sklearn.pipeline.make_pipeline

sklearn.pipeline.make_pipeline(*steps, memory=None, verbose=False) [source]

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 Estimator objects

List of the scikit-learn estimators that are chained together.

memory : *str or object with the joblib.Memory interface, default=None*

Used to cache the fitted 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 transformers before fitting. Therefore, the transformer instance given to the pipeline cannot be inspected directly. Use the attribute `named_steps` or `steps` to inspect estimators within the pipeline. Caching the transformers is advantageous when fitting is time consuming.

verbose : *bool, default=False*

If True, the time elapsed while fitting each step will be printed as it is completed.

Returns:

p : *Pipeline*

Returns a scikit-learn `Pipeline` object.

See also:

`Pipeline`

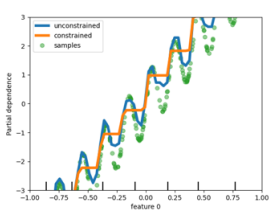
Class for creating a pipeline of transforms with a final estimator.

Examples

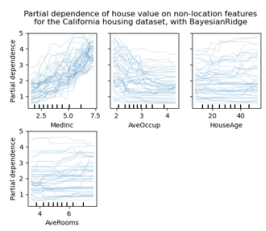
```
>>> from sklearn.naive_bayes import GaussianNB
>>> from sklearn.preprocessing import StandardScaler
>>> from sklearn.pipeline import make_pipeline
>>> make_pipeline(StandardScaler(), GaussianNB(priors=None))
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('gaussiannb', GaussianNB())])
```

Examples using `sklearn.pipeline.make_pipeline`

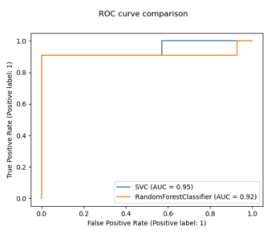
Release Highlights for scikit-learn 1.0



Release Highlights for scikit-learn 0.23



Release Highlights for scikit-learn 0.24



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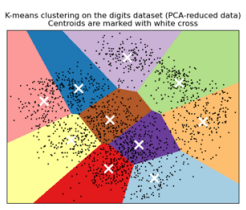
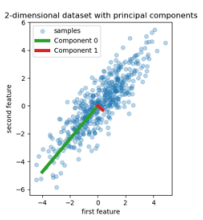
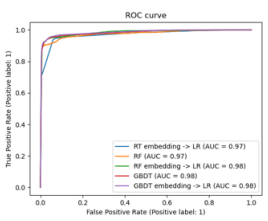


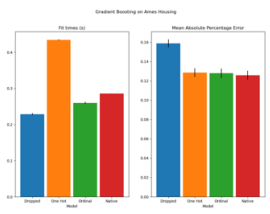
A demo of K-Means clustering on the handwritten digits data



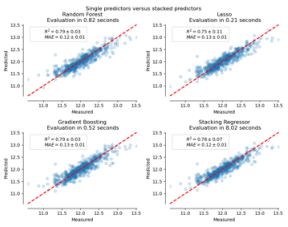
Principal Component Partial



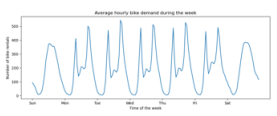
Feature transformations with ensembles



Categorical Feature Support in Gradient



Combine predictors using stacking



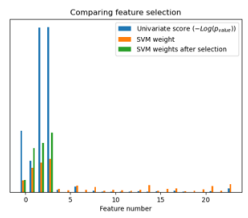
Time-related feature engineering

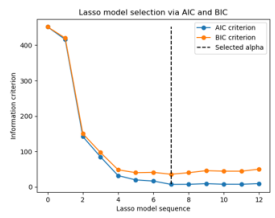
Toggle Menu

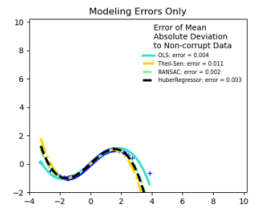
Least Squares Regression

of trees

Boosting







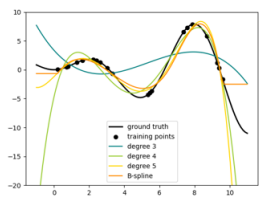
Pipeline ANOVA SVM

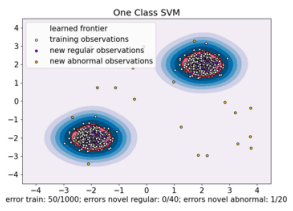
Univariate Feature Selection

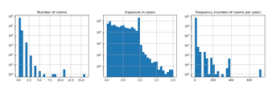
Lasso model selection via information criteria

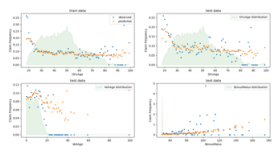
Robust linear estimator fitting

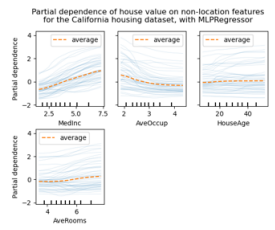
Lasso model selection: AIC-BIC / cross-validation











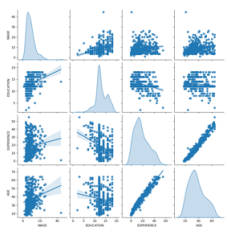
Polynomial and Spline interpolation

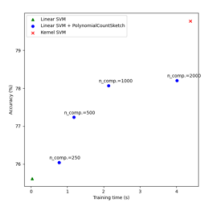
One-Class SVM versus One-Class SVM using Stochastic Gradient Descent

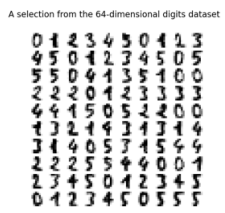
Poisson regression and non-normal loss

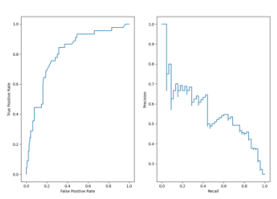
Tweedie regression on insurance claims

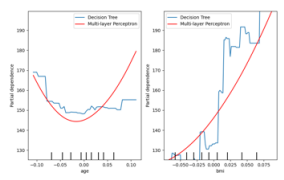
Partial Dependence and Individual Conditional Expectation Plots











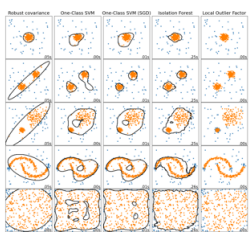
Common pitfalls in the interpretation of coefficients of linear models

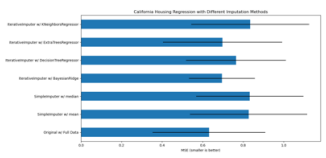
Scalable learning with polynomial kernel approximation

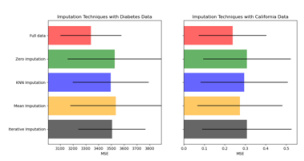
Manifold learning on handwritten digits: Locally Linear Embedding, Isomap...

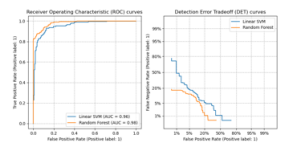
Visualizations with Display Objects

Advanced Plotting With Partial Dependence









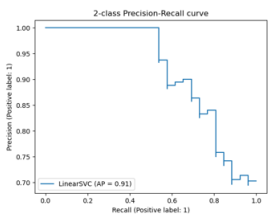
Displaying Pipelines

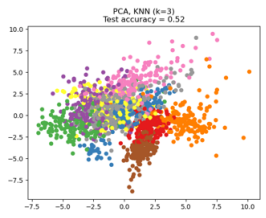
Comparing anomaly detection algorithms for outlier detection on toy datasets

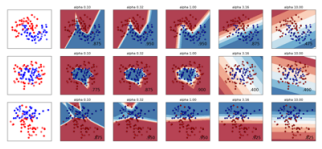
Imputing missing values with variants of IterativeImputer

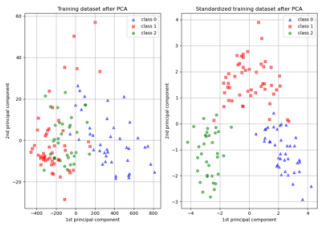
Imputing missing values before building an estimator

Detection error tradeoff (DET) curve









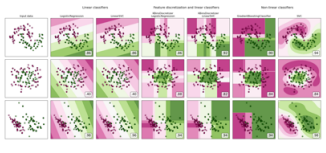
Precision-Recall

Dimensionality Reduction with Neighborhood Components Analysis

Approximate nearest neighbors in TSNE

Varying regularization in Multi-layer Perceptron

Importance of Feature Scaling



Toggle Menu