National University of Singapore School of Computing

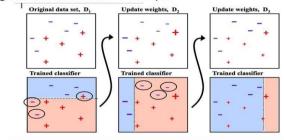
Tutorial 6:

Adaptive Boosting and Gradient Boosting

Adaptive Boosting

- The weak learners in AdaBoost are decision trees (or any other base classifier that you choose) with a single split, called decision stumps.
- AdaBoost works by putting more weight on difficult to classify instances and less on those already handled well.
- AdaBoost algorithms can be used for both classification and regression problem.

Algorithm Adaboost - Example

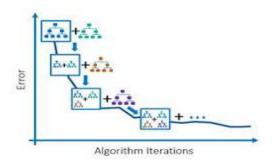


ourtesy to Alexander Ihler http://sli.ics.uci.edu/Classes/2012F-273a?action=download&upname=10-ensembles.pdf

Gradient Boosting

Gradient boosting involves three elements:

- A loss function to be optimized.
- A weak learner to make predictions.
- An additive model to add weak learners to minimize the loss function.



Application: Predict age of abalone using Decision Tree, Adaptive Boosting (AdaBoost) and Gradient Boosting (XGBoost and LightGBM)

- The UCI Abalone dataset is available from (https://archive.ics.uci.edu/ml/datasets/Abalone). It has been pre-downloaded and made available for this tutorial. The data file is "abalone.data". It can be read into your Jupyter notebook using pandas' read_csv function. The "abalone.names" file contains more information about the dataset, and the names for your headers can be found in this file.
- 2. Read the dataset into your notebook and manually populate the headers with header names.
- 3. Pre-process and one hot encode the 'sex' variable, since this variable is categorical.
- 4. Our target is the 'rings' variable. As there are many values in this column, bin the values into 3 separate bins and label them ('young', 'medium' and 'old'). The head() of the dataframe is given here:

| | sex | length | diameter | height | whole_weight | shucked_weight | viscera_weight | shell_weight | rings | bins |
|---|-----|--------|----------|--------|--------------|----------------|----------------|--------------|-------|--------|
| 0 | М | 0.455 | 0.365 | 0.095 | 0.5140 | 0.2245 | 0.1010 | 0.150 | 15 | middle |
| 1 | М | 0.350 | 0.265 | 0.090 | 0.2255 | 0.0995 | 0.0485 | 0.070 | 7 | young |
| 2 | F | 0.530 | 0.420 | 0.135 | 0.6770 | 0.2565 | 0.1415 | 0.210 | 9 | young |
| 3 | М | 0.440 | 0.365 | 0.125 | 0.5160 | 0.2155 | 0.1140 | 0.155 | 10 | young |
| 4 | - 1 | 0.330 | 0.255 | 0.080 | 0.2050 | 0.0895 | 0.0395 | 0.055 | 7 | young |

- 5. Set up the X and y variables and split your data into the training set and testing set.
- 6. Fit and predict the y variables using a **standard Decision Tree Classifier**.
- 7. Fit and predict the y variables using an **ADABoost Classifier** with n_estimators=10, learning_rate=1 and a decision tree base estimator with max_depth=3.
- 8. Fit and predict the y variables using an **XGBoost Classifier** with max_depth=3, learning_rate=0.1, and n_estimators=100.
- 9. Fit and predict the y variables using an **LightGBM Classifier** with max_depth=3, learning_rate=0.1, and n_estimators=100.
- 10. Print the accuracy score for each of these classifiers.
- 11. Perform a grid search on ADABoost, XGBoost and LightGBM using the following parameters 'n_estimators': [100, 500, 1000], 'learning_rate': [0.01, 0.1, 1], 'max_depth': [1,2,3]
- 12. Print the accuracy scores on the test set for the best estimators for each classifier from the grid search.