## **Assignment-4**

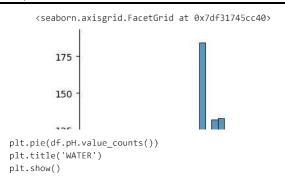
Name: Prakhar Agarwal

Reg No.: 21BIT0034

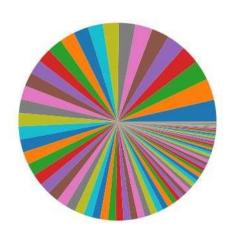
Email ID: prakhar.agarwal2021@vitstudent.ac.in

TASK 1

```
import pandas as pd
df=pd.read_csv('/content/winequality-red.csv')
df.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 volatile acidity 1599 non-null citric acid 1599 non-null residual sugar 1599 non-null chlorides 1599 non-null
                                                       float64
                                                      float64
                                                      float64
          free sulfur dioxide 1599 non-null total sulfur dioxide 1599 non-null
                                                      float64
           density 1599 non-null
                                                      float64
                                  1599 non-null
1599 non-null
      8
          рН
                                                      float64
          sulphates
                                                      float64
                              1599 non-null
      10 alcohol
                                                      float64
      11 quality
                                    1599 non-null
     dtypes: float64(11), int64(1)
     memory usage: 150.0 KB
df.shape
     (1599, 12)
TASK 2
Univariate
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.displot(df.pH)
```

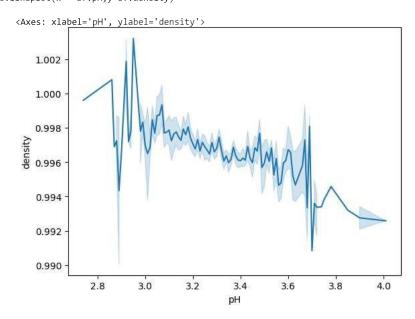


## WATER

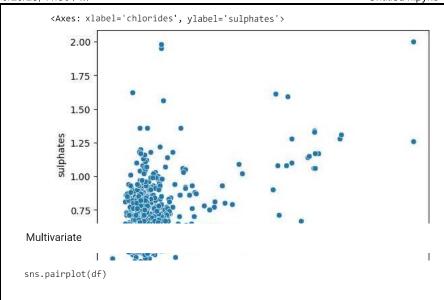


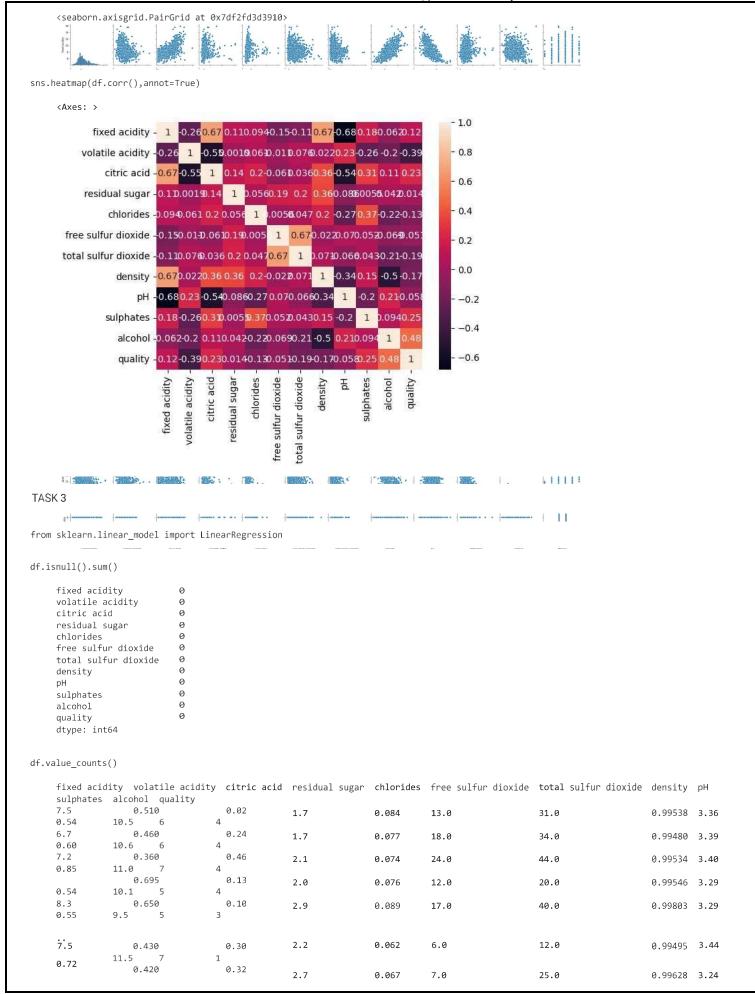
## Bivariate

sns.lineplot(x = df.pH,y=df.density)



sns.scatterplot(x = df.chlorides, y=df.sulphates)





0.44	10.4 5	1					
		0.31	1.6	0.080	15.0	42.0	0.99780 3.31
0.64	9.0 5	1					
	0.410	0.15	3.7	0.104	29.0	94.0	0.99786 3.14
0.58	9.1 5	1					
15.9	0.360	0.65	7.5	0.096	22.0	71.0	0.99760 2.98
0.84	14.9 5	1					

df.nunique()

fixed acidity 96 volatile acidity 143 80 citric acid residual sugar 91 chlorides 153 free sulfur dioxide 60 total sulfur dioxide 144 density 436 89 рН sulphates 96 alcohol 65 quality 6 dtype: int64

Length: 1359, dtype: int64

y = df['pH']
y.head()

0 3.51 1 3.20 2 3.26 3 3.16 4 3.51

Name: pH, dtype: float64

X= df.drop(columns = ['quality'],axis =1)
X.head()

	fixed acidity			residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	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

from sklearn.preprocessing import StandardScaler
scale =StandardScaler()

X\_scaled =pd.DataFrame(scale.fit\_transform(X),columns = X.columns)
X\_scaled.head()

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphate
0	-0.528360	0.961877	-1.391472	-0.453218	-0.243707	-0.466193	-0.379133	0.558274	1.288643	-0.57920
1	-0.298547	1.967442	-1.391472	0.043416	0.223875	0.872638	0.624363	0.028261	-0.719933	0.12895
2	-0.298547	1.297065	-1.186070	-0.169427	0.096353	-0.083669	0.229047	0.134264	-0.331177	-0.04808!
3	1.654856	-1.384443	1.484154	-0.453218	-0.264960	0.107592	0.411500	0.664277	-0.979104	-0.46118
4	-0.528360	0.961877	-1.391472	-0.453218	-0.243707	-0.466193	-0.379133	0.558274	1.288643	-0.57920

from sklearn.model\_selection import train\_test\_split
x\_train,x\_test,y\_train,y\_test = train\_test\_split(X\_scaled,y,test\_size =0.2,random\_state =0)

x\_train.shape

(1279, 11)

```
x_test.shape
        (320, 11)
x_test.head()
                                                                                                                 free
                                                                                                                                total
                                                         citric residual
                         fixed volatile
                                                                                       chlorides
                                                                                                             sulfur
                                                                                                                              sulfur
                                                                                                                                              density
                                                                                                                                                                       pH sulph
                      acidity acidity
                                                            acid
                                                                            sugar
                                                                                                            dioxide
                                                                                                                            dioxide
          1109
                    1.425044 -0.323013 0.816598 -0.311323
                                                                                         1.775397 1.063900
                                                                                                                           0.593954 0.770280 -0.914312
                                                                                                                                                                               0.60
          0.160114 -1.039977 -0.987312 0.950485 0.316751
                                                                                                                                                                               -0.75
                  0.448342 -1.328579 0.303093 -0.346797
                                                                                        -0.520005 -0.274931 -0.591995 -0.840962 -0.331177
          1002
                                                                                                                                                                                1.07
                    -0.732542 -1.039977 -0.987312 0.770280 -0.914312
           487
                                                                                                                                                                              -1.40
           979
                    2.229387 -0.434742 1.124700 -0.807957
                                                                                        -0.264960 -1.231239 -1.230584 0.081262 -1.173483
                                                                                                                                                                              -0.16
y_test
        1109
                     3.17
        1032
                     3.36
        1002
                     3.26
        487
                      3.17
        979
                     3.13
        794
                     3.17
        813
                     3.44
        1322
                      3.18
        704
                     3.29
        1023
                     3.27
        Name: pH, Length: 320, dtype: float64
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(x_train,y_train)

▼ LinearRegression

         LinearRegression()
y_predict = lr.predict(x_test)
y_predict
        array([3.17, 3.36, 3.26, 3.17, 3.13, 3.13, 3.12, 3.47, 3.3 , 3.27, 3.2 ,
                    3.14, 3.29, 3.74, 3.5, 3.34, 3.33, 3.15, 3.55, 3.38, 3.35, 3.27,
                    3.36, 3.3, 3.57, 3.27, 3.23, 3.35, 3.2, 3.9, 3.14, 3.31, 3.53,
                    3.5 , 3.52, 3.26, 3.46, 3.69, 3.62, 3.35, 3.33, 3.37, 3.49, 3.02,
                    3.3 , 3.19, 3.16, 3.3 , 3.58, 3.36, 3.41, 3.38, 3.38, 3.3 , 3.32,
                    3.35, 3.3, 3.09, 3.23, 3.27, 3.68, 3.32, 3.32, 3.56, 3.51, 3.42,
                    3.29, 2.92, 3.19, 3.07, 3.3, 3.04, 3.38, 3.17, 3.34, 3.58, 3.46,
                    3.45, 3.35, 3.3, 3.1, 3.39, 3.51, 3.14, 3.36, 3.4, 3.44, 3.25,
                    3.42, 3.44, 3.26, 3.22, 3.62, 3.35, 3.4, 3.3, 3.15, 3.19, 3.26,
                    3.04, 3.23, 3.38, 3.29, 3.34, 3.46, 3.39, 3.46, 3.41, 3.42, 3.23,
                    3.56, 3.1 , 3.23, 3.29, 3.33, 3.37, 3.25, 3.27, 3.45, 3.36, 3.23,
                    2.92, 3.03, 3.36, 3.27, 3.3 , 3.23, 3.13, 3.36, 3.06, 3.4 , 3.35,
                    3.32, 3.22, 3.28, 3.29, 3.06, 3. , 2.88, 3.36, 3.39, 3.19, 3.16,
                    3.67, 3.17, 3.3, 3.23, 3.33, 3.18, 3.34, 3.42, 3.39, 3.41, 3.29,
                    3.61, 3.46, 3.25, 3.28, 3.44, 3.38, 3.48, 3.42, 3.32, 3.5, 3.14,
                    3.25, 3.54, 3.41, 3.18, 3.27, 3.1, 3.35, 3.48, 3.15, 3.52, 3.21,
                    3.18, 3.34, 3.71, 3.16, 3.32, 3.38, 3.41, 3.2, 3.39, 3.2, 3.26,
                    3.29, 3.25, 3.42, 3.33, 2.94, 3.18, 3.29, 3.46, 3.28, 3.2, 3.39,
                    3.28, 3.16, 3.19, 3.41, 3.26, 3.31, 3.26, 3.59, 3.24, 3.38, 3.36,
                    3.42, 3.29, 3.25, 3.11, 3.18, 3.49, 3.47, 3.04, 3.39, 3.38, 3.28,
                    3.51, 3.16, 3.2, 3.03, 3.36, 3.12, 3.22, 3.56, 3.16, 3.39, 3.53, 3.73, 3.74, 3.75
                    3.57, 3.35, 3.23, 3.13, 3.42, 3.07, 3.33, 3.36, 3.22, 3.48, 3.4,
                    3.36, 3.39, 3.24, 3.26, 3.29, 3.29, 3. , 3.39, 3.19, 3.44, 3.23, 3.26, 3.4, 3.36, 3.21, 3.11, 3.48, 3.07, 3.44, 3.68, 3.14, 3.08, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.21, 3.
                    3.34, 3.36, 3.6, 3.28, 3.28, 3.33, 3.14, 3.17, 3.24, 3.9, 3.22,
                    3.39, 3.14, 3.21, 3.39, 3.05, 3.14, 3.27, 3.17, 3.26, 3.26, 3.55, 3.26, 3.27
                    3.36, 3.27, 3.34, 3.15, 3.49, 3.5, 3.41, 3.19, 3.26, 3.38, 3.4,
                    3.29, 3.35, 3.15, 3.44, 3.56, 3.12, 3.31, 3.35, 3.61, 3.45, 3.48,
                    3.37, 3.39, 3.36, 3.42, 3.66, 3.19, 3.2, 3.17, 3.44, 3.18, 3.29,
```

```
y_predict1 =lr.predict(x_train)
y_predict1
     array([3.39, 3.13, 3.26, ..., 3.29, 3.3, 3.25])
profit =pd.DataFrame({'Actual_pH':y_test,'Predicted_pH':y_predict})
profit
                                        \overline{\mathbf{H}}
            Actual_pH Predicted_pH
      1109
                  3.17
                                3.17
                                        th
      1032
                  3.36
                                3.36
      1002
                  3.26
                                3.26
                  3.17
                                3.17
      487
      979
                  3.13
                                 3.13
       794
                  3.17
                                3.17
      813
                  3.44
                                3.44
      1322
                  3.18
                                3.18
      704
                  3.29
                                3.29
      1023
                  3.27
                                 3.27
     320 rows × 2 columns
Task 4
from sklearn import metrics
\verb|print(metrics.r2_score(y_test,y_predict))||
     1.0
print(metrics.r2_score(y_train,y_predict1))
     1.0
print(metrics.mean_squared_error(y_test,y_predict))
     3,457429436163966e-31
print(np.sqrt(metrics.mean_squared_error(y_test,y_predict)))

    5.879991017139368e-16

                                                                + Code
                                                                             + Text
TASK 5
df.head()
                                                              free
                                                                      total
           fixed volatile citric residual
                                               chlorides
                                                           sulfur
                                                                     sulfur
                                                                             density
                                                                                        pH sulp
         acidity
                   acidity
                               acid
                                        sugar
                                                           dioxide dioxide
      0
                       0.70
                               0.00
                                           1.9
                                                    0.076
                                                               11.0
                                                                               0.9978 3.51
              7.4
                                                                        34.0
              7.8
                       0.88
                               0.00
                                           2.6
                                                    0.098
                                                              25.0
                                                                        67.0
                                                                               0.9968 3.20
      1
                                                              15.0
                       0.76
                                                    0.092
                                                                               0.9970 3.26
      2
              7.8
                               0.04
                                           2.3
                                                                        54.0
      3
                                                    0.075
                                                              17.0
             11.2
                       0.28
                               0.56
                                           1.9
                                                                        60.0
                                                                               0.9980 3.16
     4
lr.predict([[7.4, 0.70, 0.00, 1.9, 0.076, 11.0, 34.0, 0.9978, 3.51, 0.56, 9.4]])/100000
```

https://colab.research.google.com/drive/1\_Tn5fYv7h3abPmGiwzQcn9HhS82G-fta?authuser=0#scrollTo=WSWeK1yA1tqm&printMode=true

warnings.warn(

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but LinearRegression was

```
array([3.85284021e-05])
lr.predict([[7.8, 0.88, 0.00, 2.6, 0.098, 25.0, 67.0, 0.9968, 3.20, 0.68, 9.8]])/100000
    /usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but LinearRegression was
      warnings.warn(
    array([3.80499538e-05])
lr.predict([[7.4, 0.70, 0.00, 1.9, 0.076, 11.0, 34.0, 0.9978, 3.51, 0.56, 9.4]])/100000
    /usr/local/lib/python3.10/dist-packages/sklearn/base.py:439:UserWarning: X does not have valid feature names, but LinearRegression was
      warnings.warn(
    array([3.85284021e-05])
```