Machine Learning Lab 9

Ensemble Learning

Ensemble learning is the process by which multiple models, such as classifiers or experts, are strategically generated and combined. Ensemble learning is primarily used to improve the (classification, prediction, function approximation, etc.) performance of a model, or reduce the likelihood of an unfortunate selection of a poor one. Some commonly used ensemble learning techniques are bagging, boosting, stacking, random forest, gradient boosting methods and voting.

The dataset

The dataset used to perform this experiment is the wine quality dataset, it is a combination of data on two types of wine variants, namely red wine and white wine, of the portuguese "Vinho Verde" wine. The dataset contains information on the parameters for fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulphates, alcohol.

Experiment

In this experiment I used the sklearn's decision tree, random forest classifier and gradient boosted tree algorithms to predict the quality of a wine and compared their performance.

Using the pandas library in I loaded the red wine and white wine datasets into the memory from their respective csv files and then merged the two datasets into one single pandas dataframe.

Using the pandas.Dataframe.describe() function in pandas I calculated the various statistical measures of each of the columns of the dataset.

I started with a decision tree with the training data containing all the 11 features from the dataset, the tree used gini index and has a max depth of 5. Next I used a gradient boosted tree with a max depth of 5 and finally the last model I used was random forest again with the max depth of five.

After training all the models over the training data I calculated the precision, recall, Fscore and support for all the algorithms using the sklearn's function to calculate all of the above together.

I plotted the above score on a bar graph and it is evident from the graphs that GBM trees perform the best, followed by random forests and the decision trees.

The code and plots can be found in the accompanying jupyter notebook.

Ensemble Learning

November 1, 2018

1 Lab 9

2 Ensemble Learning

2.1 Submitted to: Prof. Sweetlin Hemlatha

2.2 Submitted by: Prateek Singh (15BCE1091)

```
In [15]: import numpy as np
         import pandas as pd
         import seaborn as sn

         from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LogisticRegression
         from sklearn.preprocessing import StandardScaler
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
         from sklearn.metrics import fbeta_score, accuracy_score
         from sklearn.metrics import precision_recall_fscore_support, confusion_matrix

         import matplotlib.pyplot as plt
         from matplotlib.colors import ListedColormap

         %matplotlib inline
```

```
In [7]: white_wine_data = pd.read_csv('../Dataset/winequality-white.csv', sep=';')
        red_wine_data = pd.read_csv('../Dataset/winequality-red.csv', sep=';')

        wine_data = pd.concat([white_wine_data, red_wine_data])

        bins = [1, 4, 6, 10]
        labels = [0, 1, 2]
        wine_data['quality_category'] = pd.cut(wine_data['quality'],
                                          bins=bins,
                                          labels=labels,
                                          include_lowest=True)

        wine_data.head()
```

```
Out[7]:    fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
        0            7.0              0.27         0.36            20.7      0.045
        1            6.3              0.30         0.34             1.6      0.049
        2            8.1              0.28         0.40             6.9      0.050
        3            7.2              0.23         0.32             8.5      0.058
        4            7.2              0.23         0.32             8.5      0.058

           free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
        0                 45.0                 170.0   1.0010  3.00       0.45
        1                 14.0                 132.0   0.9940  3.30       0.49
        2                 30.0                  97.0   0.9951  3.26       0.44
        3                 47.0                 186.0   0.9956  3.19       0.40
        4                 47.0                 186.0   0.9956  3.19       0.40

           alcohol  quality quality_category
        0      8.8        6                1
        1      9.5        6                1
        2     10.1        6                1
        3      9.9        6                1
        4      9.9        6                1
```

```
In [12]: features = wine_data.iloc[:, :11]
         features.head()

         labels = wine_data['quality_category']
```

```
In [13]: X_train, X_test, Y_train, Y_test = train_test_split(features,
                                                              labels,
                                                              test_size=0.2,
                                                              random_state=0)

         print("Training set has {} samples".format(X_train.shape[0]))
         print("Testing set has {} samples".format(X_test.shape[0]))
```

```
Training set has 5197 samples
Testing set has 1300 samples
```

```
In [ ]: def train_predict_evaluate(learner, sample_size, X_train, Y_train, X_test, Y_test):
            results = {}
            start = time()
            learner = learner.fit(X_train, Y_train)
            end = time()

            results['train_time'] = end - start
```

```
In [19]: simpleTree = DecisionTreeClassifier(max_depth=5)
         simpleTree.fit(X_train, Y_train)
```

```
Out[19]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=5,
                     max_features=None, max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, presort=False, random_state=None,
                     splitter='best')
```

```
In [17]: gbmTree = GradientBoostingClassifier(max_depth=5)
         gbmTree.fit(X_train, Y_train)
```

```
Out[17]: GradientBoostingClassifier(criterion='friedman_mse', init=None,
                       learning_rate=0.1, loss='deviance', max_depth=5,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       presort='auto', random_state=None, subsample=1.0, verbose=0,
                       warm_start=False)
```

```
In [20]: rfTree = RandomForestClassifier(max_depth=5)
         rfTree.fit(X_train, Y_train)
```

```
Out[20]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=5, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
                     oob_score=False, random_state=None, verbose=0,
                     warm_start=False)
```

2.3 Evaluating Classifier Performance

```
In [25]: simpleTreePerformance = precision_recall_fscore_support(Y_test,
                                                                  simpleTree.predict(X_test))
         simpleTreePerformance
```

```
Out[25]: (array([0.75      , 0.82544104, 0.51598174]),
          array([0.05660377, 0.89346734, 0.4484127 ]),
          array([0.10526316, 0.85810811, 0.47983015]),
          array([ 53, 995, 252]))
```

```
In [26]: gbmTreePerformance = precision_recall_fscore_support(Y_test,
                                                               gbmTree.predict(X_test))
         gbmTreePerformance
```

```
Out[26]: (array([0.6       , 0.84615385, 0.73255814]),
          array([0.11320755, 0.95075377, 0.5       ]),
          array([0.19047619, 0.89540937, 0.59433962]),
          array([ 53, 995, 252]))
```

```
In [27]: rfTreePerformance = precision_recall_fscore_support(Y_test,
                                                              rfTree.predict(X_test))
         rfTreePerformance
```

```
/home/prateek/anaconda3/envs/dltf/lib/python3.6/site-packages/sklearn/metrics/classification.py
  'precision', 'predicted', average, warn_for)
```

```
Out[27]: (array([0.        , 0.79801325, 0.65217391]),
          array([0.        , 0.96884422, 0.23809524]),
          array([0.        , 0.87517022, 0.34883721]),
          array([ 53, 995, 252]))
```

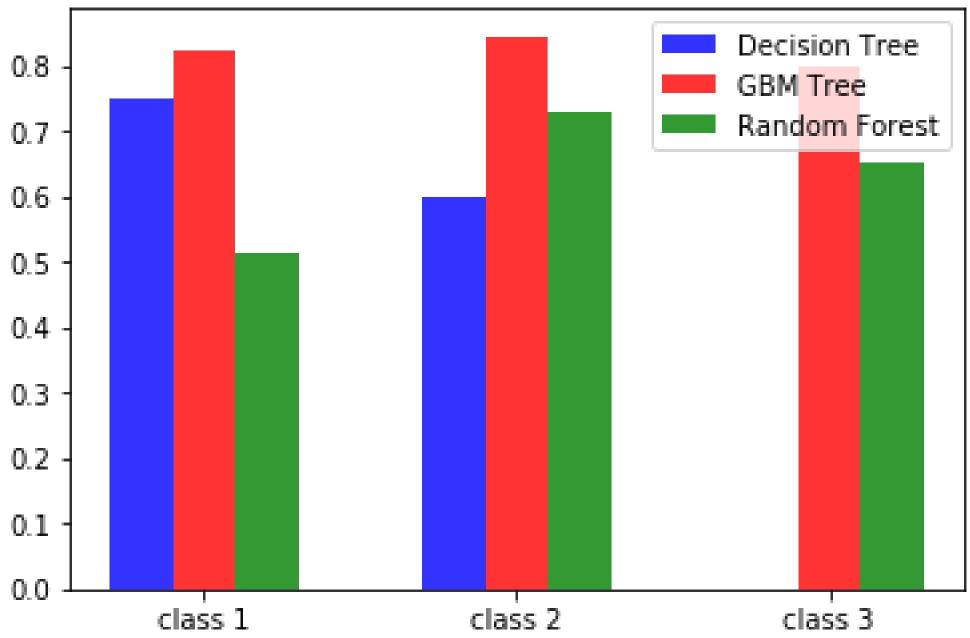
```
In [57]: print('Precision, Recall, Fscore, and Support for each class in simple, gradient boost
         for treeMethod in [simpleTreePerformance,gbmTreePerformance,rfTreePerformance]:
             print('Precision: ',treeMethod[0])
             print('Recall: ',treeMethod[1])
             print('Fscore: ',treeMethod[2])
             print('Support: ',treeMethod[3],'\n')
```

```
Precision, Recall, Fscore, and Support for each class in simple, gradient boosted, and random 

Precision:  [0.75       0.82544104 0.51598174]
Recall:  [0.05660377 0.89346734 0.4484127 ]
Fscore:  [0.10526316 0.85810811 0.47983015]
Support:  [ 53 995 252]

Precision:  [0.6        0.84615385 0.73255814]
Recall:  [0.11320755 0.95075377 0.5       ]
Fscore:  [0.19047619 0.89540937 0.59433962]
Support:  [ 53 995 252]

Precision:  [0.         0.79801325 0.65217391]
Recall:  [0.         0.96884422 0.23809524]
Fscore:  [0.         0.87517022 0.34883721]
Support:  [ 53 995 252]
```

```
In [49]: classifiers = [simpleTreePerformance, gbmTreePerformance, rfTreePerformance]

         n_classes=3
         index = np.arange(n_classes)
         bar_width = 0.2
         opacity = 0.8
         class1= [i[0][0] for i in classifiers]
         class2= [i[0][1] for i in classifiers]
         class3= [i[0][2] for i in classifiers]
```

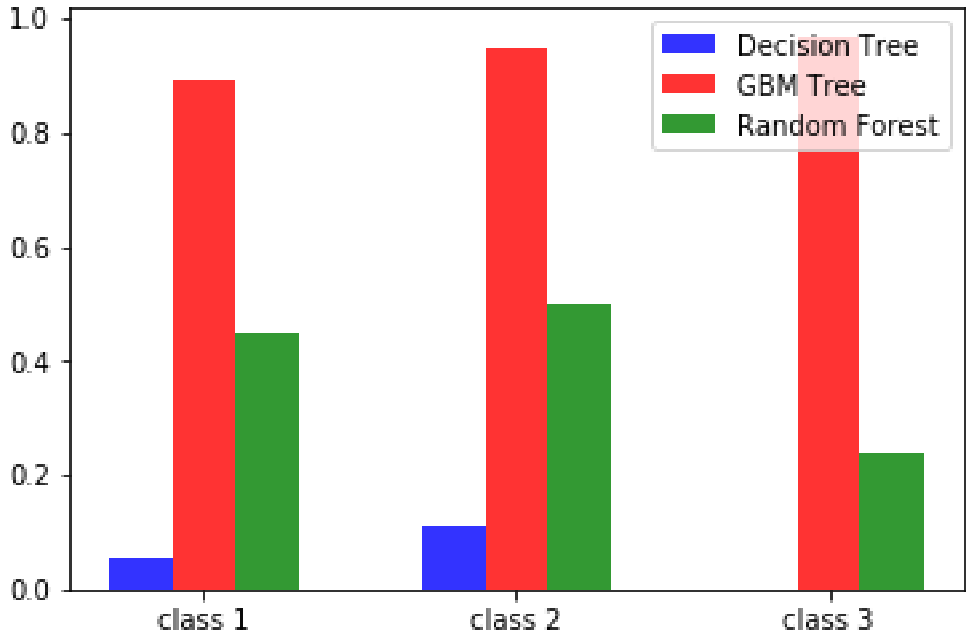
```
rects1 = plt.bar(index, class1, bar_width, alpha=opacity, color='b', label='Decision T
rects2 = plt.bar(index + bar_width, class2, bar_width, alpha=opacity, color='r', label
rects1 = plt.bar(index + 2*bar_width, class3, bar_width, alpha=opacity, color='g', lab
plt.xticks(index + bar_width, ('class 1', 'class 2', 'class 3'))
plt.legend()
```

Out[49]: <matplotlib.legend.Legend at 0x7f977988d470>



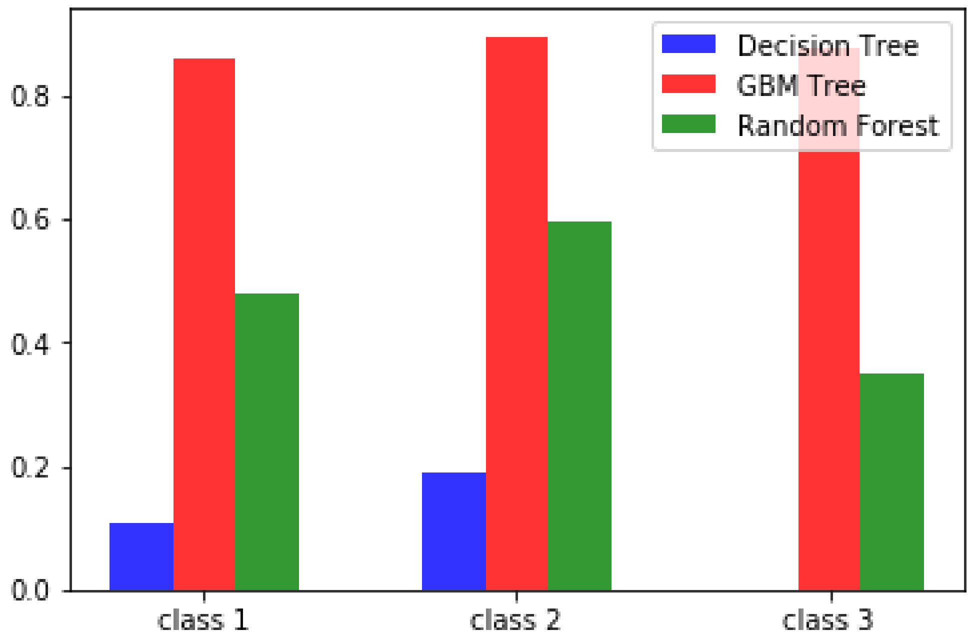

```
In [50]: class1= [i[1][0] for i in classifiers]
         class2= [i[1][1] for i in classifiers]
         class3= [i[1][2] for i in classifiers]

         rects1 = plt.bar(index, class1, bar_width, alpha=opacity, color='b', label='Decision T
         rects2 = plt.bar(index + bar_width, class2, bar_width, alpha=opacity, color='r', label
         rects1 = plt.bar(index + 2*bar_width, class3, bar_width, alpha=opacity, color='g', lab
         plt.xticks(index + bar_width, ('class 1', 'class 2', 'class 3'))
         plt.legend()
```

Out[50]: <matplotlib.legend.Legend at 0x7f977987e198>



In [53]:
```
class1= [i[2][0] for i in classifiers]
class2= [i[2][1] for i in classifiers]
class3= [i[2][2] for i in classifiers]

rects1 = plt.bar(index, class1, bar_width, alpha=opacity, color='b', label='Decision T
rects2 = plt.bar(index + bar_width, class2, bar_width, alpha=opacity, color='r', label
rects1 = plt.bar(index + 2*bar_width, class3, bar_width, alpha=opacity, color='g', lab
plt.xticks(index + bar_width, ('class 1', 'class 2', 'class 3'))
plt.legend()
```

Out[53]:
```
<matplotlib.legend.Legend at 0x7f977972f390>
```




```
In [54]: print('Confusion Matrix for simple, gradient boosted, and random forest tree classifi
         print('Simple Tree:\n',confusion_matrix(Y_test,simpleTree.predict(X_test)),'\n')
         print('Gradient Boosted:\n',confusion_matrix(Y_test,gbmTree.predict(X_test)),'\n')
         print('Random Forest:\n',confusion_matrix(Y_test,rfTree.predict(X_test)))
```

```
Confusion Matrix for simple, gradient boosted, and random forest tree classifiers:
Simple Tree:
 [[  3  49   1]
 [  1 889 105]
 [  0 139 113]]

Gradient Boosted:
 [[  6  46   1]
 [  4 946  45]
 [  0 126 126]]

Random Forest:
 [[  0  52   1]
 [  0 964  31]
 [  0 192  60]]
```

So, now that we know that the GBM tree is our favored classifier for predicting the tastiness of wines. GBM trees produce interpretable results, so we can call the feature_importances method against the GBM tree object and find out which features play the largest role in predicting tastiness.

```
In [56]: print('Feature Importances for GBM tree\n')
         for importance,feature in zip(gbmTree.feature_importances_,['fixed acidity', 'volatile
             print('{}: {}'.format(feature,importance))
```

```
Feature Importances for GBM tree

fixed acidity: 0.07266209290311769
volatile acidity: 0.09686352995424061
citric acid: 0.07400598128203767
residual sugar: 0.08346647919160737
chlorides: 0.09642196074703188
free sulfur dioxide: 0.08908900243321564
total sulfur dioxide: 0.10157934180761936
density: 0.10841709274945117
pH: 0.08082887598433434
sulphates: 0.07935625155693848
alcohol: 0.11730939139040583
```