A real estate agent want help to predict the house price for regions in Usa.he gave us the dataset to work on to use linear Regression model.Create a model that helps him to estimate

### **Data Collection**

```
#import libraries
  In [1]:
            import numpy as np
            import pandas as pd
            import matplotlib.pyplot as plt
            import seaborn as sns
In [203]:
           #import the dataset
            data=pd.read csv(r"C:\Users\user\Desktop\Vicky\11 winequality-red.csv")[0:500]
           #to display top 10 rows
In [204]:
            data.head()
Out[204]:
                                                           free
                                                                  total
                 fixed volatile citric residual
                                              chlorides
                                                         sulfur
                                                                 sulfur
                                                                                  pH sulphates alcohol
                                                                        density
               acidity
                       acidity
                                acid
                                       sugar
                                                        dioxide
                                                                dioxide
             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
                          88.0
                                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
```

0.075

0.076

17.0

11.0

60.0

34.0

0.9980 3.16

0.9978 3.51

0.58

0.56

9.8

9.4

localhost:8888/notebooks/Linear Regression.ipynb#

11.2

7.4

0.28

0.70

0.56

0.00

1.9

1.9

```
In [205]: #to display null values
data.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 12 columns):

| #  | Column               | Non-Null Count | Dtype   |
|----|----------------------|----------------|---------|
|    |                      |                |         |
| 0  | fixed acidity        | 500 non-null   | float64 |
| 1  | volatile acidity     | 500 non-null   | float64 |
| 2  | citric acid          | 500 non-null   | float64 |
| 3  | residual sugar       | 500 non-null   | float64 |
| 4  | chlorides            | 500 non-null   | float64 |
| 5  | free sulfur dioxide  | 500 non-null   | float64 |
| 6  | total sulfur dioxide | 500 non-null   | float64 |
| 7  | density              | 500 non-null   | float64 |
| 8  | рН                   | 500 non-null   | float64 |
| 9  | sulphates            | 500 non-null   | float64 |
| 10 | alcohol              | 500 non-null   | float64 |
| 11 | quality              | 500 non-null   | int64   |
|    |                      |                |         |

dtypes: float64(11), int64(1)

memory usage: 47.0 KB

In [206]: data.shape

Out[206]: (500, 12)

In [207]: #to display summary of statistics

data.describe()

#### Out[207]:

|       | fixed<br>acidity | volatile<br>acidity | citric acid | residual<br>sugar | chlorides  | free sulfur<br>dioxide | total sulfur<br>dioxide | d     |
|-------|------------------|---------------------|-------------|-------------------|------------|------------------------|-------------------------|-------|
| count | 500.00000        | 500.000000          | 500.000000  | 500.000000        | 500.000000 | 500.000000             | 500.000000              | 500.0 |
| mean  | 8.68640          | 0.533370            | 0.302460    | 2.586800          | 0.093962   | 15.041000              | 51.444000               | 0.9   |
| std   | 1.88393          | 0.176169            | 0.216569    | 1.382229          | 0.060240   | 9.783673               | 33.716947               | 0.0   |
| min   | 4.60000          | 0.180000            | 0.000000    | 1.200000          | 0.039000   | 3.000000               | 8.000000                | 0.9   |
| 25%   | 7.40000          | 0.400000            | 0.107500    | 1.900000          | 0.073000   | 7.000000               | 25.000000               | 0.9   |
| 50%   | 8.10000          | 0.530000            | 0.275000    | 2.200000          | 0.082000   | 12.000000              | 42.000000               | 0.9   |
| 75%   | 9.82500          | 0.645000            | 0.480000    | 2.700000          | 0.093000   | 20.000000              | 67.000000               | 0.9   |
| max   | 15.60000         | 1.330000            | 1.000000    | 15.500000         | 0.611000   | 68.000000              | 165.000000              | 1.0   |
|       |                  |                     |             |                   |            |                        |                         |       |

In [209]: data.fillna(value=5)

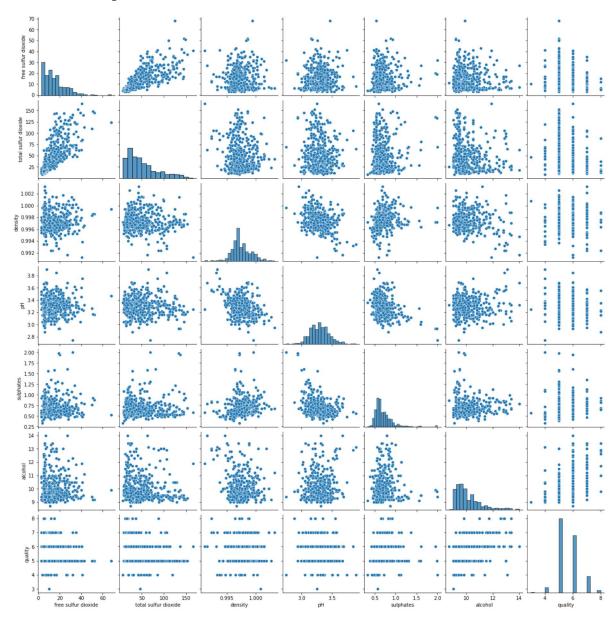
#### Out[209]:

|     | fixed<br>acidity | volatile<br>acidity | citric<br>acid | residual<br>sugar | chlorides | free<br>sulfur<br>dioxide | total<br>sulfur<br>dioxide | density | рН   | sulphates | alcoh |
|-----|------------------|---------------------|----------------|-------------------|-----------|---------------------------|----------------------------|---------|------|-----------|-------|
| 0   | 7.4              | 0.70                | 0.00           | 1.9               | 0.076     | 11.0                      | 34.0                       | 0.9978  | 3.51 | 0.56      | 9     |
| 1   | 7.8              | 0.88                | 0.00           | 2.6               | 0.098     | 25.0                      | 67.0                       | 0.9968  | 3.20 | 0.68      | 9     |
| 2   | 7.8              | 0.76                | 0.04           | 2.3               | 0.092     | 15.0                      | 54.0                       | 0.9970  | 3.26 | 0.65      | 9     |
| 3   | 11.2             | 0.28                | 0.56           | 1.9               | 0.075     | 17.0                      | 60.0                       | 0.9980  | 3.16 | 0.58      | 9     |
| 4   | 7.4              | 0.70                | 0.00           | 1.9               | 0.076     | 11.0                      | 34.0                       | 0.9978  | 3.51 | 0.56      | 9     |
|     |                  |                     |                |                   |           |                           |                            |         |      |           |       |
| 495 | 10.7             | 0.35                | 0.53           | 2.6               | 0.070     | 5.0                       | 16.0                       | 0.9972  | 3.15 | 0.65      | 11    |
| 496 | 7.8              | 0.52                | 0.25           | 1.9               | 0.081     | 14.0                      | 38.0                       | 0.9984  | 3.43 | 0.65      | 9     |
| 497 | 7.2              | 0.34                | 0.32           | 2.5               | 0.090     | 43.0                      | 113.0                      | 0.9966  | 3.32 | 0.79      | 11    |
| 498 | 10.7             | 0.35                | 0.53           | 2.6               | 0.070     | 5.0                       | 16.0                       | 0.9972  | 3.15 | 0.65      | 11    |
| 499 | 8.7              | 0.69                | 0.31           | 3.0               | 0.086     | 23.0                      | 81.0                       | 1.0002  | 3.48 | 0.74      | 11    |

500 rows × 12 columns

In [213]: sns.pairplot(data1)

Out[213]: <seaborn.axisgrid.PairGrid at 0x12533b239a0>

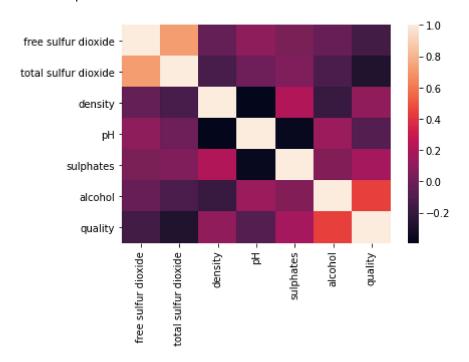


# **EDA** and Visualization

In [214]: #sns.distplot(data['Co2-Emissions'])

In [215]: sns.heatmap(data1.corr())

Out[215]: <AxesSubplot:>



In [174]: data1.fillna(value=5)

Out[174]:

|                       | id       | diagnosis | radius_mean | texture_mean | perimeter_mean | area_mean | smoothness_ |  |
|-----------------------|----------|-----------|-------------|--------------|----------------|-----------|-------------|--|
| 0                     | 842302   | М         | 17.99       | 10.38        | 122.80         | 1001.0    | 0.          |  |
| 1                     | 842517   | M         | 20.57       | 17.77        | 132.90         | 1326.0    | 0.          |  |
| 2                     | 84300903 | M         | 19.69       | 21.25        | 130.00         | 1203.0    | 0.          |  |
| 3                     | 84348301 | M         | 11.42       | 20.38        | 77.58          | 386.1     | 0.          |  |
| 4                     | 84358402 | M         | 20.29       | 14.34        | 135.10         | 1297.0    | 0.          |  |
|                       |          | •••       |             |              |                |           |             |  |
| 495                   | 914333   | В         | 14.87       | 20.21        | 96.12          | 680.9     | 0.          |  |
| 496                   | 914366   | В         | 12.65       | 18.17        | 82.69          | 485.6     | 0.          |  |
| 497                   | 914580   | В         | 12.47       | 17.31        | 80.45          | 480.1     | 0.          |  |
| 498                   | 914769   | M         | 18.49       | 17.52        | 121.30         | 1068.0    | 0.          |  |
| 499                   | 91485    | M         | 20.59       | 21.24        | 137.80         | 1320.0    | 0.          |  |
| 500 rows × 27 columns |          |           |             |              |                |           |             |  |
| 4                     |          |           |             |              |                |           | <b>&gt;</b> |  |

## To train the model

we are going to train the linear regression model; We need to split the two variable x and y

```
x=data[['fixed acidity', 'volatile acidity'
In [183]:
                  ]]
           y=data1['alcohol']
In [184]:
           #To split test and train data
           from sklearn.model_selection import train_test_split
           x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.1)
In [185]:
          from sklearn.linear_model import LinearRegression
           lr=LinearRegression()
           lr.fit(x_train,y_train)
Out[185]: LinearRegression()
In [186]: lr.intercept_
Out[186]: 38835336.15720841
          coeff = pd.DataFrame(lr.coef_,x.columns,columns=["Co-efficient"])
In [187]:
           coeff
Out[187]:
                               Co-efficient
            compactness_worst -5.751864e+07
              concavity_worst 2.734553e+07
  In [ ]:
          prediction = lr.predict(x train)
In [188]:
           plt.scatter(y_train,prediction)
Out[188]: <matplotlib.collections.PathCollection at 0x1252332bdf0>
            4.5
            4.0
            3.5
            3.0
            2.5
            2.0
            1.5
            1.0
                          ż
                                                          le8
```

```
In [189]: lr.score(x_test,y_test)
Out[189]: -0.004073209588378202
In [190]: |lr.score(x_train,y_train)
Out[190]: 0.0015226742955708472
In [191]: from sklearn.linear_model import Ridge,Lasso
In [192]: rr=Ridge(alpha=10)
          rr.fit(x_train,y_train)
          rr.score(x_test,y_test)
Out[192]: -0.009582880189396903
In [193]: la=Lasso(alpha=10)
          la.fit(x_train,y_train)
          la.score(x_test,y_test)
Out[193]: -0.0040737802210928376
In [194]: | from sklearn.linear_model import ElasticNet
          en= ElasticNet()
          en.fit(x_train,y_train)
Out[194]: ElasticNet()
In [195]: print(en.coef_)
          [-1241747.15166715 -916017.96199218]
In [196]:
          print(en.intercept_)
          32089776.5923149
```

```
prediction = en.predict(x test)
In [197]:
          prediction
Out[197]: array([31393740.13355368, 31088477.23434921, 31253514.61656909,
                 31542670.42800784, 31365755.09598579, 31882295.855237 ,
                 31913180.90717359, 31534008.63013534, 31710076.15057814,
                 31780477.09711697, 31991828.95134632, 31496373.89934802,
                 31741856.92519902, 31944222.95010149, 31769883.86167683,
                 31373511.88890291, 31168714.43934447, 31044309.26365758,
                 31874848.90308605, 31368514.77333577, 31781323.68778142,
                 31934699.37516704, 31284579.70265878, 31228892.23275906,
                 31627703.65606768, 31960955.92049683, 31496299.88949108,
                 31547727.64488157, 31849175.58418468, 30784912.09903306,
                 31439275.55225564, 31609501.3545823, 31918403.4321233,
                 31493836.73418531, 31848553.36347367, 31356747.691898
                 31664347.58357762, 31226737.5240613, 30935373.9311361,
                 31996899.68451488, 31771755.96513853, 32002412.79677851,
                 31819043.74666099, 31906922.55968469, 31666012.16821847,
                 31571940.18819558, 31242794.29848333, 31353086.52385158,
                 31404467.02644319, 31614317.40728684])
In [216]: #print(en.score(x test,y train))
In [217]: | from sklearn import metrics
In [218]: print("Mean Absolute error:", metrics.mean absolute error(y test, prediction))
          Mean Absolute error: 62586502.49745239
In [219]: print("Mean Absolute Square error:", metrics.mean_squared_error(y_test, predicti
          Mean Absolute Square error: 3.080001673006421e+16
In [220]: print("Root mean Square error:",np.sqrt(metrics.mean_squared_error(y_test,pred
          Root mean Square error: 175499335.41203
 In [ ]:
 In [ ]:
```