Problem Statement:

A real estate agent want to help to predict the house price for regions in USA.He gave us the dataset to work on to use Linear Regression modelCreate a Model that helps him to estimate of what the house would sell for

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

In [2]:
```
df=pd.read_csv("bottle.csv")
df
```

```
C:\ProgramData\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3165: DtypeW
arning: Columns (47,73) have mixed types.Specify dtype option on import or set low_memor
y=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[2]:

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	...	R
0	1	1	054.0 056.0	19-4903CR-HY-060-0930-05400560-0000A-3	0	10.500	33.4400	NaN	25.64900	NaN	...	
1	1	2	054.0 056.0	19-4903CR-HY-060-0930-05400560-0008A-3	8	10.460	33.4400	NaN	25.65600	NaN	...	
2	1	3	054.0 056.0	19-4903CR-HY-060-0930-05400560-0010A-7	10	10.460	33.4370	NaN	25.65400	NaN	...	
3	1	4	054.0 056.0	19-4903CR-HY-060-0930-05400560-0019A-3	19	10.450	33.4200	NaN	25.64300	NaN	...	
4	1	5	054.0 056.0	19-4903CR-HY-060-0930-	20	10.450	33.4210	NaN	25.64300	NaN	...	

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	...	R
				05400560-0020A-7								
...	...	...	...	...	...	...	...	...	...	...	...	
864858	34404	864859	093.4 026.4	20-1611SR-MX-310-2239-09340264-0000A-7	0	18.744	33.4083	5.805	23.87055	108.74	...	
864859	34404	864860	093.4 026.4	20-1611SR-MX-310-2239-09340264-0002A-3	2	18.744	33.4083	5.805	23.87072	108.74	...	
864860	34404	864861	093.4 026.4	20-1611SR-MX-310-2239-09340264-0005A-3	5	18.692	33.4150	5.796	23.88911	108.46	...	
864861	34404	864862	093.4 026.4	20-1611SR-MX-310-2239-09340264-0010A-3	10	18.161	33.4062	5.816	24.01426	107.74	...	
864862	34404	864863	093.4 026.4	20-1611SR-MX-310-2239-09340264-0015A-3	15	17.533	33.3880	5.774	24.15297	105.66	...	

864863 rows × 74 columns

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 864863 entries, 0 to 864862
Data columns (total 74 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   Cst_Cnt             864863 non-null  int64
 1   Btl_Cnt             864863 non-null  int64
 2   Sta_ID              864863 non-null  object
 3   Depth_ID            864863 non-null  object
 4   Depthm              864863 non-null  int64
 5   T_degC              853900 non-null  float64
 6   Salnty              817509 non-null  float64
 7   O2ml_L              696201 non-null  float64
```

```
8   STheta              812174 non-null  float64
9   O2Sat               661274 non-null  float64
10  Oxy_µmol/Kg         661268 non-null  float64
11  BtlNum              118667 non-null  float64
12  RecInd              864863 non-null  int64
13  T_prec              853900 non-null  float64
14  T_qual              23127 non-null   float64
15  S_prec              817509 non-null  float64
16  S_qual              74914 non-null   float64
17  P_qual              673755 non-null  float64
18  O_qual              184676 non-null  float64
19  SThtaq              65823 non-null   float64
20  O2Satq              217797 non-null  float64
21  ChlorA              225272 non-null  float64
22  Chlqua              639166 non-null  float64
23  Phaeop              225271 non-null  float64
24  Phaqua              639170 non-null  float64
25  PO4uM               413317 non-null  float64
26  PO4q                451786 non-null  float64
27  SiO3uM              354091 non-null  float64
28  SiO3qu              510866 non-null  float64
29  NO2uM               337576 non-null  float64
30  NO2q                529474 non-null  float64
31  NO3uM               337403 non-null  float64
32  NO3q                529933 non-null  float64
33  NH3uM               64962 non-null   float64
34  NH3q                808299 non-null  float64
35  C14As1              14432 non-null   float64
36  C14A1p              12760 non-null   float64
37  C14A1q              848605 non-null  float64
38  C14As2              14414 non-null   float64
39  C14A2p              12742 non-null   float64
40  C14A2q              848623 non-null  float64
41  DarkAs              22649 non-null   float64
42  DarkAp              20457 non-null   float64
43  DarkAq              840440 non-null  float64
44  MeanAs              22650 non-null   float64
45  MeanAp              20457 non-null   float64
46  MeanAq              840439 non-null  float64
47  IncTim              14437 non-null   object
48  LightP              18651 non-null   float64
49  R_Depth             864863 non-null  float64
50  R_TEMP              853900 non-null  float64
51  R_POTEMP            818816 non-null  float64
52  R_SALINITY          817509 non-null  float64
53  R_SIGMA             812007 non-null  float64
54  R_SVA               812092 non-null  float64
55  R_DYNHT             818206 non-null  float64
56  R_O2                696201 non-null  float64
57  R_O2Sat             666448 non-null  float64
58  R_SIO3              354099 non-null  float64
59  R_PO4               413325 non-null  float64
60  R_NO3               337411 non-null  float64
61  R_NO2               337584 non-null  float64
62  R_NH4               64982 non-null   float64
63  R_CHLA              225276 non-null  float64
64  R_PHAEO             225275 non-null  float64
65  R_PRES              864863 non-null  int64
66  R_SAMP              122006 non-null  float64
67  DIC1                1999 non-null    float64
68  DIC2                224 non-null     float64
69  TA1                 2084 non-null    float64
70  TA2                 234 non-null     float64
71  pH2                 10 non-null      float64
72  pH1                 84 non-null      float64
```

```
 73  DIC Quality Comment  55 non-null      object
dtypes: float64(65), int64(5), object(4)
memory usage: 488.3+ MB
```

In [4]:
```
df.head()
```

Out[4]:

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	T_degC	Salnty	O2ml_L	STheta	O2Sat	...	R_PHAEO
0	1	1	054.0 056.0	19-4903CR-HY-060-0930-05400560-0000A-3	0	10.50	33.440	NaN	25.649	NaN	...	NaN
1	1	2	054.0 056.0	19-4903CR-HY-060-0930-05400560-0008A-3	8	10.46	33.440	NaN	25.656	NaN	...	NaN
2	1	3	054.0 056.0	19-4903CR-HY-060-0930-05400560-0010A-7	10	10.46	33.437	NaN	25.654	NaN	...	NaN
3	1	4	054.0 056.0	19-4903CR-HY-060-0930-05400560-0019A-3	19	10.45	33.420	NaN	25.643	NaN	...	NaN
4	1	5	054.0 056.0	19-4903CR-HY-060-0930-05400560-0020A-7	20	10.45	33.421	NaN	25.643	NaN	...	NaN

5 rows × 74 columns

Data cleaning and Pre-Processing

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 864863 entries, 0 to 864862
Data columns (total 74 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   Cst_Cnt             864863 non-null  int64
```

```
1   Btl_Cnt             864863 non-null  int64
2   Sta_ID              864863 non-null  object
3   Depth_ID            864863 non-null  object
4   Depthm              864863 non-null  int64
5   T_degC              853900 non-null  float64
6   Salnty              817509 non-null  float64
7   O2ml_L              696201 non-null  float64
8   STheta              812174 non-null  float64
9   O2Sat               661274 non-null  float64
10  Oxy_µmol/Kg         661268 non-null  float64
11  BtlNum              118667 non-null  float64
12  RecInd              864863 non-null  int64
13  T_prec              853900 non-null  float64
14  T_qual              23127 non-null   float64
15  S_prec              817509 non-null  float64
16  S_qual              74914 non-null   float64
17  P_qual              673755 non-null  float64
18  O_qual              184676 non-null  float64
19  SThtaq              65823 non-null   float64
20  O2Satq              217797 non-null  float64
21  ChlorA              225272 non-null  float64
22  Chlqua              639166 non-null  float64
23  Phaeop              225271 non-null  float64
24  Phaqua              639170 non-null  float64
25  PO4uM               413317 non-null  float64
26  PO4q                451786 non-null  float64
27  SiO3uM              354091 non-null  float64
28  SiO3qu              510866 non-null  float64
29  NO2uM               337576 non-null  float64
30  NO2q                529474 non-null  float64
31  NO3uM               337403 non-null  float64
32  NO3q                529933 non-null  float64
33  NH3uM               64962 non-null   float64
34  NH3q                808299 non-null  float64
35  C14As1              14432 non-null   float64
36  C14A1p              12760 non-null   float64
37  C14A1q              848605 non-null  float64
38  C14As2              14414 non-null   float64
39  C14A2p              12742 non-null   float64
40  C14A2q              848623 non-null  float64
41  DarkAs              22649 non-null   float64
42  DarkAp              20457 non-null   float64
43  DarkAq              840440 non-null  float64
44  MeanAs              22650 non-null   float64
45  MeanAp              20457 non-null   float64
46  MeanAq              840439 non-null  float64
47  IncTim              14437 non-null   object
48  LightP              18651 non-null   float64
49  R_Depth             864863 non-null  float64
50  R_TEMP              853900 non-null  float64
51  R_POTEMP            818816 non-null  float64
52  R_SALINITY          817509 non-null  float64
53  R_SIGMA             812007 non-null  float64
54  R_SVA               812092 non-null  float64
55  R_DYNHT             818206 non-null  float64
56  R_O2                696201 non-null  float64
57  R_O2Sat             666448 non-null  float64
58  R_SIO3              354099 non-null  float64
59  R_PO4               413325 non-null  float64
60  R_NO3               337411 non-null  float64
61  R_NO2               337584 non-null  float64
62  R_NH4               64982 non-null   float64
63  R_CHLA              225276 non-null  float64
64  R_PHAEO             225275 non-null  float64
65  R_PRES              864863 non-null  int64
```

```
 66  R_SAMP               122006 non-null  float64
 67  DIC1                 1999 non-null    float64
 68  DIC2                 224 non-null     float64
 69  TA1                  2084 non-null    float64
 70  TA2                  234 non-null     float64
 71  pH2                  10 non-null      float64
 72  pH1                  84 non-null      float64
 73  DIC Quality Comment  55 non-null      object
dtypes: float64(65), int64(5), object(4)
memory usage: 488.3+ MB
```

In [6]:
```
df.describe()
```

Out[6]:

	Cst_Cnt	Btl_Cnt	Depthm	T_degC	Salnty	O2ml_L	
count	864863.000000	864863.000000	864863.000000	853900.000000	817509.000000	696201.000000	81217
mean	17138.790958	432432.000000	226.831951	10.799677	33.840350	3.392468	2
std	10240.949817	249664.587267	316.050259	4.243825	0.461843	2.073256	
min	1.000000	1.000000	0.000000	1.440000	28.431000	-0.010000	2
25%	8269.000000	216216.500000	46.000000	7.680000	33.488000	1.360000	2
50%	16848.000000	432432.000000	125.000000	10.060000	33.863000	3.440000	2
75%	26557.000000	648647.500000	300.000000	13.880000	34.196900	5.500000	2
max	34404.000000	864863.000000	5351.000000	31.140000	37.034000	11.130000	25

8 rows × 70 columns

In [7]:
```
a= df.dropna(axis='columns')
a
```

Out[7]:

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	RecInd	R_Depth	R_PRES
0	1	1	054.0 056.0	19-4903CR-HY-060-0930-05400560-0000A-3	0	3	0.0	0
1	1	2	054.0 056.0	19-4903CR-HY-060-0930-05400560-0008A-3	8	3	8.0	8
2	1	3	054.0 056.0	19-4903CR-HY-060-0930-05400560-0010A-7	10	7	10.0	10
3	1	4	054.0 056.0	19-4903CR-HY-060-0930-05400560-0019A-3	19	3	19.0	19
4	1	5	054.0 056.0	19-4903CR-HY-060-0930-05400560-0020A-7	20	7	20.0	20
...	...	...	...	...	...	...	...	...
864858	34404	864859	093.4 026.4	20-1611SR-MX-310-2239-09340264-0000A-7	0	7	0.0	0
864859	34404	864860	093.4 026.4	20-1611SR-MX-310-2239-09340264-0002A-3	2	3	2.0	2

	Cst_Cnt	Btl_Cnt	Sta_ID	Depth_ID	Depthm	RecInd	R_Depth	R_PRES
864860	34404	864861	093.4 026.4	20-1611SR-MX-310-2239-09340264-0005A-3	5	3	5.0	5
864861	34404	864862	093.4 026.4	20-1611SR-MX-310-2239-09340264-0010A-3	10	3	10.0	10
864862	34404	864863	093.4 026.4	20-1611SR-MX-310-2239-09340264-0015A-3	15	3	15.0	15

864863 rows × 8 columns

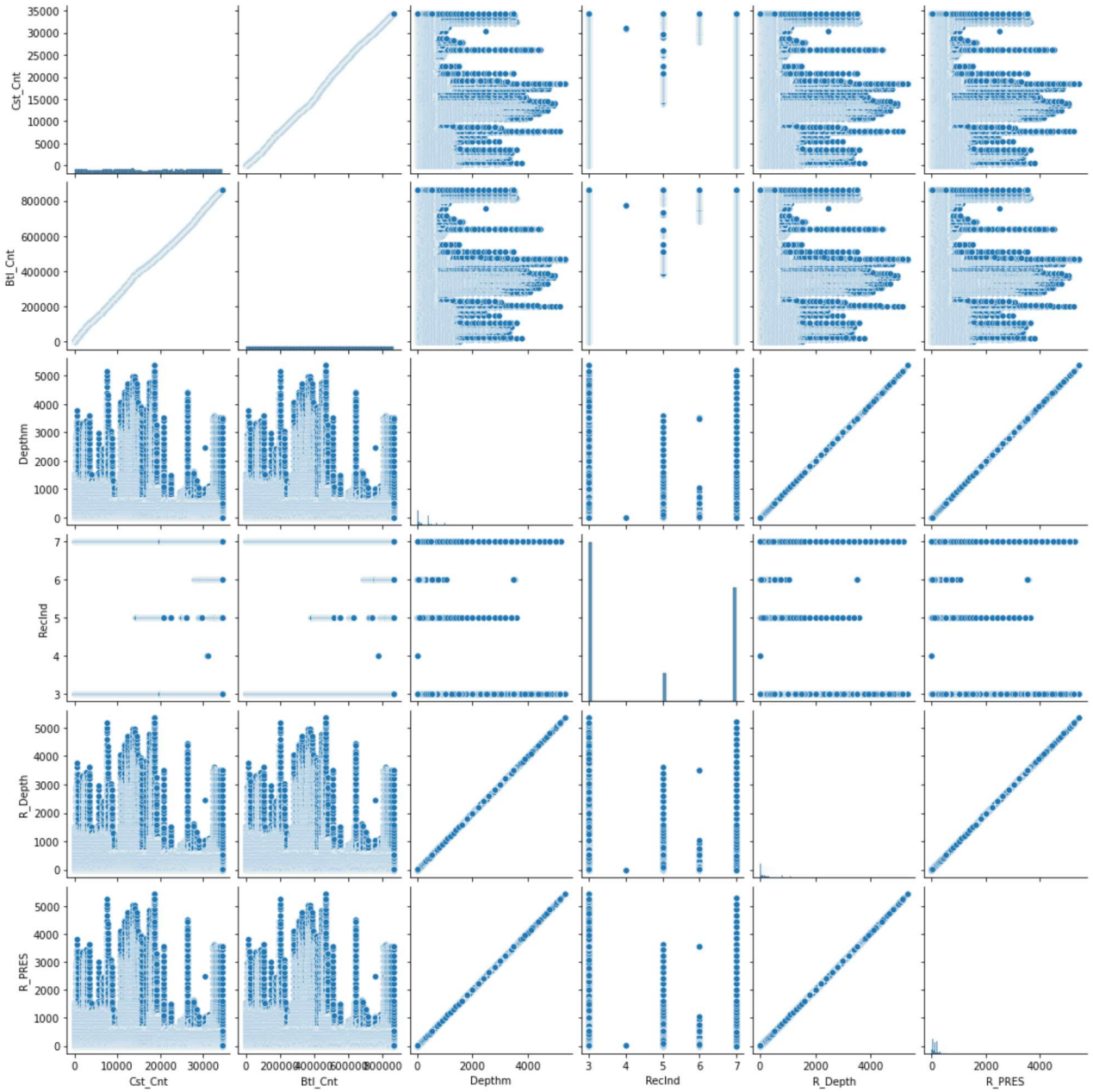
In [8]:
```
a.columns
```

Out[8]:
```
Index(['Cst_Cnt', 'Btl_Cnt', 'Sta_ID', 'Depth_ID', 'Depthm', 'RecInd',
       'R_Depth', 'R_PRES'],
      dtype='object')
```

EDA and VISUALIZATION

In [9]:
```
sns.pairplot(a)
```

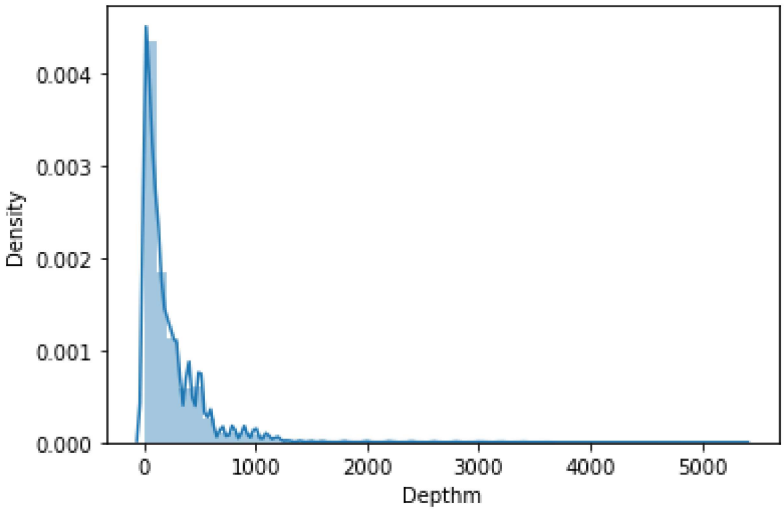
Out[9]:
```
<seaborn.axisgrid.PairGrid at 0x2a91866f220>
```



In [10]:
```
sns.distplot(a["Depthm"])
```

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

Out[10]: <AxesSubplot:xlabel='Depthm', ylabel='Density'>

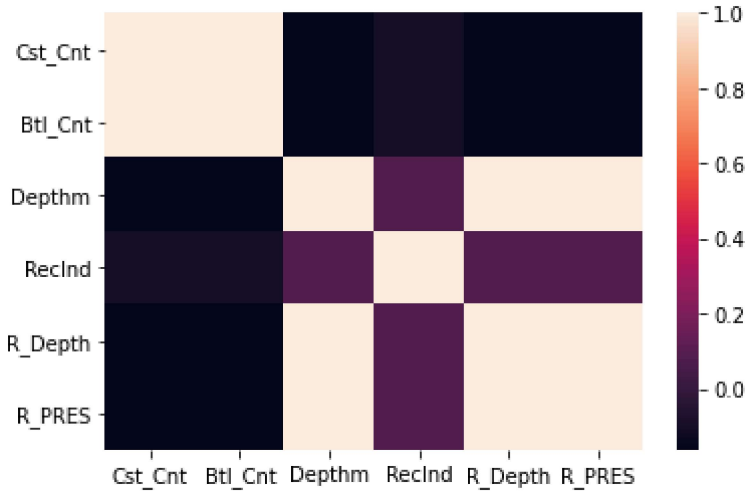


In [11]:
```
df1=a[['Cst_Cnt', 'Btl_Cnt', 'Sta_ID', 'Depth_ID', 'Depthm', 'RecInd',
       'R_Depth', 'R_PRES']]
```

Plot Using Heat Map

In [12]:
```
sns.heatmap(df1.corr())
```

Out[12]: <AxesSubplot:>



To Train The Model-Model Building

we are going to train Linera Regression Model;We need to split out data into two variables x and y where x is independent variable(input) and y is dependent on x(output) we could ignore address column as it required for our model

In [13]:
```
x=df1[['Cst_Cnt', 'Btl_Cnt',  'RecInd','R_Depth', ]]
y=df1['Depthm']
```

To Split my dataset into training and test data

In [14]:
```
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 [15]:
```
from sklearn.linear_model import LinearRegression
lr= LinearRegression()
lr.fit(x_train,y_train)
```

Out[15]:
```
LinearRegression()
```

In [16]:
```
lr.intercept_
```

Out[16]:
```
0.003076300912454144
```

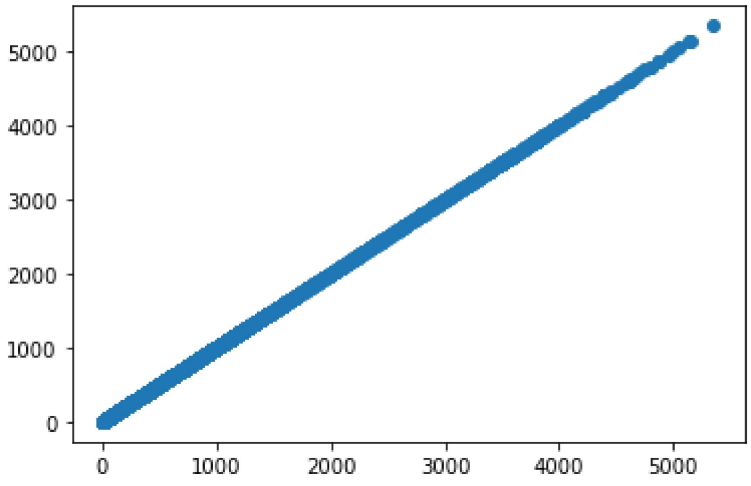
In [17]:
```
coeff = pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[17]:

	Co-efficient
Cst_Cnt	1.653176e-06
Btl_Cnt	-7.135209e-08
RecInd	-2.497648e-04
R_Depth	1.000000e+00

In [18]:
```
prediction = lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[18]:
```
<matplotlib.collections.PathCollection at 0x2a91e783370>
```



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

Out[19]: 0.9999999940276494

In [20]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [21]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
rr.score(x_test,y_test)
rr.score(x_train,y_train)
```

Out[21]: 0.9999999948141527

In [22]:
```
rr.score(x_test,y_test)
```

Out[22]: 0.9999999940276494

In [23]:
```
la = Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[23]: Lasso(alpha=10)

In [24]:
```
la.score(x_test,y_test)
```

Out[24]: 0.9999999831871389