A COMPARISON OF META-LEARNING STRATEGIES

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Introduction

- Machine learning algorithm decision is not arbitrary
- No Free Lunch for Optimization
- Does NFL theory apply to meta-learners?

BACKGROUND/NECESSARY TERMS

Meta Learners

- ▶ Brute Force Cluter on all datasets in metabase
- Active Meta Learning Cluster on datasets in metabase with most information
- ► Learning Curves Choose item in metabase with learning curve most similar to new dataset

■ Base Algorithms

- ► Linear Regression Fit Curve to data
- Support Vector Machine Sepearte data with hyperplane
- ► K-Means Clustering Draw borders around similar datapoints
- Naive Bayes Guess Likelihood of data class with Bayes theorem
- Neural Networks Decide class of data thru interconnected network of weights

■ Brute Force Meta Learner

- ► Most basic possible meta learning strategy
- Gather run statistics for a group of datasets (metabase)
- ► Take in new dataset, run clustering algorithm with metabase
- ► Use algorithm of closest set in metabase

■ Active meta-learning

- Meta Learning strategy described in "Ranking of Classifiers based on Dataset Characteristics using Active Meta Learning"
- Allows a dataset into metabase only if it has a higher uncertainty score than its peers
- ► Relative uncertainty between two datasets:

$$\delta(V_x, d_i, V_x, d_j) = \frac{|V_x, d_i - V_x, d_j|}{Max_{k \neq i}(V_x, d_k) - Min_{k \neq i}(V_x, d_k)}$$

- where:
- V_x , d_k = value of metapamater V_x for dataset d_k
- $Max_{k\neq i}(V_x, d_k)$ = Maximum V_x, d_k with dataset i removed
- $Min_{k\neq i}(V_x, d_k)$ = Minimum V_x, d_k with dataset *i* removed

- Active meta-learning (cont)
 - Selection accomplished by summing uncertainties, ranking, then selecting highest ranked dataset
 - Process reduces training time and increases classification accuracy relative to Brute Force Learner
- Nearest Learning Curve Analysis
 - Gather algorithms classification accuracy for some dataset at various fractions of the training set
 - ► Plotting these accuracies reveals a learning curve
 - Categorization of the new datasets then accomplished in 3 steps:
 - **First** Train model with each candidate algorithm at same fractions present in learning curves in metabase
 - **Second** Get distance measure between this new curve and older curves
 - **Third** Return algorithm that worked best on dataset represented by curve

METHODOLOGY

- Overall goal: Determine meta-learning dominance
- Requirements:
 - Set of meta learning strategies to compare
 - A pool of datasets from which to build metabases and on which to analyze performance
 - Analysis techniques to compare meta learners performances
- Program Flow:
 - ► Parse unprocessed datasets
 - ► Run base algorithms
 - ► Collect learning curves
 - Construct metabase sets
 - ► Populate meta learner guess tables
 - ► Compile results
 - Produce results charts

- Development Environment Description:
 - ► languages: python 3.7, bash
 - ► editors: emacs, pycharm
 - runtime environment: ipython in powershell
 - ► Personal pc metrics:
 - RAM: 16 GB
 - Processor: Intel i5-4460
 - OS: Windows 10
- Datasource Description:
 - Gathered with script from UCI Irvine Machine Learning Repository
 - ► Manual investigation of parability:

First Write code to parse data

Second Examine data to see if parsed

Third If not parsed, discover why parse failed

Fourth Repeat Sequence

- ► Resulting parser flow:
 - First Ensure file of allowed type then import if allowed

Second Check each columns data type **Third** Transform unusable columns

- System required generally applicable "meta features": features the meta learning algorithms could use to classify the datasets
- A set of meta features that met this criteria were:
 - weighted mean The mean of a distribution normalized by its maximum value
 - coefficient of variation A measure of the dispersion of a distribution.
 - skewness A measure of the asymmetry of a probility distribution.
 - kurtosis A measure of the "tailedness of a probibility distribution i.e. how many of much of the weight of a probability distribution lies in its tails
 - ► shannon entropy A measure of the minimum number of bits needed to encode a string of symbols. Is a measure of how much information is contained in a body of data.

A vector is formed using these meta features via the following process:

First Apply meta feature to each column **Second** Sum these values, divide by number of columns

$$F_{ad} = \frac{\sum_{c=i}^{N} f_{ai}}{N}$$

- where:
- $ightharpoonup F_{ad}$ Composite meta feature value
- ightharpoonup a = label of meta feature
- ▶ d = label of dataset
- c = iterator across columns in the dataset
- $ightharpoonup f_{ai}$ = value of meta feature a in column i
- ► N = overall number of columns in dataset

Third Repeat for other meta features **Fourth** Craft vector with features

$$V_d = (F_{1d}, F_{2d}, ... F_{ad})$$

DATABASE DESCRIPTION

- Database created and used via a python library called sqlalchemy
 - Object relation mapper maps data structures to sql statements
- Database Tables:
 - algorithm each row contains information on a basic algorithm
 - all_data each row contains name,path, and vector representation of a dataset
 - runs_all each row contains a combination of algorithm, dataset, training time, and test accuracy
 - learning_curves each row contains test set accuracy at 10, 20, and 30 percent training set size
 - base_set_collection tables each table contains a set of metabases
 - guesses tables each table contains meta algorithm guesses
 - results each row contains meta algorithm name, collection table name, metabase name, accuracy, training time

METHODOLOGY CONTINUED

- Ran all algorithm/dataset combinations and stored in table
- Analysis session flow:

First Parse dataset for data matrix

Second Randomize order of the data matrix's rows

Third Use first 20 percent to train algorithm

Fourth For each algorithm:

- ► Train a model with given algorithm
- Analyze test set with trained model
- save classification accuracy and training time to database
- Same procedure used to gather learning curves but training occured only at 10, 20, and 30 percent the size of the training set

REFERENCES