

cryfrziyi

October 4, 2024

```
[82]: import pandas as pd
df=pd.read_csv("smartphones.csv")
df.head()
```

```
[82]:
```

	Smartphone	Brand	Model	\
0	Realme C55 8/256GB Sunshower Libre	Realme	C55	
1	Samsung Galaxy M23 5G 4/128GB Azul Libre	Samsung	Galaxy M23	
2	Motorola Moto G13 4/128GB Azul Lavanda Libre	Motorola	Moto G13	
3	Xiaomi Redmi Note 11S 6/128GB Gris Libre	Xiaomi	Redmi Note 11S	
4	Nothing Phone (2) 12/512GB Blanco Libre	Nothing	Phone (2)	

	RAM	Storage	Color	Free	Final Price
0	8.0	256.0	Yellow	Yes	231.60
1	4.0	128.0	Blue	Yes	279.00
2	4.0	128.0	Blue	Yes	179.01
3	6.0	128.0	Gray	Yes	279.99
4	12.0	512.0	White	Yes	799.00

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[ ]:
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[ ]:
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```
[83]: df.isnull().sum()
```

```
[83]: Smartphone      0
Brand              0
Model              0
RAM               483
Storage            25
Color              0
Free              0
Final Price        0
dtype: int64
```

```
[84]: d=df['RAM'].median()
df["RAM"]=df["RAM"].fillna(d)
```

```
[85]: d=df['Storage'].median()
df["Storage"]=df["Storage"].fillna(d)
```

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[ ]:
```

```
[86]: df=df.drop("Free",axis=1)
df=df.drop("Smartphone",axis=1)
```

```
[87]: df.rename(columns={'Final Price':'Final_Price'},inplace=True)
df.head()
```

```
[87]:
```

	Brand	Model	RAM	Storage	Color	Final_Price
0	Realme	C55	8.0	256.0	Yellow	231.60
1	Samsung	Galaxy M23	4.0	128.0	Blue	279.00
2	Motorola	Moto G13	4.0	128.0	Blue	179.01
3	Xiaomi	Redmi Note 11S	6.0	128.0	Gray	279.99
4	Nothing	Phone (2)	12.0	512.0	White	799.00

```
[88]: from sklearn.preprocessing import LabelEncoder
l=LabelEncoder()
df["Model"]=l.fit_transform(df["Model"])
df.head()
```

```
[88]:
```

	Brand	Model	RAM	Storage	Color	Final_Price
0	Realme	104	8.0	256.0	Yellow	231.60
1	Samsung	162	4.0	128.0	Blue	279.00
2	Motorola	220	4.0	128.0	Blue	179.01
3	Xiaomi	301	6.0	128.0	Gray	279.99
4	Nothing	268	12.0	512.0	White	799.00

```
[88]: from sklearn.preprocessing import LabelEncoder
l=LabelEncoder()
df["Model"]=l.fit_transform(df["Model"])
df.head()
```

```
[88]:
```

	Brand	Model	RAM	Storage	Color	Final_Price
0	Realme	104	8.0	256.0	Yellow	231.60
1	Samsung	162	4.0	128.0	Blue	279.00
2	Motorola	220	4.0	128.0	Blue	179.01
3	Xiaomi	301	6.0	128.0	Gray	279.99
4	Nothing	268	12.0	512.0	White	799.00

```
[89]: from sklearn.preprocessing import LabelEncoder
l=LabelEncoder()
df["Brand"]=l.fit_transform(df["Brand"])
df.head()
```

```
[89]:
```

	Brand	Model	RAM	Storage	Color	Final_Price
0	27	104	8.0	256.0	Yellow	231.60
1	29	162	4.0	128.0	Blue	279.00
2	20	220	4.0	128.0	Blue	179.01
3	35	301	6.0	128.0	Gray	279.99
4	22	268	12.0	512.0	White	799.00

```
[90]: from sklearn.preprocessing import LabelEncoder
l=LabelEncoder()
df["Color"]=l.fit_transform(df["Color"])
df.head()
```

```
[90]:
```

	Brand	Model	RAM	Storage	Color	Final_Price
0	27	104	8.0	256.0	16	231.60
1	29	162	4.0	128.0	1	279.00
2	20	220	4.0	128.0	1	179.01
3	35	301	6.0	128.0	6	279.99
4	22	268	12.0	512.0	15	799.00

```
[91]: df.corr()
```

```
[91]:
```

	Brand	Model	RAM	Storage	Color	Final_Price
Brand	1.000000	-0.390551	0.008972	-0.207144	-0.066083	-0.282915
Model	-0.390551	1.000000	0.020172	0.190821	0.104543	0.202905
RAM	0.008972	0.020172	1.000000	0.413640	0.064912	0.442088
Storage	-0.207144	0.190821	0.413640	1.000000	0.088489	0.696851
Color	-0.066083	0.104543	0.064912	0.088489	1.000000	0.129461
Final_Price	-0.282915	0.202905	0.442088	0.696851	0.129461	1.000000

```
[92]: x=df[["Storage"]]
y=df.Final_Price
```

```
[93]: from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=2)
```

```
[94]: from sklearn.linear_model import LinearRegression
la=LinearRegression()
la.fit(x_train,y_train)
```

```
[94]: LinearRegression()
```

```
[95]: ypred=la.predict(x_test)
print(ypred)
```

```
[ 420.74811292  420.74811292  420.74811292  420.74811292  672.92877511
 420.74811292  420.74811292  672.92877511  420.74811292  420.74811292
 672.92877511  672.92877511  294.65778182  294.65778182  294.65778182]
```

420.74811292	420.74811292	672.92877511	294.65778182	672.92877511
420.74811292	294.65778182	672.92877511	294.65778182	294.65778182
420.74811292	294.65778182	420.74811292	294.65778182	420.74811292
420.74811292	672.92877511	420.74811292	672.92877511	672.92877511
672.92877511	294.65778182	2138.72887411	420.74811292	420.74811292
420.74811292	672.92877511	1177.2900995	420.74811292	294.65778182
294.65778182	420.74811292	420.74811292	420.74811292	420.74811292
231.61261628	294.65778182	294.65778182	672.92877511	294.65778182
420.74811292	420.74811292	420.74811292	672.92877511	420.74811292
672.92877511	420.74811292	2138.72887411	1177.2900995	294.65778182
1177.2900995	420.74811292	420.74811292	231.61261628	672.92877511
174.477935	672.92877511	420.74811292	420.74811292	420.74811292
420.74811292	420.74811292	294.65778182	672.92877511	420.74811292
420.74811292	1177.2900995	200.0900335	672.92877511	294.65778182
420.74811292	231.61261628	420.74811292	420.74811292	1177.2900995
420.74811292	420.74811292	672.92877511	420.74811292	184.32874212
1177.2900995	294.65778182	231.61261628	420.74811292	672.92877511
294.65778182	672.92877511	294.65778182	672.92877511	420.74811292
231.61261628	420.74811292	420.74811292	672.92877511	294.65778182
420.74811292	294.65778182	672.92877511	420.74811292	420.74811292
420.74811292	420.74811292	294.65778182	420.74811292	420.74811292
420.74811292	420.74811292	172.50777358	420.74811292	672.92877511
672.92877511	420.74811292	672.92877511	420.74811292	1177.2900995
672.92877511	294.65778182	420.74811292	420.74811292	420.74811292
420.74811292	420.74811292	420.74811292	420.74811292	672.92877511
294.65778182	672.92877511	294.65778182	1177.2900995	420.74811292
294.65778182	294.65778182	672.92877511	420.74811292	420.74811292
420.74811292	294.65778182	672.92877511	294.65778182	1177.2900995
420.74811292	420.74811292	1177.2900995	294.65778182	420.74811292
420.74811292	231.61261628	420.74811292	672.92877511	231.61261628
294.65778182	672.92877511	1177.2900995	420.74811292	672.92877511
420.74811292	672.92877511	672.92877511	294.65778182	420.74811292
672.92877511	420.74811292	420.74811292	184.32874212	420.74811292
1177.2900995	294.65778182	420.74811292	1177.2900995	294.65778182
294.65778182	420.74811292	420.74811292	420.74811292	294.65778182
420.74811292	420.74811292	672.92877511	420.74811292	420.74811292
420.74811292	420.74811292	672.92877511	231.61261628	2138.72887411
672.92877511	231.61261628	672.92877511	420.74811292	420.74811292
231.61261628	420.74811292	420.74811292	294.65778182	231.61261628
420.74811292	1177.2900995	420.74811292	672.92877511	420.74811292
420.74811292	420.74811292	294.65778182	294.65778182	294.65778182
420.74811292	420.74811292	420.74811292	672.92877511	294.65778182
231.61261628	420.74811292	1177.2900995	420.74811292	672.92877511
420.74811292	420.74811292	1177.2900995	672.92877511	294.65778182
294.65778182	420.74811292	420.74811292	294.65778182	231.61261628
294.65778182	672.92877511	1177.2900995	672.92877511	672.92877511
231.61261628	231.61261628	294.65778182	672.92877511	420.74811292
672.92877511	294.65778182	672.92877511	672.92877511	294.65778182

```

672.92877511 294.65778182 672.92877511 672.92877511 672.92877511
294.65778182 200.0900335 294.65778182 420.74811292 294.65778182
672.92877511 231.61261628 672.92877511 294.65778182 231.61261628
294.65778182 672.92877511 420.74811292 2138.72887411 420.74811292
672.92877511 294.65778182 672.92877511 420.74811292 294.65778182
294.65778182 294.65778182 420.74811292 672.92877511 672.92877511
672.92877511 294.65778182 420.74811292 420.74811292 420.74811292
420.74811292 231.61261628 294.65778182 672.92877511 294.65778182
420.74811292 420.74811292 420.74811292 420.74811292 294.65778182
672.92877511 420.74811292 420.74811292 231.61261628 420.74811292
420.74811292 672.92877511 672.92877511 420.74811292 420.74811292
420.74811292 672.92877511 294.65778182 420.74811292 420.74811292
420.74811292 294.65778182 294.65778182 294.65778182 294.65778182
294.65778182 420.74811292 294.65778182 294.65778182 672.92877511
420.74811292 294.65778182 231.61261628 200.0900335 420.74811292
294.65778182 420.74811292 672.92877511 420.74811292 231.61261628
420.74811292 672.92877511 420.74811292 420.74811292 1177.2900995
294.65778182 294.65778182 420.74811292 231.61261628 672.92877511
672.92877511 420.74811292 294.65778182 231.61261628 672.92877511
420.74811292 294.65778182 420.74811292 672.92877511 420.74811292
420.74811292 294.65778182 231.61261628 420.74811292 294.65778182
420.74811292 420.74811292 294.65778182 420.74811292]

```

```

[96]: from sklearn.metrics import mean_absolute_error, r2_score
      a=r2_score(y_test, ypred)
      a.

```

[96]: 0.5355034837506185

[]:

1 multiple regression

```

[97]: x=df[["Storage", "RAM", "Brand"]]
      y=df.Final_Price

```

```

[98]: from sklearn.model_selection import train_test_split
      x_train, x_test, y_train, y_test=train_test_split(x, y, test_size=0.2, random_state=2)

```

```

[99]: from sklearn.linear_model import LinearRegression
      la=LinearRegression()
      la.fit(x_train, y_train)

```

[99]: LinearRegression()

```
[100]: yped=la.predict(x_test)
print(yped)
```

```
[ 362.0185266  397.62692805  397.62692805  362.0185266  601.60900483
 285.80598123  397.62692805  767.78154492  451.03953022  509.44787486
 677.82155019  865.85504237  260.02748821  145.70867016  295.63588966
 397.62692805  321.41438268  677.82155019  145.70867016  677.82155019
 438.23107196  183.81494284  684.69527488  183.81494284  295.63588966
 397.62692805  219.42334429  321.41438268  145.70867016  563.79946815
 379.82272732  654.08261589  303.61018196  677.82155019  677.82155019
 842.11610807  237.22754502  1787.2548261  397.62692805  321.41438268
 626.26456414  871.78977595  1279.7539295  397.62692805  260.02748821
 183.81494284  285.80598123  397.62692805  285.80598123  285.80598123
 100.64788454  219.42334429  367.79168367  601.60900483  295.63588966
 357.02278413  563.79946815  509.44787486  677.82155019  397.62692805
 701.56048449  333.28384983  1953.4273662  1175.74569848  320.31381507
1175.74569848  321.41438268  556.92574346  130.32155242  842.11610807
 281.51195124  871.78977595  321.41438268  444.16580554  563.79946815
 563.79946815  563.79946815  228.79494021  713.42995164  333.28384983
 362.0185266  1175.74569848  42.97858584  677.82155019  183.81494284
 563.79946815  130.32155242  438.23107196  563.79946815  1175.74569848
 367.95326017  333.28384983  731.23415237  473.83947341  236.06739894
1175.74569848  260.02748821  272.75515821  473.83947341  767.78154492
 461.80842976  853.98557522  260.02748821  642.21314874  397.62692805
 94.71315097  438.23107196  285.80598123  642.21314874  243.16227859
 321.41438268  255.03174574  677.82155019  397.62692805  527.25207559
 285.80598123  397.62692805  295.63588966  303.61018196  362.0185266
 409.4963952  563.79946815  351.13514417  362.0185266  830.24664092
 677.82155019  473.83947341  806.50770662  473.83947341  1009.57315838
 601.60900483  231.29281144  285.80598123  480.7131981  485.70894056
 438.23107196  279.87124766  362.0185266  285.80598123  767.78154492
 272.83594647  767.78154492  461.80842976  1009.57315838  321.41438268
 183.81494284  260.02748821  865.85504237  397.62692805  397.62692805
 362.0185266  461.80842976  660.95634058  219.42334429  1175.74569848
 444.16580554  438.23107196  1175.74569848  145.70867016  574.72994419
 556.92574346  154.06048672  362.0185266  642.21314874  142.19101957
 145.70867016  859.9203088  1175.74569848  397.62692805  731.23415237
 397.62692805  642.21314874  601.60900483  349.98748294  563.79946815
 601.60900483  485.70894056  497.57840771  236.06739894  285.80598123
1238.21079448  349.98748294  438.23107196  1009.57315838  183.81494284
 243.16227859  626.26456414  486.64793167  374.82698486  255.03174574
 409.4963952  362.0185266  642.21314874  486.64793167  333.28384983
 473.83947341  397.62692805  859.9203088  56.60687828  1953.4273662
 642.21314874  142.19101957  767.78154492  397.62692805  626.26456414
 50.67214471  527.25207559  404.50065273  145.70867016  225.27728961
 362.0185266  1175.74569848  473.83947341  767.78154492  421.36586235
 404.50065273  480.7131981  183.81494284  231.29281144  183.81494284]
```

438.23107196	563.79946815	509.44787486	677.82155019	467.74316333
56.60687828	285.80598123	1009.57315838	509.44787486	859.9203088
473.83947341	410.43538631	1009.57315838	601.60900483	461.80842976
461.80842976	438.23107196	374.82698486	219.42334429	225.27728961
219.42334429	677.82155019	1009.57315838	830.24664092	713.42995164
225.27728961	110.01948046	461.80842976	830.24664092	473.83947341
701.56048449	461.80842976	601.60900483	642.21314874	125.4065982
766.84255382	461.80842976	865.85504237	865.85504237	767.78154492
367.79168367	253.19213219	260.02748821	556.92574346	255.03174574
601.60900483	225.27728961	642.21314874	183.81494284	130.32155242
243.16227859	601.60900483	397.62692805	1953.4273662	473.83947341
767.78154492	231.29281144	642.21314874	485.70894056	219.42334429
195.68440999	195.68440999	291.74071481	642.21314874	767.78154492
865.85504237	308.44434792	473.83947341	438.23107196	563.79946815
397.62692805	410.81291056	295.63588966	654.08261589	125.4065982
563.79946815	528.1910667	563.79946815	404.50065273	219.42334429
713.42995164	397.62692805	528.1910667	94.71315097	397.62692805
485.70894056	767.78154492	601.60900483	451.03953022	421.36586235
397.62692805	767.78154492	145.70867016	480.7131981	397.62692805
503.51314129	183.81494284	461.80842976	231.29281144	461.80842976
295.63588966	563.79946815	367.79168367	183.81494284	901.46344382
563.79946815	231.29281144	199.04048408	225.07734444	473.83947341
295.63588966	321.41438268	853.98557522	545.99526742	56.60687828
321.41438268	767.78154492	397.62692805	445.10479665	1175.74569848
367.79168367	349.98748294	397.62692805	410.81291056	767.78154492
601.60900483	362.0185266	219.42334429	266.82042464	842.11610807
622.20781279	183.81494284	321.41438268	601.60900483	397.62692805
485.70894056	260.02748821	74.41107901	492.58266525	195.68440999
433.2353295	473.83947341	195.68440999	438.23107196]	

```
[101]: from sklearn.metrics import mean_absolute_error, r2_score
a=r2_score(y_test, yped)
a
```

[101]: 0.5544441601000103

2 knn algo

```
[102]: from sklearn.neighbors import KNeighborsRegressor
kn=KNeighborsRegressor(n_neighbors=3, metric='euclidean')
kn.fit(x_train, y_train)
```

[102]: KNeighborsRegressor(metric='euclidean', n_neighbors=3)

yped=la.predict(x_test) print(yped)

```
[103]: from sklearn.metrics import mean_absolute_error, r2_score
a=r2_score(y_test, ypred)
a
```

```
[103]: 0.5544441601000103
```

3 svm alg

```
[104]: from sklearn.svm import LinearSVC, SVR
#sc=LinearSVC()
import warnings
warnings.simplefilter("ignore")
sc=SVR(kernel = "linear")
sc.fit(x_train, y_train)
```

```
[104]: SVR(kernel='linear')
```

```
[105]: ypred=la.predict(x_test)
print(ypred)
```

```
[ 362.0185266  397.62692805  397.62692805  362.0185266  601.60900483
 285.80598123  397.62692805  767.78154492  451.03953022  509.44787486
 677.82155019  865.85504237  260.02748821  145.70867016  295.63588966
 397.62692805  321.41438268  677.82155019  145.70867016  677.82155019
 438.23107196  183.81494284  684.69527488  183.81494284  295.63588966
 397.62692805  219.42334429  321.41438268  145.70867016  563.79946815
 379.82272732  654.08261589  303.61018196  677.82155019  677.82155019
 842.11610807  237.22754502  1787.2548261  397.62692805  321.41438268
 626.26456414  871.78977595  1279.7539295  397.62692805  260.02748821
 183.81494284  285.80598123  397.62692805  285.80598123  285.80598123
 100.64788454  219.42334429  367.79168367  601.60900483  295.63588966
 357.02278413  563.79946815  509.44787486  677.82155019  397.62692805
 701.56048449  333.28384983  1953.4273662  1175.74569848  320.31381507
 1175.74569848  321.41438268  556.92574346  130.32155242  842.11610807
 281.51195124  871.78977595  321.41438268  444.16580554  563.79946815
 563.79946815  563.79946815  228.79494021  713.42995164  333.28384983
 362.0185266  1175.74569848  42.97858584  677.82155019  183.81494284
 563.79946815  130.32155242  438.23107196  563.79946815  1175.74569848
 367.95326017  333.28384983  731.23415237  473.83947341  236.06739894
 1175.74569848  260.02748821  272.75515821  473.83947341  767.78154492
 461.80842976  853.98557522  260.02748821  642.21314874  397.62692805
 94.71315097  438.23107196  285.80598123  642.21314874  243.16227859
 321.41438268  255.03174574  677.82155019  397.62692805  527.25207559
 285.80598123  397.62692805  295.63588966  303.61018196  362.0185266
 409.4963952  563.79946815  351.13514417  362.0185266  830.24664092
 677.82155019  473.83947341  806.50770662  473.83947341  1009.57315838]
```


601.60900483	231.29281144	285.80598123	480.7131981	485.70894056
438.23107196	279.87124766	362.0185266	285.80598123	767.78154492
272.83594647	767.78154492	461.80842976	1009.57315838	321.41438268
183.81494284	260.02748821	865.85504237	397.62692805	397.62692805
362.0185266	461.80842976	660.95634058	219.42334429	1175.74569848
444.16580554	438.23107196	1175.74569848	145.70867016	574.72994419
556.92574346	154.06048672	362.0185266	642.21314874	142.19101957
145.70867016	859.9203088	1175.74569848	397.62692805	731.23415237
397.62692805	642.21314874	601.60900483	349.98748294	563.79946815
601.60900483	485.70894056	497.57840771	236.06739894	285.80598123
1238.21079448	349.98748294	438.23107196	1009.57315838	183.81494284
243.16227859	626.26456414	486.64793167	374.82698486	255.03174574
409.4963952	362.0185266	642.21314874	486.64793167	333.28384983
473.83947341	397.62692805	859.9203088	56.60687828	1953.4273662
642.21314874	142.19101957	767.78154492	397.62692805	626.26456414
50.67214471	527.25207559	404.50065273	145.70867016	225.27728961
362.0185266	1175.74569848	473.83947341	767.78154492	421.36586235
404.50065273	480.7131981	183.81494284	231.29281144	183.81494284
438.23107196	563.79946815	509.44787486	677.82155019	467.74316333
56.60687828	285.80598123	1009.57315838	509.44787486	859.9203088
473.83947341	410.43538631	1009.57315838	601.60900483	461.80842976
461.80842976	438.23107196	374.82698486	219.42334429	225.27728961
219.42334429	677.82155019	1009.57315838	830.24664092	713.42995164
225.27728961	110.01948046	461.80842976	830.24664092	473.83947341
701.56048449	461.80842976	601.60900483	642.21314874	125.4065982
766.84255382	461.80842976	865.85504237	865.85504237	767.78154492
367.79168367	253.19213219	260.02748821	556.92574346	255.03174574
601.60900483	225.27728961	642.21314874	183.81494284	130.32155242
243.16227859	601.60900483	397.62692805	1953.4273662	473.83947341
767.78154492	231.29281144	642.21314874	485.70894056	219.42334429
195.68440999	195.68440999	291.74071481	642.21314874	767.78154492
865.85504237	308.44434792	473.83947341	438.23107196	563.79946815
397.62692805	410.81291056	295.63588966	654.08261589	125.4065982
563.79946815	528.1910667	563.79946815	404.50065273	219.42334429
713.42995164	397.62692805	528.1910667	94.71315097	397.62692805
485.70894056	767.78154492	601.60900483	451.03953022	421.36586235
397.62692805	767.78154492	145.70867016	480.7131981	397.62692805
503.51314129	183.81494284	461.80842976	231.29281144	461.80842976
295.63588966	563.79946815	367.79168367	183.81494284	901.46344382
563.79946815	231.29281144	199.04048408	225.07734444	473.83947341
295.63588966	321.41438268	853.98557522	545.99526742	56.60687828
321.41438268	767.78154492	397.62692805	445.10479665	1175.74569848
367.79168367	349.98748294	397.62692805	410.81291056	767.78154492
601.60900483	362.0185266	219.42334429	266.82042464	842.11610807
622.20781279	183.81494284	321.41438268	601.60900483	397.62692805
485.70894056	260.02748821	74.41107901	492.58266525	195.68440999
433.2353295	473.83947341	195.68440999	438.23107196]	

```
[106]: from sklearn.metrics import mean_absolute_error, r2_score
a=r2_score(y_test, ypred)
a
```

[106]: 0.5544441601000103

4 Decision tree

```
[107]: from sklearn.tree import DecisionTreeRegressor
f=DecisionTreeRegressor()
f.fit(x, y)
```

[107]: DecisionTreeRegressor()

```
[108]: ypred=la.predict(x_test)
print(ypred)
```

```
[ 362.0185266   397.62692805  397.62692805  362.0185266   601.60900483
 285.80598123  397.62692805  767.78154492  451.03953022  509.44787486
 677.82155019  865.85504237  260.02748821  145.70867016  295.63588966
 397.62692805  321.41438268  677.82155019  145.70867016  677.82155019
 438.23107196  183.81494284  684.69527488  183.81494284  295.63588966
 397.62692805  219.42334429  321.41438268  145.70867016  563.79946815
 379.82272732  654.08261589  303.61018196  677.82155019  677.82155019
 842.11610807  237.22754502 1787.2548261   397.62692805  321.41438268
 626.26456414  871.78977595 1279.7539295   397.62692805  260.02748821
 183.81494284  285.80598123  397.62692805  285.80598123  285.80598123
 100.64788454  219.42334429  367.79168367  601.60900483  295.63588966
 357.02278413  563.79946815  509.44787486  677.82155019  397.62692805
 701.56048449  333.28384983 1953.4273662  1175.74569848  320.31381507
1175.74569848  321.41438268  556.92574346  130.32155242  842.11610807
 281.51195124  871.78977595  321.41438268  444.16580554  563.79946815
 563.79946815  563.79946815  228.79494021  713.42995164  333.28384983
 362.0185266  1175.74569848   42.97858584  677.82155019  183.81494284
 563.79946815  130.32155242  438.23107196  563.79946815 1175.74569848
 367.95326017  333.28384983  731.23415237  473.83947341  236.06739894
1175.74569848  260.02748821  272.75515821  473.83947341  767.78154492
 461.80842976  853.98557522  260.02748821  642.21314874  397.62692805
  94.71315097  438.23107196  285.80598123  642.21314874  243.16227859
 321.41438268  255.03174574  677.82155019  397.62692805  527.25207559
 285.80598123  397.62692805  295.63588966  303.61018196  362.0185266
 409.4963952   563.79946815  351.13514417  362.0185266   830.24664092
 677.82155019  473.83947341  806.50770662  473.83947341 1009.57315838
 601.60900483  231.29281144  285.80598123  480.7131981   485.70894056
 438.23107196  279.87124766  362.0185266   285.80598123  767.78154492
 272.83594647  767.78154492  461.80842976 1009.57315838  321.41438268
 183.81494284  260.02748821  865.85504237  397.62692805  397.62692805]
```

362.0185266	461.80842976	660.95634058	219.42334429	1175.74569848
444.16580554	438.23107196	1175.74569848	145.70867016	574.72994419
556.92574346	154.06048672	362.0185266	642.21314874	142.19101957
145.70867016	859.9203088	1175.74569848	397.62692805	731.23415237
397.62692805	642.21314874	601.60900483	349.98748294	563.79946815
601.60900483	485.70894056	497.57840771	236.06739894	285.80598123
1238.21079448	349.98748294	438.23107196	1009.57315838	183.81494284
243.16227859	626.26456414	486.64793167	374.82698486	255.03174574
409.4963952	362.0185266	642.21314874	486.64793167	333.28384983
473.83947341	397.62692805	859.9203088	56.60687828	1953.4273662
642.21314874	142.19101957	767.78154492	397.62692805	626.26456414
50.67214471	527.25207559	404.50065273	145.70867016	225.27728961
362.0185266	1175.74569848	473.83947341	767.78154492	421.36586235
404.50065273	480.7131981	183.81494284	231.29281144	183.81494284
438.23107196	563.79946815	509.44787486	677.82155019	467.74316333
56.60687828	285.80598123	1009.57315838	509.44787486	859.9203088
473.83947341	410.43538631	1009.57315838	601.60900483	461.80842976
461.80842976	438.23107196	374.82698486	219.42334429	225.27728961
219.42334429	677.82155019	1009.57315838	830.24664092	713.42995164
225.27728961	110.01948046	461.80842976	830.24664092	473.83947341
701.56048449	461.80842976	601.60900483	642.21314874	125.4065982
766.84255382	461.80842976	865.85504237	865.85504237	767.78154492
367.79168367	253.19213219	260.02748821	556.92574346	255.03174574
601.60900483	225.27728961	642.21314874	183.81494284	130.32155242
243.16227859	601.60900483	397.62692805	1953.4273662	473.83947341
767.78154492	231.29281144	642.21314874	485.70894056	219.42334429
195.68440999	195.68440999	291.74071481	642.21314874	767.78154492
865.85504237	308.44434792	473.83947341	438.23107196	563.79946815
397.62692805	410.81291056	295.63588966	654.08261589	125.4065982
563.79946815	528.1910667	563.79946815	404.50065273	219.42334429
713.42995164	397.62692805	528.1910667	94.71315097	397.62692805
485.70894056	767.78154492	601.60900483	451.03953022	421.36586235
397.62692805	767.78154492	145.70867016	480.7131981	397.62692805
503.51314129	183.81494284	461.80842976	231.29281144	461.80842976
295.63588966	563.79946815	367.79168367	183.81494284	901.46344382
563.79946815	231.29281144	199.04048408	225.07734444	473.83947341
295.63588966	321.41438268	853.98557522	545.99526742	56.60687828
321.41438268	767.78154492	397.62692805	445.10479665	1175.74569848
367.79168367	349.98748294	397.62692805	410.81291056	767.78154492
601.60900483	362.0185266	219.42334429	266.82042464	842.11610807
622.20781279	183.81494284	321.41438268	601.60900483	397.62692805
485.70894056	260.02748821	74.41107901	492.58266525	195.68440999
433.2353295	473.83947341	195.68440999	438.23107196]	

```
[109]: from sklearn.metrics import mean_absolute_error, r2_score
a=r2_score(y_test, ypred)
a
```

[109]: 0.5544441601000103

[]: