DATA COLLECTION

In [1]:
```
# import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# To Import Dataset
sd=pd.read_csv(r"c:\Users\user\Downloads\11_winequality-red.csv")
sd
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcol
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	
...	...	...	...	...	...	...	...	...	...	...	
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	1
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	1
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	1
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	1
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	1

1599 rows × 12 columns

In [3]:
```
# to display top 10 rows
sd.head(10)
```

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	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
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
5	7.4	0.66	0.00	1.8	0.075	13.0	40.0	0.9978	3.51	0.56	9.4
6	7.9	0.60	0.06	1.6	0.069	15.0	59.0	0.9964	3.30	0.46	9.4
7	7.3	0.65	0.00	1.2	0.065	15.0	21.0	0.9946	3.39	0.47	10.0
8	7.8	0.58	0.02	2.0	0.073	9.0	18.0	0.9968	3.36	0.57	9.5
9	7.5	0.50	0.36	6.1	0.071	17.0	102.0	0.9978	3.35	0.80	10.5

DATA CLEANING AND PRE_PROCESSING

In [4]:
```
sd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

In [5]:
```
# to display summary of statistics
sd.describe()
```

Out[5]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfu dioxid
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.00000
mean	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

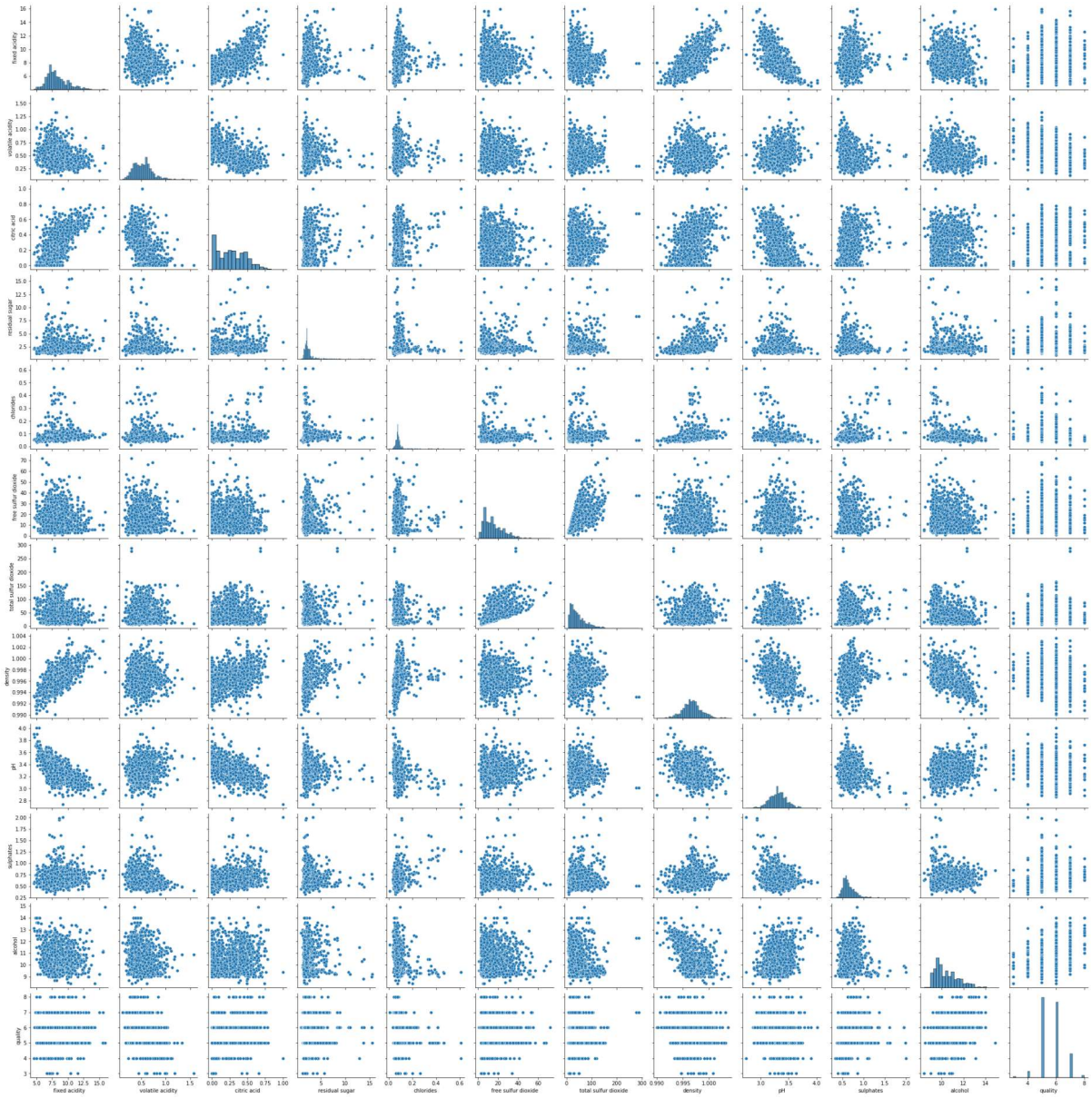
In [6]:
```
#to display colums heading
sd.columns
```

Out[6]:
```
Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol', 'quality'],
      dtype='object')
```

EDA and visualization

In [7]:
```
sns.pairplot(sd)
```

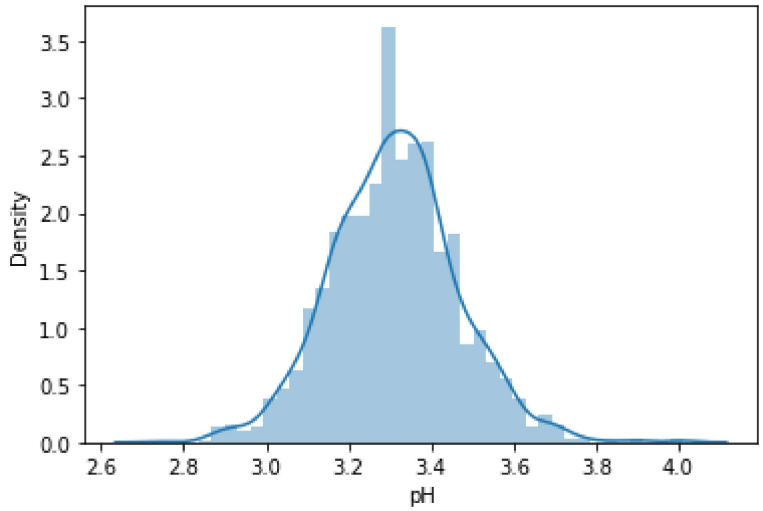
Out[7]: <seaborn.axisgrid.PairGrid at 0x1a288ef2790>



In [8]:
```
sns.distplot(sd['pH'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: Fut
ureWarning: `distplot` is a deprecated function and will be removed in a futu
re version. Please adapt your code to use either `displot` (a figure-level fu
nction with similar flexibility) or `histplot` (an axes-level function for hi
stograms).
  warnings.warn(msg, FutureWarning)
```

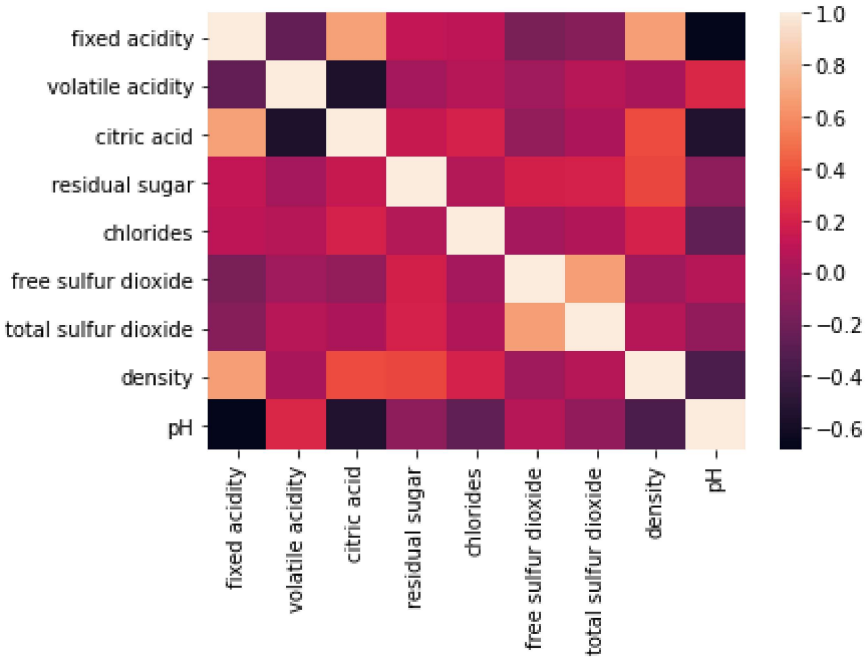
Out[8]:
```
<AxesSubplot:xlabel='pH', ylabel='Density'>
```



In [9]:
```
sd1=sd[['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
        'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density','p
```

In [10]:
```
sns.heatmap(sd1.corr())
```

Out[10]:
```
<AxesSubplot:>
```



TO TRAIN THE MODEL _MODEL BUILDING

we are goint train Liner Regression model; we need to split out the data into two varibles x and y where x is independent on x (output) and y is dependent on x(output) adress coloumn as it is not required our model

In [11]:
```
x= sd1[['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density']]
y=sd1['pH']
```

In [12]:
```
# To split my dataset  into training data and test data
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)
```

In [13]:
```
from sklearn.linear_model import LinearRegression

lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[13]:
```
LinearRegression()
```

In [14]:
```
from sklearn.linear_model import LinearRegression

lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[14]:
```
LinearRegression()
```

In [15]:
```
print(lr.intercept_)
```

```
-24.504882619217348
```

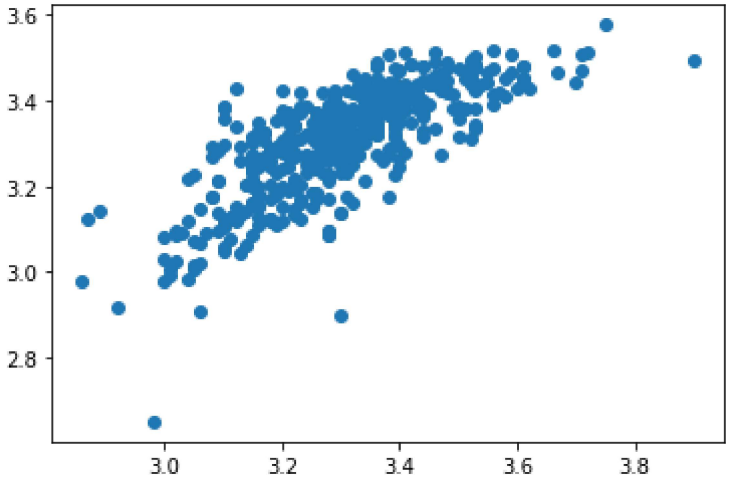
In [16]:
```
coeff= pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[16]:

	Co-efficient
fixed acidity	-0.083262
volatile acidity	0.072834
citric acid	0.060884
residual sugar	-0.008224
chlorides	-0.901501
free sulfur dioxide	0.001931
total sulfur dioxide	-0.001189
density	28.672951

In [17]:
```
prediction = lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[17]:
```
<matplotlib.collections.PathCollection at 0x1a2927e3220>
```



In [18]:
```
print(lr.score(x_test,y_test))
```

```
0.576512555583697
```

In [19]:
```
lr.score(x_test,y_test)
```

Out[19]:
```
0.576512555583697
```

In [20]:
```
lr.score(x_train,y_train)
```

Out[20]:
```
0.5905763678429211
```

In [21]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [22]:
```
dr=Ridge(alpha=10)
dr.fit(x_train,y_train)
```

Out[22]:
```
Ridge(alpha=10)
```

In [23]:
```
dr.score(x_test,y_test)
```

Out[23]:
```
0.5107869295836952
```

In [24]:
```
dr.score(x_train,y_train)
```

Out[24]:
```
0.5158723607556093
```

In [25]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[25]:
```
Lasso(alpha=10)
```

In [26]:
```
la.score(x_test,y_test)
```
Out[26]:
```
-0.0006313856506627857
```

In [27]:
```
la.score(x_train,y_train)
```
Out[27]:
```
0.0
```

ElasticNet

In [28]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```
Out[28]:
```
ElasticNet()
```

In [29]:
```
print(en.coef_)
```
```
[-0.  0. -0. -0. -0.  0. -0. -0.]
```

In [30]:
```
print(en.intercept_)
```
```
3.3122341376228777
```

In [31]:
```
prediction=en.predict(x_test)
```

In [32]:
```
print(en.score(x_test,y_test))
```
```
-0.0006313856506627857
```

Evaluation metrics

In [33]:
```
from sklearn import metrics
```

In [34]:
```
print("mean Absolytre Error:",metrics.mean_absolute_error(y_test,prediction))
```
```
mean Absolytre Error: 0.11620878016085791
```

In [35]:
```
print("mean squared Error:",metrics.mean_squared_error(y_test,prediction))
```
```
mean squared Error: 0.022098360450453255
```

In [36]:
```
print("Root mean Absolytre Error:",np.sqrt(metrics.mean_squared_error(y_test,pr
```
```
Root mean Absolytre Error: 0.14865517296903347
```

In [ ]: