# 2.1.5 Boosting - wisdom of the crowd (practice)

February 22, 2017

## 1 Boosting - Wisdom of the Crowd (practice)

**This chapter includes**: - Data preparation - Using single decision tree - Boosting with AdaBoost - Gradient Boosted Trees - why not?

Now let's time to see how boosting is applied in practice. Hopefully the `scikit-learn` package provides all described packages. Begin with importing all required libraries. XGBoost package will be described more in later lectures.

```
In [1]: import numpy as np
        import subprocess

        from IPython.display import Image

        from collections import Counter

        from sklearn.datasets import make_classification
        from sklearn.cross_validation import train_test_split
        from sklearn.metrics import log_loss, accuracy_score

        # classifiers
        from sklearn.tree import DecisionTreeClassifier, export_graphviz
        from sklearn.ensemble import AdaBoostClassifier
        from sklearn.ensemble import GradientBoostingClassifier

        # reproducibility
        seed = 104
```

### 1.0.1 Prepare data

In all examples we will be dealing with **binary classification**. Generate 20 dimensional artificial dataset with 1000 samples, where 8 features holding information, 3 are redundant and 2 repeated.

```
In [2]: X, y = make_classification(n_samples=1000, n_features=20, n_informative=8, n_redundant=3
```

And finally perform a split into train/test parts. It will be useful for validating the performance of all methods.

```
In [3]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=se
```

All algorithms won't be tuned at this point. A sensible set of default settings will be applied, making the whole things less complicated.

> *Logarithmic loss* and accuracy were chosen to evaluate the results. It's also important to remeber about reproducibility - you should always set all `seed` parameters to the same value.

Let's perform a target variable distribution sanity check before digging into algorithms.

```
In [4]: print("Train label distribution:")
        print(Counter(y_train))

        print("\nTest label distribution:")
        print(Counter(y_test))
```

```
Train label distribution:
Counter({1: 405, 0: 395})

Test label distribution:
Counter({0: 104, 1: 96})
```

Target variable is equally distribued across both dataset.

### 1.0.2 Single Decision Tree

The following code will create a single decision tree, fit it using training data and evaluate the results using test sample.

```
In [5]: decision_tree = DecisionTreeClassifier(random_state=seed)

        # train classifier
        decision_tree.fit(X_train, y_train)

        # predict output
        decision_tree_y_pred  = decision_tree.predict(X_test)
        decision_tree_y_pred_prob  = decision_tree.predict_proba(X_test)

        # evaluation
        decision_tree_accuracy = accuracy_score(y_test, decision_tree_y_pred)
        decision_tree_logloss = log_loss(y_test, decision_tree_y_pred_prob)

        print("== Decision Tree ==")
        print("Accuracy: {0:.2f}".format(decision_tree_accuracy))
        print("Log loss: {0:.2f}".format(decision_tree_logloss))
        print("Number of nodes created: {}".format(decision_tree.tree_.node_count))
```

```
== Decision Tree ==
Accuracy: 0.78
```

```
Log loss: 7.60
Number of nodes created: 167
```

We can see two things:

1. the log loss score is not very promising (due to the fact that leaves in decision tree outputs either `0` or `1` as probability which is heaviliy penalized in case of errors, but the accuracy score is quite decent,
2. the tree is complicated (large number of nodes)

You can inspect first few predicted outputs, and see that only 2 instances out of 5 were classified correctly.

```
In [6]: print('True labels:')
        print(y_test[:5,])
        print('\nPredicted labels:')
        print(decision_tree_y_pred[:5,])
        print('\nPredicted probabilities:')
        print(decision_tree_y_pred_prob[:5,])
```

```
True labels:
[1 1 1 0 1]

Predicted labels:
[0 0 1 0 0]

Predicted probabilities:
[[ 1.  0.]
 [ 1.  0.]
 [ 0.  1.]
 [ 1.  0.]
 [ 1.  0.]]
```

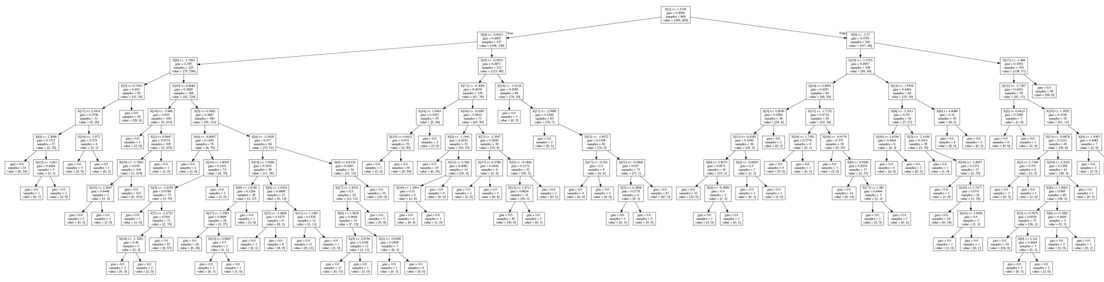
```
In [7]: dt_viz_file = '../images/dt.dot'
        dt_png_file = '../images/dt.png'

        # create visualization
        export_graphviz(decision_tree, out_file=dt_viz_file)

        # convert to PNG
        command = ["dot", "-Tpng", dt_viz_file, "-o", dt_png_file]
        subprocess.check_call(command)

        # display image
        Image(filename=dt_png_file)
```

```
Out[7]:
```



### 1.0.3 AdaBoost

In the example below we are creating a AdaBoost classifier running on 1000 iterations (1000 trees created). Also we are growing decision node up to first split (they are called *decision stumps*). We are also going to use `SAMME` algorithm which is inteneded to work with discrete data (output from `base_estimator` is 0 or 1). Please refer to the documentation and here for more details.

```
In [8]: adaboost = AdaBoostClassifier(
            base_estimator=DecisionTreeClassifier(max_depth=1),
            algorithm='SAMME',
            n_estimators=1000,
            random_state=seed)

        # train classifier
        adaboost.fit(X_train, y_train)

        # calculate predictions
        adaboost_y_pred = adaboost.predict(X_test)
        adaboost_y_pred_prob = adaboost.predict_proba(X_test)

        # evaluate
        adaboost_accuracy = accuracy_score(y_test, adaboost_y_pred)
        adaboost_logloss = log_loss(y_test, adaboost_y_pred_prob)

        print("== AdaBoost ==")
        print("Accuracy: {0:.2f}".format(adaboost_accuracy))
        print("Log loss: {0:.2f}".format(adaboost_logloss))
```

```
== AdaBoost ==
Accuracy: 0.78
Log loss: 0.69
```

The log-loss metrics is much lower than in single decision tree (mainly to the fact that now we obtain probabilities output). The accuracy is the same, but notice that the structure of the tree is much simpler. We are creating 1000 **decision tree stumps**.

Also here a quick peek into predicted values show that now 4 out of 5 first test instances are classified correctly.

```
In [9]: print('True labels:')
        print(y_test[:5,])
        print('\nPredicted labels:')
        print(adaboost_y_pred[:5,])
        print('\nPredicted probabilities:')
        print(adaboost_y_pred_prob[:5,])
```

```
True labels:
[1 1 1 0 1]

Predicted labels:
[1 0 1 0 1]

Predicted probabilities:
[[ 0.50211294  0.49788706]
 [ 0.5021334   0.4978666 ]
 [ 0.50162035  0.49837965]
 [ 0.51639587  0.48360413]
 [ 0.49926165  0.50073835]]
```

Just for clarity, let's check how the first tree looks like.

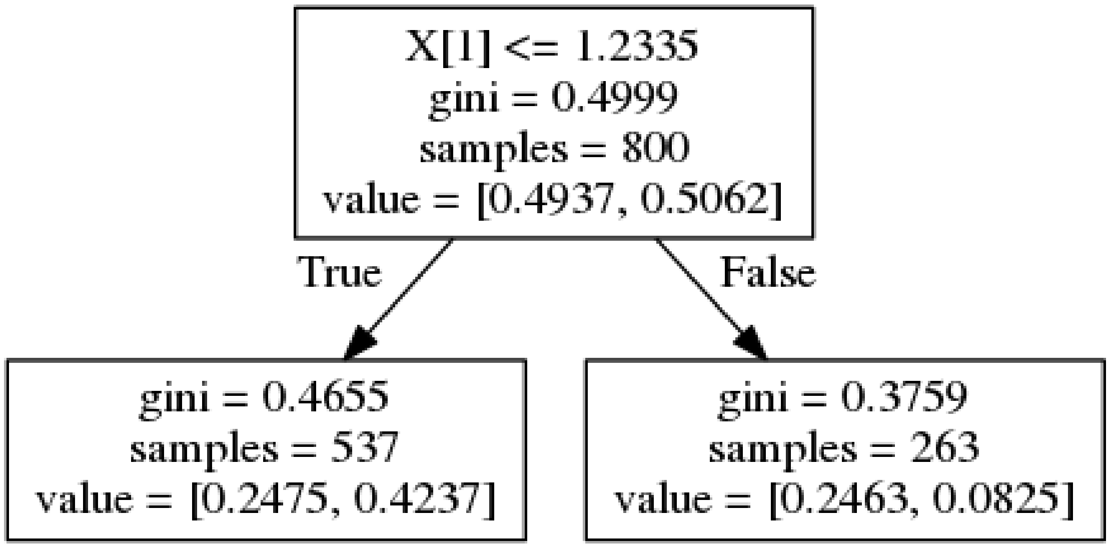
```
In [10]: ada_t1 = adaboost.estimators_[0]
         ada_t1_viz_file = '../images/ada-t1.dot'
         ada_t1_png_file = '../images/ada-t1.png'

         # create visualization
         export_graphviz(ada_t1, out_file=ada_t1_viz_file)

         # convert to PNG
         command = ["dot", "-Tpng", ada_t1_viz_file, "-o", ada_t1_png_file]
         subprocess.check_call(command)

         # display image
         Image(filename=ada_t1_png_file)
```

```
Out[10]:
```



What's it's error and contribution into final ensemble

```
In [11]: print("Error: {0:.2f}".format(adaboost.estimator_errors_[0]))
         print("Tree importance: {0:.2f}".format(adaboost.estimator_weights_[0]))
```

```
Error: 0.33
Tree importance: 0.71
```

### 1.0.4 Gradient Boosted Trees

Let's construct a gradient boosted tree consiting of 1000 trees where each successive one will be created with gradient optimization. Again we are going to leave most parameters with their default values, specifiy only maximum depth of the tree to 1 (again decision stumps), and setting warm start for more intelligent computations. Please refer to the docs if something is not clear.

```
In [12]: gbc = GradientBoostingClassifier(
             max_depth=1,
             n_estimators=1000,
             warm_start=True,
             random_state=seed)
         gbc.fit(X_train, y_train)

         # make predictions
         gbc_y_pred = gbc.predict(X_test)
         gbc_y_pred_prob = gbc.predict_proba(X_test)

         # calculate log loss
         gbc_accuracy = accuracy_score(y_test, gbc_y_pred)
         gbc_logloss = log_loss(y_test, gbc_y_pred_prob)
         print("== Gradient Boosting ==")
         print("Accuracy: {0:.2f}".format(gbc_accuracy))
         print("Log loss: {0:.2f}".format(gbc_logloss))
```

```
== Gradient Boosting ==
Accuracy: 0.81
Log loss: 0.48
```

The obtained results are obviously the best of all presented algorithm. We have obtained most accurate algorithm giving more sensible predictions about class probabilities.

```
In [13]: print('True labels:')
         print(y_test[:5,])
         print('\nPredicted labels:')
         print(gbc_y_pred[:5,])
         print('\nPredicted probabilities:')
         print(gbc_y_pred_prob[:5,])
```

```
True labels:
[1 1 1 0 1]

Predicted labels:
[1 0 1 0 1]

Predicted probabilities:
[[ 0.3698346   0.6301654 ]
 [ 0.77521996  0.22478004]
 [ 0.45077105  0.54922895]
 [ 0.9660623   0.0339377 ]
 [ 0.31039421  0.68960579]]
```

The difference is that GBC uses `DecisionTreeRegressor` classifier as the estimator with *mean-square error* as criterion. This results of slightly different output of the tree - now the leaf contains a predicted value (while the first splitting point remains the same).

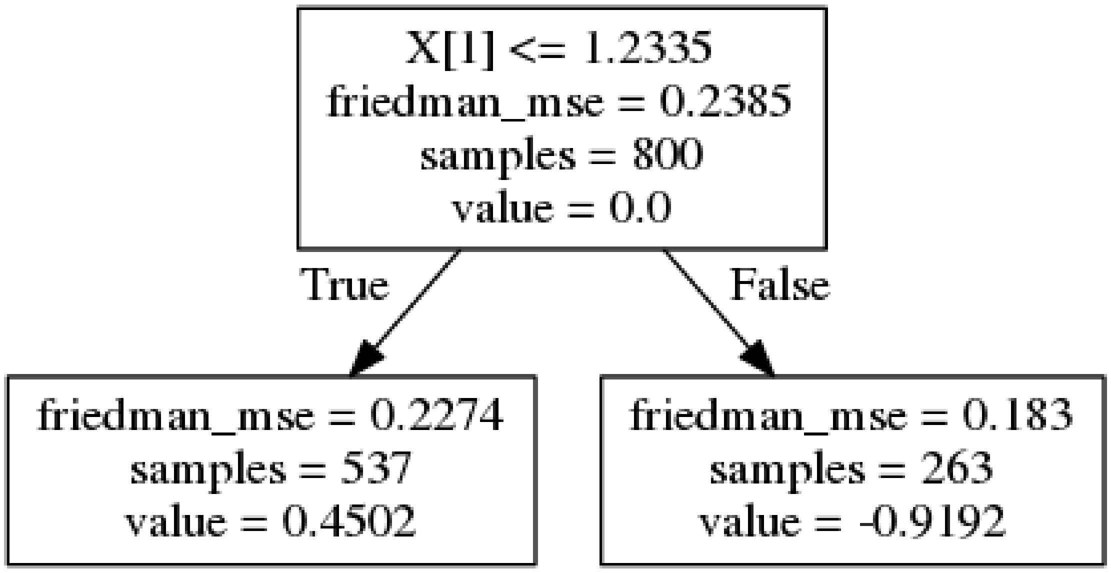
```
In [14]: gbc_t1 = gbc.estimators_[2][0]
         gbc_t1_viz_file = '../images/gbc-t1.dot'
         gbc_t1_png_file = '../images/gbc-t1.png'

         # create visualization
         export_graphviz(gbc_t1, out_file=gbc_t1_viz_file)

         # convert to PNG
         command = ["dot", "-Tpng", gbc_t1_viz_file, "-o", gbc_t1_png_file]
         subprocess.check_call(command)
```

```
# display image
Image(filename=gbc_t1_png_file)
```

Out[14]:


X[1] <= 1.2335
friedman_mse = 0.2385
samples = 800
value = 0.0
True
False
friedman_mse = 0.2274
samples = 537
value = 0.4502
friedman_mse = 0.183
samples = 263
value = -0.9192