Ensemble Learning

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1 Lab 9

2 Ensemble Learning

2.1 Submitted to: Prof. Sweetlin Hemlatha

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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]))
```

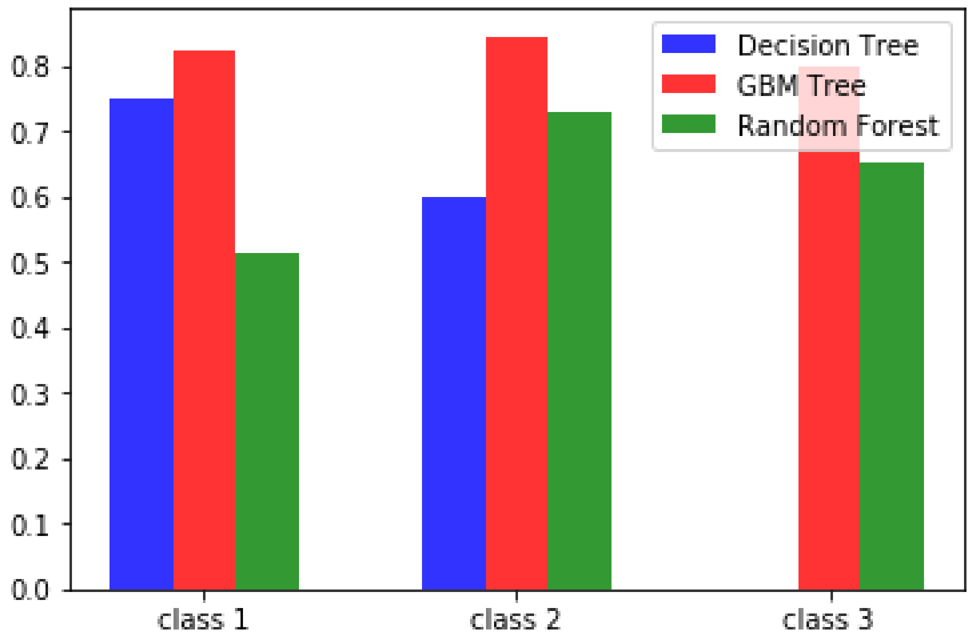
```
In [57]: print('Precision, Recall, Fscore, and Support for each class in simple, gradient boost
         for treeMethod in [simpleTreePerformance,gbmTreePerformance,rfTreePerformance]:
             print('Precision: ',treeMethod[0])
             print('Recall: ',treeMethod[1])
             print('Fscore: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

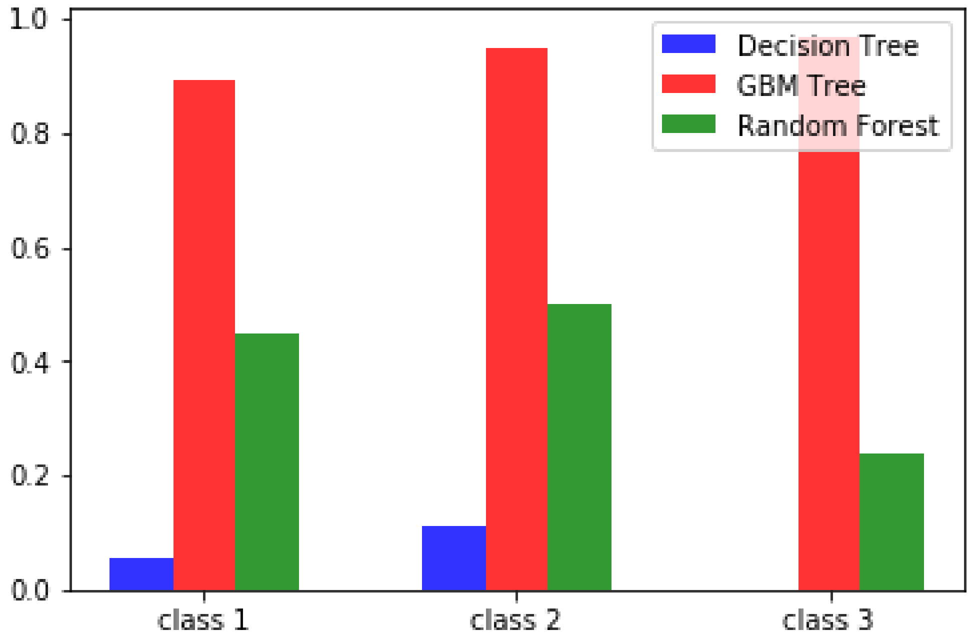
```
rects1 = plt.bar(index, class1, bar_width, alpha=opacity, color='b', label='Decision T
rects2 = plt.bar(index + bar_width, class2, bar_width, alpha=opacity, color='r', label
rects1 = plt.bar(index + 2*bar_width, class3, bar_width, alpha=opacity, color='g', lab
plt.xticks(index + bar_width, ('class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

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

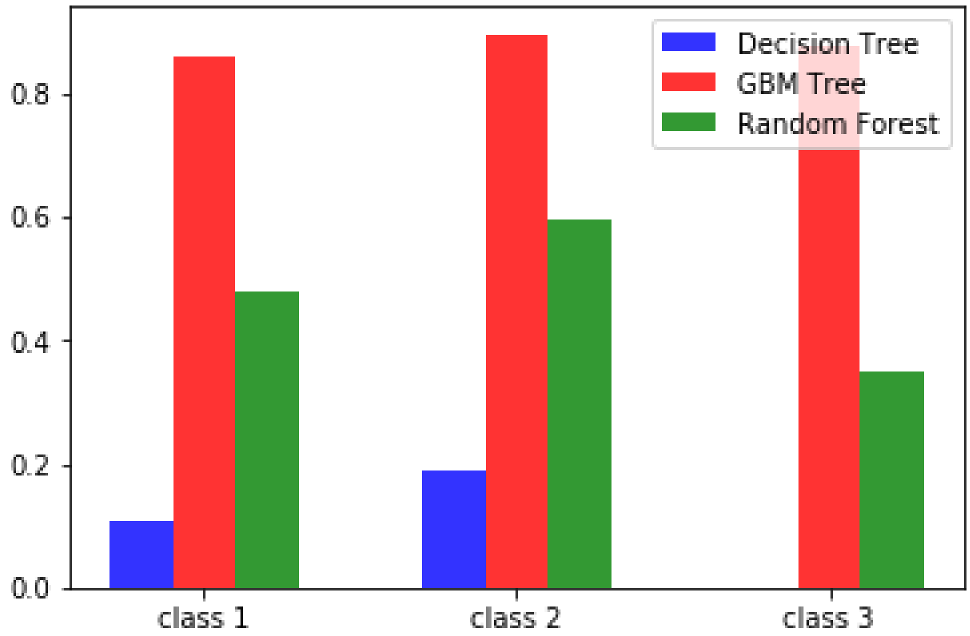


In [50]:
```
class1= [i[1][0] for i in classifiers]
class2= [i[1][1] for i in classifiers]
class3= [i[1][2] for i in classifiers]

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 classifie
         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
```