1. DataSet Breast Cancer

DATA COLLECTION:

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
a=pd.read_csv(r"C:\Users\user\Downloads\8_BreastCancerPrediction.csv")
a
```

Out[2]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothne
0	842302	M	17.99	10.38	122.80	1001.0	
1	842517	M	20.57	17.77	132.90	1326.0	
2	84300903	M	19.69	21.25	130.00	1203.0	
3	84348301	M	11.42	20.38	77.58	386.1	
4	84358402	M	20.29	14.34	135.10	1297.0	
...	...	...	...	...	...	...	
564	926424	M	21.56	22.39	142.00	1479.0	
565	926682	M	20.13	28.25	131.20	1261.0	
566	926954	M	16.60	28.08	108.30	858.1	
567	927241	M	20.60	29.33	140.10	1265.0	
568	92751	B	7.76	24.54	47.92	181.0	

569 rows × 33 columns

In [3]:

```
b=a.head(10)
b
```

Out[3]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness
0	842302	M	17.99	10.38	122.80	1001.0	
1	842517	M	20.57	17.77	132.90	1326.0	
2	84300903	M	19.69	21.25	130.00	1203.0	
3	84348301	M	11.42	20.38	77.58	386.1	
4	84358402	M	20.29	14.34	135.10	1297.0	
5	843786	M	12.45	15.70	82.57	477.1	
6	844359	M	18.25	19.98	119.60	1040.0	
7	84458202	M	13.71	20.83	90.20	577.9	
8	844981	M	13.00	21.82	87.50	519.8	
9	84501001	M	12.46	24.04	83.97	475.9	

10 rows × 33 columns

DATA CLEANING AND PRE-PROCESSING

In [4]:

```
b.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 33 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   id                       10 non-null     int64  
 1   diagnosis                10 non-null     object 
 2   radius_mean              10 non-null     float64
 3   texture_mean             10 non-null     float64
 4   perimeter_mean           10 non-null     float64
 5   area_mean                10 non-null     float64
 6   smoothness_mean          10 non-null     float64
 7   compactness_mean         10 non-null     float64
 8   concavity_mean           10 non-null     float64
 9   concave points_mean      10 non-null     float64
 10  symmetry_mean            10 non-null     float64
 11  fractal_dimension_mean   10 non-null     float64
 12  radius_se                10 non-null     float64
 13  texture_se               10 non-null     float64
 14  perimeter_se             10 non-null     float64
 15  area_se                  10 non-null     float64
 16  smoothness_se            10 non-null     float64
 17  compactness_se           10 non-null     float64
 18  concavity_se             10 non-null     float64
 19  concave points_se        10 non-null     float64
 20  symmetry_se              10 non-null     float64
 21  fractal_dimension_se     10 non-null     float64
 22  radius_worst             10 non-null     float64
 23  texture_worst            10 non-null     float64
 24  perimeter_worst          10 non-null     float64
 25  area_worst               10 non-null     float64
 26  smoothness_worst         10 non-null     float64
 27  compactness_worst        10 non-null     float64
 28  concavity_worst          10 non-null     float64
 29  concave points_worst     10 non-null     float64
 30  symmetry_worst           10 non-null     float64
 31  fractal_dimension_worst  10 non-null     float64
 32  Unnamed: 32              0 non-null      float64
dtypes: float64(31), int64(1), object(1)
memory usage: 2.7+ KB
```

In [5]:

```
b.describe()
```

Out[5]:

	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_
count	1.000000e+01	10.000000	10.00000	10.000000	10.000000	10.0(
mean	4.261848e+07	15.983000	18.64900	106.222000	830.380000	0.1'
std	4.403463e+07	3.686001	4.10719	23.680745	377.613035	0.0'
min	8.423020e+05	11.420000	10.38000	77.580000	386.100000	0.08
25%	8.439292e+05	12.595000	16.21750	84.852500	487.775000	0.1(
50%	4.257294e+07	15.850000	20.18000	104.900000	789.450000	0.1'
75%	8.435588e+07	19.330000	21.14500	128.200000	1162.250000	0.12
max	8.450100e+07	20.570000	24.04000	135.100000	1326.000000	0.14

8 rows × 32 columns

In [6]:

```
a.isna()
```

Out[6]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_
0	False	False	False	False	False	False	
1	False	False	False	False	False	False	
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
...	...	...	...	...	...	...	
564	False	False	False	False	False	False	
565	False	False	False	False	False	False	
566	False	False	False	False	False	False	
567	False	False	False	False	False	False	
568	False	False	False	False	False	False	

569 rows × 33 columns

In [7]:

```
b=a.dropna(axis=1)
b
```

Out[7]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothne
0	842302	M	17.99	10.38	122.80	1001.0	
1	842517	M	20.57	17.77	132.90	1326.0	
2	84300903	M	19.69	21.25	130.00	1203.0	
3	84348301	M	11.42	20.38	77.58	386.1	
4	84358402	M	20.29	14.34	135.10	1297.0	
...	...	...	...	...	...	...	
564	926424	M	21.56	22.39	142.00	1479.0	
565	926682	M	20.13	28.25	131.20	1261.0	
566	926954	M	16.60	28.08	108.30	858.1	
567	927241	M	20.60	29.33	140.10	1265.0	
568	92751	B	7.76	24.54	47.92	181.0	

569 rows × 32 columns

In [8]:

```
d=b.head(100)
d
```

Out[8]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothnes
0	842302	M	17.990	10.38	122.80	1001.0	
1	842517	M	20.570	17.77	132.90	1326.0	
2	84300903	M	19.690	21.25	130.00	1203.0	
3	84348301	M	11.420	20.38	77.58	386.1	
4	84358402	M	20.290	14.34	135.10	1297.0	
...	...	...	...	...	...	...	
95	86208	M	20.260	23.03	132.40	1264.0	
96	86211	B	12.180	17.84	77.79	451.1	
97	862261	B	9.787	19.94	62.11	294.5	
98	862485	B	11.600	12.84	74.34	412.6	
99	862548	M	14.420	19.77	94.48	642.5	

100 rows × 32 columns

In [9]:

```
c=d.columns[2:10]
c
```

Out[9]:

```
Index(['radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean',
       'smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave points_mean'],
      dtype='object')
```

In [10]:

```
c1=d[['radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean',
       'smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave points_mean']]
c1
```

Out[10]:

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness
0	17.990	10.38	122.80	1001.0	0.11840	(
1	20.570	17.77	132.90	1326.0	0.08474	(
2	19.690	21.25	130.00	1203.0	0.10960	(
3	11.420	20.38	77.58	386.1	0.14250	(
4	20.290	14.34	135.10	1297.0	0.10030	(
...	...	...	...	...	...	
95	20.260	23.03	132.40	1264.0	0.09078	(
96	12.180	17.84	77.79	451.1	0.10450	(
97	9.787	19.94	62.11	294.5	0.10240	(
98	11.600	12.84	74.34	412.6	0.08983	(
99	14.420	19.77	94.48	642.5	0.09752	

100 rows × 8 columns

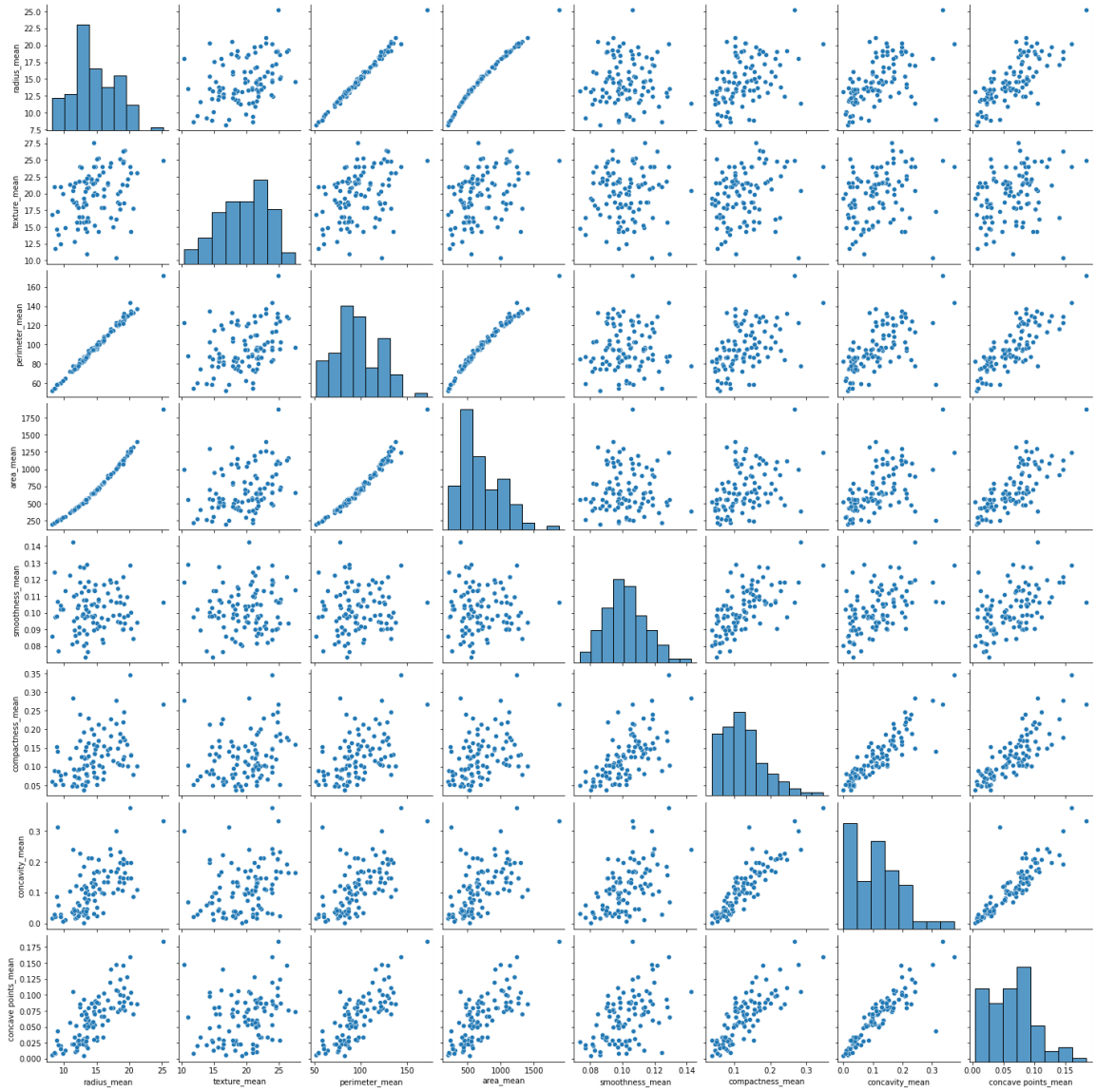
EDA and VISUALIZATION

In [11]:

```
sns.pairplot(c1)
```

Out[11]:

```
<seaborn.axisgrid.PairGrid at 0x202b030fc40>
```



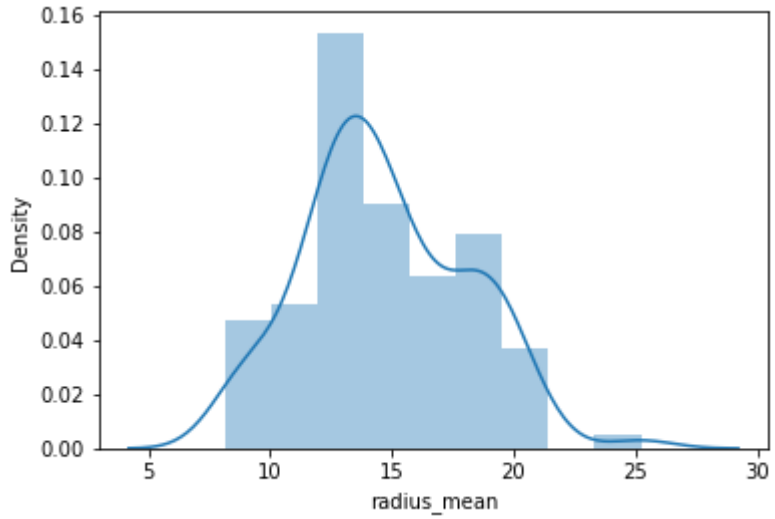
In [12]:

```
sns.distplot(c1['radius_mean'])
```

```
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 adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[12]:

```
<AxesSubplot:xlabel='radius_mean', ylabel='Density'>
```

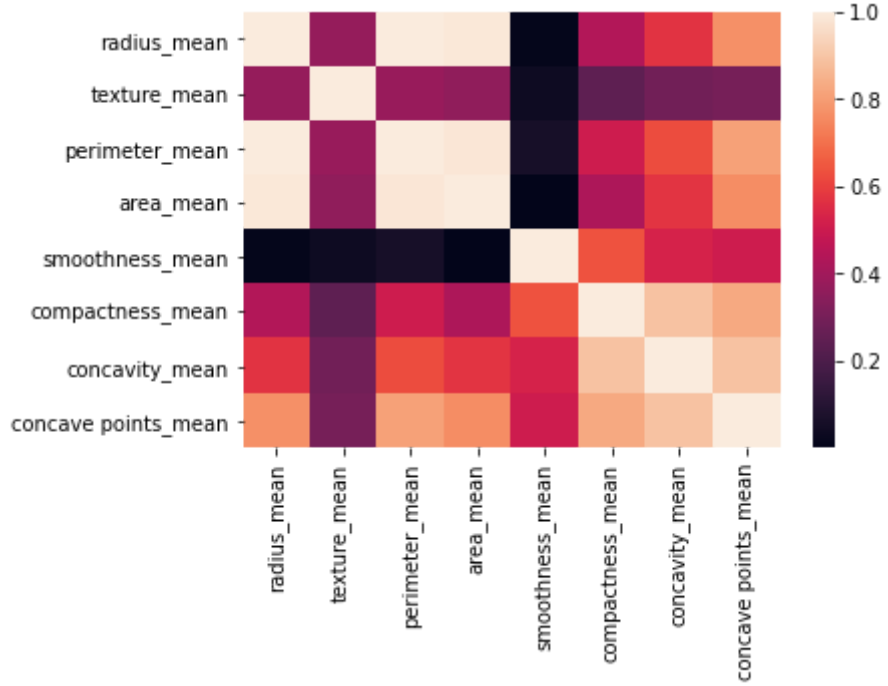


In [13]:

```
sns.heatmap(c1.corr())
```

Out[13]:

```
<AxesSubplot:>
```



In [14]:

```
x=d[['radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean',
       'smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave points_mean']]
y=d['perimeter_worst']
```

In [15]:

```
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 [16]:

```
from sklearn.linear_model import LinearRegression

lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[16]:

```
LinearRegression()
```

In [17]:

```
print(lr.intercept_)
```

```
-1.8823473579823968
```

In [18]:

```
coe=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coe
```

Out[18]:

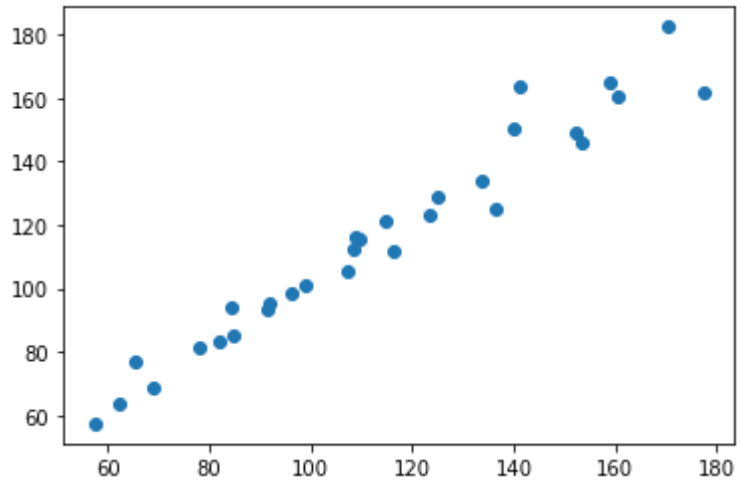
	Co-efficient
radius_mean	11.098458
texture_mean	0.187070
perimeter_mean	-0.905654
area_mean	0.031594
smoothness_mean	7.163876
compactness_mean	70.076658
concavity_mean	21.115769
concave points_mean	85.200670

In [19]:

```
prediction=lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[19]:

```
<matplotlib.collections.PathCollection at 0x202b4960880>
```



In [20]:

```
print(lr.score(x_test,y_test))
```

```
0.948173808822813
```

In [21]:

```
from sklearn.linear_model import Ridge,Lasso
```

In [22]:

```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[22]:

```
Ridge(alpha=10)
```

In [23]:

```
rr.score(x_test,y_test)
```

Out[23]:

```
0.9426188562278557
```

In [24]:

```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[24]:

```
Lasso(alpha=10)
```

In [25]:

```
la.score(x_test,y_test)
```

Out[25]:

```
0.9412421258676236
```

In [26]:

```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[26]:

```
ElasticNet()
```

In [27]:

```
print(en.coef_)
```

```
[-0.          0.08003669  1.42981205 -0.00250128  0.          0.
  0.          0.        ]
```

In [28]:

```
print(en.intercept_)
```

```
-20.22629712258707
```

In [29]:

```
prediction=en.predict(x_test)
print(en.score(x_test,y_test))
```

```
0.9445570030710522
```

Evaluation Metrics

In [30]:

```
from sklearn import metrics
```

In [31]:

```
print('Mean Absolute Error:',metrics.mean_absolute_error(y_test,prediction))
```

```
Mean Absolute Error: 5.810724681951212
```

In [32]:

```
print("mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
mean Squared Error: 60.82460139587615
```

In [33]:

```
print("Root mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
Root mean Squared Error: 7.7990128475260345
```

2. DataSet Uber

In [34]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [35]:

```
a1=pd.read_csv(r"C:\Users\user\Downloads\uber - uber.csv")
a1
```

Out[35]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude
0	24238194	2015-05-07 19:52:06	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354
1	27835199	2009-07-17 20:04:56	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225
2	44984355	2009-08-24 21:45:00	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770
3	25894730	2009-06-26 8:22:21	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844
4	17610152	2014-08-28 17:47:00	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085
...	...	...	...	...	...	...
199995	42598914	2012-10-28 10:49:00	3.0	2012-10-28 10:49:00 UTC	-73.987042	40.739367
199996	16382965	2014-03-14 1:09:00	7.5	2014-03-14 01:09:00 UTC	-73.984722	40.736837
199997	27804658	2009-06-29 0:42:00	30.9	2009-06-29 00:42:00 UTC	-73.986017	40.756487
199998	20259894	2015-05-20 14:56:25	14.5	2015-05-20 14:56:25 UTC	-73.997124	40.725452
199999	11951496	2010-05-15 4:08:00	14.1	2010-05-15 04:08:00 UTC	-73.984395	40.720077

200000 rows × 9 columns

In [36]:

```
c1=a1.head(10)
c1
```

Out[36]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	drop
0	24238194	2015-05-07 19:52:06	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	
1	27835199	2009-07-17 20:04:56	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	
2	44984355	2009-08-24 21:45:00	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	
3	25894730	2009-06-26 8:22:21	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	
4	17610152	2014-08-28 17:47:00	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	
5	44470845	2011-02-12 2:27:09	4.9	2011-02-12 02:27:09 UTC	-73.969019	40.755910	
6	48725865	2014-10-12 7:04:00	24.5	2014-10-12 07:04:00 UTC	-73.961447	40.693965	
7	44195482	2012-12-11 13:52:00	2.5	2012-12-11 13:52:00 UTC	0.000000	0.000000	
8	15822268	2012-02-17 9:32:00	9.7	2012-02-17 09:32:00 UTC	-73.975187	40.745767	
9	50611056	2012-03-29 19:06:00	12.5	2012-03-29 19:06:00 UTC	-74.001065	40.741787	

In [37]:

```
a1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   Unnamed: 0         200000 non-null  int64  
 1   key                200000 non-null  object 
 2   fare_amount        200000 non-null  float64
 3   pickup_datetime    200000 non-null  object 
 4   pickup_longitude   200000 non-null  float64
 5   pickup_latitude    200000 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    200000 non-null  int64  
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB
```

In [38]:

```
a1.describe()
```

Out[38]:

	Unnamed: 0	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dro
count	2.000000e+05	200000.000000	200000.000000	200000.000000	199999.000000	19
mean	2.771250e+07	11.359955	-72.527638	39.935885	-72.525292	
std	1.601382e+07	9.901776	11.437787	7.720539	13.117408	
min	1.000000e+00	-52.000000	-1340.648410	-74.015515	-3356.666300	
25%	1.382535e+07	6.000000	-73.992065	40.734796	-73.991407	
50%	2.774550e+07	8.500000	-73.981823	40.752592	-73.980093	
75%	4.155530e+07	12.500000	-73.967153	40.767158	-73.963659	
max	5.542357e+07	499.000000	57.418457	1644.421482	1153.572603	

In [39]:

```
a1.columns
```

Out[39]:

```
Index(['Unnamed: 0', 'key', 'fare_amount', 'pickup_datetime',
       'pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
       'dropoff_latitude', 'passenger_count'],
      dtype='object')
```

In [40]:

```
b1=c1[['pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
       'dropoff_latitude', 'passenger_count']]
b1
```

Out[40]:

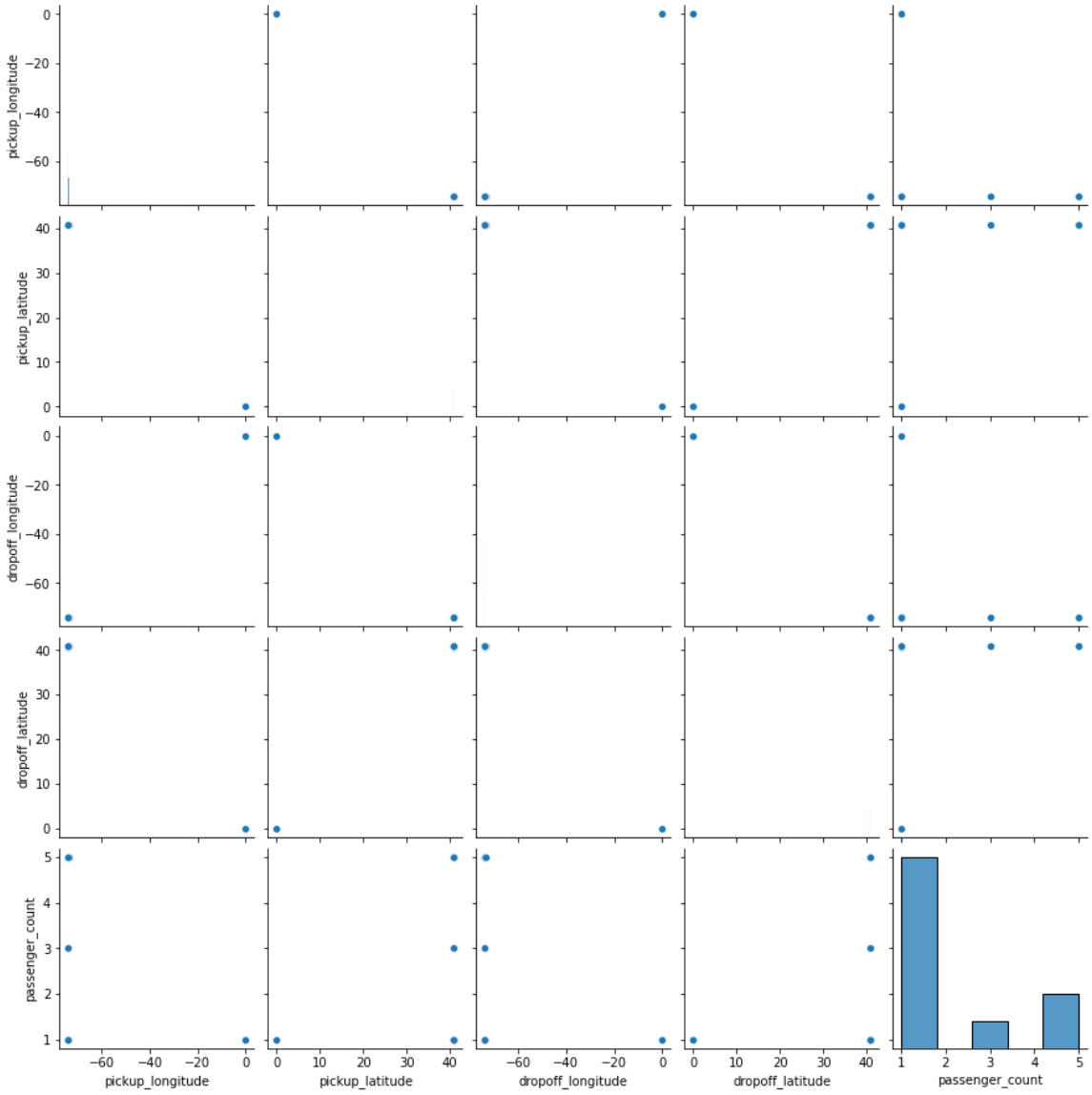
	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
0	-73.999817	40.738354	-73.999512	40.723217	1
1	-73.994355	40.728225	-73.994710	40.750325	1
2	-74.005043	40.740770	-73.962565	40.772647	1
3	-73.976124	40.790844	-73.965316	40.803349	3
4	-73.925023	40.744085	-73.973082	40.761247	5
5	-73.969019	40.755910	-73.969019	40.755910	1
6	-73.961447	40.693965	-73.871195	40.774297	5
7	0.000000	0.000000	0.000000	0.000000	1
8	-73.975187	40.745767	-74.002720	40.743537	1
9	-74.001065	40.741787	-73.963040	40.775012	1

In [41]:

```
sns.pairplot(b1)
```

Out[41]:

```
<seaborn.axisgrid.PairGrid at 0x202b4dcdaf0>
```



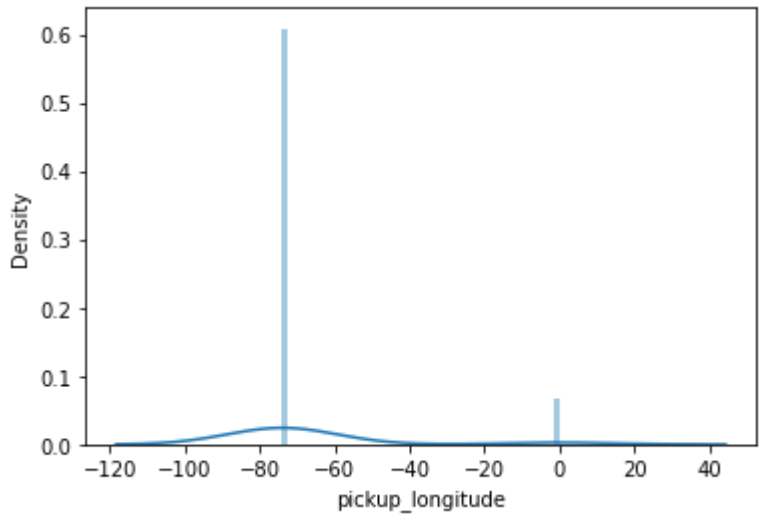
In [42]:

```
sns.distplot(b1['pickup_longitude'])
```

```
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 adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[42]:

```
<AxesSubplot:xlabel='pickup_longitude', ylabel='Density'>
```



In [43]:

```
x1=c1[['pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
       'dropoff_latitude', 'passenger_count']]
y1=c1['fare_amount']
```

In [44]:

```
x1_train,x1_test,y1_train,y1_test=train_test_split(x1,y1,test_size=0.3)
```

In [45]:

```
lr=LinearRegression()
lr.fit(x1_train,y1_train)
```

Out[45]:

```
LinearRegression()
```

In [46]:

```
print(lr.intercept_)
```

```
1.8972061175406054
```

In [47]:

```
coe1=pd.DataFrame(lr.coef_,x1.columns,columns=['Co-efficient'])
coe1
```

Out[47]:

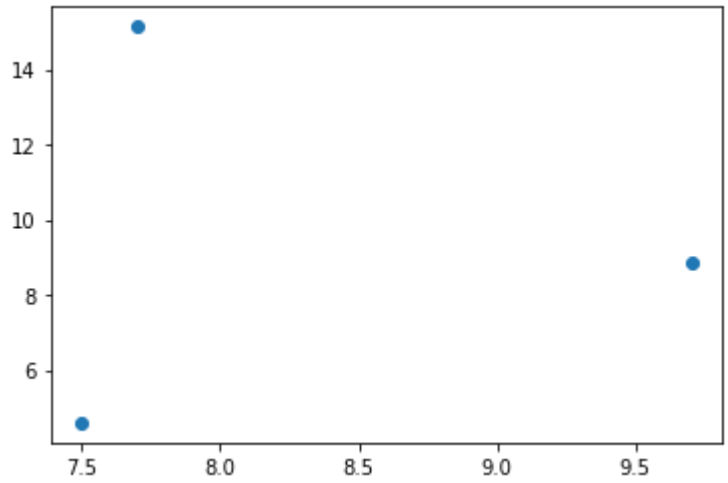
	Co-efficient
pickup_longitude	52.761430
pickup_latitude	-363.259789
dropoff_longitude	-108.736201
dropoff_latitude	261.733131
passenger_count	0.602711

In [48]:

```
prediction=lr.predict(x1_test)
plt.scatter(y1_test,prediction)
```

Out[48]:

```
<matplotlib.collections.PathCollection at 0x202bf698670>
```



In [49]:

```
print(lr.score(x1_test,y1_test))
```

```
-20.771778892999862
```

In [50]:

```
from sklearn.linear_model import Ridge,Lasso
```

In [51]:

```
rr=Ridge(alpha=10)
rr.fit(x1_train,y1_train)
```

Out[51]:

```
Ridge(alpha=10)
```

In [52]:

```
rr.score(x1_test,y1_test)
```

Out[52]:

```
-3.212501722480094
```

In [53]:

```
la=Lasso(alpha=10)
la.fit(x1_train,y1_train)
```

Out[53]:

```
Lasso(alpha=10)
```

In [54]:

```
la.score(x1_test,y1_test)
```

Out[54]:

```
-18.111892905993855
```

In [55]:

```
en=ElasticNet()
en.fit(x1_train,y1_train)
```

Out[55]:

```
ElasticNet()
```

In [56]:

```
print(en.coef_)
```

```
[-0.09506921  0.         -0.          0.          1.85568551]
```

In [57]:

```
print(en.intercept_)
```

```
0.6940062237256512
```

In [58]:

```
prediction=en.predict(x1_test)
print(en.score(x1_test,y1_test))
```

```
-1.6725306351797022
```

Evaluation Metrics

In [59]:

```
print('Mean Absolute Error:',metrics.mean_absolute_error(y1_test,prediction))
```

```
Mean Absolute Error: 1.3622061181240694
```

In [60]:

```
print("mean Squared Error:",metrics.mean_squared_error(y1_test,prediction))
```

```
mean Squared Error: 2.6368968933773047
```

In [61]:

```
print("Root mean Squared Error:",np.sqrt(metrics.mean_squared_error(y1_test,prediction)))
```

```
Root mean Squared Error: 1.6238524851036515
```

3. DataSet SalesWorkload

In [62]:

```
a2=pd.read_csv(r"C:\Users\user\Downloads\6_Salesworkload1.csv")
a2
```

Out[62]:

	MonthYear	Time index	Country	StoreID	City	Dept_ID	Dept. Name	HoursOwn	Hour
0	10.2016	1.0	United Kingdom	88253.0	London (I)	1.0	Dry	3184.764	
1	10.2016	1.0	United Kingdom	88253.0	London (I)	2.0	Frozen	1582.941	
2	10.2016	1.0	United Kingdom	88253.0	London (I)	3.0	other	47.205	
3	10.2016	1.0	United Kingdom	88253.0	London (I)	4.0	Fish	1623.852	
4	10.2016	1.0	United Kingdom	88253.0	London (I)	5.0	Fruits & Vegetables	1759.173	
...	...	...	...	...	...	...	...	...	
7653	06.2017	9.0	Sweden	29650.0	Gothenburg	12.0	Checkout	6322.323	
7654	06.2017	9.0	Sweden	29650.0	Gothenburg	16.0	Customer Services	4270.479	
7655	06.2017	9.0	Sweden	29650.0	Gothenburg	11.0	Delivery	0	
7656	06.2017	9.0	Sweden	29650.0	Gothenburg	17.0	others	2224.929	
7657	06.2017	9.0	Sweden	29650.0	Gothenburg	18.0	all	39652.2	

7658 rows × 14 columns

In [63]:

```
b2=a2.fillna(value=17)
b2
```

Out[63]:

	MonthYear	Time index	Country	StoreID	City	Dept_ID	Dept. Name	HoursOwn	Hour
0	10.2016	1.0	United Kingdom	88253.0	London (I)	1.0	Dry	3184.764	
1	10.2016	1.0	United Kingdom	88253.0	London (I)	2.0	Frozen	1582.941	
2	10.2016	1.0	United Kingdom	88253.0	London (I)	3.0	other	47.205	
3	10.2016	1.0	United Kingdom	88253.0	London (I)	4.0	Fish	1623.852	
4	10.2016	1.0	United Kingdom	88253.0	London (I)	5.0	Fruits & Vegetables	1759.173	
...	...	...	...	...	...	...	...	...	
7653	06.2017	9.0	Sweden	29650.0	Gothenburg	12.0	Checkout	6322.323	
7654	06.2017	9.0	Sweden	29650.0	Gothenburg	16.0	Customer Services	4270.479	
7655	06.2017	9.0	Sweden	29650.0	Gothenburg	11.0	Delivery	0	
7656	06.2017	9.0	Sweden	29650.0	Gothenburg	17.0	others	2224.929	
7657	06.2017	9.0	Sweden	29650.0	Gothenburg	18.0	all	39652.2	

7658 rows × 14 columns

In [64]:

```
c2=b2.head(10)
c2
```

Out[64]:

	MonthYear	Time index	Country	StoreID	City	Dept_ID	Dept. Name	HoursOwn	HoursLease
0	10.2016	1.0	United Kingdom	88253.0	London (I)	1.0	Dry	3184.764	0.0
1	10.2016	1.0	United Kingdom	88253.0	London (I)	2.0	Frozen	1582.941	0.0
2	10.2016	1.0	United Kingdom	88253.0	London (I)	3.0	other	47.205	0.0
3	10.2016	1.0	United Kingdom	88253.0	London (I)	4.0	Fish	1623.852	0.0
4	10.2016	1.0	United Kingdom	88253.0	London (I)	5.0	Fruits & Vegetables	1759.173	0.0
5	10.2016	1.0	United Kingdom	88253.0	London (I)	6.0	Meat	8270.316	0.0
6	10.2016	1.0	United Kingdom	88253.0	London (I)	13.0	Food	16468.251	0.0
7	10.2016	1.0	United Kingdom	88253.0	London (I)	7.0	Clothing	4698.471	0.0
8	10.2016	1.0	United Kingdom	88253.0	London (I)	8.0	Household	1183.272	0.0
9	10.2016	1.0	United Kingdom	88253.0	London (I)	9.0	Hardware	2029.815	0.0

In [65]:

```
c2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MonthYear      10 non-null     object 
 1   Time index     10 non-null     float64
 2   Country        10 non-null     object 
 3   StoreID        10 non-null     float64
 4   City           10 non-null     object 
 5   Dept_ID        10 non-null     float64
 6   Dept. Name     10 non-null     object 
 7   HoursOwn       10 non-null     object 
 8   HoursLease     10 non-null     float64
 9   Sales units    10 non-null     float64
 10  Turnover       10 non-null     float64
 11  Customer       10 non-null     float64
 12  Area (m2)      10 non-null     object 
 13  Opening hours  10 non-null     object 
dtypes: float64(7), object(7)
memory usage: 1.2+ KB
```

In [66]:

```
c2.describe()
```

Out[66]:

	Time index	StoreID	Dept_ID	HoursLease	Sales units	Turnover	Customer
count	10.0	10.0	10.000000	10.0	1.000000e+01	1.000000e+01	10.0
mean	1.0	88253.0	5.800000	0.0	6.543725e+05	1.978511e+06	17.0
std	0.0	0.0	3.614784	0.0	9.914003e+05	2.861420e+06	0.0
min	1.0	88253.0	1.000000	0.0	5.491500e+04	2.904000e+05	17.0
25%	1.0	88253.0	3.250000	0.0	1.034225e+05	4.033612e+05	17.0
50%	1.0	88253.0	5.500000	0.0	2.615525e+05	5.770455e+05	17.0
75%	1.0	88253.0	7.750000	0.0	4.284400e+05	1.518067e+06	17.0
max	1.0	88253.0	13.000000	0.0	3.107935e+06	8.714679e+06	17.0

In [67]:

```
c2.columns
```

Out[67]:

```
Index(['MonthYear', 'Time index', 'Country', 'StoreID', 'City', 'Dept_ID',
       'Dept. Name', 'HoursOwn', 'HoursLease', 'Sales units', 'Turnover',
       'Customer', 'Area (m2)', 'Opening hours'],
      dtype='object')
```

In [68]:

```
d2=c2[['Time index','StoreID','HoursLease', 'Sales units', 'Turnover',
       'Customer', 'Area (m2)']]
d2
```

Out[68]:

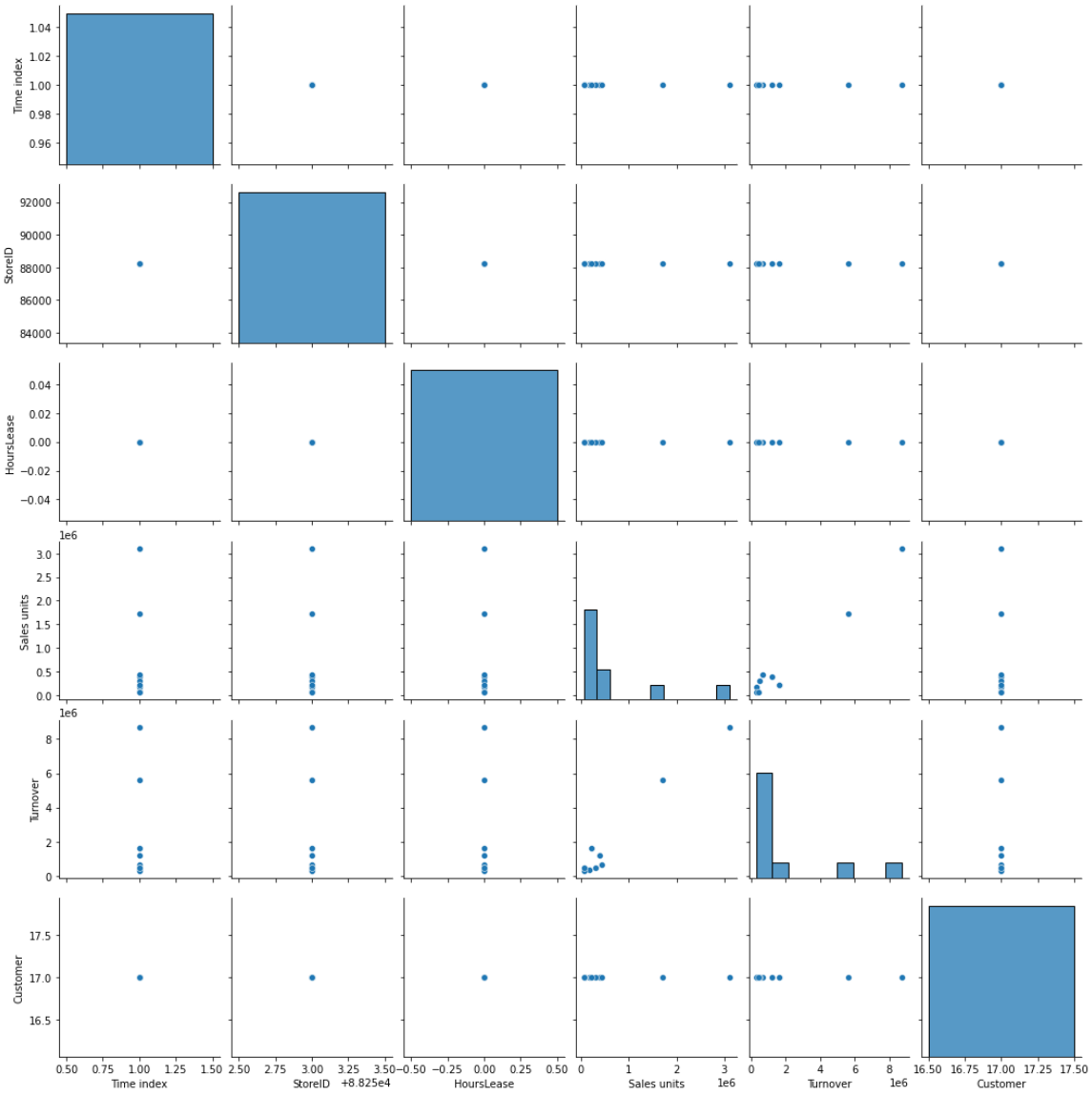
	Time index	StoreID	HoursLease	Sales units	Turnover	Customer	Area (m2)
0	1.0	88253.0	0.0	398560.0	1226244.0	17.0	953.04
1	1.0	88253.0	0.0	82725.0	387810.0	17.0	720.48
2	1.0	88253.0	0.0	438400.0	654657.0	17.0	966.72
3	1.0	88253.0	0.0	309425.0	499434.0	17.0	1053.36
4	1.0	88253.0	0.0	165515.0	329397.0	17.0	1053.36
5	1.0	88253.0	0.0	1713310.0	5617137.0	17.0	11735.16
6	1.0	88253.0	0.0	3107935.0	8714679.0	17.0	19865.64
7	1.0	88253.0	0.0	213680.0	1615341.0	17.0	8513.52
8	1.0	88253.0	0.0	54915.0	290400.0	17.0	4842.72
9	1.0	88253.0	0.0	59260.0	450015.0	17.0	5608.8

In [69]:

```
sns.pairplot(d2)
```

Out[69]:

```
<seaborn.axisgrid.PairGrid at 0x202bf5d11f0>
```



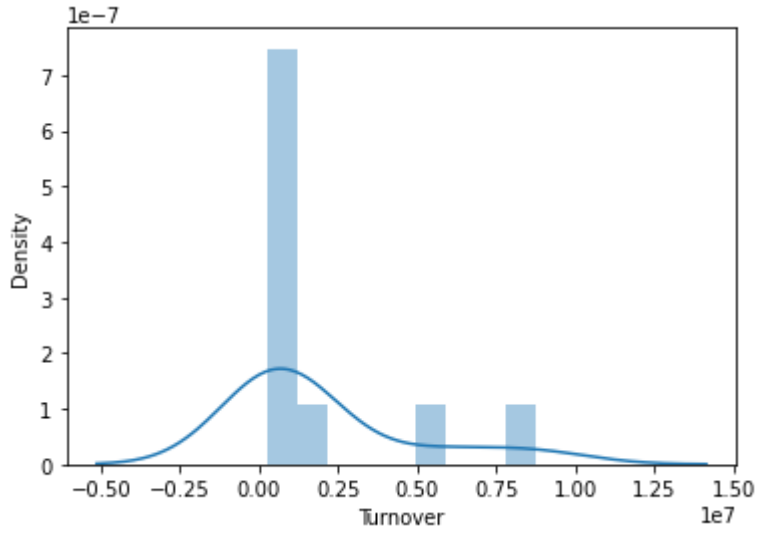
In [70]:

```
sns.distplot(d2['Turnover'])
```

```
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 adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[70]:

```
<AxesSubplot:xlabel='Turnover', ylabel='Density'>
```

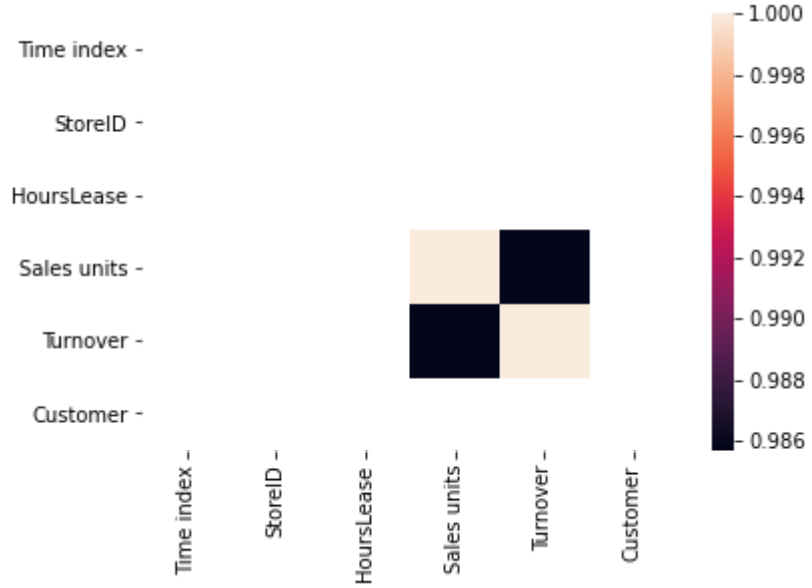


In [71]:

```
sns.heatmap(d2.corr())
```

Out[71]:

```
<AxesSubplot:>
```



In [72]:

```
x2=d2[['Time index','StoreID','HoursLease', 'Sales units', 'Turnover',
       'Customer', 'Area (m2)']]
y2=c2['Dept_ID']
```

In [73]:

```
x2_train,x2_test,y2_train,y2_test=train_test_split(x2,y2,test_size=0.3)
```

In [74]:

```
lr=LinearRegression()
lr.fit(x2_train,y2_train)
```

Out[74]:

```
LinearRegression()
```

In [75]:

```
print(lr.intercept_)
```

```
2.472879358953885
```

In [76]:

```
coeff=pd.DataFrame(lr.coef_,x2.columns,columns=['Co-efficient'])
coeff
```

Out[76]:

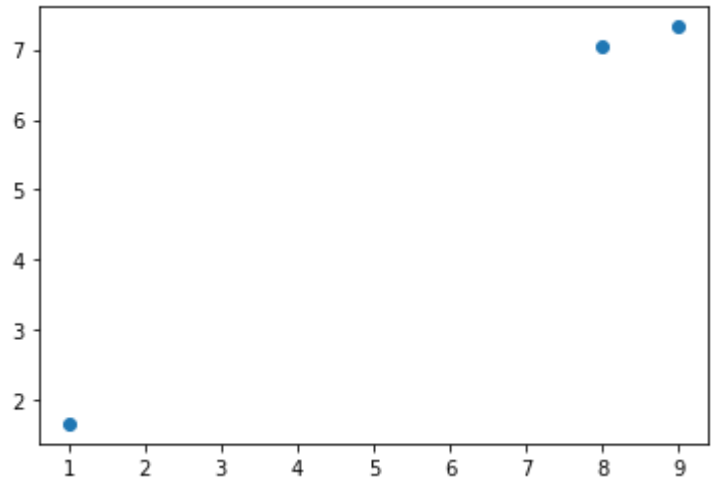
	Co-efficient
Time index	0.000000e+00
StoreID	8.806856e-17
HoursLease	5.590417e-20
Sales units	6.707399e-06
Turnover	-3.681219e-06
Customer	6.842278e-49
Area (m2)	1.089345e-03

In [77]:

```
prediction=lr.predict(x2_test)
plt.scatter(y2_test,prediction)
```

Out[77]:

```
<matplotlib.collections.PathCollection at 0x202c3f05dc0>
```



In [78]:

```
print(lr.score(x2_test,y2_test))
```

```
0.8903561103946025
```

In [79]:

```
from sklearn.linear_model import Ridge,Lasso
```

In [80]:

```
rr=Ridge(alpha=10)
rr.fit(x2_train,y2_train)
```

Out[80]:

```
Ridge(alpha=10)
```

In [81]:

```
rr.score(x2_test,y2_test)
```

Out[81]:

```
0.8903556634616461
```

In [82]:

```
la=Lasso(alpha=10)
la.fit(x2_train,y2_train)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinat
e_descent.py:530: ConvergenceWarning: Objective did not converge. You migh
t want to increase the number of iterations. Duality gap: 0.11098329091749
148, tolerance: 0.007942857142857142
  model = cd_fast.enet_coordinate_descent(
```

Out[82]:

```
Lasso(alpha=10)
```

In [83]:

```
la.score(x2_test,y2_test)
```

Out[83]:

```
0.8874302865940572
```

In [84]:

```
en=ElasticNet()
en.fit(x2_train,y2_train)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_coordinat
e_descent.py:530: ConvergenceWarning: Objective did not converge. You migh
t want to increase the number of iterations. Duality gap: 1.30857533753957
48, tolerance: 0.007942857142857142
  model = cd_fast.enet_coordinate_descent(
```

Out[84]:

```
ElasticNet()
```

In [85]:

```
print(en.coef_)
```

```
[ 0.00000000e+00  0.00000000e+00  0.00000000e+00  6.70554776e-06
 -3.67998080e-06  0.00000000e+00  1.08906387e-03]
```

In [86]:

```
print(en.intercept_)
```

```
2.473086133430166
```

In [87]:

```
prediction=en.predict(x2_test)
print(en.score(x2_test,y2_test))
```

```
0.8902044320944766
```

Evaluation Metrics

In [88]:

```
print('Mean Absolute Error:',metrics.mean_absolute_error(y2_test,prediction))
```

```
Mean Absolute Error: 1.1005260911673889
```

In [89]:

```
print("mean Squared Error:",metrics.mean_squared_error(y2_test,prediction))
```

```
mean Squared Error: 1.39074386013663
```

In [90]:

```
print("Root mean Squared Error:",np.sqrt(metrics.mean_squared_error(y2_test,prediction)))
```

```
Root mean Squared Error: 1.1792980370273793
```

4. DataSet Instagram

In [91]:

```
a=pd.read_csv(r"C:\Users\user\Downloads\5_Instagram data.csv")
a
```

Out[91]:

	Impressions	From Home	From Hashtags	From Explore	From Other	Saves	Comments	Shares	Likes	Profile Visits
0	3920	2586	1028	619	56	98	9	5	162	35
1	5394	2727	1838	1174	78	194	7	14	224	48
2	4021	2085	1188	0	533	41	11	1	131	62
3	4528	2700	621	932	73	172	10	7	213	23
4	2518	1704	255	279	37	96	5	4	123	8
...	...	...	...	...	...	...	...	...	...	...
114	13700	5185	3041	5352	77	573	2	38	373	73
115	5731	1923	1368	2266	65	135	4	1	148	20
116	4139	1133	1538	1367	33	36	0	1	92	34
117	32695	11815	3147	17414	170	1095	2	75	549	148
118	36919	13473	4176	16444	2547	653	5	26	443	611

119 rows × 13 columns

In [92]:

```
b=a.head(10)
b
```

Out[92]:

	Impressions	From Home	From Hashtags	From Explore	From Other	Saves	Comments	Shares	Likes	Profile Visits
0	3920	2586	1028	619	56	98	9	5	162	35
1	5394	2727	1838	1174	78	194	7	14	224	48
2	4021	2085	1188	0	533	41	11	1	131	62
3	4528	2700	621	932	73	172	10	7	213	23
4	2518	1704	255	279	37	96	5	4	123	8
5	3884	2046	1214	329	43	74	7	10	144	9
6	2621	1543	599	333	25	22	5	1	76	26
7	3541	2071	628	500	60	135	4	9	124	12
8	3749	2384	857	248	49	155	6	8	159	36
9	4115	2609	1104	178	46	122	6	3	191	31

In [93]:

```
a.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119 entries, 0 to 118
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Impressions     119 non-null    int64 
 1   From Home       119 non-null    int64 
 2   From Hashtags   119 non-null    int64 
 3   From Explore    119 non-null    int64 
 4   From Other      119 non-null    int64 
 5   Saves           119 non-null    int64 
 6   Comments        119 non-null    int64 
 7   Shares          119 non-null    int64 
 8   Likes           119 non-null    int64 
 9   Profile Visits  119 non-null    int64 
 10  Follows         119 non-null    int64 
 11  Caption         119 non-null    object
 12  Hashtags        119 non-null    object
dtypes: int64(11), object(2)
memory usage: 12.2+ KB
```

In [94]:

```
a.describe()
```

Out[94]:

	Impressions	From Home	From Hashtags	From Explore	From Other	Saves	Co
count	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000	11
mean	5703.991597	2475.789916	1887.512605	1078.100840	171.092437	153.310924	
std	4843.780105	1489.386348	1884.361443	2613.026132	289.431031	156.317731	
min	1941.000000	1133.000000	116.000000	0.000000	9.000000	22.000000	
25%	3467.000000	1945.000000	726.000000	157.500000	38.000000	65.000000	
50%	4289.000000	2207.000000	1278.000000	326.000000	74.000000	109.000000	
75%	6138.000000	2602.500000	2363.500000	689.500000	196.000000	169.000000	
max	36919.000000	13473.000000	11817.000000	17414.000000	2547.000000	1095.000000	1

In [95]:

```
a.columns
```

Out[95]:

```
Index(['Impressions', 'From Home', 'From Hashtags', 'From Explore',
       'From Other', 'Saves', 'Comments', 'Shares', 'Likes', 'Profile Visi
ts',
       'Follows', 'Caption', 'Hashtags'],
      dtype='object')
```

In [96]:

```
c=b[['Impressions', 'From Home', 'From Hashtags', 'From Explore',
       'From Other', 'Saves', 'Comments', 'Shares', 'Likes', 'Profile Visits',
       'Follows']]
c
```

Out[96]:

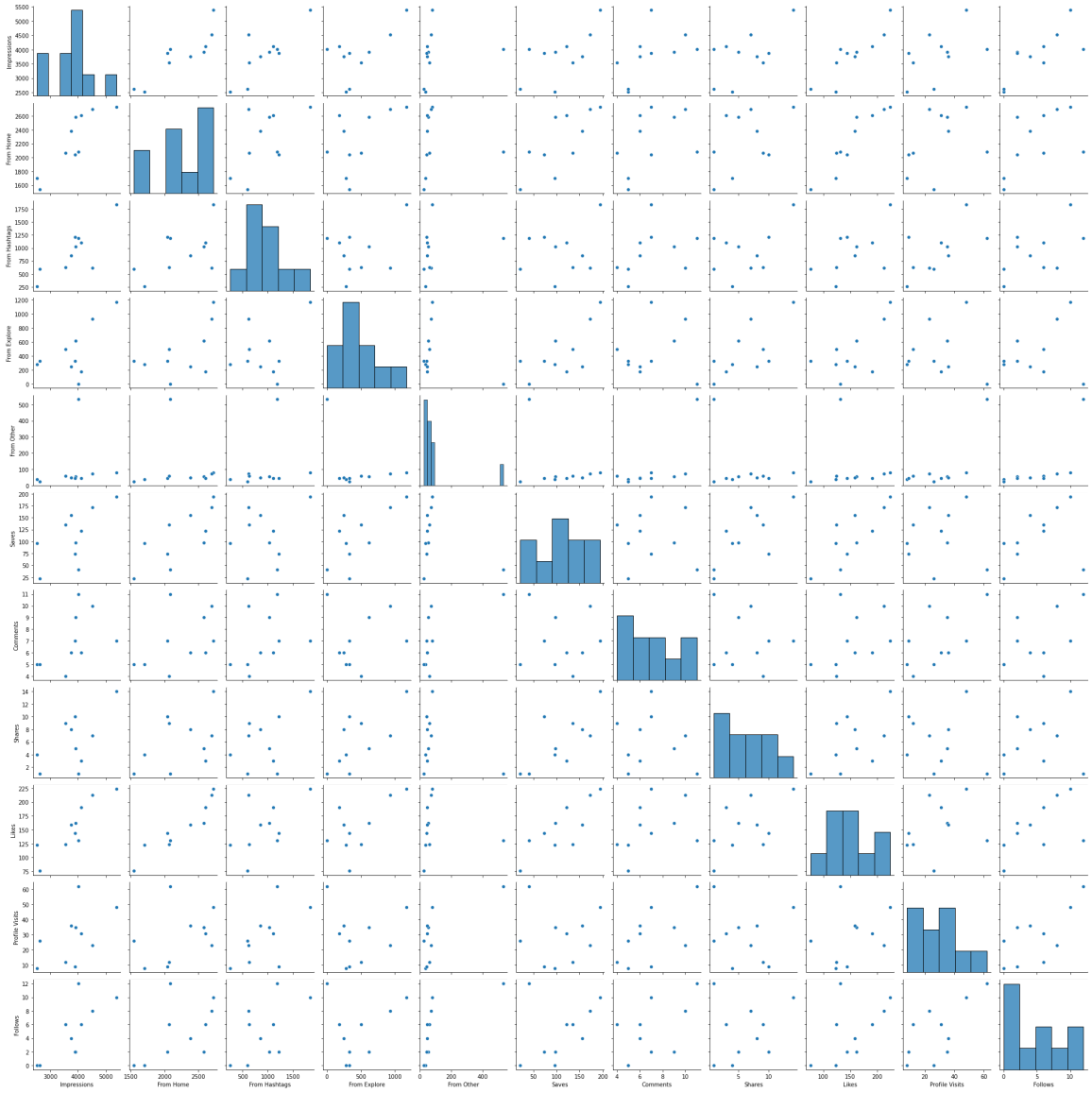
	Impressions	From Home	From Hashtags	From Explore	From Other	Saves	Comments	Shares	Likes	Profile Visits
0	3920	2586	1028	619	56	98	9	5	162	35
1	5394	2727	1838	1174	78	194	7	14	224	48
2	4021	2085	1188	0	533	41	11	1	131	62
3	4528	2700	621	932	73	172	10	7	213	23
4	2518	1704	255	279	37	96	5	4	123	8
5	3884	2046	1214	329	43	74	7	10	144	9
6	2621	1543	599	333	25	22	5	1	76	26
7	3541	2071	628	500	60	135	4	9	124	12
8	3749	2384	857	248	49	155	6	8	159	36
9	4115	2609	1104	178	46	122	6	3	191	31

In [97]:

```
sns.pairplot(c)
```

Out[97]:

```
<seaborn.axisgrid.PairGrid at 0x202c3f989d0>
```



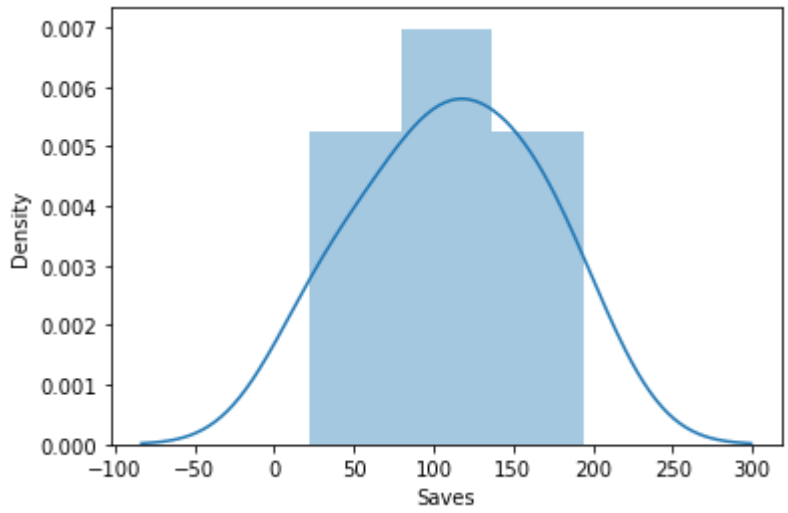
In [98]:

```
sns.distplot(c['Saves'])
```

```
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 adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[98]:

```
<AxesSubplot:xlabel='Saves', ylabel='Density'>
```

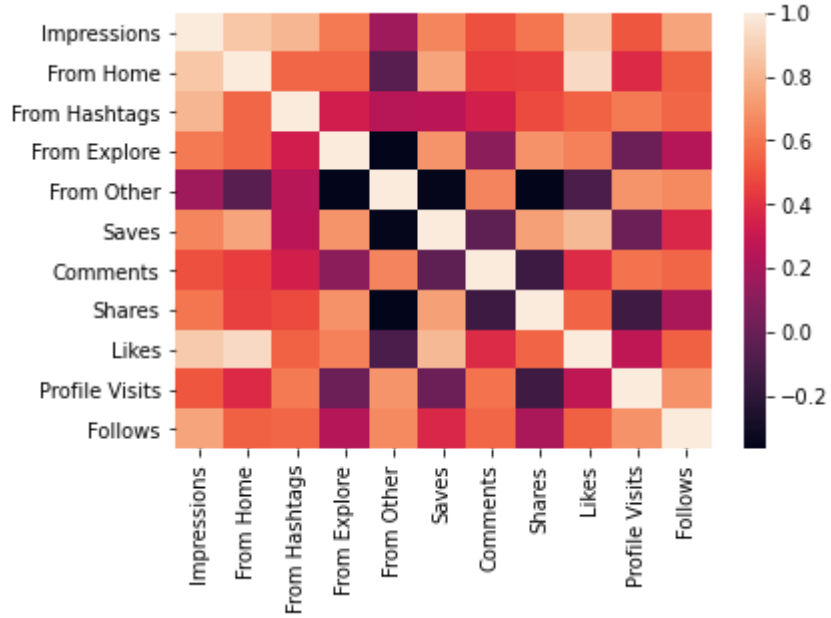


In [99]:

```
sns.heatmap(c.corr())
```

Out[99]:

```
<AxesSubplot:>
```



In [100]:

```
x4=c[['Impressions', 'From Home', 'From Hashtags', 'From Explore',
       'From Other', 'Saves', 'Comments', 'Shares', 'Likes', 'Profile Visits',
       'Follows']]
y4=c['Saves']
```

In [101]:

```
x4_train,x4_test,y4_train,y4_test=train_test_split(x4,y4,test_size=0.3)
```

In [102]:

```
lr=LinearRegression()
lr.fit(x4_train,y4_train)
```

Out[102]:

```
LinearRegression()
```

In [103]:

```
print(lr.intercept_)
```

```
-80.34197563055119
```

In [104]:

```
coeff=pd.DataFrame(lr.coef_,x4.columns,columns=['Co-efficient'])
coeff
```

Out[104]:

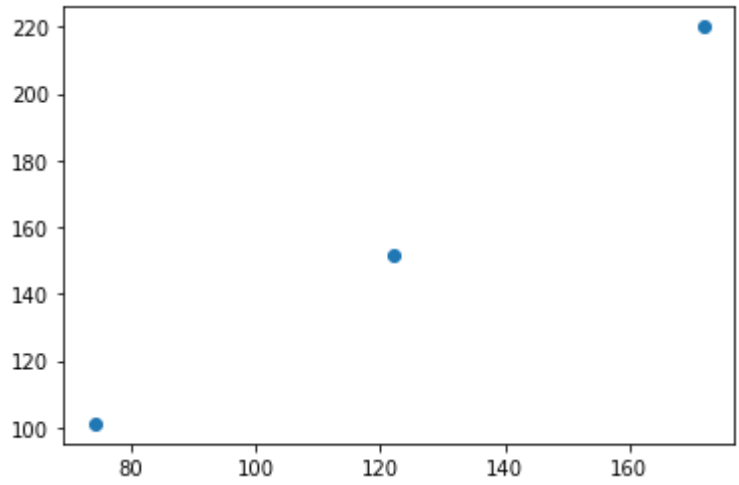
	Co-efficient
Impressions	0.076749
From Home	-0.052559
From Hashtags	-0.080066
From Explore	-0.041580
From Other	-0.122631
Saves	0.541621
Comments	-0.001456
Shares	0.020914
Likes	0.464713
Profile Visits	-0.003694
Follows	-0.005075

In [105]:

```
prediction=lr.predict(x4_test)
plt.scatter(y4_test,prediction)
```

Out[105]:

```
<matplotlib.collections.PathCollection at 0x202ca4d3100>
```



In [106]:

```
print(lr.score(x4_test,y4_test))
```

```
0.18285974215213086
```

In [107]:

```
from sklearn.linear_model import Ridge,Lasso
```

In [108]:

```
rr=Ridge(alpha=10)
rr.fit(x4_train,y4_train)
```

Out[108]:

```
Ridge(alpha=10)
```

In [109]:

```
rr.score(x4_test,y4_test)
```

Out[109]:

```
0.17855037390050987
```

In [110]:

```
la=Lasso(alpha=10)
la.fit(x4_train,y4_train)
```

Out[110]:

```
Lasso(alpha=10)
```

In [111]:

```
la.score(x4_test,y4_test)
```

Out[111]:

```
0.9992595495404736
```

In [112]:

```
en=ElasticNet()
en.fit(x4_train,y4_train)
```

Out[112]:

```
ElasticNet()
```

In [113]:

```
print(en.coef_)
```

```
[ 0.01069771 -0.00707138 -0.01123564 -0.00557079 -0.01688413  0.93630978
 -0.          0.          0.06149639 -0.          0.        ]
```

In [114]:

```
print(en.intercept_)
```

```
-11.362186525748939
```

In [115]:

```
prediction=en.predict(x4_test)
print(en.score(x4_test,y4_test))
```

```
0.9844321185658315
```

Evaluation Metrics

In [116]:

```
print('Mean Absolute Error:',metrics.mean_absolute_error(y4_test,prediction))
```

```
Mean Absolute Error: 4.800836647656486
```

In [117]:

```
print("mean Squared Error:",metrics.mean_squared_error(y4_test,prediction))
```

```
mean Squared Error: 24.92244841150003
```

In [118]:

```
print("Root mean Squared Error:",np.sqrt(metrics.mean_squared_error(y4_test,prediction)))
```

```
Root mean Squared Error: 4.992238817554708
```

5. DataSet Drug

In [119]:

```
a=pd.read_csv(r"C:\Users\user\Downloads\4_drug200.csv")
a
```

Out[119]:

	Age	Sex	BP	Cholesterol	Na_to_K	Drug
0	23	F	HIGH	HIGH	25.355	drugY
1	47	M	LOW	HIGH	13.093	drugC
2	47	M	LOW	HIGH	10.114	drugC
3	28	F	NORMAL	HIGH	7.798	drugX
4	61	F	LOW	HIGH	18.043	drugY
...	...	...	...	...	...	...
195	56	F	LOW	HIGH	11.567	drugC
196	16	M	LOW	HIGH	12.006	drugC
197	52	M	NORMAL	HIGH	9.894	drugX
198	23	M	NORMAL	NORMAL	14.020	drugX
199	40	F	LOW	NORMAL	11.349	drugX

200 rows × 6 columns

In [120]:

```
b=a.head(10)
b
```

Out[120]:

	Age	Sex	BP	Cholesterol	Na_to_K	Drug
0	23	F	HIGH	HIGH	25.355	drugY
1	47	M	LOW	HIGH	13.093	drugC
2	47	M	LOW	HIGH	10.114	drugC
3	28	F	NORMAL	HIGH	7.798	drugX
4	61	F	LOW	HIGH	18.043	drugY
5	22	F	NORMAL	HIGH	8.607	drugX
6	49	F	NORMAL	HIGH	16.275	drugY
7	41	M	LOW	HIGH	11.037	drugC
8	60	M	NORMAL	HIGH	15.171	drugY
9	43	M	LOW	NORMAL	19.368	drugY

In [121]:

```
a.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Age          200 non-null    int64  
 1   Sex          200 non-null    object 
 2   BP           200 non-null    object 
 3   Cholesterol  200 non-null    object 
 4   Na_to_K      200 non-null    float64
 5   Drug         200 non-null    object 
dtypes: float64(1), int64(1), object(4)
memory usage: 9.5+ KB
```

In [122]:

```
a.describe()
```

Out[122]:

	Age	Na_to_K
count	200.000000	200.000000
mean	44.315000	16.084485
std	16.544315	7.223956
min	15.000000	6.269000
25%	31.000000	10.445500
50%	45.000000	13.936500
75%	58.000000	19.380000
max	74.000000	38.247000

In [123]:

```
a.columns
```

Out[123]:

```
Index(['Age', 'Sex', 'BP', 'Cholesterol', 'Na_to_K', 'Drug'], dtype='objec
t')
```

In [124]:

```
c=b[['Age','Na_to_K']]
c
```

Out[124]:

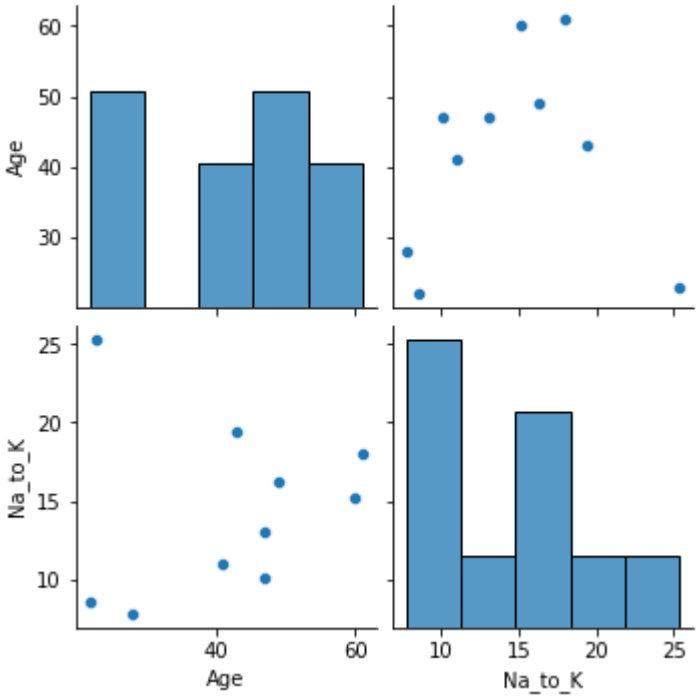
	Age	Na_to_K
0	23	25.355
1	47	13.093
2	47	10.114
3	28	7.798
4	61	18.043
5	22	8.607
6	49	16.275
7	41	11.037
8	60	15.171
9	43	19.368

In [125]:

```
sns.pairplot(c)
```

Out[125]:

```
<seaborn.axisgrid.PairGrid at 0x202ca501730>
```



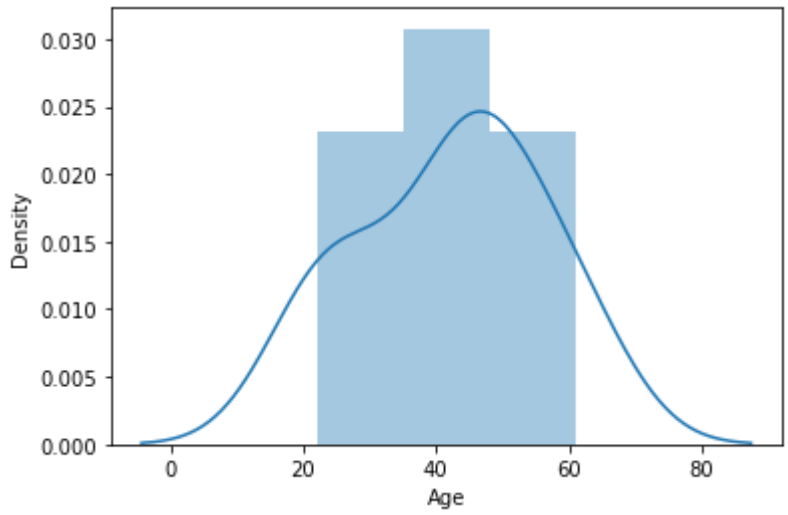
In [126]:

```
sns.distplot(c['Age'])
```

```
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 adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[126]:

```
<AxesSubplot:xlabel='Age', ylabel='Density'>
```

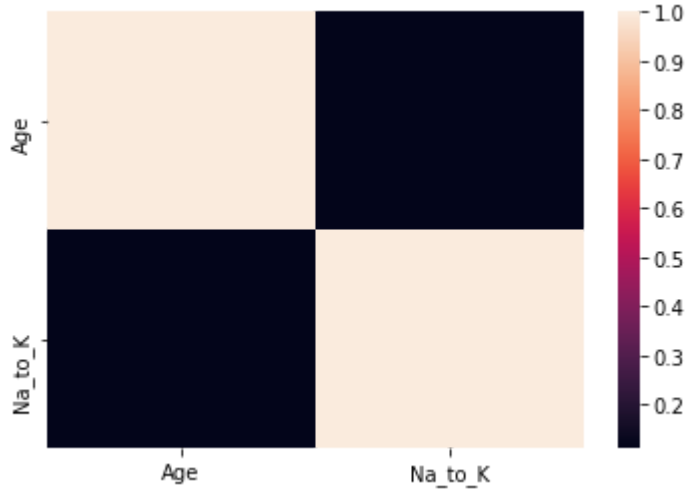


In [127]:

```
sns.heatmap(c.corr())
```

Out[127]:

```
<AxesSubplot:>
```



In [128]:

```
x5=b[['Age','Na_to_K']]
y5=b['Age']
```

In [129]:

```
x5_train,x5_test,y5_train,y5_test=train_test_split(x5,y5,test_size=0.3)
```

In [130]:

```
lr=LinearRegression()
lr.fit(x5_train,y5_train)
```

Out[130]:

```
LinearRegression()
```

In [131]:

```
print(lr.intercept_)
```

```
3.552713678800501e-14
```

In [132]:

```
coeff=pd.DataFrame(lr.coef_,x5.columns,columns=['Co-efficient'])
coeff
```

Out[132]:

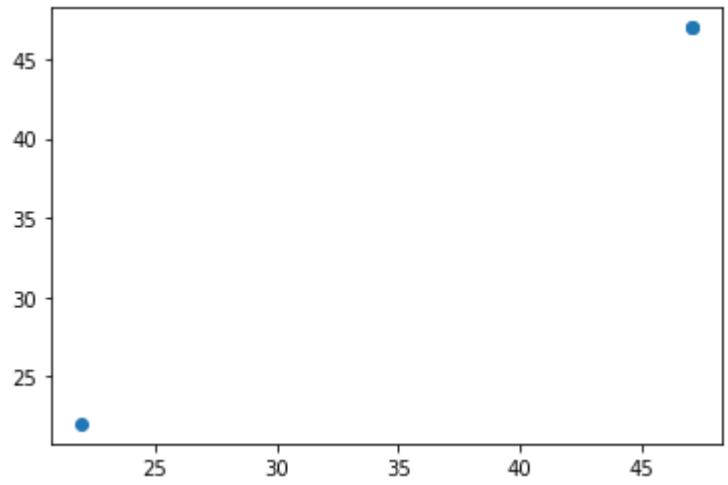
	Co-efficient
Age	1.000000e+00
Na_to_K	1.056848e-16

In [133]:

```
prediction=lr.predict(x5_test)
plt.scatter(y5_test,prediction)
```

Out[133]:

```
<matplotlib.collections.PathCollection at 0x202ca7dec70>
```



In [134]:

```
print(lr.score(x5_test,y5_test))
```

```
1.0
```

In [135]:

```
from sklearn.linear_model import Ridge,Lasso
```

In [136]:

```
rr=Ridge(alpha=10)
rr.fit(x5_train,y5_train)
```

Out[136]:

```
Ridge(alpha=10)
```

In [137]:

```
rr.score(x5_test,y5_test)
```

Out[137]:

```
0.999922509631937
```

In [138]:

```
la=Lasso(alpha=10)
la.fit(x5_train,y5_train)
```

Out[138]:

```
Lasso(alpha=10)
```

In [139]:

```
la.score(x5_test,y5_test)
```

Out[139]:

```
0.9964676452036432
```

In [140]:

```
en=ElasticNet()
en.fit(x5_train,y5_train)
```

Out[140]:

```
ElasticNet()
```

In [141]:

```
print(en.coef_)
```

```
[ 0.99452789 -0.        ]
```

In [142]:

```
print(en.intercept_)
```

```
0.23842760623150383
```

In [143]:

```
prediction=en.predict(x5_test)
print(en.score(x5_test,y5_test))
```

```
0.9999648694819091
```

Evaluation Metrics

In [144]:

```
print('Mean Absolute Error:',metrics.mean_absolute_error(y5_test,prediction))
```

```
Mean Absolute Error: 0.0518547471476154
```

In [145]:

```
print("mean Squared Error:",metrics.mean_squared_error(y5_test,prediction))
```

```
mean Squared Error: 0.004879238623733456
```

In [146]:

```
print("Root mean Squared Error:",np.sqrt(metrics.mean_squared_error(y5_test,prediction)))
```

```
Root mean Squared Error: 0.06985154703894149
```

6. DataSet Vehicle

In [147]:

```
a=pd.read_csv(r"C:\Users\user\Downloads\Vehicle.csv")
a
```

Out[147]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.6115
1	2.0	pop	51.0	1186.0	32500.0	1.0	45.666359	12.241
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.634
4	5.0	pop	73.0	3074.0	106880.0	1.0	41.903221	12.495
...	...	...	...	...	...	...	...	
1544	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1545	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1546	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Null
1547	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1548	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

1549 rows × 11 columns

In [148]:

```
b=a.head(10)
b
```

Out[148]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	l
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.6115598
1	2.0	pop	51.0	1186.0	32500.0	1.0	45.666359	12.241889
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11.417
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.634609
4	5.0	pop	73.0	3074.0	106880.0	1.0	41.903221	12.495650
5	6.0	pop	74.0	3623.0	70225.0	1.0	45.000702	7.682270
6	7.0	lounge	51.0	731.0	11600.0	1.0	44.907242	8.6115598
7	8.0	lounge	51.0	1521.0	49076.0	1.0	41.903221	12.495650
8	9.0	sport	73.0	4049.0	76000.0	1.0	45.548000	11.549469
9	10.0	sport	51.0	3653.0	89000.0	1.0	45.438301	10.991700

In [149]:

```
c=b.dropna(axis=1)
c
```

Out[149]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	l
0	1.0	lounge	51.0	882.0	25000.0	1.0	44.907242	8.6115598
1	2.0	pop	51.0	1186.0	32500.0	1.0	45.666359	12.241889
2	3.0	sport	74.0	4658.0	142228.0	1.0	45.503300	11.417
3	4.0	lounge	51.0	2739.0	160000.0	1.0	40.633171	17.634609
4	5.0	pop	73.0	3074.0	106880.0	1.0	41.903221	12.495650
5	6.0	pop	74.0	3623.0	70225.0	1.0	45.000702	7.682270
6	7.0	lounge	51.0	731.0	11600.0	1.0	44.907242	8.6115598
7	8.0	lounge	51.0	1521.0	49076.0	1.0	41.903221	12.495650
8	9.0	sport	73.0	4049.0	76000.0	1.0	45.548000	11.549469
9	10.0	sport	51.0	3653.0	89000.0	1.0	45.438301	10.991700

In [150]:

```
a.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1549 entries, 0 to 1548
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   ID               1538 non-null   float64
 1   model            1538 non-null   object 
 2   engine_power     1538 non-null   float64
 3   age_in_days      1538 non-null   float64
 4   km               1538 non-null   float64
 5   previous_owners  1538 non-null   float64
 6   lat              1538 non-null   float64
 7   lon              1549 non-null   object 
 8   price            1549 non-null   object 
 9   Unnamed: 9       0 non-null      float64
 10  Unnamed: 10      1 non-null      object 
dtypes: float64(7), object(4)
memory usage: 133.2+ KB
```

In [151]:

```
a.describe()
```

Out[151]:

	ID	engine_power	age_in_days	km	previous_owners	la
count	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000	1538.000000
mean	769.500000	51.904421	1650.980494	53396.011704	1.123537	43.54136
std	444.126671	3.988023	1289.522278	40046.830723	0.416423	2.13351
min	1.000000	51.000000	366.000000	1232.000000	1.000000	36.85583
25%	385.250000	51.000000	670.000000	20006.250000	1.000000	41.80299
50%	769.500000	51.000000	1035.000000	39031.000000	1.000000	44.39409
75%	1153.750000	51.000000	2616.000000	79667.750000	1.000000	45.46796
max	1538.000000	77.000000	4658.000000	235000.000000	4.000000	46.79561

In [152]:

```
a.columns
```

Out[152]:

```
Index(['ID', 'model', 'engine_power', 'age_in_days', 'km', 'previous_owner
s',
       'lat', 'lon', 'price', 'Unnamed: 9', 'Unnamed: 10'],
      dtype='object')
```

In [153]:

```
d=c[['engine_power', 'age_in_days', 'km', 'previous_owners',
       'lat', 'lon', 'price']]
d
```

Out[153]:

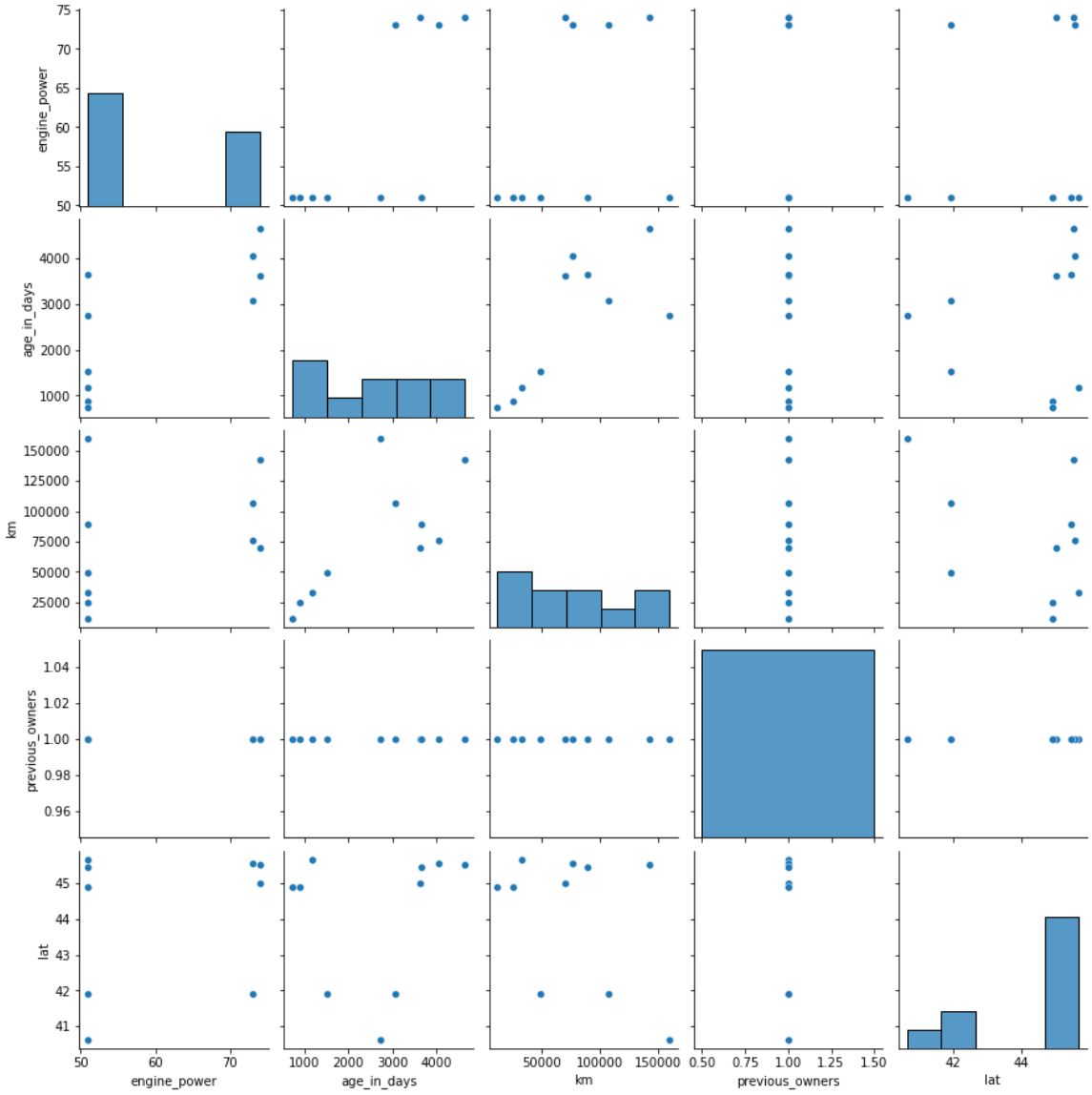
	engine_power	age_in_days	km	previous_owners	lat	lon	price
0	51.0	882.0	25000.0	1.0	44.907242	8.611559868	8900
1	51.0	1186.0	32500.0	1.0	45.666359	12.24188995	8800
2	74.0	4658.0	142228.0	1.0	45.503300	11.41784	4200
3	51.0	2739.0	160000.0	1.0	40.633171	17.63460922	6000
4	73.0	3074.0	106880.0	1.0	41.903221	12.49565029	5700
5	74.0	3623.0	70225.0	1.0	45.000702	7.68227005	7900
6	51.0	731.0	11600.0	1.0	44.907242	8.611559868	10750
7	51.0	1521.0	49076.0	1.0	41.903221	12.49565029	9190
8	73.0	4049.0	76000.0	1.0	45.548000	11.54946995	5600
9	51.0	3653.0	89000.0	1.0	45.438301	10.99170017	6000

In [154]:

```
sns.pairplot(d)
```

Out[154]:

```
<seaborn.axisgrid.PairGrid at 0x202ca833640>
```



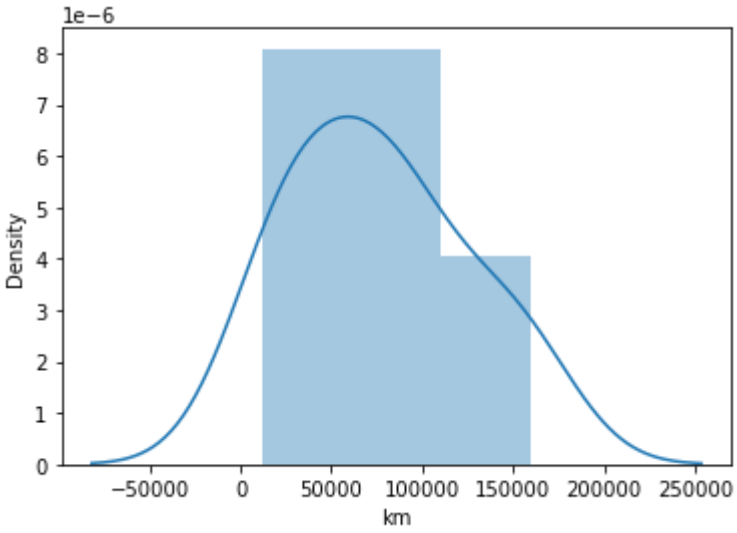
In [155]:

```
sns.distplot(d['km'])
```

```
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 adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[155]:

```
<AxesSubplot:xlabel='km', ylabel='Density'>
```

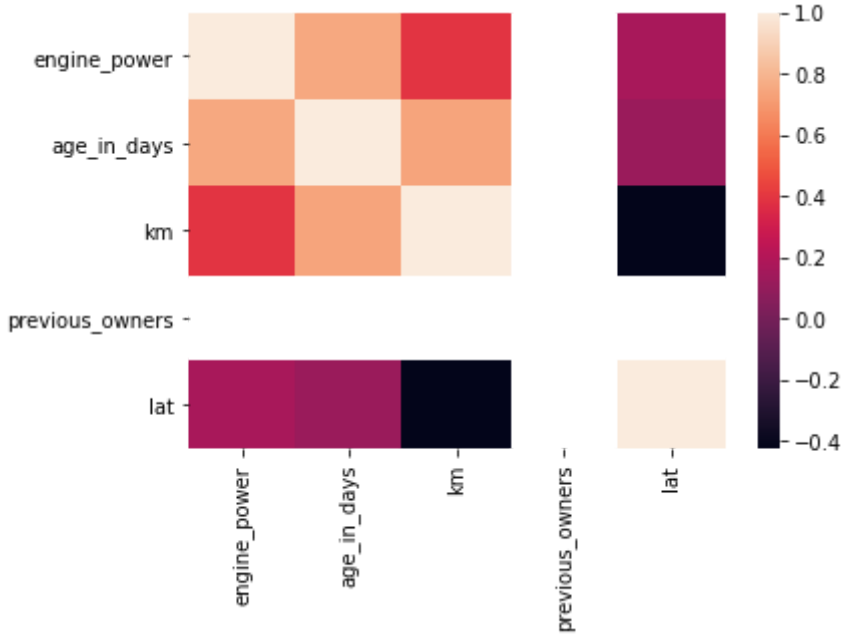


In [156]:

```
sns.heatmap(d.corr())
```

Out[156]:

```
<AxesSubplot:>
```



In [157]:

```
x6=d[['engine_power', 'age_in_days', 'km', 'previous_owners',
       'lat', 'lon', 'price']]
y6=d['price']
```

In [158]:

```
x6_train,x6_test,y6_train,y6_test=train_test_split(x6,y6,test_size=0.3)
```

In [159]:

```
lr=LinearRegression()
lr.fit(x6_train,y6_train)
```

Out[159]:

```
LinearRegression()
```

In [160]:

```
print(lr.intercept_)
```

```
2.7284841053187847e-12
```

In [161]:

```
coeff=pd.DataFrame(lr.coef_,x6.columns,columns=['Co-efficient'])
coeff
```

Out[161]:

	Co-efficient
engine_power	-3.072973e-14
age_in_days	1.337040e-16
km	1.164091e-16
previous_owners	0.000000e+00
lat	-9.874181e-14
lon	-1.550932e-13
price	1.000000e+00

In [162]:

```
prediction=lr.predict(x6_test)
plt.scatter(y6_test,prediction)
```

Out[162]:

```
<matplotlib.collections.PathCollection at 0x202cb81e580>
```

In [163]:

```
print(lr.score(x6_test,y6_test))
```

```
1.0
```

In [164]:

```
from sklearn.linear_model import Ridge,Lasso
```

In [165]:

```
rr=Ridge(alpha=10)
rr.fit(x6_train,y6_train)
```

Out[165]:

```
Ridge(alpha=10)
```

In [166]:

```
rr.score(x6_test,y6_test)
```

Out[166]:

```
0.9999999999243495
```

In [167]:

```
la=Lasso(alpha=10)
la.fit(x6_train,y6_train)
```

Out[167]:

```
Lasso(alpha=10)
```

In [168]:

```
la.score(x6_test,y6_test)
```

Out[168]:

```
0.9999949111307507
```

In [169]:

```
en=ElasticNet()
en.fit(x6_train,y6_train)
```

Out[169]:

```
ElasticNet()
```

In [170]:

```
print(en.coef_)
```

```
[ 0.00000000e+00 -1.81464528e-04 -1.06207687e-05  0.00000000e+00
 -0.00000000e+00  0.00000000e+00  9.99684816e-01]
```

In [171]:

```
print(en.intercept_)
```

```
3.4826682706498104
```

In [172]:

```
prediction=en.predict(x6_test)
print(en.score(x6_test,y6_test))
```

```
0.9999997778573139
```

Evaluation Metrics

In [173]:

```
print('Mean Absolute Error:',metrics.mean_absolute_error(y6_test,prediction))
```

```
Mean Absolute Error: 0.34398250310368894
```

In [174]:

```
print("mean Squared Error:",metrics.mean_squared_error(y6_test,prediction))
```

```
mean Squared Error: 0.17820779931262035
```

In [175]:

```
print("Root mean Squared Error:",np.sqrt(metrics.mean_squared_error(y6_test,prediction)))
```

```
Root mean Squared Error: 0.4221466561665748
```

7. DataSet 2015

In [176]:

```
a=pd.read_csv(r"C:\Users\user\Downloads\2015 - 2015.csv")
a
```

Out[176]:

	Country	Region	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)
0	Switzerland	Western Europe	1	7.587	0.03411	1.39651	1.34951	0.94143
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563
...	...	...	...	...	...	...	...	...
153	Rwanda	Sub-Saharan Africa	154	3.465	0.03464	0.22208	0.77370	0.42864
154	Benin	Sub-Saharan Africa	155	3.340	0.03656	0.28665	0.35386	0.31910
155	Syria	Middle East and Northern Africa	156	3.006	0.05015	0.66320	0.47489	0.72193
156	Burundi	Sub-Saharan Africa	157	2.905	0.08658	0.01530	0.41587	0.22396
157	Togo	Sub-Saharan Africa	158	2.839	0.06727	0.20868	0.13995	0.28443

158 rows × 12 columns

In [177]:

```
b=a.head(10)
b
```

Out[177]:

	Country	Region	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	F
0	Switzerland	Western Europe	1	7.587	0.03411	1.39651	1.34951	0.94143	
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784	
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464	
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521	
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563	
5	Finland	Western Europe	6	7.406	0.03140	1.29025	1.31826	0.88911	
6	Netherlands	Western Europe	7	7.378	0.02799	1.32944	1.28017	0.89284	
7	Sweden	Western Europe	8	7.364	0.03157	1.33171	1.28907	0.91087	
8	New Zealand	Australia and New Zealand	9	7.286	0.03371	1.25018	1.31967	0.90837	
9	Australia	Australia and New Zealand	10	7.284	0.04083	1.33358	1.30923	0.93156	

In [178]:

```
a.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 158 entries, 0 to 157
Data columns (total 12 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Country                        158 non-null    object 
 1   Region                         158 non-null    object 
 2   Happiness Rank                 158 non-null    int64  
 3   Happiness Score                158 non-null    float64
 4   Standard Error                 158 non-null    float64
 5   Economy (GDP per Capita)       158 non-null    float64
 6   Family                         158 non-null    float64
 7   Health (Life Expectancy)       158 non-null    float64
 8   Freedom                        158 non-null    float64
 9   Trust (Government Corruption)  158 non-null    float64
 10  Generosity                     158 non-null    float64
 11  Dystopia Residual              158 non-null    float64
dtypes: float64(9), int64(1), object(2)
memory usage: 14.9+ KB
```

In [179]:

```
a.describe()
```

Out[179]:

	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom
count	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000
mean	79.493671	5.375734	0.047885	0.846137	0.991046	0.630259	0.428615
std	45.754363	1.145010	0.017146	0.403121	0.272369	0.247078	0.150693
min	1.000000	2.839000	0.018480	0.000000	0.000000	0.000000	0.000000
25%	40.250000	4.526000	0.037268	0.545808	0.856823	0.439185	0.328330
50%	79.500000	5.232500	0.043940	0.910245	1.029510	0.696705	0.435515
75%	118.750000	6.243750	0.052300	1.158448	1.214405	0.811013	0.549092
max	158.000000	7.587000	0.136930	1.690420	1.402230	1.025250	0.669730

In [180]:

```
a.columns
```

Out[180]:

```
Index(['Country', 'Region', 'Happiness Rank', 'Happiness Score',
       'Standard Error', 'Economy (GDP per Capita)', 'Family',
       'Health (Life Expectancy)', 'Freedom', 'Trust (Government Corruptio
n)',
       'Generosity', 'Dystopia Residual'],
      dtype='object')
```

In [181]:

```
c=b[['Happiness Rank', 'Happiness Score',
       'Standard Error', 'Economy (GDP per Capita)', 'Family',
       'Health (Life Expectancy)', 'Freedom', 'Trust (Government Corruption)',
       'Generosity', 'Dystopia Residual']]
c
```

Out[181]:

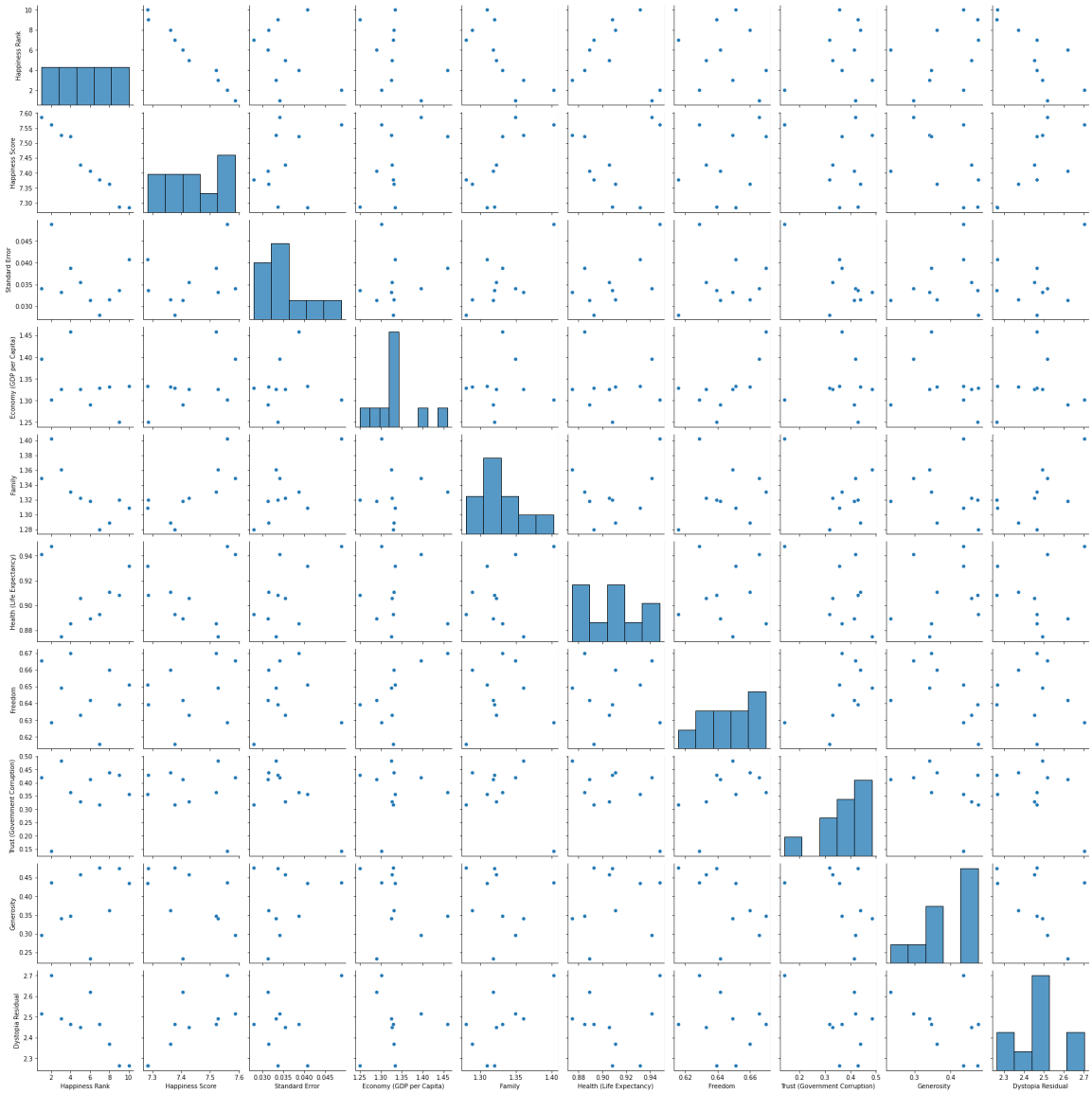
	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	Trust (Government Corruption)
0	1	7.587	0.03411	1.39651	1.34951	0.94143	0.66557	0.41978
1	2	7.561	0.04884	1.30232	1.40223	0.94784	0.62877	0.14145
2	3	7.527	0.03328	1.32548	1.36058	0.87464	0.64938	0.48357
3	4	7.522	0.03880	1.45900	1.33095	0.88521	0.66973	0.36503
4	5	7.427	0.03553	1.32629	1.32261	0.90563	0.63297	0.32957
5	6	7.406	0.03140	1.29025	1.31826	0.88911	0.64169	0.41372
6	7	7.378	0.02799	1.32944	1.28017	0.89284	0.61576	0.31814
7	8	7.364	0.03157	1.33171	1.28907	0.91087	0.65980	0.43844
8	9	7.286	0.03371	1.25018	1.31967	0.90837	0.63938	0.42922
9	10	7.284	0.04083	1.33358	1.30923	0.93156	0.65124	0.35637

In [182]:

```
sns.pairplot(c)
```

Out[182]:

```
<seaborn.axisgrid.PairGrid at 0x202cb868af0>
```



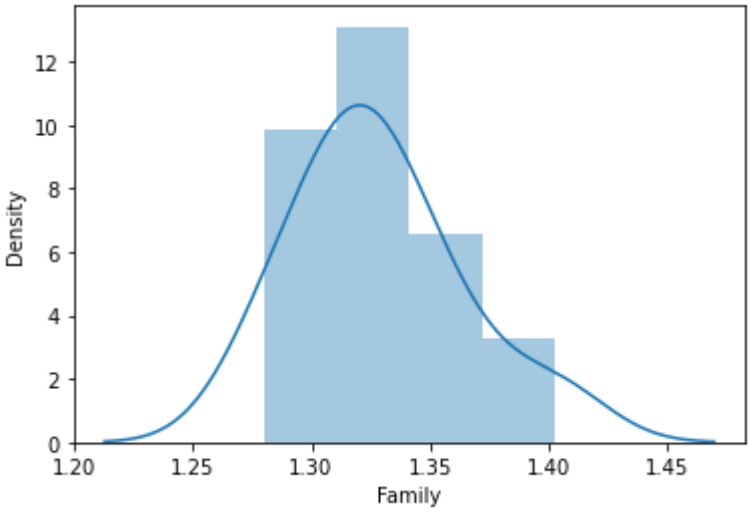
In [183]:

```
sns.distplot(c['Family'])
```

```
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 adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[183]:

```
<AxesSubplot:xlabel='Family', ylabel='Density'>
```

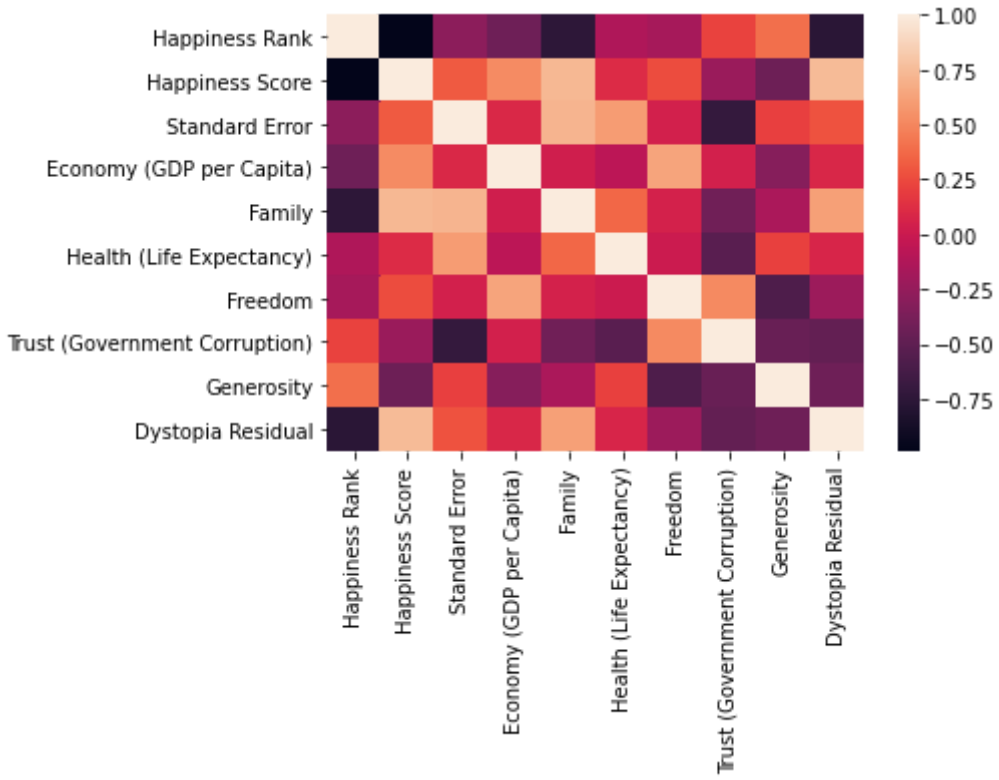


In [184]:

```
sns.heatmap(c.corr())
```

Out[184]:

<AxesSubplot:>



In [185]:

```
x=b[['Happiness Rank', 'Happiness Score',
       'Standard Error', 'Economy (GDP per Capita)', 'Family',
       'Health (Life Expectancy)', 'Freedom', 'Trust (Government Corruption)',
       'Generosity', 'Dystopia Residual']]
y=b['Generosity']
```

In [186]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [187]:

```
lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[187]:

```
LinearRegression()
```

In [188]:

```
print(lr.intercept_)
```

```
2.022444100662339
```

In [189]:

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

Out[189]:

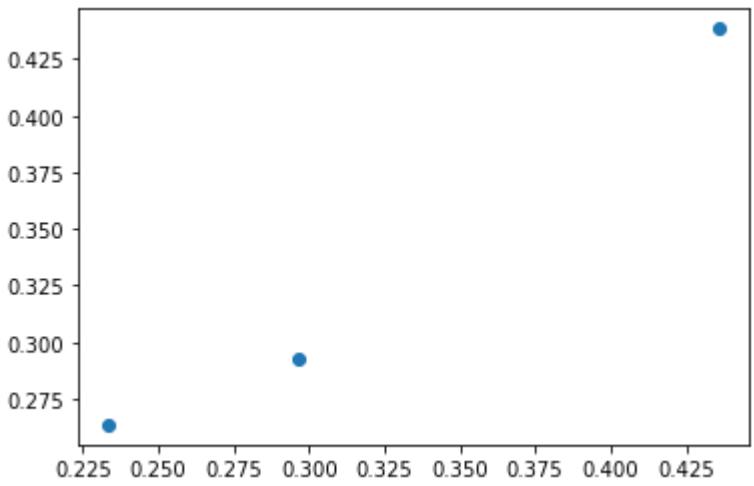
	Co-efficient
Happiness Rank	-0.005336
Happiness Score	-0.141832
Standard Error	-0.035067
Economy (GDP per Capita)	-0.074127
Family	-0.010368
Health (Life Expectancy)	-0.256154
Freedom	-0.247316
Trust (Government Corruption)	-0.175551
Generosity	0.732712
Dystopia Residual	-0.106161

In [190]:

```
prediction=lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[190]:

```
<matplotlib.collections.PathCollection at 0x202d1191ca0>
```



In [191]:

```
print(lr.score(x_test,y_test))
```

```
0.9568058784794542
```

In [192]:

```
la=Ridge(alpha=10)
la.fit(x_train,y_train)
```

Out[192]:

```
Ridge(alpha=10)
```

In [193]:

```
la.score(x_test,y_test)
```

Out[193]:

```
-0.930652102054202
```

In [194]:

```
rr=Lasso(alpha=10)
rr.fit(x_train,y_train)
```

Out[194]:

```
Lasso(alpha=10)
```

In [195]:

```
rr.score(x_test,y_test)
```

Out[195]:

```
-1.1831921054055696
```

In [196]:

```
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[196]:

```
ElasticNet()
```

In [197]:

```
print(en.coef_)
```

```
[ 0. -0. -0. -0. -0.  0. -0. -0.  0. -0.]
```

In [198]:

```
print(en.intercept_)
```

```
0.41378857142857145
```

In [199]:

```
prediction=en.predict(x_test)
print(en.score(x_test,y_test))
```

```
-1.1831921054055696
```

Evaluation Metrics

In [200]:

```
print('Mean Absolute Error:',metrics.mean_absolute_error(y_test,prediction))
```

```
Mean Absolute Error: 0.10637285714285716
```

In [201]:

```
print("mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
mean Squared Error: 0.01555599345918368
```

In [202]:

```
print("Root mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
Root mean Squared Error: 0.12472366840012235
```

8. DataSet Win_Equality

In [203]:

```
a=pd.read_csv(r"C:\Users\user\Downloads\11_winequality-red.csv")
a
```

Out[203]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	a
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	
...	...	...	...	...	...	...	...	...	...	...	
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	

1599 rows × 12 columns

In [204]:

```
b=a.head(10)
b
```

Out[204]:

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

In [205]:

```
a.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   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   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 [206]:

```
a.describe()
```

Out[206]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total di
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.0
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.4
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.8
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.0
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.0
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.0
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.0
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.0

In [207]:

```
a.columns
```

Out[207]:

```
Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual suga
r',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'densit
y',
       'pH', 'sulphates', 'alcohol', 'quality'],
      dtype='object')
```

In [208]:

```
c=b[['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide']]
c
```

Out[208]:

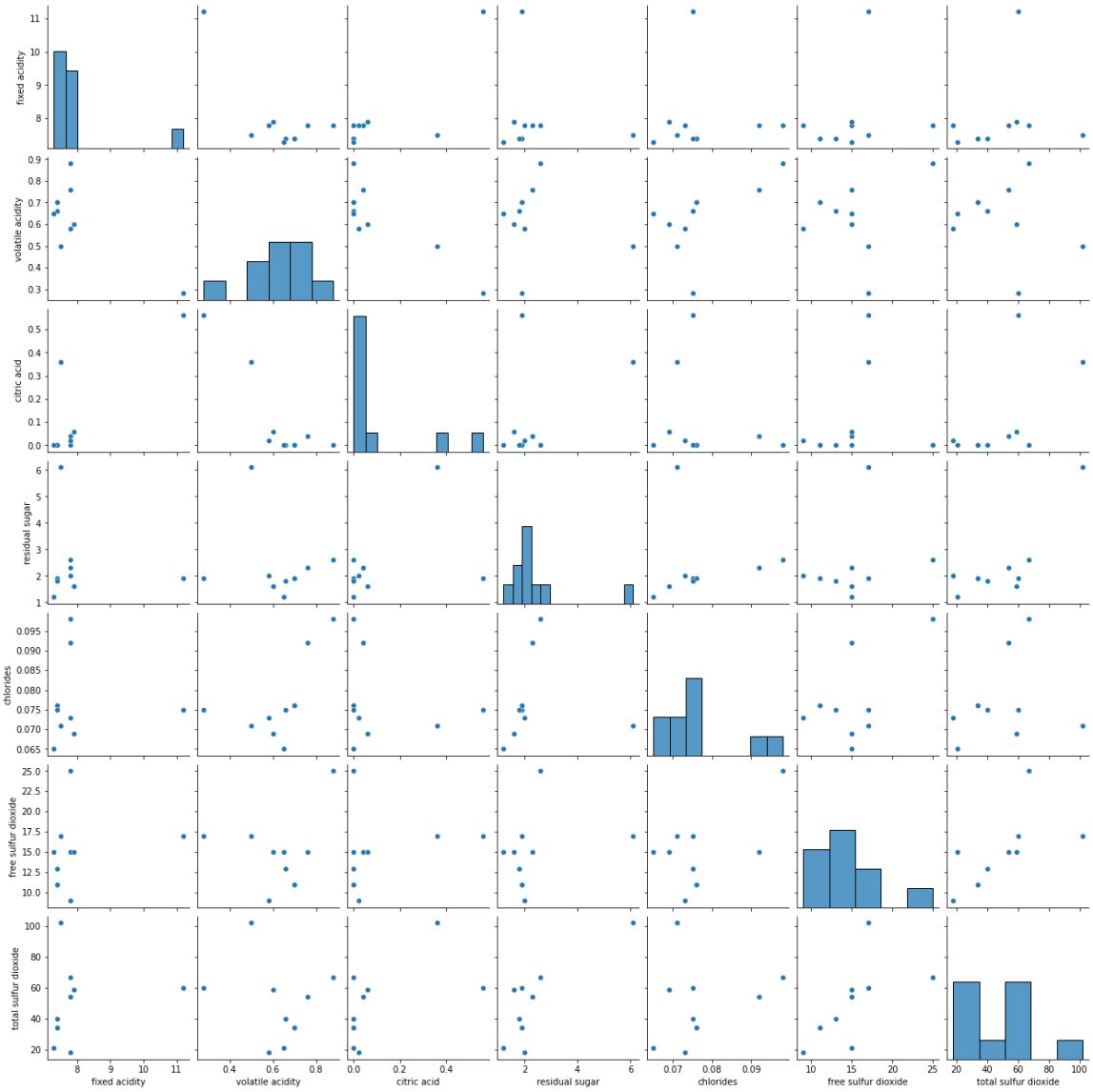
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0
5	7.4	0.66	0.00	1.8	0.075	13.0	40.0
6	7.9	0.60	0.06	1.6	0.069	15.0	59.0
7	7.3	0.65	0.00	1.2	0.065	15.0	21.0
8	7.8	0.58	0.02	2.0	0.073	9.0	18.0
9	7.5	0.50	0.36	6.1	0.071	17.0	102.0

In [209]:

```
sns.pairplot(c)
```

Out[209]:

```
<seaborn.axisgrid.PairGrid at 0x202ba43a850>
```



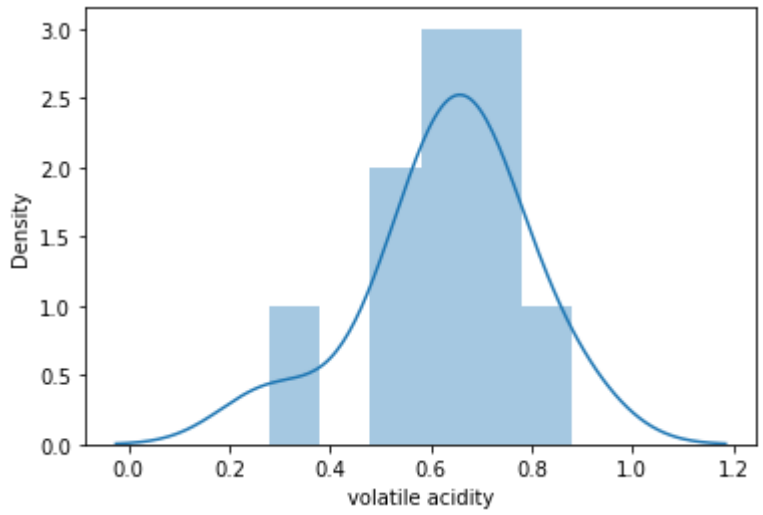
In [210]:

```
sns.distplot(c['volatile acidity'])
```

```
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 adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[210]:

```
<AxesSubplot:xlabel='volatile acidity', ylabel='Density'>
```

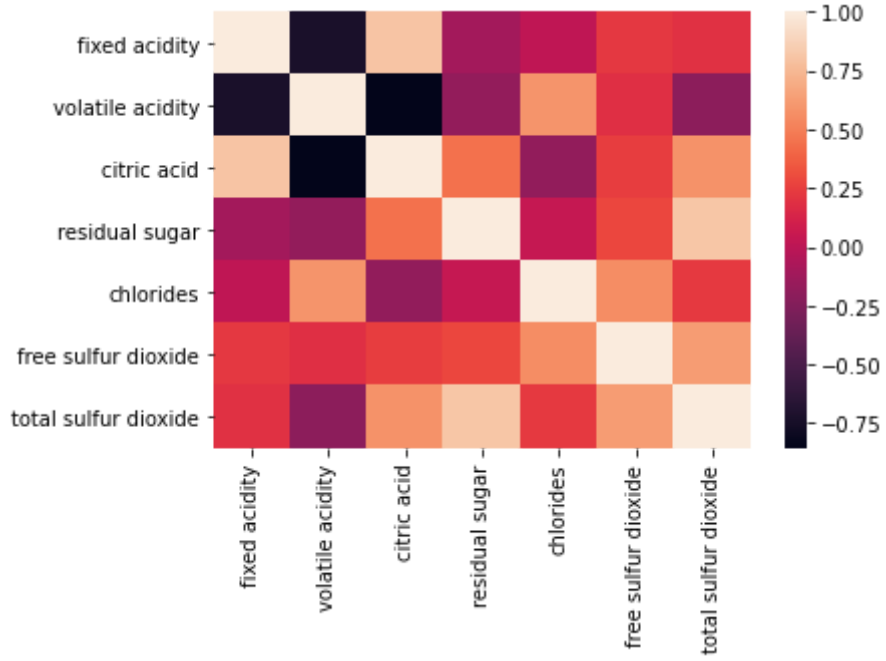


In [211]:

```
sns.heatmap(c.corr())
```

Out[211]:

```
<AxesSubplot:>
```



In [212]:

```
x=b[['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide']]
y=b['free sulfur dioxide']
```

In [213]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [214]:

```
lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[214]:

```
LinearRegression()
```

In [215]:

```
print(lr.intercept_)
```

```
-0.00016174477367414397
```

In [216]:

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

Out[216]:

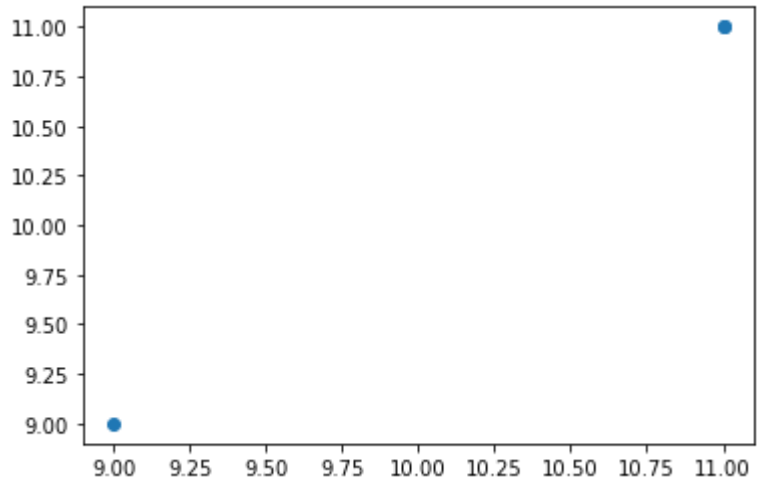
	Co-efficient
fixed acidity	2.353647e-05
volatile acidity	9.052542e-05
citric acid	-8.828680e-05
residual sugar	1.218843e-05
chlorides	-1.004625e-03
free sulfur dioxide	9.999990e-01
total sulfur dioxide	-1.356651e-07

In [217]:

```
prediction=lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[217]:

```
<matplotlib.collections.PathCollection at 0x202d3f28550>
```



In [218]:

```
print(lr.score(x_test,y_test))
```

```
0.9999999999128394
```

In [219]:

```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[219]:

```
Ridge(alpha=10)
```

In [220]:

```
rr.score(x_test,y_test)
```

Out[220]:

```
0.7221438205430756
```

In [221]:

```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[221]:

```
Lasso(alpha=10)
```

In [222]:

```
la.score(x_test,y_test)
```

Out[222]:

```
-21.75913849317975
```

In [223]:

```
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[223]:

```
ElasticNet()
```

In [224]:

```
print(en.coef_)
```

```
[ 0.          0.         -0.         -0.          0.          0.91678092
  0.00403667]
```

In [225]:

```
print(en.intercept_)
```

```
1.1585507903395005
```

In [226]:

```
prediction=en.predict(x_test)
print(en.score(x_test,y_test))
```

```
0.8042710130209593
```

Evaluation Metrics

In [227]:

```
print('Mean Absolute Error:',metrics.mean_absolute_error(y_test,prediction))
```

```
Mean Absolute Error: 0.41433808594759647
```

In [228]:

```
print("mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
mean Squared Error: 0.17398132175914735
```

In [229]:

```
print("Root mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
Root mean Squared Error: 0.4171106828638501
```

9. DataSet Mobile_prices

In [230]:

```
a=pd.read_csv(r"C:\Users\user\Downloads\12_mobile_prices_2023.csv")
a
```

Out[230]:

	Phone Name	Rating ?/5	Number of Ratings	RAM	ROM/Storage	Back/Rare Camera	Front Camera	Battery	Processor
0	POCO C50 (Royal Blue, 32 GB)	4.2	33,561	2 GB RAM	32 GB ROM	8MP Dual Camera	5MP Front Camera	5000 mAh	Mediatek Helio A22 Processor, Upto 2.0 GHz Pro...
1	POCO M4 5G (Cool Blue, 64 GB)	4.2	77,128	4 GB RAM	64 GB ROM	50MP + 2MP	8MP Front Camera	5000 mAh	Mediatek Dimensity 700 Processor
2	POCO C51 (Royal Blue, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor
3	POCO C55 (Cool Blue, 64 GB)	4.2	22,621	4 GB RAM	64 GB ROM	50MP Dual Rear Camera	5MP Front Camera	5000 mAh	Mediatek Helio G85 Processor
4	POCO C51 (Power Black, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor
...	...	...	...	...	...	...	...	...	...
1831	Infinix Note 7 (Forest Green, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + AI Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor
1832	Infinix Note 7 (Bolivia Blue, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + AI Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor
1833	Infinix Note 7 (Aether Black, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + AI Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor
1834	Infinix Zero 8i (Silver Diamond, 128 GB)	4.2	7,117	8 GB RAM	128 GB ROM	48MP + 8MP + 2MP + AI Lens Camera	16MP + 8MP Dual Front Camera	4500 mAh	MediaTek Helio G90T Processor
1835	Infinix S5 (Quetzal Cyan, 64 GB)	4.3	15,701	4 GB RAM	64 GB ROM	16MP + 5MP + 2MP + Low Light Sensor	32MP Front Camera	4000 mAh	Helio P22 (MTK6762) Processor

1836 rows × 11 columns

In [231]:

```
b=a.dropna()
b
```

Out[231]:

	Phone Name	Rating ?/5	Number of Ratings	RAM	ROM/Storage	Back/Rare Camera	Front Camera	Battery	Processor
0	POCO C50 (Royal Blue, 32 GB)	4.2	33,561	2 GB RAM	32 GB ROM	8MP Dual Camera	5MP Front Camera	5000 mAh	Mediatek Helio A22 Processor, Upto 2.0 GHz Pro...
1	POCO M4 5G (Cool Blue, 64 GB)	4.2	77,128	4 GB RAM	64 GB ROM	50MP + 2MP	8MP Front Camera	5000 mAh	Mediatek Dimensity 700 Processor
2	POCO C51 (Royal Blue, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor
3	POCO C55 (Cool Blue, 64 GB)	4.2	22,621	4 GB RAM	64 GB ROM	50MP Dual Rear Camera	5MP Front Camera	5000 mAh	Mediatek Helio G85 Processor
4	POCO C51 (Power Black, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor
...	...	...	...	...	...	...	...	...	...
1831	Infinix Note 7 (Forest Green, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + AI Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor
1832	Infinix Note 7 (Bolivia Blue, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + AI Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor
1833	Infinix Note 7 (Aether Black, 64 GB)	4.3	25,582	4 GB RAM	64 GB ROM	48MP + 2MP + 2MP + AI Lens Camera	16MP Front Camera	5000 mAh	MediaTek Helio G70 Processor
1834	Infinix Zero 8i (Silver Diamond, 128 GB)	4.2	7,117	8 GB RAM	128 GB ROM	48MP + 8MP + 2MP + AI Lens Camera	16MP + 8MP Dual Front Camera	4500 mAh	MediaTek Helio G90T Processor
1835	Infinix S5 (Quetzal Cyan, 64 GB)	4.3	15,701	4 GB RAM	64 GB ROM	16MP + 5MP + 2MP + Low Light Sensor	32MP Front Camera	4000 mAh	Helio P22 (MTK6762) Processor

1291 rows × 11 columns

In [232]:

```
c=b.head(10)
c
```

Out[232]:

	Phone Name	Rating ?/5	Number of Ratings	RAM	ROM/Storage	Back/Rare Camera	Front Camera	Battery	Processor	Pri
0	POCO C50 (Royal Blue, 32 GB)	4.2	33,561	2 GB RAM	32 GB ROM	8MP Dual Camera	5MP Front Camera	5000 mAh	Mediatek Helio A22 Processor, Upto 2.0 GHz Pro...	₹5
1	POCO M4 5G (Cool Blue, 64 GB)	4.2	77,128	4 GB RAM	64 GB ROM	50MP + 2MP	8MP Front Camera	5000 mAh	Mediatek Dimensity 700 Processor	₹11
2	POCO C51 (Royal Blue, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor	₹6
3	POCO C55 (Cool Blue, 64 GB)	4.2	22,621	4 GB RAM	64 GB ROM	50MP Dual Rear Camera	5MP Front Camera	5000 mAh	Mediatek Helio G85 Processor	₹7
4	POCO C51 (Power Black, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor	₹6
5	POCO M4 5G (Power Black, 64 GB)	4.2	77,128	4 GB RAM	64 GB ROM	50MP + 2MP	8MP Front Camera	5000 mAh	Mediatek Dimensity 700 Processor	₹11
6	POCO C55 (Power Black, 64 GB)	4.2	22,621	4 GB RAM	64 GB ROM	50MP Dual Rear Camera	5MP Front Camera	5000 mAh	Mediatek Helio G85 Processor	₹7
7	POCO C55 (Forest Green, 64 GB)	4.2	22,621	4 GB RAM	64 GB ROM	50MP Dual Rear Camera	5MP Front Camera	5000 mAh	Mediatek Helio G85 Processor	₹7
8	POCO C55 (Cool Blue, 128 GB)	4.1	13,647	6 GB RAM	128 GB ROM	50MP Dual Rear Camera	5MP Front Camera	5000 mAh	Mediatek Helio G85 Processor	₹9
9	POCO M4 5G (Yellow, 128 GB)	4.2	40,525	6 GB RAM	128 GB ROM	50MP + 2MP	8MP Front Camera	5000 mAh	Mediatek Dimensity 700 Processor	₹13

In [233]:

```
a.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1836 entries, 0 to 1835
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Phone Name         1836 non-null   object 
 1   Rating ?/5         1836 non-null   float64
 2   Number of Ratings  1836 non-null   object 
 3   RAM                1836 non-null   object 
 4   ROM/Storage        1662 non-null   object 
 5   Back/Rare Camera   1827 non-null   object 
 6   Front Camera       1435 non-null   object 
 7   Battery            1826 non-null   object 
 8   Processor          1781 non-null   object 
 9   Price in INR       1836 non-null   object 
 10  Date of Scraping   1836 non-null   object 
dtypes: float64(1), object(10)
memory usage: 157.9+ KB
```

In [234]:

```
a.describe()
```

Out[234]:

	Rating ?/5
count	1836.000000
mean	4.210512
std	0.543912
min	0.000000
25%	4.200000
50%	4.300000
75%	4.400000
max	4.800000

In [235]:

```
a.columns
```

Out[235]:

```
Index(['Phone Name', 'Rating ?/5', 'Number of Ratings', 'RAM', 'ROM/Storag
e',
       'Back/Rare Camera', 'Front Camera', 'Battery', 'Processor',
       'Price in INR', 'Date of Scraping'],
      dtype='object')
```

In [236]:

```
d=c[['Rating ?/5', 'Number of Ratings']]
d
```

Out[236]:

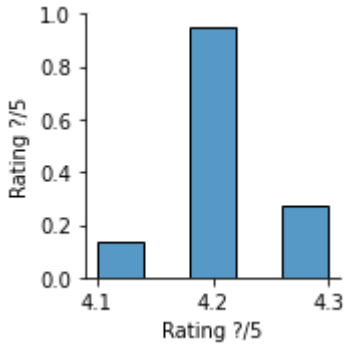
	Rating ?/5	Number of Ratings
0	4.2	33,561
1	4.2	77,128
2	4.3	15,175
3	4.2	22,621
4	4.3	15,175
5	4.2	77,128
6	4.2	22,621
7	4.2	22,621
8	4.1	13,647
9	4.2	40,525

In [237]:

```
sns.pairplot(d)
```

Out[237]:

```
<seaborn.axisgrid.PairGrid at 0x202d3f60a60>
```



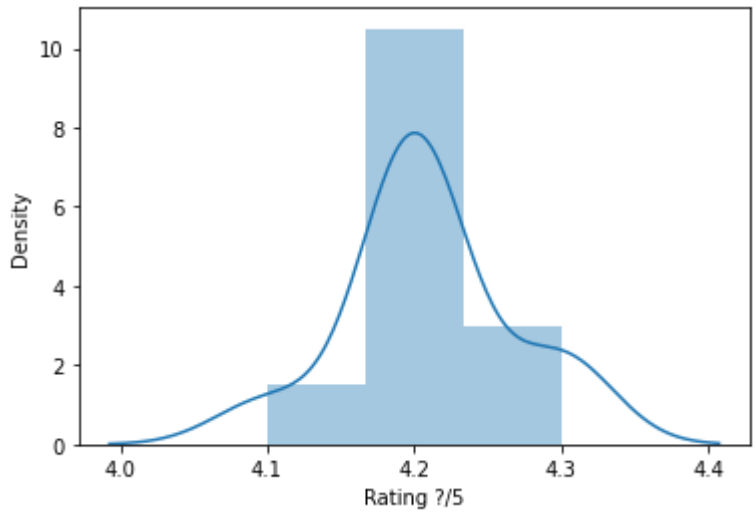
In [238]:

```
sns.distplot(d['Rating ?/5'])
```

```
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 adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[238]:

```
<AxesSubplot:xlabel='Rating ?/5', ylabel='Density'>
```



In [239]:

```
sns.heatmap(d.corr())
```

Out[239]:

```
<AxesSubplot:>
```

In [240]:

```
x=c[['Rating ?/5']]
y=c['Rating ?/5']
```

In [241]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [242]:

```
lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[242]:

```
LinearRegression()
```

In [243]:

```
print(lr.intercept_)
```

```
1.7763568394002505e-15
```

In [244]:

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

Out[244]:

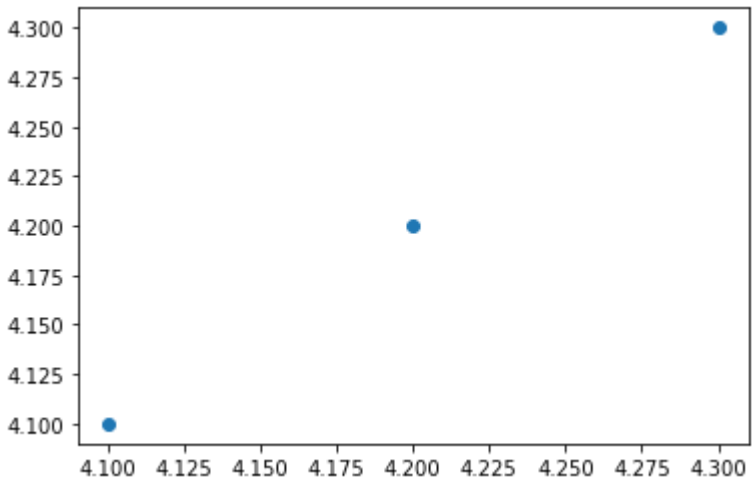
	Co-efficient
Rating ?/5	1.0

In [245]:

```
prediction=lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[245]:

```
<matplotlib.collections.PathCollection at 0x202d41669a0>
```



In [246]:

```
print(lr.score(x_test,y_test))
```

```
1.0
```

In [247]:

```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[247]:

```
Ridge(alpha=10)
```

In [248]:

```
rr.score(x_test,y_test)
```

Out[248]:

```
-0.028847750009799222
```

In [249]:

```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[249]:

```
Lasso(alpha=10)
```

In [250]:

```
la.score(x_test,y_test)
```

Out[250]:

```
-0.030612244897960217
```

In [251]:

```
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[251]:

```
ElasticNet()
```

In [252]:

```
print(en.coef_)
```

```
[0.]
```

In [253]:

```
print(en.intercept_)
```

```
4.214285714285714
```

In [254]:

```
prediction=en.predict(x_test)
print(en.score(x_test,y_test))
```

```
-0.030612244897960217
```

Evaluation Metrics

In [255]:

```
print('Mean Absolute Error:',metrics.mean_absolute_error(y_test,prediction))
```

```
Mean Absolute Error: 0.07142857142857147
```

In [256]:

```
print("mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
mean Squared Error: 0.006870748299319746
```

In [257]:

```
print("Root mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
Root mean Squared Error: 0.08288997707394873
```

10. DataSet Placement

In [258]:

```
a=pd.read_csv(r"C:\Users\user\Downloads\13_placement.csv")
a
```

Out[258]:

	cgpa	placement_exam_marks	placed
0	7.19	26.0	1
1	7.46	38.0	1
2	7.54	40.0	1
3	6.42	8.0	1
4	7.23	17.0	0
...	...	...	...
995	8.87	44.0	1
996	9.12	65.0	1
997	4.89	34.0	0
998	8.62	46.0	1
999	4.90	10.0	1

1000 rows × 3 columns

In [259]:

```
b=a.head(10)
b
```

Out[259]:

	cgpa	placement_exam_marks	placed
0	7.19	26.0	1
1	7.46	38.0	1
2	7.54	40.0	1
3	6.42	8.0	1
4	7.23	17.0	0
5	7.30	23.0	1
6	6.69	11.0	0
7	7.12	39.0	1
8	6.45	38.0	0
9	7.75	94.0	1

In [260]:

```
a.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 3 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   cgpa                  1000 non-null   float64
 1   placement_exam_marks  1000 non-null   float64
 2   placed                1000 non-null   int64  
dtypes: float64(2), int64(1)
memory usage: 23.6 KB
```

In [261]:

```
a.describe()
```

Out[261]:

	cgpa	placement_exam_marks	placed
count	1000.000000	1000.000000	1000.000000
mean	6.961240	32.225000	0.489000
std	0.615898	19.130822	0.500129
min	4.890000	0.000000	0.000000
25%	6.550000	17.000000	0.000000
50%	6.960000	28.000000	0.000000
75%	7.370000	44.000000	1.000000
max	9.120000	100.000000	1.000000

In [262]:

```
a.columns
```

Out[262]:

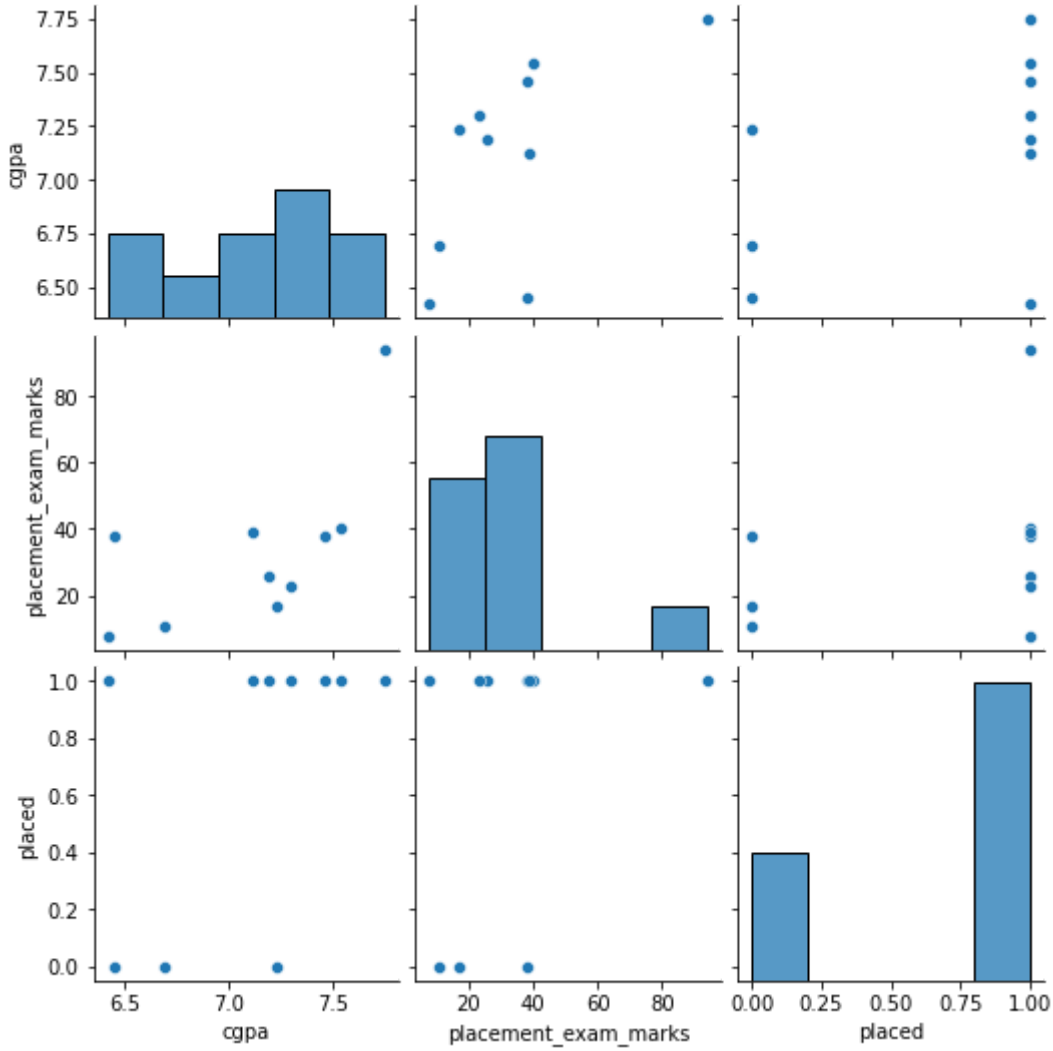
```
Index(['cgpa', 'placement_exam_marks', 'placed'], dtype='object')
```

In [263]:

```
sns.pairplot(b)
```

Out[263]:

```
<seaborn.axisgrid.PairGrid at 0x202d41b8a30>
```



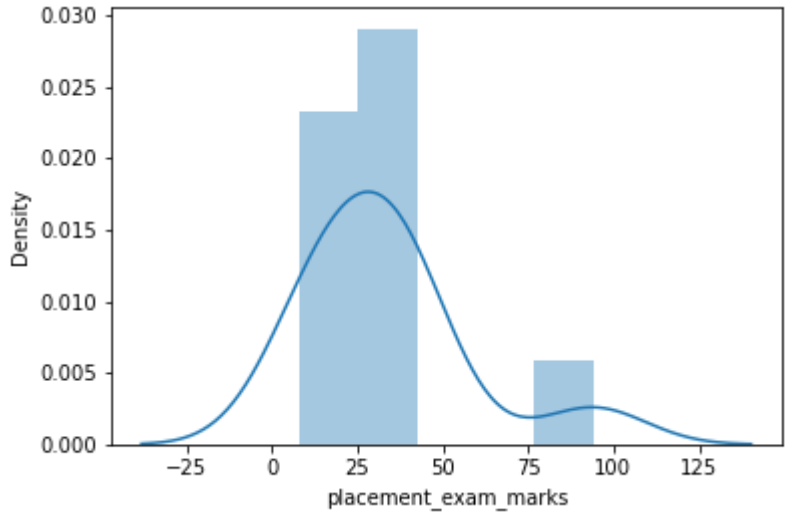
In [264]:

```
sns.distplot(b['placement_exam_marks'])
```

```
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 adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[264]:

```
<AxesSubplot:xlabel='placement_exam_marks', ylabel='Density'>
```

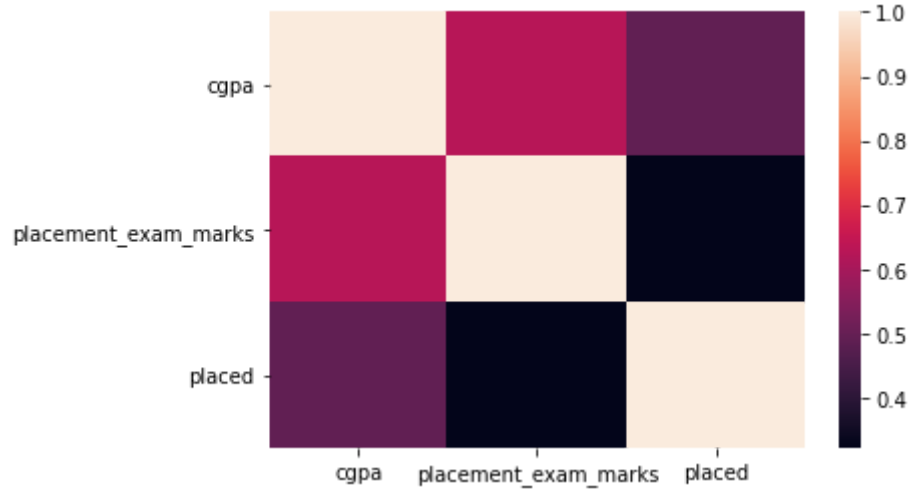


In [265]:

```
sns.heatmap(b.corr())
```

Out[265]:

```
<AxesSubplot:>
```



In [266]:

```
x=b[['cgpa', 'placement_exam_marks', 'placed']]
y=b['cgpa']
```

In [267]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [268]:

```
lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[268]:

```
LinearRegression()
```

In [269]:

```
print(lr.intercept_)
```

```
-4.440892098500626e-15
```

In [270]:

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

Out[270]:

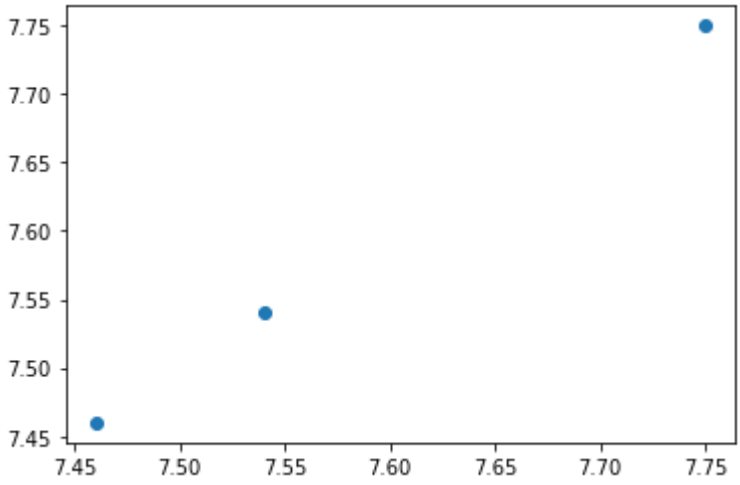
	Co-efficient
cgpa	1.000000e+00
placement_exam_marks	3.954327e-18
placed	-1.525863e-16

In [271]:

```
prediction=lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[271]:

```
<matplotlib.collections.PathCollection at 0x202d48a56d0>
```



In [272]:

```
print(lr.score(x_test,y_test))
```

```
1.0
```

In [273]:

```
rr=Ridge(alpha=15)
rr.fit(x_train,y_train)
```

Out[273]:

```
Ridge(alpha=15)
```

In [274]:

```
rr.score(x_test,y_test)
```

Out[274]:

```
-11.863193559697113
```

In [275]:

```
la=Lasso(alpha=20)
la.fit(x_train,y_train)
```

Out[275]:

```
Lasso(alpha=20)
```

In [276]:

```
la.score(x_test,y_test)
```

Out[276]:

```
-29.9303302301603
```

In [277]:

```
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[277]:

```
ElasticNet()
```

In [278]:

```
print(en.coef_)
```

```
[0.         0.00207681 0.        ]
```

In [279]:

```
print(en.intercept_)
```

```
6.866222469587343
```

In [280]:

```
prediction=en.predict(x_test)
print(en.score(x_test,y_test))
```

```
-23.252393153670212
```

Evaluation Metrics ¶

In [281]:

```
print('Mean Absolute Error:',metrics.mean_absolute_error(y_test,prediction))
```

```
Mean Absolute Error: 0.5980406032175128
```

In [282]:

```
print("mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
mean Squared Error: 0.3627080131648901
```

In [283]:

```
print("Root mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
Root mean Squared Error: 0.6022524496960474
```