Importing Libraries

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns

from warnings import filterwarnings
filterwarnings(action='ignore')
```

Loading Dataset

```
wine = pd.read_csv("winequality-red.csv")
print("Successfully Imported Data!")
wine.head()
```

```
Successfully Imported Data!
```

```
   fixed acidity  volatile acidity  citric acid  residual sugar  
chlorides  \
0            7.4              0.70         0.00             1.9      
0.076   
1            7.8              0.88         0.00             2.6      
0.098   
2            7.8              0.76         0.04             2.3      
0.092   
3           11.2              0.28         0.56             1.9      
0.075   
4            7.4              0.70         0.00             1.9      
0.076   

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  
\
0                 11.0                  34.0   0.9978  3.51       0.56   

1                 25.0                  67.0   0.9968  3.20       0.68   

2                 15.0                  54.0   0.9970  3.26       0.65   

3                 17.0                  60.0   0.9980  3.16       0.58   

4                 11.0                  34.0   0.9978  3.51       0.56   


   alcohol  quality  
0      9.4        5  
1      9.8        5  
```

```
2       9.8         5
3       9.8         6
4       9.4         5
```

```python
print(wine.shape)
```

```
(1599, 12)
```

Description

```python
wine.describe(include='all')
```

```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    1599.000000       1599.000000  1599.000000     1599.000000
mean        8.319637          0.527821     0.270976        2.538806
std         1.741096          0.179060     0.194801        1.409928
min         4.600000          0.120000     0.000000        0.900000
25%         7.100000          0.390000     0.090000        1.900000
50%         7.900000          0.520000     0.260000        2.200000
75%         9.200000          0.640000     0.420000        2.600000
max        15.900000          1.580000     1.000000       15.500000

         chlorides  free sulfur dioxide  total sulfur dioxide
density  \
count  1599.000000          1599.000000           1599.000000
1599.000000
mean      0.087467            15.874922             46.467792
0.996747
std       0.047065            10.460157             32.895324
0.001887
min       0.012000             1.000000              6.000000
0.990070
25%       0.070000             7.000000             22.000000
0.995600
50%       0.079000            14.000000             38.000000
0.996750
75%       0.090000            21.000000             62.000000
0.997835
max       0.611000            72.000000            289.000000
1.003690

                pH    sulphates      alcohol      quality
count  1599.000000  1599.000000  1599.000000  1599.000000
mean      3.311113     0.658149    10.422983     5.636023
std       0.154386     0.169507     1.065668     0.807569
min       2.740000     0.330000     8.400000     3.000000
25%       3.210000     0.550000     9.500000     5.000000
50%       3.310000     0.620000    10.200000     6.000000
```

```
75%        3.400000     0.730000    11.100000     6.000000
max        4.010000     2.000000    14.900000     8.000000
```

Finding Null Values

```
print(wine.isna().sum())
```

```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

```
wine.corr()
```

```
                      fixed acidity  volatile acidity  citric acid  \
fixed acidity              1.000000         -0.256131     0.671703   
volatile acidity          -0.256131          1.000000    -0.552496   
citric acid                0.671703         -0.552496     1.000000   
residual sugar             0.114777          0.001918     0.143577   
chlorides                  0.093705          0.061298     0.203823   
free sulfur dioxide       -0.153794         -0.010504    -0.060978   
total sulfur dioxide      -0.113181          0.076470     0.035533   
density                    0.668047          0.022026     0.364947   
pH                        -0.682978          0.234937    -0.541904   
sulphates                  0.183006         -0.260987     0.312770   
alcohol                   -0.061668         -0.202288     0.109903   
quality                    0.124052         -0.390558     0.226373   

                      residual sugar  chlorides  free sulfur 
dioxide  \
fixed acidity               0.114777   0.093705            -0.153794   

volatile acidity            0.001918   0.061298            -0.010504   

citric acid                 0.143577   0.203823            -0.060978   

residual sugar              1.000000   0.055610             0.187049   

chlorides                   0.055610   1.000000             0.005562   
```

```
free sulfur dioxide          0.187049   0.005562             1.000000

total sulfur dioxide         0.203028   0.047400             0.667666

density                      0.355283   0.200632            -0.021946

pH                          -0.085652  -0.265026             0.070377

sulphates                    0.005527   0.371260             0.051658

alcohol                      0.042075  -0.221141            -0.069408

quality                      0.013732  -0.128907            -0.050656


                      total sulfur dioxide   density        pH
sulphates  \
fixed acidity                    -0.113181  0.668047 -0.682978
0.183006
volatile acidity                  0.076470  0.022026  0.234937  -
0.260987
citric acid                       0.035533  0.364947 -0.541904
0.312770
residual sugar                    0.203028  0.355283 -0.085652
0.005527
chlorides                         0.047400  0.200632 -0.265026
0.371260
free sulfur dioxide               0.667666 -0.021946  0.070377
0.051658
total sulfur dioxide              1.000000  0.071269 -0.066495
0.042947
density                           0.071269  1.000000 -0.341699
0.148506
pH                               -0.066495 -0.341699  1.000000  -
0.196648
sulphates                         0.042947  0.148506 -0.196648
1.000000
alcohol                          -0.205654 -0.496180  0.205633
0.093595
quality                          -0.185100 -0.174919 -0.057731
0.251397

                       alcohol   quality
fixed acidity        -0.061668  0.124052
volatile acidity     -0.202288 -0.390558
citric acid           0.109903  0.226373
residual sugar        0.042075  0.013732
chlorides            -0.221141 -0.128907
free sulfur dioxide  -0.069408 -0.050656
total sulfur dioxide -0.205654 -0.185100
```

```
density              -0.496180 -0.174919
pH                    0.205633 -0.057731
sulphates             0.093595  0.251397
alcohol               1.000000  0.476166
quality               0.476166  1.000000
```

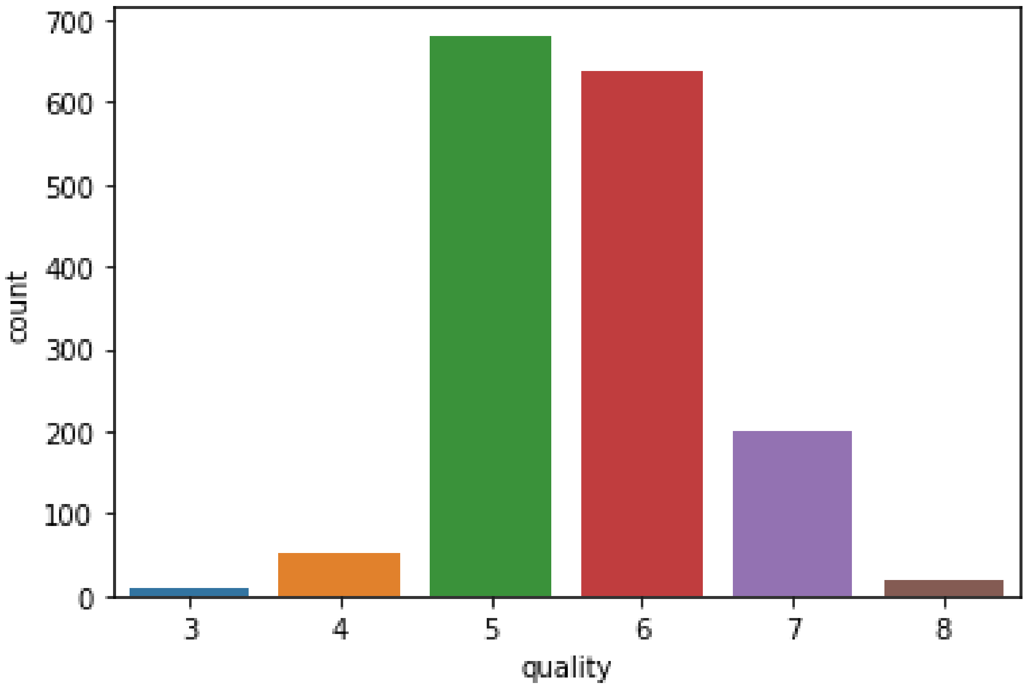
```
wine.groupby('quality').mean()
```

```
         fixed acidity  volatile acidity  citric acid  residual sugar  \
quality
3             8.360000          0.884500     0.171000        2.635000
4             7.779245          0.693962     0.174151        2.694340
5             8.167254          0.577041     0.243686        2.528855
6             8.347179          0.497484     0.273824        2.477194
7             8.872362          0.403920     0.375176        2.720603
8             8.566667          0.423333     0.391111        2.577778

         chlorides  free sulfur dioxide  total sulfur dioxide
density  \
quality
3         0.122500            11.000000             24.900000
0.997464
4         0.090679            12.264151             36.245283
0.996542
5         0.092736            16.983847             56.513950
0.997104
6         0.084956            15.711599             40.869906
0.996615
7         0.076588            14.045226             35.020101
0.996104
8         0.068444            13.277778             33.444444
0.995212

               pH  sulphates    alcohol
quality
3        3.398000   0.570000   9.955000
4        3.381509   0.596415  10.265094
5        3.304949   0.620969   9.899706
6        3.318072   0.675329  10.629519
7        3.290754   0.741256  11.465913
8        3.267222   0.767778  12.094444
```

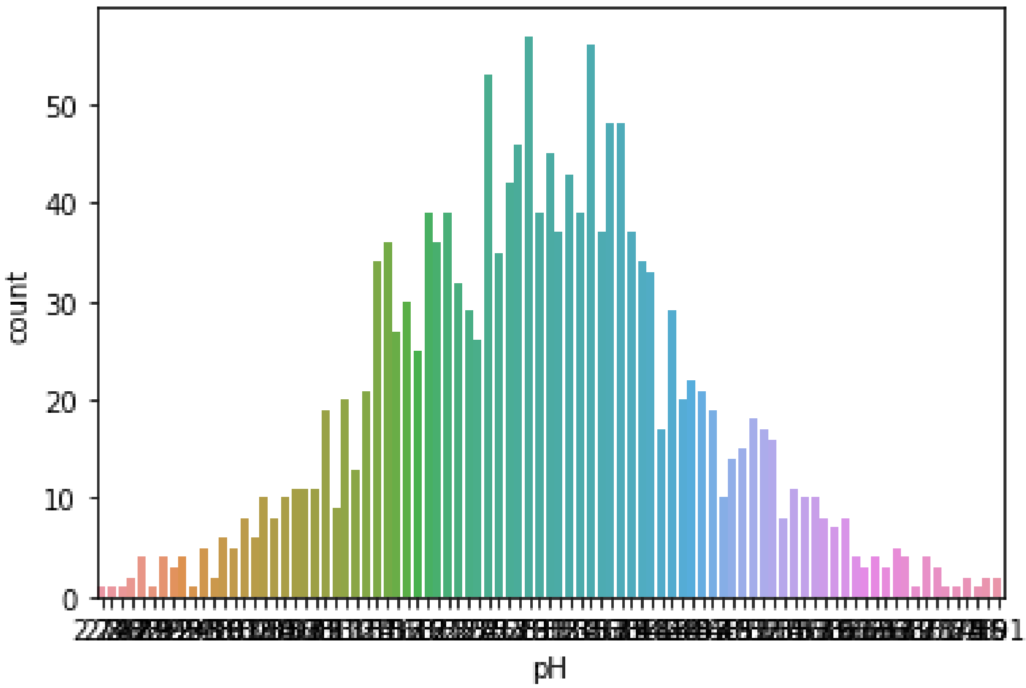
Data Analysis

Countplot:

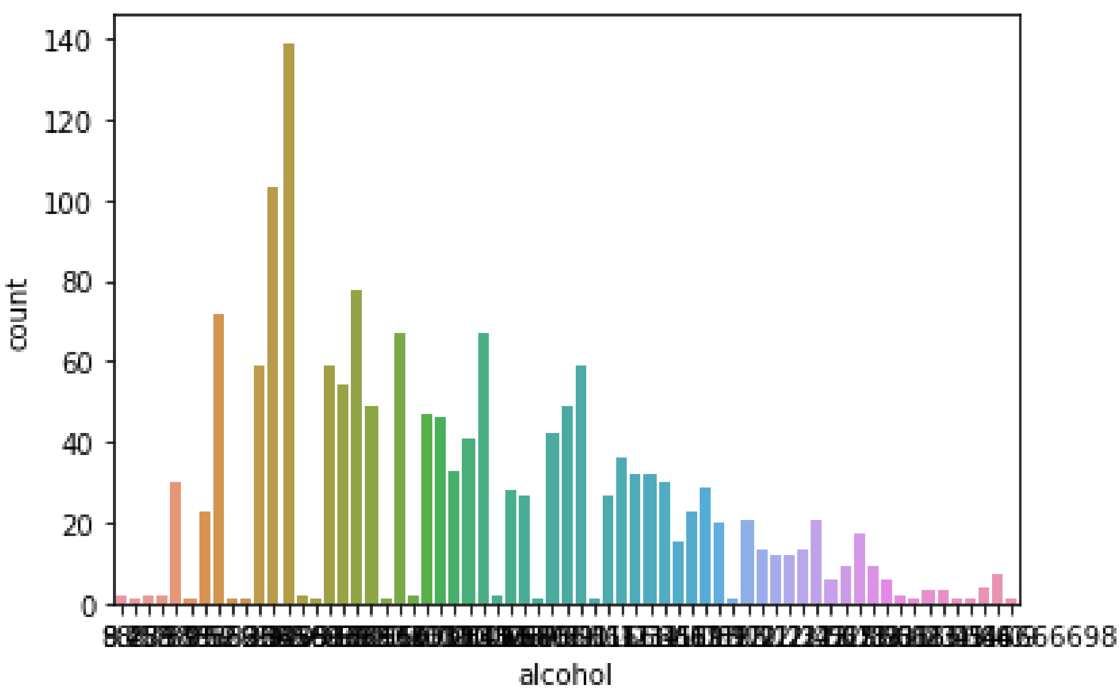
```
sns.countplot(wine['quality'])
plt.show()
```



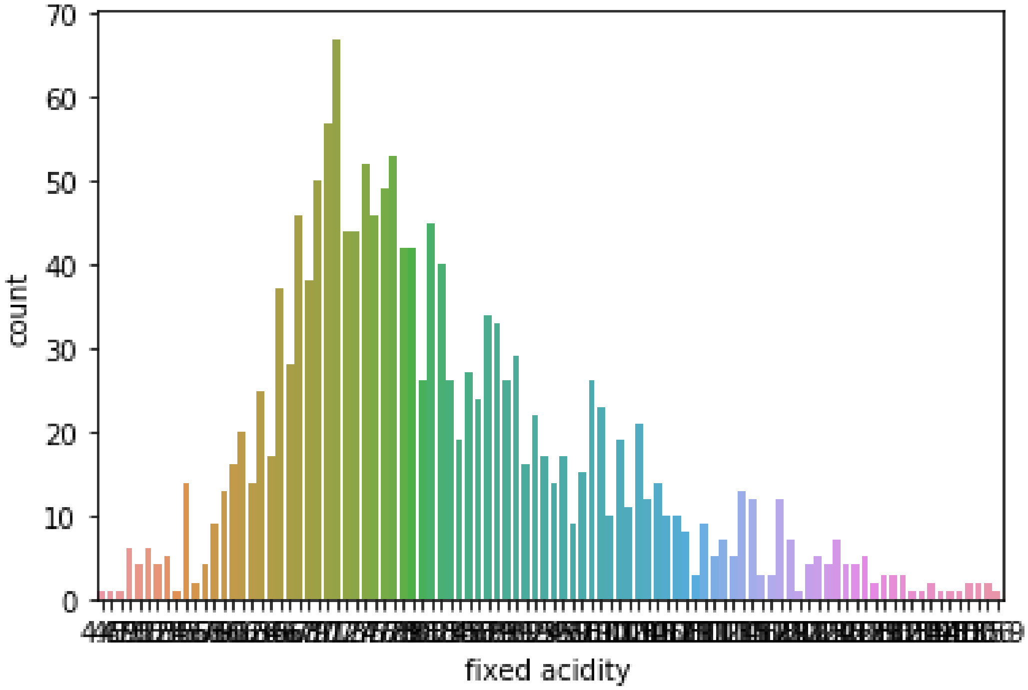

```
sns.countplot(wine['pH'])
plt.show()
```



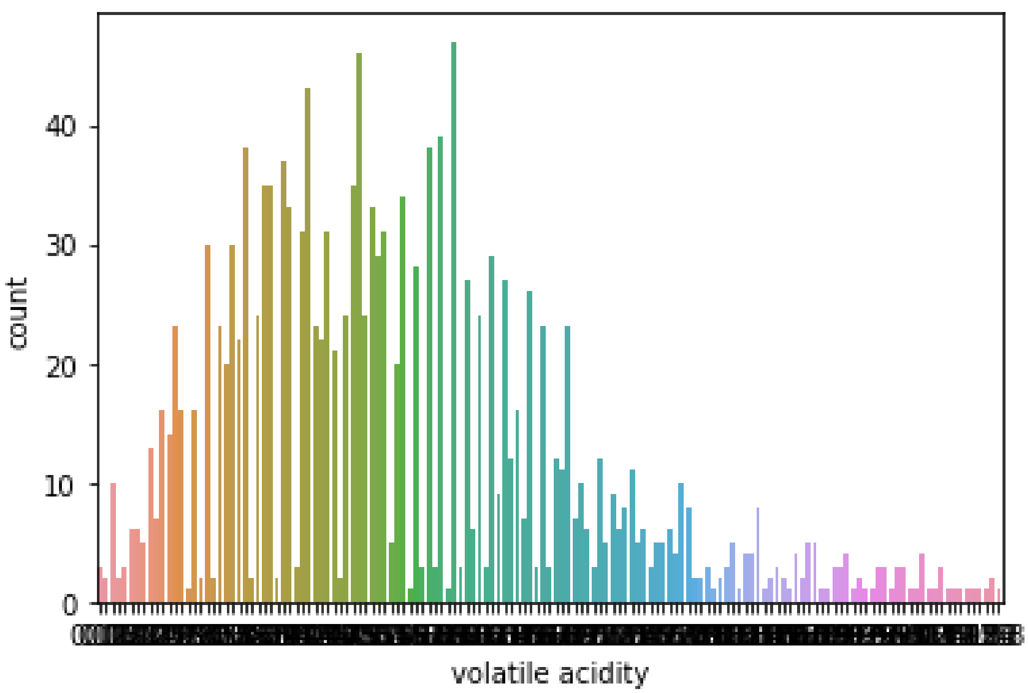

```
sns.countplot(wine['alcohol'])
plt.show()
```



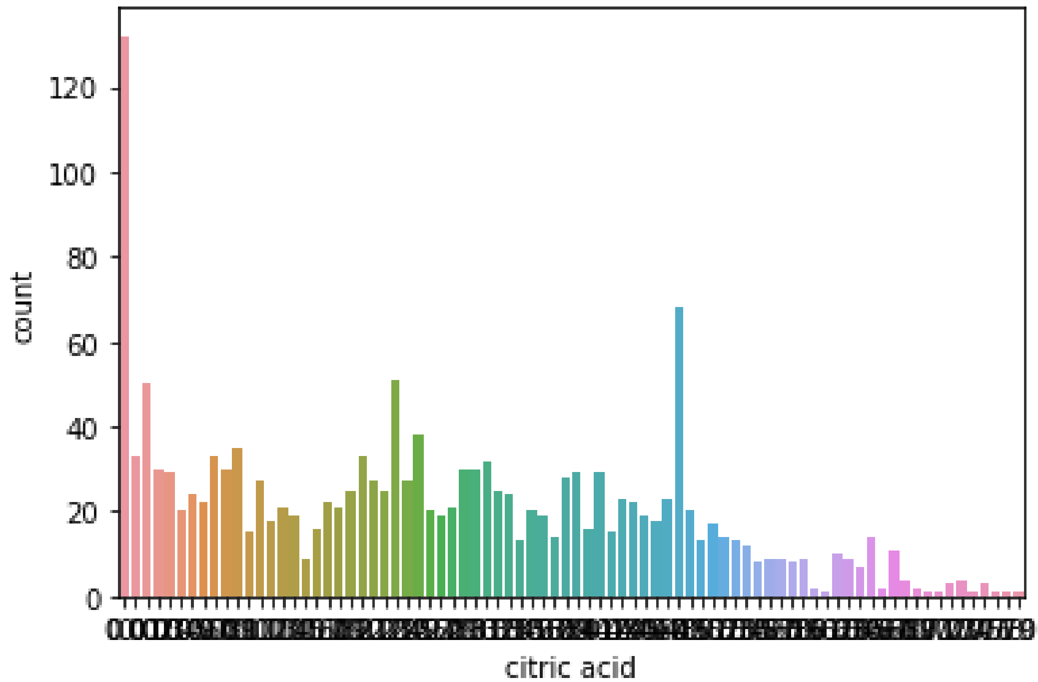

```
sns.countplot(wine['fixed acidity'])
plt.show()
```



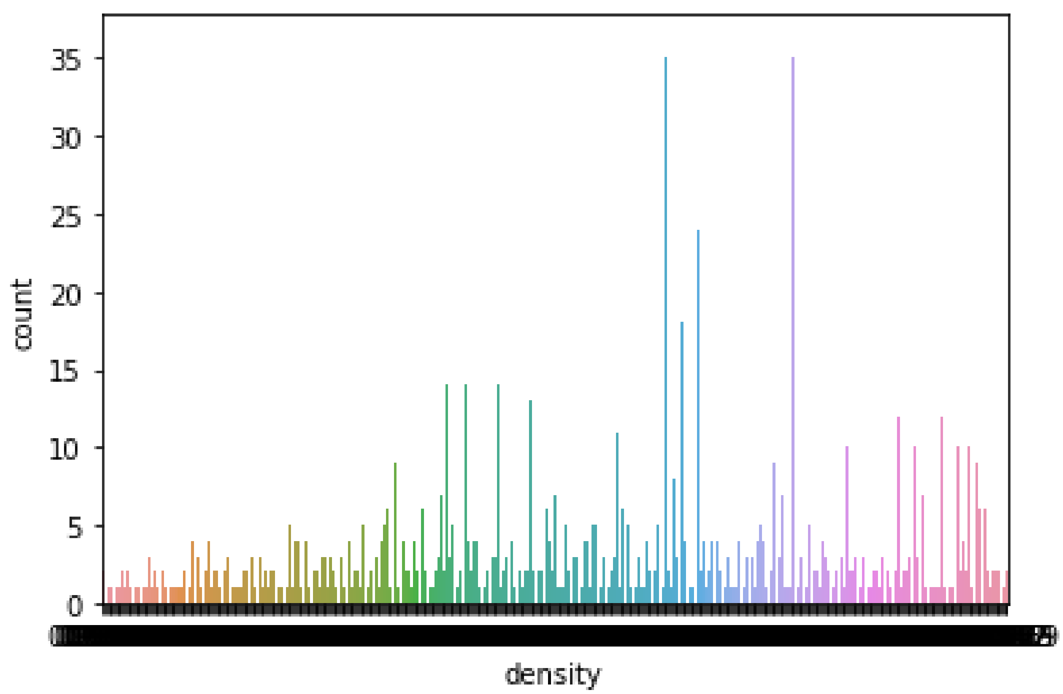

```
sns.countplot(wine['volatile acidity'])
plt.show()
```




```
sns.countplot(wine['citric acid'])
plt.show()
```



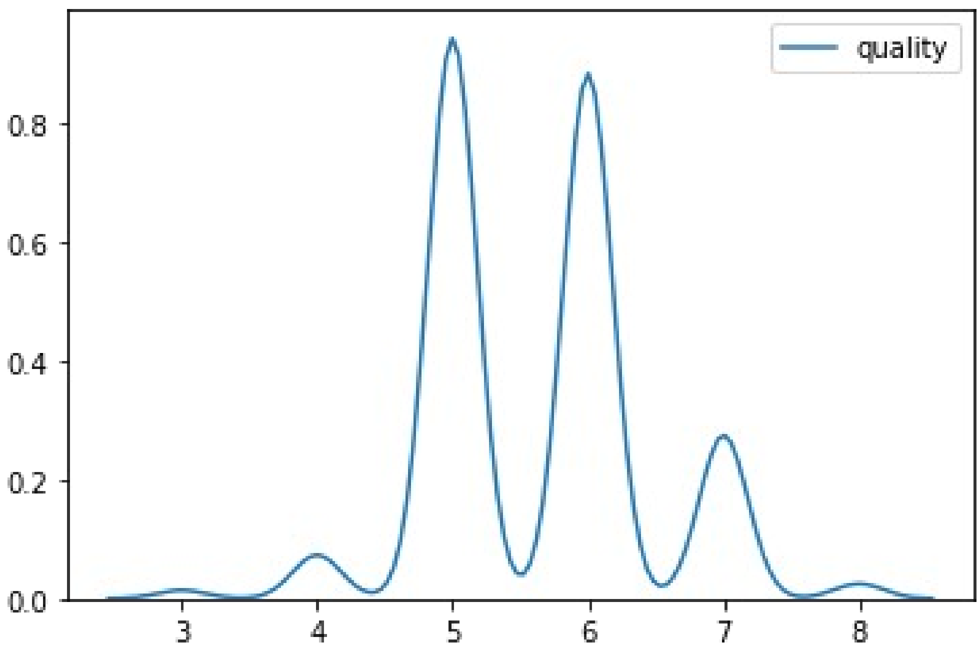

```
sns.countplot(wine['density'])
plt.show()
```



KDE plot:

```
sns.kdeplot(wine.query('quality > 2').quality)
```

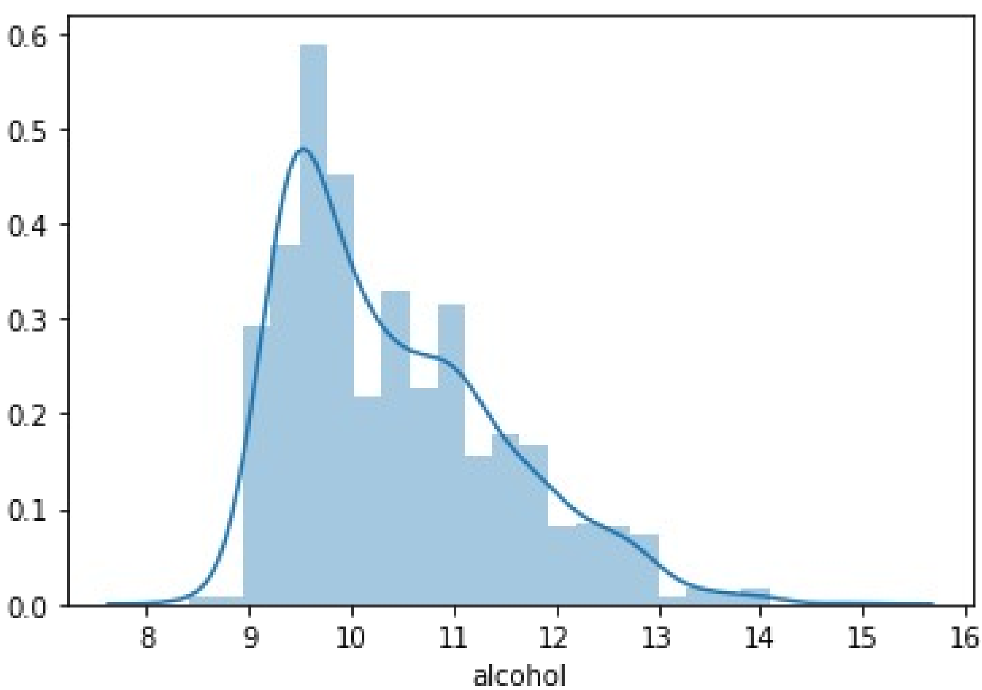
```
<matplotlib.axes._subplots.AxesSubplot at 0x24217cefc48>
```



Distplot:

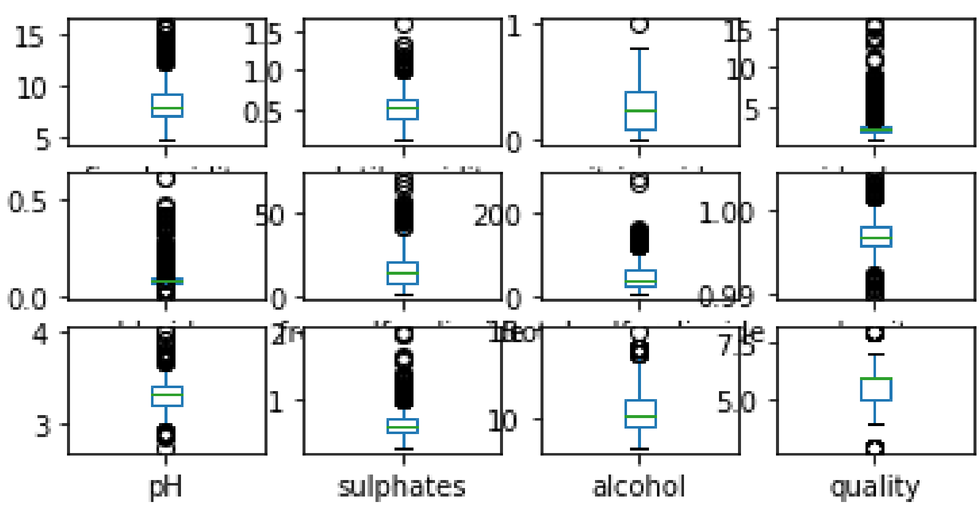
```
sns.distplot(wine['alcohol'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x24217e2c148>
```



```python
wine.plot(kind ='box',subplots = True, layout =(4,4),sharex = False)
```

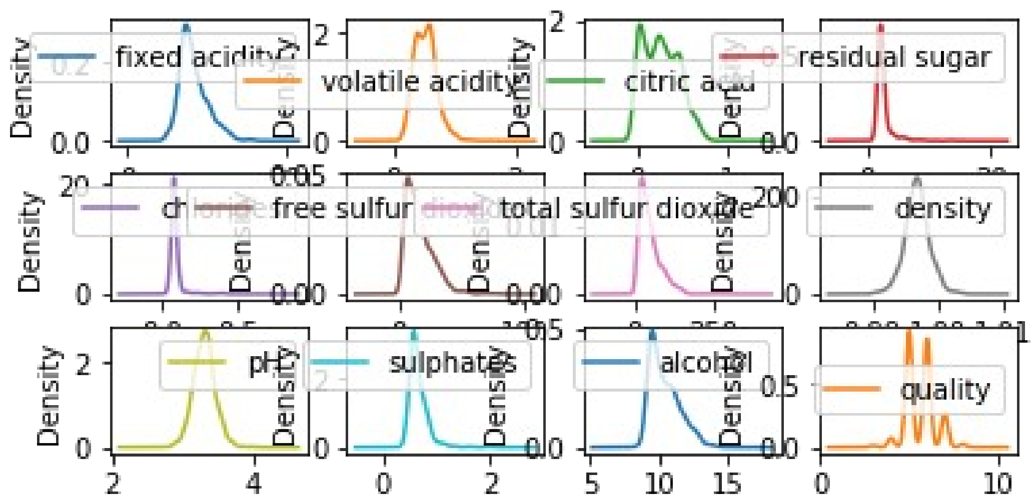
```
fixed acidity
AxesSubplot(0.125,0.71587;0.168478x0.16413)
volatile acidity
AxesSubplot(0.327174,0.71587;0.168478x0.16413)
citric acid
AxesSubplot(0.529348,0.71587;0.168478x0.16413)
residual sugar
AxesSubplot(0.731522,0.71587;0.168478x0.16413)
chlorides
AxesSubplot(0.125,0.518913;0.168478x0.16413)
free sulfur dioxide
AxesSubplot(0.327174,0.518913;0.168478x0.16413)
total sulfur dioxide
AxesSubplot(0.529348,0.518913;0.168478x0.16413)
density
AxesSubplot(0.731522,0.518913;0.168478x0.16413)
pH
AxesSubplot(0.125,0.321957;0.168478x0.16413)
sulphates
AxesSubplot(0.327174,0.321957;0.168478x0.16413)
alcohol
AxesSubplot(0.529348,0.321957;0.168478x0.16413)
quality
AxesSubplot(0.731522,0.321957;0.168478x0.16413)
dtype: object
```




```python
wine.plot(kind ='density',subplots = True, layout =(4,4),sharex =
False)
```

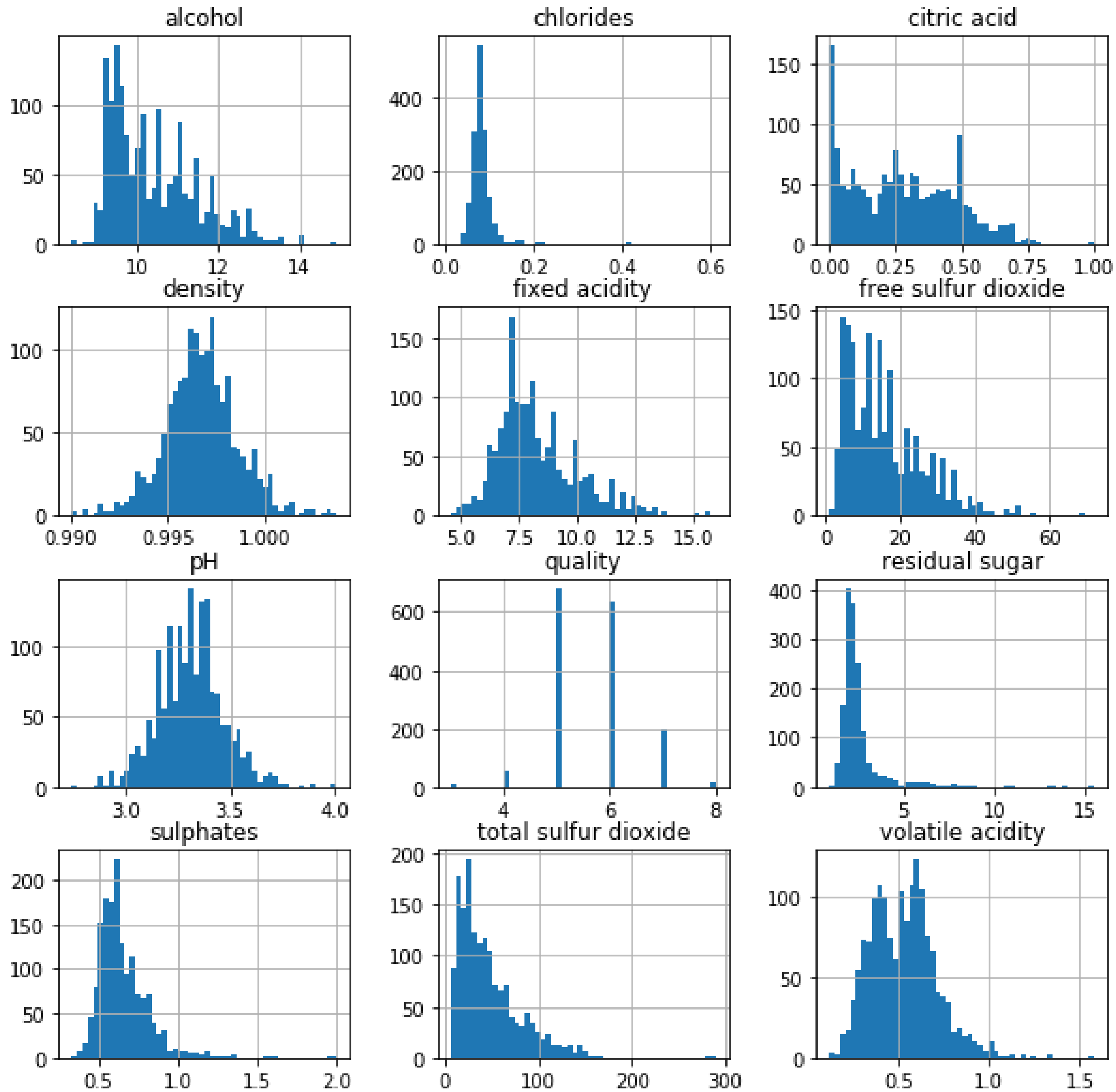
```
array([[<matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0BE3F748>,
```

```
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C2D7688>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C2FCDC8>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C338808>],
       [<matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C372208>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C3A7BC8>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C3E6E48>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C41A788>],
       [<matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C425388>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C45F548>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C4C4AC8>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C4FDB48>],
       [<matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C534C48>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C56DE48>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C5AB048>,
        <matplotlib.axes._subplots.AxesSubplot object at
0x000001DF0C5E3208>]],
      dtype=object)
```



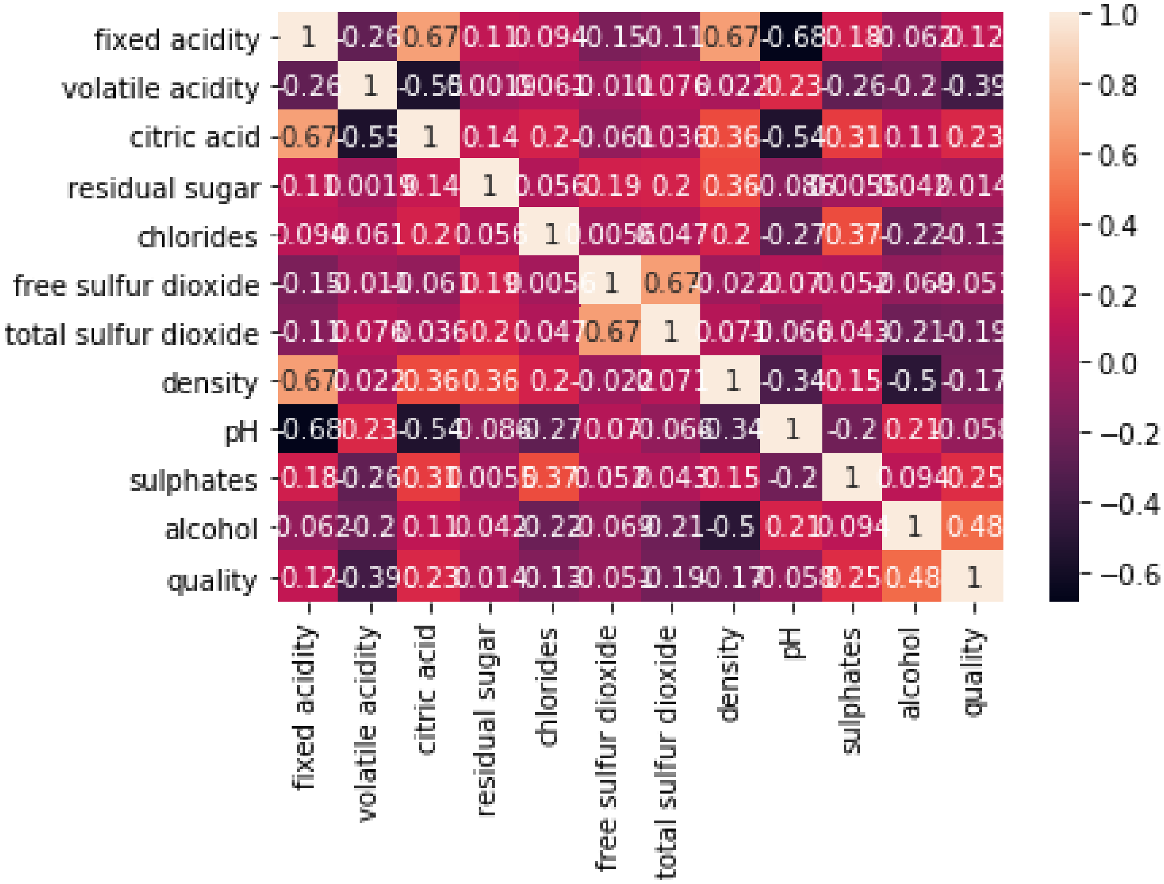
Histogram

```
wine.hist(figsize=(10,10),bins=50)
plt.show()
```



Heatmap for expressing correlation

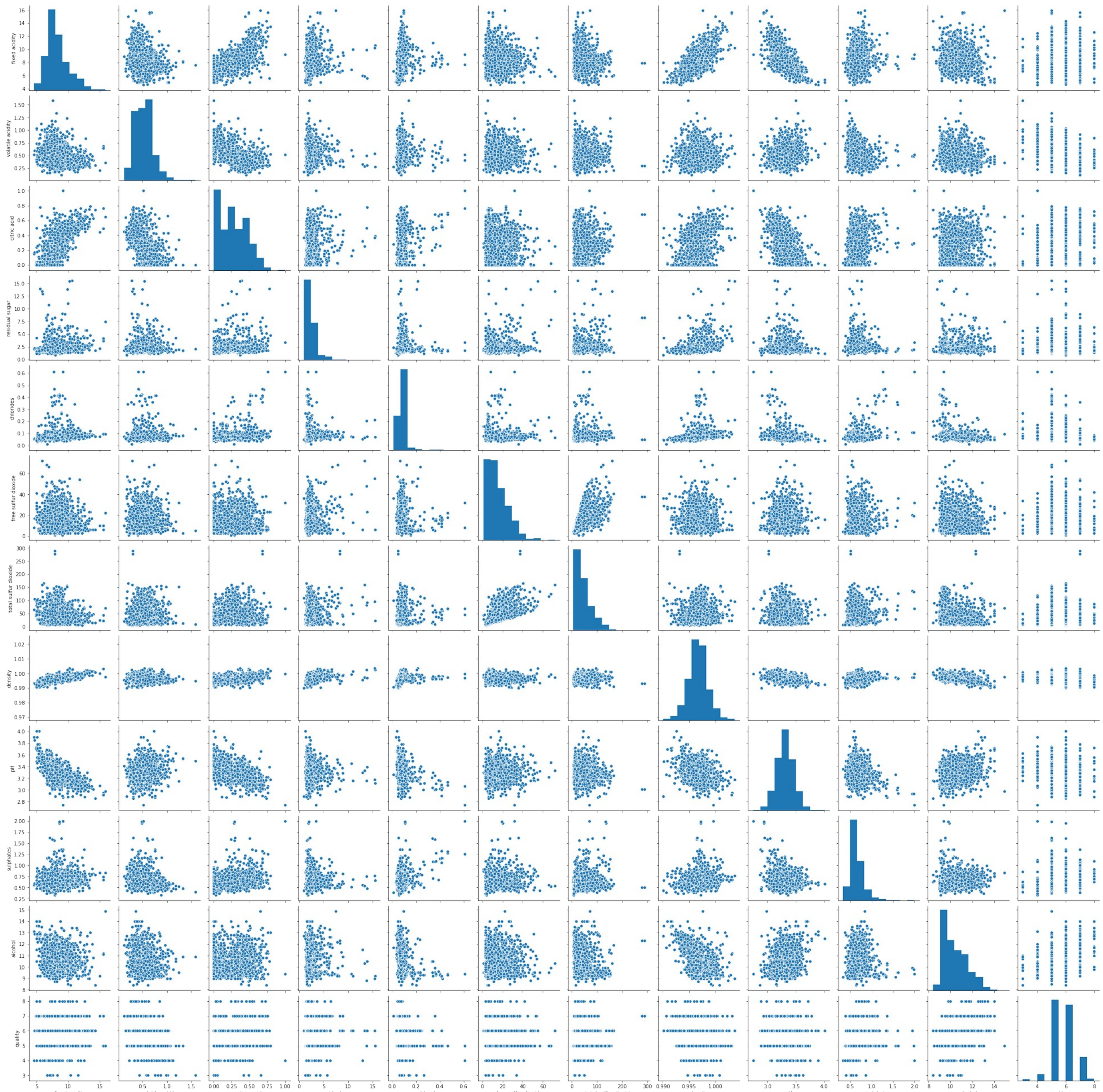
```
corr = wine.corr()
sns.heatmap(corr,annot=True)

<matplotlib.axes._subplots.AxesSubplot at 0x1df1779a288>
```



Pair Plot:

```
sns.pairplot(wine)
```

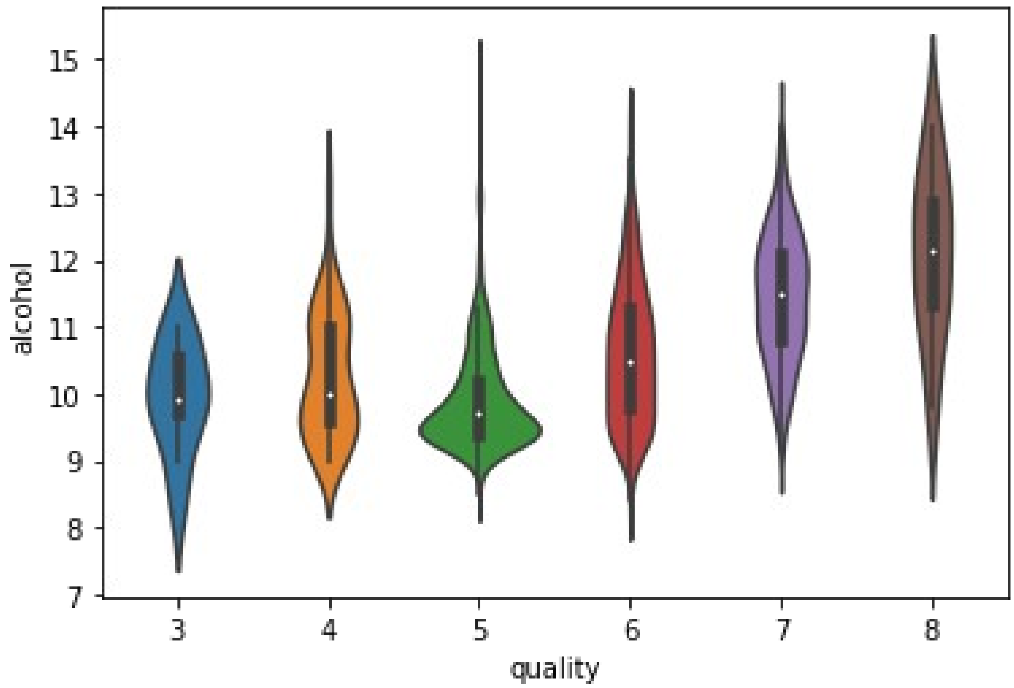
```
<seaborn.axisgrid.PairGrid at 0x1df1627c208>
```



Violinplot:

```
sns.violinplot(x='quality', y='alcohol', data=wine)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x242182ba6c8>
```



Feature Selection

```
# Create Classification version of target variable
wine['goodquality'] = [1 if x >= 7 else 0 for x in wine['quality']]# Separate feature variables and target variable
X = wine.drop(['quality','goodquality'], axis = 1)
Y = wine['goodquality']

# See proportion of good vs bad wines
wine['goodquality'].value_counts()

0    1382
1     217
Name: goodquality, dtype: int64

X

      fixed acidity  volatile acidity  citric acid  residual sugar
chlorides  \
0               7.4             0.700         0.00             1.9
0.076
1               7.8             0.880         0.00             2.6
0.098
2               7.8             0.760         0.04             2.3
0.092
3              11.2             0.280         0.56             1.9
0.075
```

```
4               7.4             0.700         0.00              1.9
0.076
...             ...               ...          ...              ...
...
1594            6.2             0.600         0.08              2.0
0.090
1595            5.9             0.550         0.10              2.2
0.062
1596            6.3             0.510         0.13              2.3
0.076
1597            5.9             0.645         0.12              2.0
0.075
1598            6.0             0.310         0.47              3.6
0.067

      free sulfur dioxide  total sulfur dioxide  density    pH
sulphates  \
0                    11.0                  34.0  0.99780  3.51
0.56
1                    25.0                  67.0  0.99680  3.20
0.68
2                    15.0                  54.0  0.99700  3.26
0.65
3                    17.0                  60.0  0.99800  3.16
0.58
4                    11.0                  34.0  0.99780  3.51
0.56
...                   ...                   ...      ...   ...
...
1594                 32.0                  44.0  0.99490  3.45
0.58
1595                 39.0                  51.0  0.99512  3.52
0.76
1596                 29.0                  40.0  0.99574  3.42
0.75
1597                 32.0                  44.0  0.99547  3.57
0.71
1598                 18.0                  42.0  0.99549  3.39
0.66

      alcohol
0         9.4
1         9.8
2         9.8
3         9.8
4         9.4
...       ...
1594     10.5
1595     11.2
```

```
1596     11.0
1597     10.2
1598     11.0

[1599 rows x 11 columns]
```

```
print(Y)
```

```
0       0
1       0
2       0
3       0
4       0
       ..
1594    0
1595    0
1596    0
1597    0
1598    0
Name: goodquality, Length: 1599, dtype: int64
```

Feature Importance

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()

from sklearn.ensemble import ExtraTreesClassifier
classifiern = ExtraTreesClassifier()
classifiern.fit(X,Y)
score = classifiern.feature_importances_
print(score)
```

```
[0.07559736 0.10044708 0.09365305 0.07359705 0.066992   0.06781859
 0.08279496 0.09134226 0.06870351 0.11031286 0.1687413 ]
```

Splitting Dataset

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test =
train_test_split(X,Y,test_size=0.3,random_state=7)
```

LogisticRegression:

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
```

```
model.fit(X_train,Y_train)
Y_pred = model.predict(X_test)

from sklearn.metrics import accuracy_score,confusion_matrix
print("Accuracy Score:",accuracy_score(Y_test,Y_pred))

Accuracy Score: 0.8708333333333333

confusion_mat = confusion_matrix(Y_test,Y_pred)
print(confusion_mat)

[[399  18]
 [ 44  19]]
```

Using KNN:

```
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier(n_neighbors=3)
model.fit(X_train,Y_train)
y_pred = model.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred))

Accuracy Score: 0.8729166666666667
```

Using SVC:

```
from sklearn.svm import SVC
model = SVC()
model.fit(X_train,Y_train)
pred_y = model.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,pred_y))

Accuracy Score: 0.86875
```

Using Decision Tree:

```
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier(criterion='entropy',random_state=7)
model.fit(X_train,Y_train)
y_pred = model.predict(X_test)
```

```
from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred))

Accuracy Score: 0.8645833333333334
```

Using GaussianNB:

```
from sklearn.naive_bayes import GaussianNB
model3 = GaussianNB()
model3.fit(X_train,Y_train)
y_pred3 = model3.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred3))

Accuracy Score: 0.8333333333333334
```

Using Random Forest:

```
from sklearn.ensemble import RandomForestClassifier
model2 = RandomForestClassifier(random_state=1)
model2.fit(X_train, Y_train)
y_pred2 = model2.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred2))

Accuracy Score: 0.89375
```

Using Xgboost:

```
import xgboost as xgb
model5 = xgb.XGBClassifier(random_state=1)
model5.fit(X_train, Y_train)
y_pred5 = model5.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred5))

Accuracy Score: 0.8791666666666667

results = pd.DataFrame({
    'Model': ['Logistic Regression','KNN', 'SVC','Decision
Tree' ,'GaussianNB','Random Forest','Xgboost'],
    'Score': [0.870,0.872,0.868,0.864,0.833,0.893,0.879]})
```

```
result_df = results.sort_values(by='Score', ascending=False)
result_df = result_df.set_index('Score')
result_df
```

	Model
Score	
0.893	Random Forest
0.879	Xgboost
0.872	KNN
0.870	Logistic Regression
0.868	SVC
0.864	Decision Tree
0.833	GaussianNB

```
#Hence I will use Random Forest algorithms for training my model.
```