANGE LOG IS REASONABLY WELL CURATED SOME TOOLS FOR THESE TASKS INCLUDE
•MAINTTOOLSSORTWHATSNEWPY CAN PUT WHAT'S NEW ENTRIES INTO SECTIONS
• THEMAINTTOOLSWHATSMISSINGSH SCRIPT MAY BE USED TO IDENTIFY PULL REQUESTS THAT WERE MERGED BUT LIKELY MISSING FROM WHAT'S NEW
PREPARING A BUGFIXRELEASE
SINCE ANY COMMITS TO A RELEASED BRANCH EG 0999X WILL AUTOMATICALLY UPDATE THE WEB SITE DOCUMENTATION IT IS BEST TO DEVELOP A BUGFIX RELEASE WITH A PULL REQUEST IN WHICH 0999X IS THE BASE IT ALSO ALLOWS YOU TO KEEP TRACK OF ANY TASKS TOWARDS RELEASE WITH A TO DO LIST
MOST DEVELOPMENT OF THE BUG FIX RELEASE AND ITS DOCUMENTATION SHOULD HAPPEN IN MASTER TO AVOID ASYNCHRONY TO SELECT COMMITS FROM MASTER FOR USE IN THE BUG FIX VERSION 09993 YOU CAN USE
 GIT CHECKOUT B RELEASE09993 MASTER
 GIT REBASE I 0999X
THEN PICK THE COMMITS FOR RELEASE AND RESOLVE ANY ISSUES AND CREATE A PULL REQUEST WITH 0999X AS BASE ADD A COMMIT UPDATING SKLEARNVERSION ADDITIONAL COMMITS CAN BE CHERRYPICKED INTO THE RELEASE0 9993 BRANCH WHILE PREPARING THE RELEASE
762 MAKING A RELEASE
1 UPDATE DOCS
• EDIT THE DOCWHATSNEWRST FILE TO ADD RELEASE TITLE AND COMMIT STATISTICS YOU CAN RETRIEVE COMMIT STATISTICS WITH
 GIT SHORTLOG S 09933 CUT F2 SORT IGNORECASE TR N
‘→SED S GS
• UPDATE THE RELEASE DATE IN WHATSNEWRST
• EDIT THE DOCINDEXRST TO CHANGE THE 'NEWS' ENTRY OF THE FRONT PAGE

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• NOTE THAT THESE CHANGES SHOULD BE MADE IN MASTER AND CHERRYPICKED INTO THE RELEASE BRANCH

2 ON THE BRANCH FOR RELEASING UPDATE THE VERSION NUMBER IN SKLEARNINITPY THE VERSION VARIABLE BY REMOVINGDEVONLY WHEN READY TO RELEASE ON MASTER INCREMENT THE VERSON IN THE SAME PLACE WHEN BRANCHING FOR RELEASE

3 CREATE THE TAG AND PUSH IT

```
GIT TAG A 0999
GIT PUSH GITGITHUBCOMSCIKITLEARNSCIKITLEARNGIT TAGS
```

4 CREATE THE SOURCE TARBALL

• WIPE CLEAN YOUR REPO

```
GIT CLEAN XFD
```

• GENERATE THE TARBALL

```
PYTHON SETUPPY SDIST
```

THE RESULT SHOULD BE IN THE DIST FOLDER WE WILL UPLOAD IT LATER WITH THE WHEELS CHECK THAT YOU CAN INSTALL IT IN A NEW VIRTUALENV AND THAT THE TESTS PASS

5 UPDATE THE DEPENDENCY VERSIONS AND SET BUILDCOMMIT VARIABLE TO THE RELEASE TAG AT HTTPSGITHUBCOMMACPYTHONSCIKITLEARNWHEELS

ONCE THE CI HAS COMPLETED SUCCESSFULLY COLLECT THE GENERATED BINARY WHEEL PACKAGES AND UPLOAD THEM TO PYPI BY RUNNING THE FOLLOWING COMMANDS IN THE SCIKITLEARN SOURCE FOLDER CHECKED OUT AT THE RELEASE TAG

```
PIP INSTALL U WHEELHOUSEUPLOADER TWINE
PYTHON SETUPPY FETCHARTIFACTS
```

6 CHECK THE CONTENT OF THE DIST FOLDER IT SHOULD CONTAIN ALL THE WHEELS ALONG WITH THE SOURCE TARBALL “SCIKIT LEARNXXXTARGZ”

MAKE SURE THAT YOU DO NOT HAVE DEVELOPER VERSIONS OR OLDER VERSIONS OF THE SCIKITLEARN PACKAGE IN THAT FOLDER UPLOAD EVERYTHING AT ONCE TO HTTPSPYPIORG

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TWINE UPLOAD DIST
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7 FOR MAJORMINOR NOT BUGFIX RELEASE UPDATE THE SYMLINK FOR STABLE IN HTTPSGITHUBCOMSCIKITLEARN SCIKITLEARNGITHUBIO

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THE FOLLOWING GITHUB CHECKLIST MIGHT BE HELPFUL IN A RELEASE PR

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UPDATE NEWS ANDWHATS NEW DATE IN MASTER AND RELEASE BRANCH
CREATE TAG
UPDATE DEPENDENCIES ANDRELEASE TAG AT HTTPSGITHUBCOMMACPYTHONSCIKIT
‘→LEARNWHEELS
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TWINE THE WHEELS TO PYPI WHEN THATS GREEN
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‘→MASTERDOCSETSSCIKIT

763 THE SCIKITLEARNORG WEB SITE

THE SCIKITLEARN WEB SITE HTTPSCIKITLEARNORG IS HOSTED AT GITHUB BUT SHOULD RARELY BE UPDATED MANUALLY BY PUSHING TO THE HTTPSGITHUBCOMSCIKITLEARNSCIKITLEARNGITHUBIO REPOSITORY MOST UPDATES CAN BE MADE BY PUSHING TO MASTER FOR DEV OR A RELEASE BRANCH LIKE 099X FROM WHICH CIRCLE CI BUILDS AND UPLOADS THE DOCUMENTATION AUTOMATICALLY

764 TRAVIS CRON JOBS

FROM HTTPSDOCSTRAVISCICOMUSERCRONJOBS TRAVIS CI CRON JOBS WORK SIMILARLY TO THE CRON UTILITY THEY RUN BUILDS AT REGULAR SCHEDULED INTERVALS INDEPENDENTLY OF WHETHER ANY COMMITS WERE PUSHED TO THE REPOSITORY CRON JOBS ALWAYS FETCH THE MOST RECENT COMMIT ON A PARTICULAR BRANCH AND BUILD THE PROJECT AT THAT STATE CRON JOBS CAN RUN DAILY WEEKLY OR MONTHLY WHICH IN PRACTICE MEANS UP TO AN HOUR AFTER THE SELECTED TIME SPAN AND YOU CANNOT SET THEM TO RUN AT A SPECIFIC TIME

FOR SCIKITLEARN CRON JOBS ARE USED FOR BUILDS THAT WE DO NOT WANT TO RUN IN EACH PR AS AN EXAMPLE THE BUILD WITH THE DEV VERSIONS OF NUMPY AND SCIPY IS RUN AS A CRON JOB MOST OF THE TIME WHEN THIS NUMPYDEV BUILD FAIL IT IS RELATED TO A NUMPY CHANGE AND NOT A SCIKITLEARN ONE SO IT WOULD NOT MAKE SENSE TO BLAME THE PR AUTHOR FOR THE TRAVIS FAILURE

THE DEFINITION OF WHAT GETS RUN IN THE CRON JOB IS DONE IN THE TRAVISYML CONFIG FILE EXACTLY THE SAME WAY AS THE OTHER TRAVIS JOBS WE USE A IF TYPE CRON FILTER IN ORDER FOR THE BUILD TO BE RUN ONLY IN CRON JOBS

THE BRANCH TARGETED BY THE CRON JOB AND THE FREQUENCY OF THE CRON JOB IS SET VIA THE WEB UI AT HTTPSWWWTRAVISCI ORGSCIKITLEARNSCIKITLEARNSETTINGS

765 EXPERIMENTAL FEATURES

THESKLEARNEXPERIMENTAL MODULE WAS INTRODUCED IN 021 AND CONTAINS EXPERIMENTAL FEATURES ESTIMATORS THAT ARE SUBJECT TO CHANGE WITHOUT DEPRECATION CYCLE

TO CREATE AN EXPERIMENTAL MODULE YOU CAN JUST COPY AND MODIFY THE CONTENT OF ENABLEHISTGRADIENTBOOSTINGPY OR ENABLEITERATIVEIMPUTERPY

NOTE THAT THE PUBLIC IMPORT PATH MUST BE TO A PUBLIC SUBPACKAGE LIKE SKLEARNENSEMBLE ORSKLEARNIMPUTE NOT JUST APY MODULE ALSO THE PRIVATE EXPERIMENTAL FEATURES THAT ARE IMPORTED MUST BE IN A SUBMODULESUBPACKAGE OF THE PUBLIC SUBPACKAGE EG SKLEARNENSEMBLEHISTGRADIENTBOOSTING ORSKLEARNIMPUTE ITERATIVEPY THIS IS NEEDED SO THAT PICKLES STILL WORK IN THE FUTURE WHEN THE FEATURES AREN’T EXPERIMENTAL ANYMORE

PLEASE ALSO WRITE BASIC TESTS FOLLOWING THOSE IN TESTENABLEHISTGRADIENTBOOSTINGPY

MAKE SURE EVERY USERFACING CODE YOU WRITE EXPLICITLY MENTIONS THAT THE FEATURE IS EXPERIMENTAL AND ADD A NOQA COMMENT TO AVOID PEP8RELATED WARNINGS

TO USE THIS EXPERIMENTAL FEATURE WE NEED TO EXPLICITLY ASK FOR IT

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FROM SKLEARNEXPERIMENTAL IMPORT ENABLEHISTGRADIENTBOOSTING  NOQA
FROM SKLEARNENSEMBLE IMPORT HISTGRADIENTBOOSTINGREGRESSOR
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SCIKITLEARN USER GUIDE RELEASE 0213
FOR THE DOCS TO RENDER PROPERLY PLEASE ALSO IMPORT ENABLEMYEXPERIMENTALFEATURE INDOCCONFPY
ELSE SPHINX WON’T BE able TO IMPORT THE CORRESPONDING MODULES NOTE THAT USING FROM SKLEARNEXPERIMENTAL
IMPORTDOES NOT WORK
NOTE THAT SOME EXPERIMENTAL CLASSES FUNCTIONS ARE NOT INCLUDED IN THE SKLEARNEXPERIMENTAL MODULE
SKLEARNDATASETSFETCHOPENML

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