## **Problem statement**

predicting the house price in USA. To create a model to help him estimate of what the house would sell for.

# To display top 10 rows

```
In [3]: 1 df.head(10)
```

#### Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
5	7.4	0.66	0.00	1.8	0.075	13.0	40.0	0.9978	3.51	0.56	9.4	5
6	7.9	0.60	0.06	1.6	0.069	15.0	59.0	0.9964	3.30	0.46	9.4	5
7	7.3	0.65	0.00	1.2	0.065	15.0	21.0	0.9946	3.39	0.47	10.0	7
8	7.8	0.58	0.02	2.0	0.073	9.0	18.0	0.9968	3.36	0.57	9.5	7
9	7.5	0.50	0.36	6.1	0.071	17.0	102.0	0.9978	3.35	0.80	10.5	5

## **Data Cleaning And Pre-Processing**

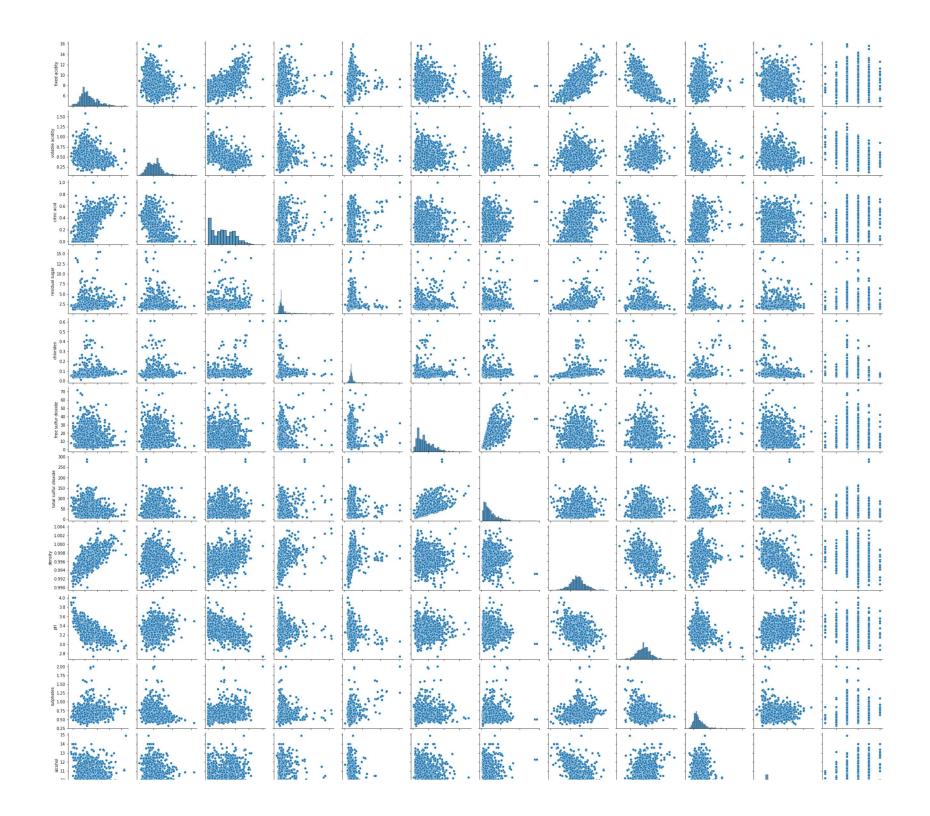
```
In [4]:
        1 df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 1599 entries, 0 to 1598
        Data columns (total 12 columns):
             Column
                                   Non-Null Count
                                                  Dtype
        --- -----
            fixed acidity
                                                  float64
                                  1599 non-null
             volatile acidity
                                  1599 non-null
                                                  float64
         1
             citric acid
                                  1599 non-null
                                                  float64
             residual sugar
                                  1599 non-null
                                                  float64
             chlorides
                                                  float64
         4
                                  1599 non-null
           free sulfur dioxide
                                                  float64
                                  1599 non-null
           total sulfur dioxide 1599 non-null
                                                  float64
                                  1599 non-null
         7
             density
                                                  float64
         8
             рН
                                  1599 non-null
                                                  float64
             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
```

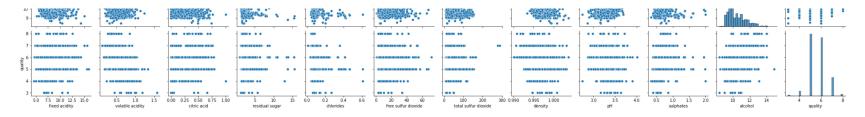
```
In [5]:
           1 | # Display the statistical summary
           2 df.describe()
Out[5]:
                                  volatile
                                                          residual
                                                                                 free sulfur
                                                                                             total sulfur
                 fixed acidity
                                            citric acid
                                                                     chlorides
                                                                                                            density
                                                                                                                             Hq
                                                                                                                                   sulphat
                                  acidity
                                                                                                dioxide
                                                            sugar
                                                                                    dioxide
          count 1599,000000
                             1599.000000 1599.000000
                                                      1599.000000
                                                                   1599.000000
                                                                               1599.000000
                                                                                            1599.000000 1599.000000 1599.000000
                                                                                                                                 1599.0000
           mean
                    8.319637
                                 0.527821
                                             0.270976
                                                         2.538806
                                                                      0.087467
                                                                                 15.874922
                                                                                              46.467792
                                                                                                           0.996747
                                                                                                                        3.311113
                                                                                                                                   0.6581
            std
                    1.741096
                                0.179060
                                             0.194801
                                                         1.409928
                                                                      0.047065
                                                                                 10.460157
                                                                                              32.895324
                                                                                                           0.001887
                                                                                                                       0.154386
                                                                                                                                   0.1695
                    4.600000
                                 0.120000
                                             0.000000
                                                         0.900000
                                                                      0.012000
                                                                                  1.000000
                                                                                              6.000000
                                                                                                           0.990070
                                                                                                                       2.740000
                                                                                                                                   0.3300
            min
            25%
                    7.100000
                                                                                  7.000000
                                                                                                                                   0.5500
                                 0.390000
                                             0.090000
                                                         1.900000
                                                                      0.070000
                                                                                              22.000000
                                                                                                           0.995600
                                                                                                                       3.210000
            50%
                    7.900000
                                 0.520000
                                             0.260000
                                                         2.200000
                                                                      0.079000
                                                                                 14.000000
                                                                                              38.000000
                                                                                                           0.996750
                                                                                                                       3.310000
                                                                                                                                   0.6200
            75%
                    9.200000
                                 0.640000
                                             0.420000
                                                         2.600000
                                                                      0.090000
                                                                                 21.000000
                                                                                             62.000000
                                                                                                           0.997835
                                                                                                                       3.400000
                                                                                                                                   0.7300
                   15.900000
                                 1.580000
                                             1.000000
                                                        15.500000
                                                                      0.611000
                                                                                 72.000000
                                                                                             289.000000
                                                                                                           1.003690
                                                                                                                       4.010000
                                                                                                                                    2.0000
            max
           1 # To display the col headings
In [6]:
           2 df.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')
           1 cols=df.dropna(axis=1)
In [7]:
In [8]:
           1 cols.columns
Out[8]: Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
                  'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
                  'pH', 'sulphates', 'alcohol', 'quality'],
                 dtvpe='object')
```

### **EDA and Visualization**

```
In [9]: 1 sns.pairplot(cols)
```

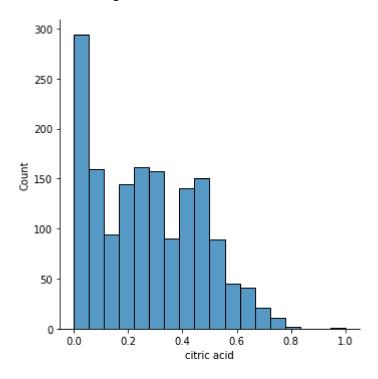
Out[9]: <seaborn.axisgrid.PairGrid at 0x1c4572acfd0>





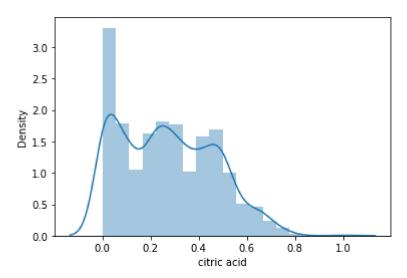
In [10]: 1 sns.displot(df['citric acid'])

Out[10]: <seaborn.axisgrid.FacetGrid at 0x1c45d079af0>



C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a dep recated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms). warnings.warn(msg, FutureWarning)

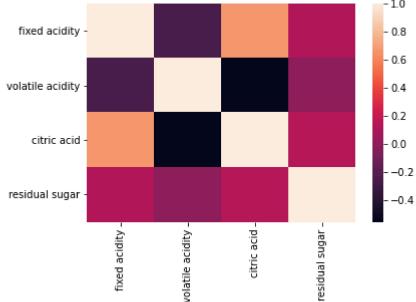
Out[11]: <AxesSubplot:xlabel='citric acid', ylabel='Density'>



### Out[12]:

	fixed acidity	volatile acidity	citric acid	residual sugar
0	7.4	0.700	0.00	1.9
1	7.8	0.880	0.00	2.6
2	7.8	0.760	0.04	2.3
3	11.2	0.280	0.56	1.9
4	7.4	0.700	0.00	1.9
1594	6.2	0.600	0.08	2.0
1595	5.9	0.550	0.10	2.2
1596	6.3	0.510	0.13	2.3
1597	5.9	0.645	0.12	2.0
1598	6.0	0.310	0.47	3.6

1599 rows × 4 columns



## To train the model - MODEL BUILD

Going to train linear regression model; We split our data into 2 variables x and y where x is independent var(input) and y is dependent on x(output), we could ignore address col as it is not required for our model

# To split the dataset into test data

```
In [15]: 1 # importing lib for splitting test data
2 from sklearn.model_selection import train_test_split
```

```
1 x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.3)
In [16]:
In [17]:
          1 from sklearn.linear_model import LinearRegression
          3 lr=LinearRegression()
          4 lr.fit(x_train,y_train)
Out[17]: LinearRegression()
In [18]:
          1 print(lr.intercept_)
         [9.99200722e-16]
         1 print(lr.score(x_test,y_test))
In [19]:
         1.0
In [20]:
          1 coeff=pd.DataFrame(lr.coef_)
          2 coeff
Out[20]:
                                    2
                                               3
```

**0** -1.098859e-16 1.0 6.043738e-16 -5.921732e-18

```
1 pred = lr.predict(x_test)
In [21]:
           plt.scatter(y_test,pred)
Out[21]: <matplotlib.collections.PathCollection at 0x1c460b7f610>
          1.2
          1.0
          0.8
          0.6
          0.4
          0.2
                              0.6
                                     0.8
                                           1.0
                                                 1.2
                 0.2
                       0.4
In [22]:
          1 from sklearn.linear model import Ridge,Lasso
           1 rr=Ridge(alpha=20)
In [23]:
           2 rr.fit(x_train,y_train)
Out[23]: Ridge(alpha=20)
In [24]:
          1 rr.score(x_test,y_test)
Out[24]: 0.8827801692931591
In [26]:
           1 la=Lasso(alpha=20)
           2 la.fit(x_train,y_train)
Out[26]: Lasso(alpha=20)
           1 la.score(x_test,y_test)
In [27]:
Out[27]: -0.0017611704992219757
```

In [ ]: 1