## ML LAB 2

Explore and implement Linear regression algorithm in a given business scenario and comment on its efficiency and performance.

In [2]: import numpy as np
 import pandas as pd
 import matplotlib.pyplot as plt
 from sklearn import preprocessing
%matplotlib inline

In [5]: df=pd.read\_csv("E:\DS\Datasets\winequalityN.csv")

In [7]: df.head(20)

Out[7]:

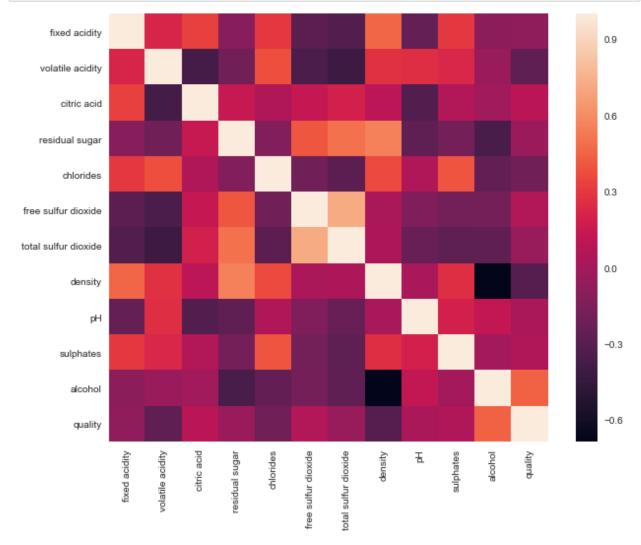
	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates a
0	white	7.0	0.27	0.36	20.70	0.045	45.0	170.0	1.0010	3.00	0.45
1	white	6.3	0.30	0.34	1.60	0.049	14.0	132.0	0.9940	3.30	0.49
2	white	8.1	0.28	0.40	6.90	0.050	30.0	97.0	0.9951	3.26	0.44
3	white	7.2	0.23	0.32	8.50	0.058	47.0	186.0	0.9956	3.19	0.40
4	white	7.2	0.23	0.32	8.50	0.058	47.0	186.0	0.9956	3.19	0.40
5	white	8.1	0.28	0.40	6.90	0.050	30.0	97.0	0.9951	3.26	0.44
6	white	6.2	0.32	0.16	7.00	0.045	30.0	136.0	0.9949	3.18	0.47
7	white	7.0	0.27	0.36	20.70	0.045	45.0	170.0	1.0010	3.00	0.45
8	white	6.3	0.30	0.34	1.60	0.049	14.0	132.0	0.9940	3.30	0.49
9	white	8.1	0.22	0.43	1.50	0.044	28.0	129.0	0.9938	3.22	0.45
10	white	8.1	0.27	0.41	1.45	0.033	11.0	63.0	0.9908	2.99	0.56
11	white	8.6	0.23	0.40	4.20	0.035	17.0	109.0	0.9947	3.14	0.53
12	white	7.9	0.18	0.37	1.20	0.040	16.0	75.0	0.9920	3.18	0.63
13	white	6.6	0.16	0.40	1.50	0.044	48.0	143.0	0.9912	3.54	0.52
14	white	8.3	0.42	0.62	19.25	0.040	41.0	172.0	1.0002	2.98	0.67
15	white	6.6	0.17	0.38	1.50	0.032	28.0	112.0	0.9914	3.25	0.55
16	white	6.3	0.48	0.04	1.10	0.046	30.0	99.0	0.9928	3.24	0.36
17	white	NaN	0.66	0.48	1.20	0.029	29.0	75.0	0.9892	3.33	0.39
18	white	7.4	0.34	0.42	1.10	0.033	17.0	171.0	0.9917	3.12	0.53
19	white	6.5	0.31	0.14	7.50	0.044	34.0	133.0	0.9955	3.22	0.50
4											•

```
In [12]: | df.columns
Out[12]: Index(['type', 'fixed acidity', 'volatile acidity', 'citric acid',
                 'residual sugar', 'chlorides', 'free sulfur dioxide',
                 'total sulfur dioxide', 'density', 'pH', 'sulphates', 'alcohol',
                 'quality'],
               dtype='object')
In [13]: | df.shape
Out[13]: (6497, 13)
In [14]: | print(df.info())
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 6497 entries, 0 to 6496
         Data columns (total 13 columns):
         type
                                  6497 non-null object
         fixed acidity
                                  6487 non-null float64
         volatile acidity
                                  6489 non-null float64
         citric acid
                                  6494 non-null float64
         residual sugar
                                  6495 non-null float64
         chlorides
                                  6495 non-null float64
         free sulfur dioxide
                                  6497 non-null float64
         total sulfur dioxide
                                  6497 non-null float64
                                  6497 non-null float64
         density
                                  6488 non-null float64
         рΗ
                                  6493 non-null float64
         sulphates
         alcohol
                                  6497 non-null float64
                                  6497 non-null int64
         quality
         dtypes: float64(11), int64(1), object(1)
         memory usage: 659.9+ KB
         None
In [15]: df.isna().sum()
Out[15]: type
                                   0
         fixed acidity
                                  10
         volatile acidity
                                   8
         citric acid
                                   3
                                   2
         residual sugar
         chlorides
                                   2
         free sulfur dioxide
                                   0
         total sulfur dioxide
                                   0
         density
                                   0
         рΗ
                                   9
         sulphates
                                   4
         alcohol
                                   0
                                   0
         quality
         dtype: int64
In [16]: df=df.fillna(df.mean())
```

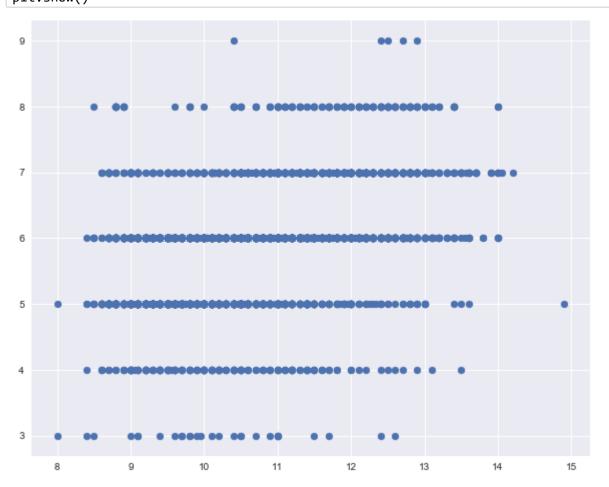
In [17]: df.describe()

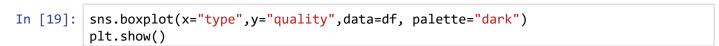
Out[17]:

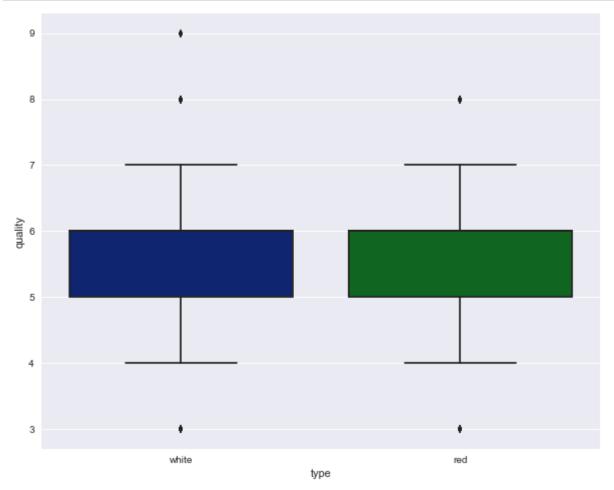
total sulfur dioxide	free sulfur dioxide	chlorides	residual sugar	citric acid	volatile acidity	fixed acidity	
6497.000000	6497.000000	6497.000000	6497.000000	6497.000000	6497.000000	6497.000000	count
115.744574	30.525319	0.056042	5.444326	0.318722	0.339691	7.216579	mean
56.521855	17.749400	0.035031	4.757392	0.145231	0.164548	1.295751	std
6.000000	1.000000	0.009000	0.600000	0.000000	0.080000	3.800000	min
77.000000	17.000000	0.038000	1.800000	0.250000	0.230000	6.400000	25%
118.000000	29.000000	0.047000	3.000000	0.310000	0.290000	7.000000	50%
156.000000	41.000000	0.065000	8.100000	0.390000	0.400000	7.700000	75%
440.000000	289.000000	0.611000	65.800000	1.660000	1.580000	15.900000	max
•							4



In [73]: plt.scatter("alcohol","quality",data=df)
 plt.show()







```
In [20]: df=df[df.columns.drop('type')]
```

11/26/21, 1:40 PM

```
ML Lab 2
In [21]: df.head(5)
Out[21]:
                                                          free
                                                                  total
                      volatile
                fixed
                              citric
                                    residual
                                             chlorides
                                                        sulfur
                                                                 sulfur
                                                                       density
                                                                                 pH sulphates alcohol
                      acidity
                                      sugar
              acidity
                               acid
                                                       dioxide
                                                               dioxide
           0
                  7.0
                         0.27
                               0.36
                                        20.7
                                                 0.045
                                                          45.0
                                                                 170.0
                                                                               3.00
                                                                                          0.45
                                                                                                   8.8
                                                                        1.0010
           1
                         0.30
                                                 0.049
                                                          14.0
                                                                 132.0
                                                                                          0.49
                  6.3
                               0.34
                                         1.6
                                                                        0.9940
                                                                               3.30
                                                                                                   9.5
           2
                  8.1
                         0.28
                               0.40
                                        6.9
                                                 0.050
                                                          30.0
                                                                  97.0
                                                                        0.9951
                                                                               3.26
                                                                                          0.44
                                                                                                   10.1
            3
                  7.2
                         0.23
                               0.32
                                         8.5
                                                 0.058
                                                          47.0
                                                                 186.0
                                                                        0.9956
                                                                                3.19
                                                                                          0.40
                                                                                                   9.9
            4
                  7.2
                         0.23
                               0.32
                                         8.5
                                                 0.058
                                                          47.0
                                                                 186.0
                                                                        0.9956 3.19
                                                                                          0.40
                                                                                                   9.9
In [22]: print(df.nunique())
          fixed acidity
                                      107
          volatile acidity
                                      188
          citric acid
                                       90
           residual sugar
                                      317
           chlorides
                                      215
           free sulfur dioxide
                                      135
          total sulfur dioxide
                                      276
                                      998
          density
          рΗ
                                      109
           sulphates
                                      112
           alcohol
                                      111
          quality
                                        7
           dtype: int64
In [23]: from sklearn.model selection import train test split
           training, testing =train_test_split(df, test_size= 0.30, random_state=24)
In [24]: training.shape
Out[24]: (4547, 12)
In [25]: | testing.shape
Out[25]: (1950, 12)
In [28]:
          X = training['alcohol']
In [29]:
          X.shape
Out[29]: (4547,)
```

In [30]: | x= np.array(X)

In [31]: x = x.reshape(4547,1)

```
In [32]: x.shape
Out[32]: (4547, 1)
In [33]: Y = training['quality']
In [34]: Y.shape
Out[34]: (4547,)
In [35]: Y= np.array(Y)
In [36]: y = Y.reshape(4547,1)
In [37]: | y.shape
Out[37]: (4547, 1)
In [38]: from sklearn.linear model import LinearRegression
         lr= LinearRegression()
         model=lr.fit(x, y)
In [39]: print(model)
         LinearRegression(copy X=True, fit intercept=True, n jobs=1, normalize=False)
         print(model.coef_[0][0]) ## Printing the coefficients
In [50]:
         print(model.intercept [0]) ### printing the Intercept term
         print("The linear model is: Y = {:.5} + {:.5}X".format(model.intercept_[0], model
         0.32546629798314014
         2.4029999180573034
         The linear model is: Y = 2.403 + 0.32547X
In [52]:
          X_test=testing['alcohol']
In [53]: X_test.shape
Out[53]: (1950,)
In [82]: X_test = X_test.reshape(1950,1)
In [83]: X_test.shape
Out[83]: (1950, 1)
In [84]: Y_test=testing['quality']
In [85]: Y_test.shape
Out[85]: (1950,)
```

```
In [86]:
         Y_test = Y_test.reshape(1950,1)
         C:\Users\PRANAV\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: FutureWarn
         ing: reshape is deprecated and will raise in a subsequent release. Please use .
         values.reshape(...) instead
In [88]: Y_test.shape
Out[88]: (1950, 1)
In [94]:
         Y test
Out[94]: array([[5],
                [4],
                [5],
                [5],
                [7],
                [5]], dtype=int64)
In [89]: Y pred = lr.predict(X test)
In [90]: Y pred
Out[90]: array([[5.72275616],
                [5.52747638],
                [5.3321966],
                [5.56002301],
                [5.75530279],
                [5.46238312]])
In [91]:
          from sklearn.metrics import mean_squared_error
In [92]:
         LR_score= mean_squared_error(Y_test,Y_pred)
In [93]:
         LR score
Out[93]: 0.610874859296884
```

## Interpretation:

The wine quality has been predicted using Linear Regression, with LR score of 61%

```
In [ ]:
```