```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification
from sklearn.tree import DecisionTreeClassifier
%matplotlib inline
```

Explore and Clean the Data

```
In [2]: os.getcwd()
Out[2]: 'C:\\Users\\tural'
In [3]: os.chdir("C:\\Users\\tural\\OneDrive\\Desktop\\Study Materials\\Datasets")
In [4]: df = pd.read_csv("WineQT.csv")
df.head(20)
```

Out[4]:

•		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	С
	0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	_
	1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	
	2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	
	3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	
	4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	
	5	7.4	0.660	0.00	1.8	0.075	13.0	40.0	0.9978	3.51	0.56	9.4	
	6	7.9	0.600	0.06	1.6	0.069	15.0	59.0	0.9964	3.30	0.46	9.4	
	7	7.3	0.650	0.00	1.2	0.065	15.0	21.0	0.9946	3.39	0.47	10.0	
	8	7.8	0.580	0.02	2.0	0.073	9.0	18.0	0.9968	3.36	0.57	9.5	
	9	6.7	0.580	0.08	1.8	0.097	15.0	65.0	0.9959	3.28	0.54	9.2	
	10	5.6	0.615	0.00	1.6	0.089	16.0	59.0	0.9943	3.58	0.52	9.9	
	11	7.8	0.610	0.29	1.6	0.114	9.0	29.0	0.9974	3.26	1.56	9.1	
	12	8.5	0.280	0.56	1.8	0.092	35.0	103.0	0.9969	3.30	0.75	10.5	
	13	7.9	0.320	0.51	1.8	0.341	17.0	56.0	0.9969	3.04	1.08	9.2	
	14	7.6	0.390	0.31	2.3	0.082	23.0	71.0	0.9982	3.52	0.65	9.7	
	15	7.9	0.430	0.21	1.6	0.106	10.0	37.0	0.9966	3.17	0.91	9.5	
	16	8.5	0.490	0.11	2.3	0.084	9.0	67.0	0.9968	3.17	0.53	9.4	
	17	6.9	0.400	0.14	2.4	0.085	21.0	40.0	0.9968	3.43	0.63	9.7	
	18	6.3	0.390	0.16	1.4	0.080	11.0	23.0	0.9955	3.34	0.56	9.3	
	19	7.6	0.410	0.24	1.8	0.080	4.0	11.0	0.9962	3.28	0.59	9.5	
)	>

In [5]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
         RangeIndex: 1143 entries, 0 to 1142
         Data columns (total 13 columns):
               Column
          #
                                       Non-Null Count
                                                        Dtype
              _ _ _ _ _
                                       _____
              fixed acidity
          0
                                       1143 non-null
                                                        float64
          1
              volatile acidity
                                       1143 non-null
                                                        float64
          2
              citric acid
                                       1143 non-null
                                                        float64
          3
              residual sugar
                                       1143 non-null
                                                        float64
          4
              chlorides
                                                        float64
                                       1143 non-null
              free sulfur dioxide
                                       1143 non-null
                                                        float64
          6
              total sulfur dioxide
                                       1143 non-null
                                                        float64
          7
              density
                                       1143 non-null
                                                        float64
          8
                                       1143 non-null
                                                        float64
              рΗ
          9
              sulphates
                                       1143 non-null
                                                        float64
                                       1143 non-null
                                                        float64
              alcohol
                                                        int64
          11
              quality
                                       1143 non-null
          12
              Ιd
                                       1143 non-null
                                                        int64
         dtypes: float64(11), int64(2)
         memory usage: 116.2 KB
         a = np.arange(1143)
In [6]:
         df['Id'] = a
         df.columns = df.columns.str.lower()
         df.columns = df.columns.str.replace(' ', '_')
         df.columns = df.columns.str.replace(' dioxide', '')
         df.round(3)
Out[6]:
               fixed_acidity
                            volatile_acidity citric_acid residual_sugar chlorides free_sulfur
                                                                                         total_sulfur
            0
                        7.4
                                     0.700
                                                0.00
                                                                1.9
                                                                        0.076
                                                                                                34.0
                                                                                    11.0
            1
                        7.8
                                     0.880
                                                0.00
                                                                2.6
                                                                        0.098
                                                                                    25.0
                                                                                                67.0
            2
                                                0.04
                        7.8
                                     0.760
                                                                2.3
                                                                        0.092
                                                                                    15.0
                                                                                                54.0
            3
                       11.2
                                     0.280
                                                0.56
                                                                1.9
                                                                        0.075
                                                                                    17.0
                                                                                                60.0
            4
                        7.4
                                     0.700
                                                0.00
                                                                1.9
                                                                        0.076
                                                                                    11.0
                                                                                                34.0
         1138
                        6.3
                                     0.510
                                                0.13
                                                                2.3
                                                                        0.076
                                                                                    29.0
                                                                                                40.0
         1139
                        6.8
                                     0.620
                                                0.08
                                                                1.9
                                                                        0.068
                                                                                    28.0
                                                                                                38.0
         1140
                                     0.600
                                                0.08
                                                                2.0
                                                                                    32.0
                        6.2
                                                                        0.090
                                                                                                44.0
```

1143 rows × 13 columns

5.9

5.9

0.550

0.645

1141

1142

In []:

0.10

0.12

2.2

2.0

0.062

0.075

39.0

32.0

Descriptive Statistics

0

0

0

0

0

0

0

0

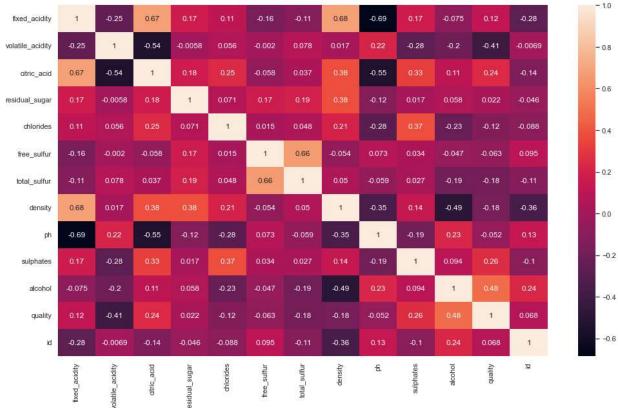
0

0

51.0

44.0

```
df.value_counts('quality')
In [8]:
          quality
Out[8]:
                 483
                 462
           6
                 143
           4
                  33
           8
                  16
          dtype: int64
           sns.set(rc = {'figure.figsize':(17,10)})
In [9]:
           sns.heatmap(df.corr(), annot = True)
           <AxesSubplot:>
Out[9]:
                                    0.67
            fixed_acidity
                                                                      0.68
                                                                            -0.69
                      -0.25
                             1
                                                                                                 -0.41
           volatile_acidity
                                          -0.0058
                                                 0.056
                                                        -0.002
                                                               0.078
                                                                                   -0.28
                                                                                                       -0.0069
```



Lets create groups for quality and divide it into 2 groups which are poor quality(0) and good quality(1)

```
In [11]: df['label'] = pd.cut(x=df['quality'], bins=[0, 5, 8,],labels=[0, 1])
```

Decision Tree Model

As we see there is not any highly correlated variable to quality. That is the reason we cannot use linear regression and we will be choosing decision tree model.

```
In [14]: df.set_index('id')
```

Out[14]

:		fixed_acidity	volatile_acidity	citric_acid	residual_sugar	chlorides	free_sulfur	total_sulfur	deı
	id								
	0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99
	1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99
	2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99
	3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99
	4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99
	•••								
	1138	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99
	1139	6.8	0.620	0.08	1.9	0.068	28.0	38.0	0.99
	1140	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99
	1141	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99
	1142	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99

1143 rows × 13 columns

```
X = df.drop('label', axis = 1)
In [21]:
         y = df['label']
In [22]:
In [30]:
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
         dtree = DecisionTreeClassifier()
In [33]:
         dtree.fit(X_train,y_train)
In [34]:
         DecisionTreeClassifier()
Out[34]:
         predictions = dtree.predict(X_test)
In [35]:
         print(confusion_matrix(y_test,predictions))
In [36]:
         print("\n")
         print(classification_report(y_test, predictions))
```

```
[[155 0]
[ 0 188]]
```

[0 188]]

In [39]:

In [40]:

Out[40]:

```
precision
                            recall f1-score
                                                support
           0
                   1.00
                              1.00
                                        1.00
                                                    155
           1
                   1.00
                              1.00
                                        1.00
                                                    188
                                                    343
                                        1.00
    accuracy
                   1.00
                                        1.00
                                                    343
   macro avg
                              1.00
weighted avg
                   1.00
                              1.00
                                        1.00
                                                    343
rfc = RandomForestClassifier(n_estimators = 200)
rfc.fit(X_train, y_train)
RandomForestClassifier(n_estimators=200)
```

```
In [41]: rfc_pred = rfc.predict(X_test)
In [42]: print(confusion_matrix(y_test,rfc_pred))
```

```
In [42]: print(confusion_matrix(y_test,rfc_pred))
    print("\n")
    print(classification_report(y_test, rfc_pred))

[[155 0]
```

```
precision
                            recall f1-score
                                                support
           0
                    1.00
                              1.00
                                         1.00
                                                     155
                    1.00
           1
                              1.00
                                         1.00
                                                     188
                                         1.00
                                                     343
    accuracy
                    1.00
                              1.00
                                         1.00
                                                     343
   macro avg
weighted avg
                    1.00
                              1.00
                                         1.00
                                                     343
```

As we can see from the confusion metrics, decision tree works perfectly fine and there is not any type of errors. We can conclude that we do not need to create random forests for this dataset and we can predict the wine quality with decision trees.