Machine Learning Lab 5

Decision Tree

Decision tree is one of the most popular machine learning algorithms used all along. A decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements

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 algorithms to predict the quality of a wine.

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.

For performing the experiment I started with plotting the scatter plot for each of the features in the dataset with every other feature, this helped to find if there were any features which were linearly separable. In the case of my dataset they were not.

Next used a decision tree with the training data containing all the 11 features from the dataset, the tree uses gini index and has a max depth of 3. With this decision tree I was able to obtain a training accuracy of 0.817 and a test accuracy of 0.816

Looking at the visualization of decision tree it is evident that the decision tree is overfitting and thus we would need something better than a single decision tree and this would be a random forest.

Using the random forest classifier in sklearn I calculated the feature importance for the features of the dataset and used those featured in a random forest classifier to achieve a training accuracy score of 1.0 and a test accuracy score of 0.89 which are much greater than those obtained with a decision tree.

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

Decision Trees

November 1, 2018

1 Lab 5

2 Decision Trees

2.1 Submitted to: Prof. Sweetlin Hemlatha

2.2 Submitted by: Prateek Singh (15BCE1091)

```
In [14]: import numpy as np
         import pandas as pd
         import seaborn as sb
         import graphviz

         from sklearn.preprocessing import StandardScaler
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.tree import export_graphviz
         from sklearn.cross_validation import train_test_split
         from sklearn.ensemble import RandomForestClassifier

         import matplotlib.pyplot as plt
         from matplotlib.colors import ListedColormap
         %matplotlib inline
```

```
In [5]: red_wine_data = pd.read_csv('../Dataset/winequality-red.csv', sep=';')
        white_wine_data = pd.read_csv('../Dataset/winequality-white.csv', sep=';')

        wine_data = pd.concat([red_wine_data, white_wine_data])
        bins = (2, 6.5, 10)
        group_names = ['bad', 'good']
        wine_data['quality'] = pd.cut(wine_data['quality'], bins = bins, labels = group_names)
        wine_data.iloc[:, :11].describe()
```

```
Out[5]:        fixed acidity  volatile acidity  citric acid  residual sugar  \
        count    6497.000000       6497.000000  6497.000000     6497.000000
        mean        7.215307          0.339666     0.318633        5.443235
        std         1.296434          0.164636     0.145318        4.757804
        min         3.800000          0.080000     0.000000        0.600000
        25%         6.400000          0.230000     0.250000        1.800000
```

```
50%         7.000000          0.290000     0.310000        3.000000
75%         7.700000          0.400000     0.390000        8.100000
max        15.900000          1.580000     1.660000       65.800000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  6497.000000          6497.000000           6497.000000  6497.000000
mean      0.056034            30.525319            115.744574     0.994697
std       0.035034            17.749400             56.521855     0.002999
min       0.009000             1.000000              6.000000     0.987110
25%       0.038000            17.000000             77.000000     0.992340
50%       0.047000            29.000000            118.000000     0.994890
75%       0.065000            41.000000            156.000000     0.996990
max       0.611000           289.000000            440.000000     1.038980

                pH    sulphates      alcohol
count  6497.000000  6497.000000  6497.000000
mean      3.218501     0.531268    10.491801
std       0.160787     0.148806     1.192712
min       2.720000     0.220000     8.000000
25%       3.110000     0.430000     9.500000
50%       3.210000     0.510000    10.300000
75%       3.320000     0.600000    11.300000
max       4.010000     2.000000    14.900000
```

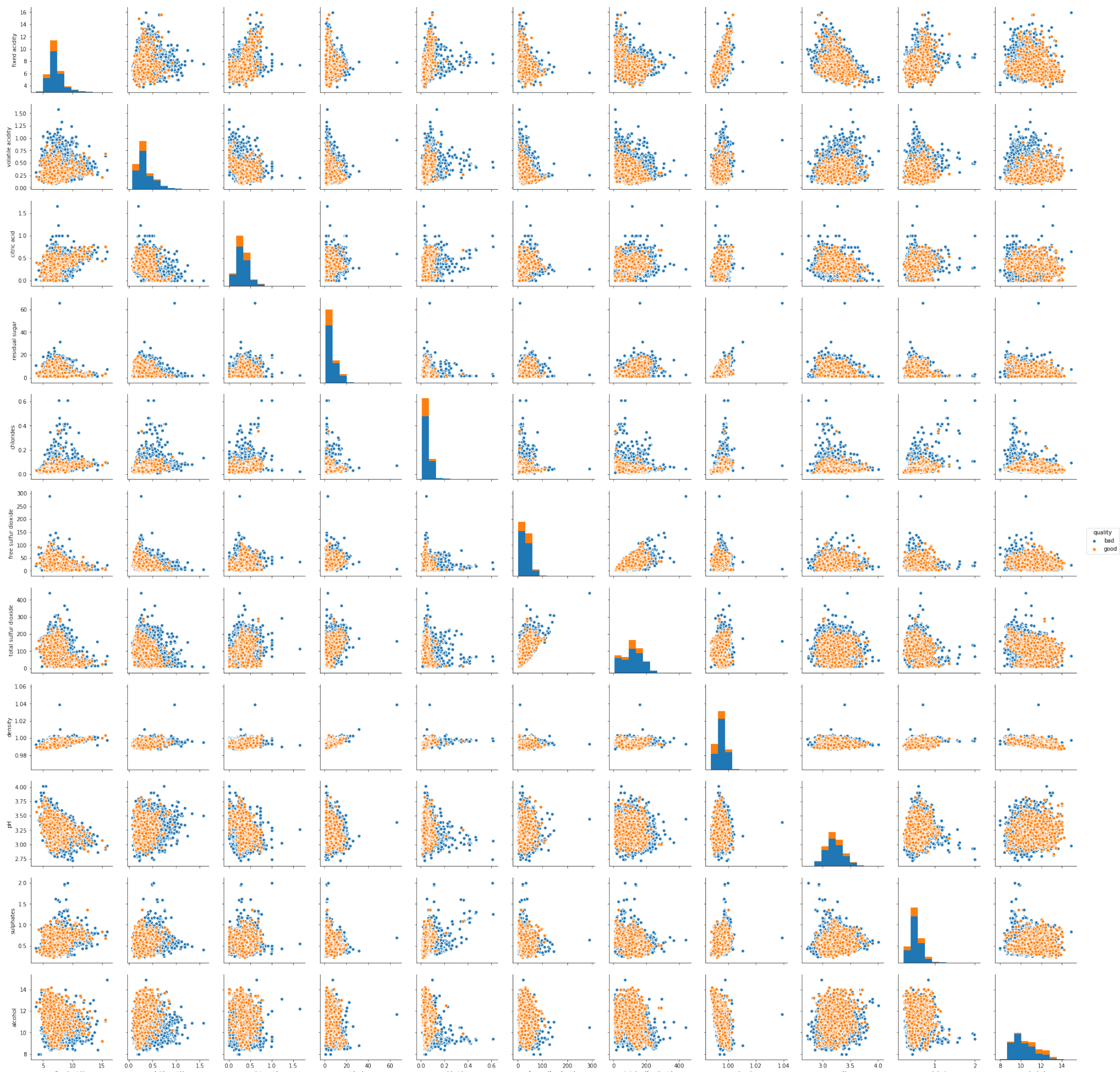
In [6]:
```
scaler = StandardScaler()

data = wine_data.iloc[:,:11].values
scaled_features = scaler.fit_transform(data)

wine_data_scaled = pd.DataFrame(scaled_features, index=wine_data.index, columns=wine_da
wine_data_scaled.head()
```

Out[6]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0       0.142473          2.188833    -2.192833       -0.744778   0.569958
1       0.451036          3.282235    -2.192833       -0.597640   1.197975
2       0.451036          2.553300    -1.917553       -0.660699   1.026697
3       3.073817         -0.362438     1.661085       -0.744778   0.541412
4       0.142473          2.188833    -2.192833       -0.744778   0.569958

   free sulfur dioxide  total sulfur dioxide   density        pH  sulphates  \
0            -1.100140             -1.446359  1.034993  1.813090   0.193097
1            -0.311320             -0.862469  0.701486 -0.115073   0.999579
2            -0.874763             -1.092486  0.768188  0.258120   0.797958
3            -0.762074             -0.986324  1.101694 -0.363868   0.327510
4            -1.100140             -1.446359  1.034993  1.813090   0.193097

    alcohol
0 -0.915464
```

```
1 -0.580068
2 -0.580068
3 -0.580068
4 -0.915464
```

```
In [7]: sb.pairplot(wine_data.dropna(), size=2.5, hue="quality")
```

```
Out[7]: <seaborn.axisgrid.PairGrid at 0x7f05a8cf9748>
```




```
In [8]: X_train, X_test, Y_train, Y_test = train_test_split(wine_data.iloc[:, :11],
                                                            wine_data.iloc[:, 11],
                                                            test_size=0.2,
                                                            random_state=42)
```

```
In [21]: tree = DecisionTreeClassifier(criterion='gini',
                                       max_depth=3, random_state=0)
         tree.fit(X_train, Y_train)
         print("Accuracy on training set: {:.3f}".format(tree.score(X_train,Y_train)))
         print("Accuracy on test set: {:.3f}".format(tree.score(X_test,Y_test)))
```

```
Accuracy on training set: 0.817
Accuracy on test set: 0.816
```

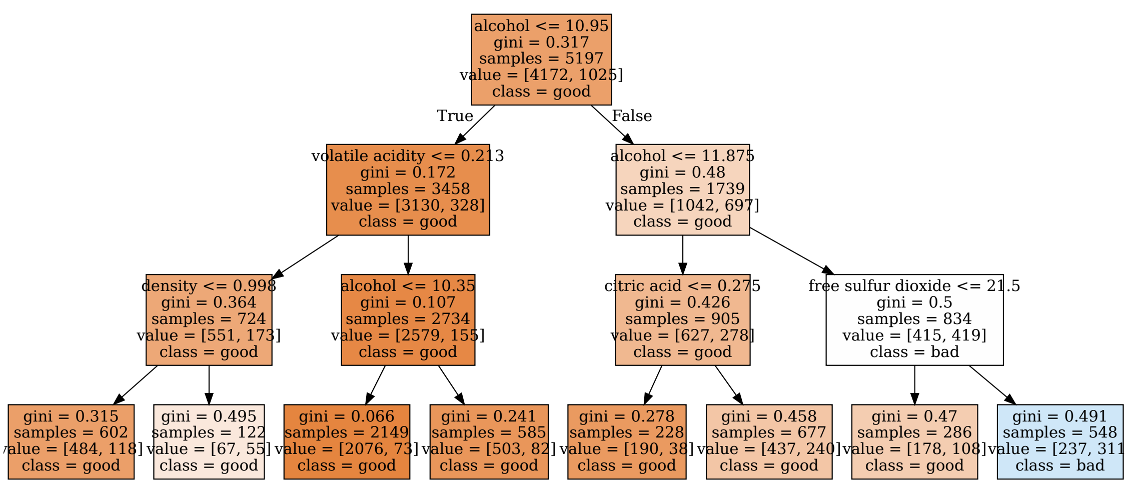
```
In [22]: X_train.columns.values
```

```
Out[22]: array(['fixed acidity', 'volatile acidity', 'citric acid',
                'residual sugar', 'chlorides', 'free sulfur dioxide',
                'total sulfur dioxide', 'density', 'pH', 'sulphates', 'alcohol'],
               dtype=object)
```

```
In [23]: export_graphviz(tree,
                         out_file='tree.odt',
                         class_names=['good','bad'],
                         feature_names=X_train.columns,
                         filled='weathersit')
```

```
In [24]: with open("tree.odt") as f:
             dot_graph = f.read()
         graphviz.Source(dot_graph)
```

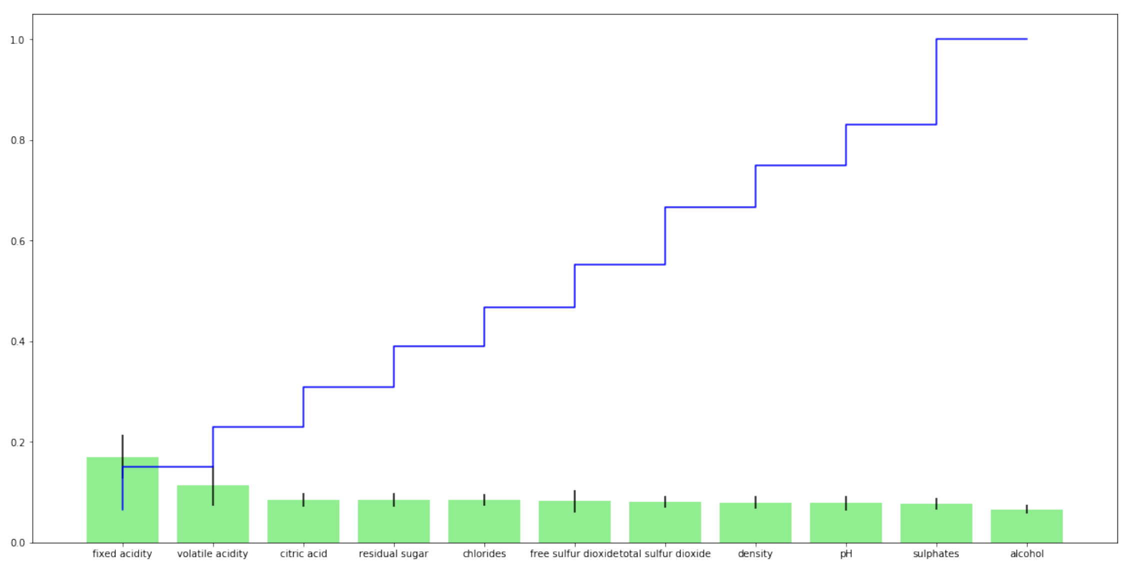
Out[24]:




```
In [11]: forest = RandomForestClassifier(n_estimators=30, random_state=0, n_jobs=-1)
         forest.fit(X_train, Y_train)
```

```
importances = forest.feature_importances_
std = np.std([tree.feature_importances_ for tree in forest.estimators_], axis=0)
cum_imp = np.cumsum(importances)
indices = np.argsort(importances)[::-1]

print('Feature rankings')

for f in range(data.shape[1]):
    print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))

plt.figure(figsize=(20, 10))
plt.bar(range(data.shape[1]), importances[indices], color="lightgreen", yerr=std[indic
plt.step(range(data.shape[1]), cum_imp, 'b')
plt.xticks(range(data.shape[1]), list(wine_data.columns.values[:11]))
plt.xlim([-1, data.shape[1]])
plt.show()
```

```
Feature rankings
1. feature 10 (0.170518)
2. feature 7 (0.112865)
3. feature 1 (0.084866)
4. feature 6 (0.084767)
5. feature 8 (0.084456)
6. feature 4 (0.082162)
7. feature 9 (0.079930)
8. feature 3 (0.079630)
9. feature 2 (0.077950)
10. feature 5 (0.077013)
11. feature 0 (0.065844)
```



```
In [12]: print("Accuracy on training set: {:.3f}".format(forest.score(X_train,Y_train)))
         print("Accuracy on test set: {:.3f}".format(forest.score(X_test,Y_test)))
```

```
Accuracy on training set: 1.000
Accuracy on test set: 0.890
```