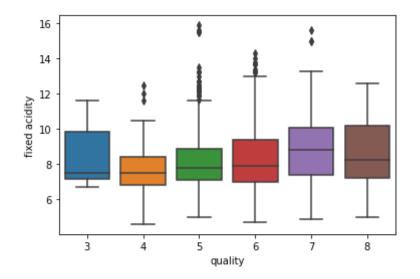
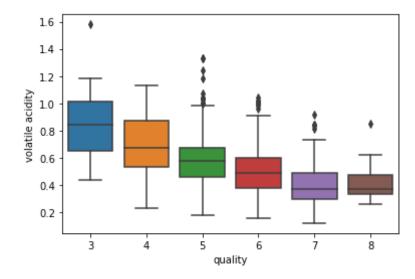
```
In [27]: # import libraries
          import pandas as pd
          import numpy as np
          import sklearn
          import seaborn as sns
          import matplotlib.pyplot as plt
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.svm import SVC
          from sklearn.linear model import SGDClassifier
          from sklearn.metrics import confusion matrix, classification report
          from sklearn.preprocessing import StandardScaler, LabelEncoder
          from sklearn.model selection import train test split, GridSearchCV, cro
          ss val score
          %matplotlib inline
          data = pd.read csv("redwine.csv")
 In [3]: data.head()
 Out[3]:
                                                    free
                                                           total
               fixed volatile citric residual
                                         chlorides
                                                   sulfur
                                                          sulfur density
                                                                        pH sulphates alcohol
                     acidity
              acidity
                            acid
                                   sugar
                                                  dioxide dioxide
                            0.00
                                                                 0.9978 3.51
                7.4
                       0.70
                                     1.9
                                            0.076
                                                    11.0
                                                           34.0
                                                                                 0.56
                                                                                         9.4
           1
                7.8
                       0.88
                            0.00
                                     2.6
                                            0.098
                                                    25.0
                                                           67.0
                                                                 0.9968 3.20
                                                                                 0.68
                                                                                         9.8
           2
                7.8
                       0.76
                            0.04
                                     2.3
                                            0.092
                                                    15.0
                                                            54.0
                                                                 0.9970 3.26
                                                                                 0.65
                                                                                         9.8
           3
                11.2
                       0.28
                            0.56
                                     1.9
                                            0.075
                                                    17.0
                                                           60.0
                                                                 0.9980 3.16
                                                                                 0.58
                                                                                         9.8
                7.4
                       0.70
                            0.00
                                     1.9
                                            0.076
                                                    11.0
                                                           34.0
                                                                 0.9978 3.51
                                                                                 0.56
                                                                                         9.4
 In [4]: data.columns
 Out[4]: Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual su
```

```
gar',
               'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'den
        sity',
               'pH', 'sulphates', 'alcohol', 'quality'],
              dtvpe='object')
In [5]: data.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 1599 entries, 0 to 1598
        Data columns (total 12 columns):
                                  Non-Null Count Dtype
         #
            Column
            _ _ _ _ _
            fixed acidity
                                  1599 non-null
                                                 float64
            volatile acidity
                                  1599 non-null float64
         2
            citric acid
                                  1599 non-null float64
                                 1599 non-null float64
            residual sugar
            chlorides
                                 1599 non-null float64
            free sulfur dioxide 1599 non-null float64
            total sulfur dioxide 1599 non-null float64
            density
                                  1599 non-null float64
                                  1599 non-null float64
             Hq
                                  1599 non-null float64
            sulphates
         10 alcohol
                                  1599 non-null
                                                 float64
         11 quality
                                  1599 non-null
                                                 int64
        dtypes: float64(11), int64(1)
        memory usage: 150.0 KB
In [6]: sns.boxplot('quality', 'fixed acidity', data = data)
Out[6]: <matplotlib.axes. subplots.AxesSubplot at 0x231d08eb550>
```



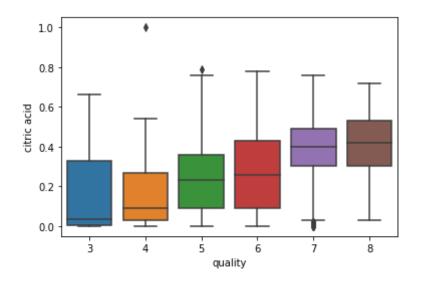
In [7]: sns.boxplot('quality', 'volatile acidity', data = data)

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x231d1024c40>



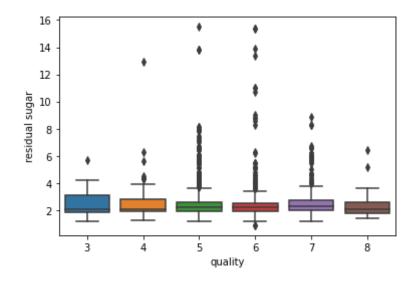
In [8]: sns.boxplot('quality', 'citric acid', data = data)

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x231d11792e0>



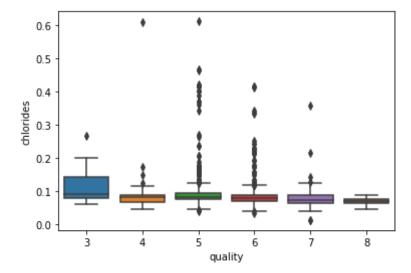
In [9]: sns.boxplot('quality', 'residual sugar', data = data)

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x231d11791c0>



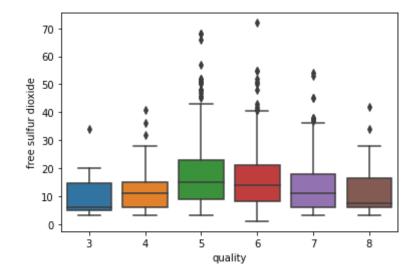
In [10]: sns.boxplot('quality', 'chlorides', data = data)

```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x231d13025b0>
```



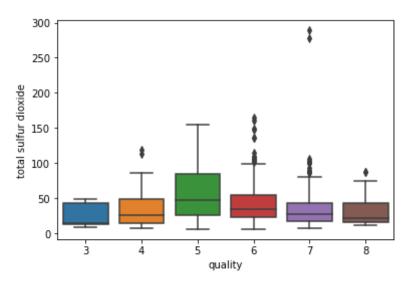
In [11]: sns.boxplot('quality', 'free sulfur dioxide', data = data)

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x231d13bf400>



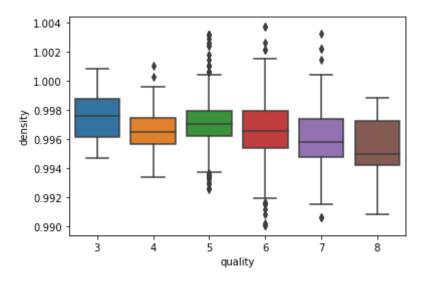
In [12]: sns.boxplot('quality', 'total sulfur dioxide', data = data)

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x231d1474820>



In [13]: sns.boxplot('quality', 'density', data = data)

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x231d1523280>



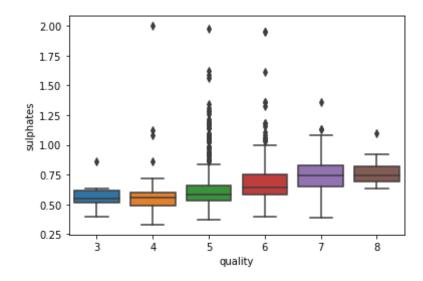
In [14]: | sns.boxplot('quality', 'pH', data = data)
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x231d15fbfd0>

4.0
3.8
3.6
3.4
3.2
3.0
2.8

quality

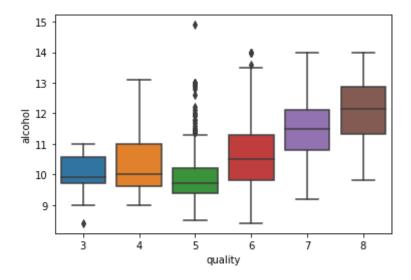
In [15]: sns.boxplot('quality', 'sulphates', data = data)

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x231d16ab460>



In [16]: sns.boxplot('quality', 'alcohol', data = data)

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x231d140f6d0>

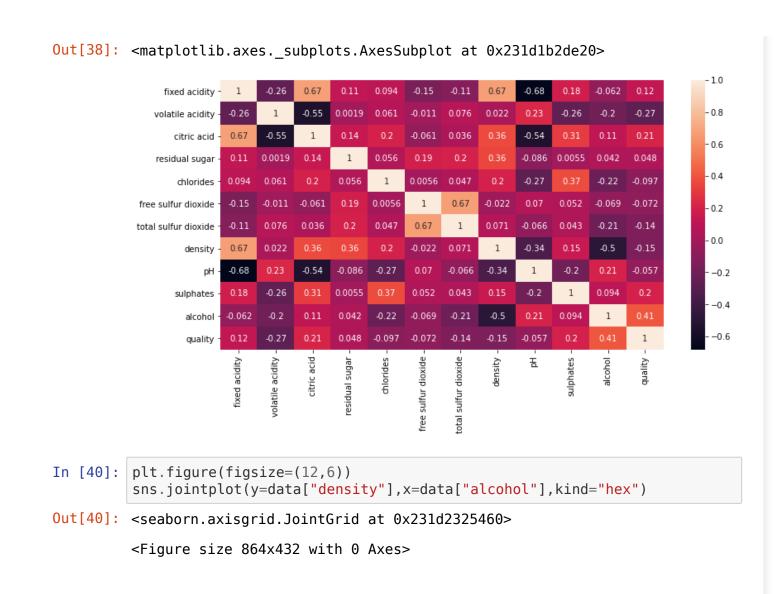


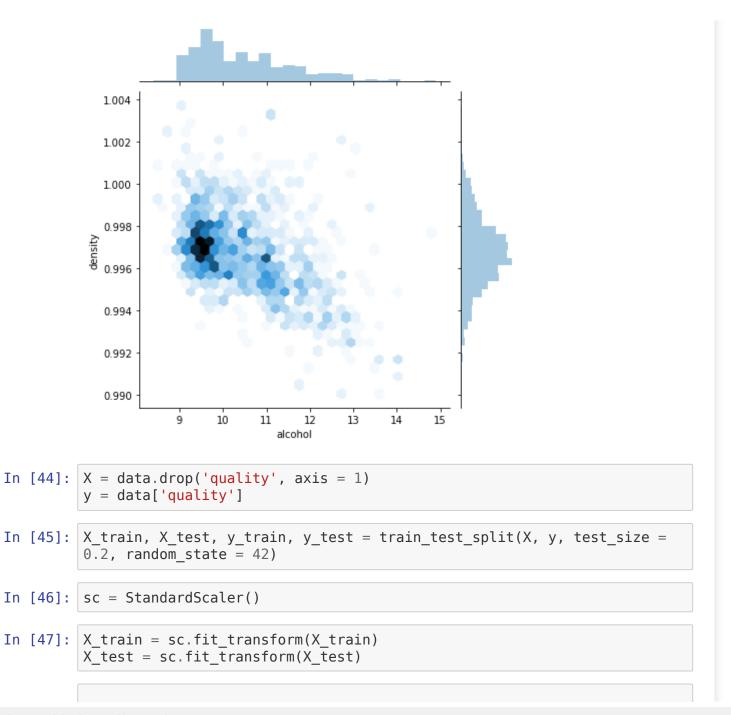
In [17]: data.describe()

Out[17]:

		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulf dioxid
С	ount	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.00000
n	nean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.46779
	std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.89532
	min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.00000
	25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.00000
	50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.00000
	75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.00000
	max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.00000
4								>

```
In [24]: bins = (2, 6.5, 8)
         group_names = ['bad', 'good']
         data['quality'] = pd.cut(data['quality'], bins = bins, labels = group n
         ames)
In [28]: label quality = LabelEncoder()
In [31]: data['quality'] = label quality.fit transform(data['quality'])
In [33]: data['quality'].value counts()
Out[33]: 0
              1382
               217
         Name: quality, dtype: int64
In [35]: sns.countplot(data['quality'])
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x231d1ee6820>
            1400
            1200
            1000
             800
          count
             600
             400
             200
                                  quality
In [38]: plt.figure(figsize=(12,6))
         sns.heatmap(data.corr(),annot=True)
```





```
In [58]: from sklearn.ensemble import RandomForestClassifier
         rf = RandomForestClassifier()
         rf.fit(X train, y train)
         rf predict=rf.predict(X test)
In [59]: rf conf matrix = confusion matrix(y test, rf predict)
         rf acc score = accuracy score(y test, rf predict)
         print(rf conf matrix)
         print(rf acc score*100)
         [[264 9]
          [ 28 1911
         88.4375
In [53]: from sklearn.linear model import LogisticRegression
         from sklearn.metrics import confusion matrix, accuracy score
         lr = LogisticRegression()
         lr.fit(X train, y train)
         lr predict = lr.predict(X test)
In [54]: lr conf matrix = confusion matrix(y test, lr predict)
         lr acc score = accuracy score(y test, lr predict)
         print(lr conf matrix)
         print(lr acc score*100)
         [[268 5]
          [ 35 12]]
         87.5
In [55]: from sklearn.tree import DecisionTreeClassifier
         dt = DecisionTreeClassifier()
         dt.fit(X train,y train)
         dt predict = dt.predict(X test)
In [56]: dt conf matrix = confusion matrix(y test, dt predict)
         dt acc score = accuracy score(y test, dt predict)
```

```
print(dt conf matrix)
         print(dt acc score*100)
         [[247 26]
          [ 24 23]]
         84.375
In [65]: from sklearn.svm import SVC
         svc = SVC()
         svc.fit(X train,y train)
         pred svc =svc.predict(X test)
In [66]: from sklearn.metrics import classification report, accuracy score
         print(classification report(y test,pred svc))
                                    recall f1-score
                                                       support
                       precision
                            0.88
                                      0.98
                                                0.93
                                                            273
                    0
                            0.71
                                      0.26
                                                0.37
                    1
                                                             47
                                                0.88
                                                            320
             accuracy
                                                0.65
                                                            320
                            0.80
                                      0.62
            macro avq
                                      0.88
                                                0.85
                                                            320
         weighted avg
                            0.86
In [63]: lin svc conf matrix = confusion matrix(y test, rf predict)
         lin svc acc score = accuracy score(y test, rf predict)
         print(lin svc conf matrix)
         print(lin svc acc score*100)
         [[264 9]
          [ 28 1911
         88.4375
In [68]: conclusion = pd.DataFrame({'models': ["Random Forest", "Logistic Regress"]
         ion", "Decission Tree", "Supprot vector machine"],
                                    'accuracies': [accuracy score(y test, rf pre
         dict),accuracy_score(y_test, lr predict),accuracy_score(y_test, dt pred
```

```
ict),accuracy_score(y_test,pred_svc)]})
           conclusion
Out[68]:
                          models accuracies
           0
                    Random Forest
                                    0.884375
                 Logistic Regression
                                    0.875000
           1
                     Decission Tree
                                    0.843750
           2
            3 Supprot vector machine
                                    0.875000
In [ ]:
```