Importing necessary modules

In [1]:

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

import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
df = pd.read_csv("cars.csv")
df.head()
```

Out[2]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type
0	3	?	alfa-romero	gas	convertible	rwd	front	64.1	48.8	dohc
1	3	?	alfa-romero	gas	convertible	rwd	front	64.1	48.8	dohc
2	1	?	alfa-romero	gas	hatchback	rwd	front	65.5	52.4	ohcv
3	2	164	audi	gas	sedan	fwd	front	66.2	54.3	ohc
4	2	164	audi	gas	sedan	4wd	front	66.4	54.3	ohc

Exploratory Data Analysis

In [3]:

```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          205 non-null    int64  
 1   normalized-losses  205 non-null    object 
 2   make               205 non-null    object 
 3   fuel-type          205 non-null    object 
 4   body-style         205 non-null    object 
 5   drive-wheels       205 non-null    object 
 6   engine-location    205 non-null    object 
 7   width              205 non-null    float64
 8   height             205 non-null    float64
 9   engine-type        205 non-null    object 
 10  engine-size        205 non-null    int64  
 11  horsepower         205 non-null    object 
 12  city-mpg           205 non-null    int64  
 13  highway-mpg        205 non-null    int64  
 14  price              205 non-null    int64  
dtypes: float64(2), int64(5), object(8)
memory usage: 24.1+ KB
```

In [4]:

```
1 df.describe()
```

Out[4]:

	symboling	width	height	engine-size	city-mpg	highway-mpg	price
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000
mean	0.834146	65.907805	53.724878	126.907317	25.219512	30.751220	13227.478049
std	1.245307	2.145204	2.443522	41.642693	6.542142	6.886443	7902.651615
min	-2.000000	60.300000	47.800000	61.000000	13.000000	16.000000	5118.000000
25%	0.000000	64.100000	52.000000	97.000000	19.000000	25.000000	7788.000000
50%	1.000000	65.500000	54.100000	120.000000	24.000000	30.000000	10345.000000
75%	2.000000	66.900000	55.500000	141.000000	30.000000	34.000000	16500.000000
max	3.000000	72.300000	59.800000	326.000000	49.000000	54.000000	45400.000000

In [5]:

```
df.isna().sum()
```

Out[5]:

```
symboling            0
normalized-losses    0
make                 0
fuel-type            0
body-style           0
drive-wheels         0
engine-location      0
width                0
height               0
engine-type          0
engine-size          0
horsepower           0
city-mpg             0
highway-mpg          0
price                0
dtype: int64
```

In [6]:

```
df["horsepower"].value_counts()
```

Out[6]:

```
68     19
70     11
69     10
116     9
110     8
95      7
114     6
62      6
88      6
101     6
160     6
102     5
76      5
145     5
82      5
84      5
97      5
111     4
92      4
86      4
123     4
73      3
182     3
90      3
121     3
207     3
152     3
85      3
176     2
?       2
184     2
100     2
162     2
155     2
112     2
94      2
156     2
161     2
52      2
56      2
72      1
60      1
58      1
135     1
142     1
288     1
64      1
134     1
154     1
175     1
78      1
115     1
120     1
262     1
48      1
```

```
200     1
106     1
140     1
55      1
143     1
Name: horsepower, dtype: int64
```

In [7]:

```
df["normalized-losses"].value_counts()
```

Out[7]:

```
?      41
161    11
91      8
150     7
134     6
104     6
128     6
168     5
95      5
94      5
85      5
103     5
102     5
65      5
74      5
118     4
122     4
93      4
148     4
106     4
154     3
125     3
137     3
83      3
115     3
101     3
87      2
153     2
81      2
129     2
113     2
192     2
110     2
158     2
194     2
188     2
164     2
145     2
108     2
89      2
119     2
197     2
186     1
256     1
142     1
107     1
90      1
121     1
98      1
77      1
231     1
78      1
Name: normalized-losses, dtype: int64
```

In [8]:

```
#replacing the missing values with their mean value
df["horsepower"].replace("?", np.nan, inplace=True)
df["horsepower"] =df["horsepower"].astype("float")
npmean = df["horsepower"].mean()
df["horsepower"].fillna(npmean, inplace=True)
df["horsepower"].value_counts()
```

Out[8]:

```
68.000000     19
70.000000     11
69.000000     10
116.000000     9
110.000000     8
95.000000      7
88.000000      6
114.000000     6
62.000000      6
160.000000     6
101.000000     6
97.000000      5
102.000000     5
82.000000      5
76.000000      5
84.000000      5
145.000000     5
86.000000      4
111.000000     4
123.000000     4
92.000000      4
207.000000     3
85.000000      3
152.000000     3
73.000000      3
182.000000     3
121.000000     3
90.000000      3
56.000000      2
155.000000     2
162.000000     2
94.000000      2
52.000000      2
104.256158     2
176.000000     2
112.000000     2
100.000000     2
161.000000     2
156.000000     2
184.000000     2
288.000000     1
140.000000     1
175.000000     1
78.000000      1
48.000000      1
134.000000     1
120.000000     1
60.000000      1
```

```
106.000000     1
142.000000     1
58.000000      1
72.000000      1
64.000000      1
135.000000     1
262.000000     1
154.000000     1
143.000000     1
55.000000      1
200.000000     1
115.000000     1
Name: horsepower, dtype: int64
```

In [9]:

```
df["normalized-losses"].replace("?", np.nan, inplace=True)
df["normalized-losses"] =df["normalized-losses"].astype("float")
npmean = df["normalized-losses"].mean()
df["normalized-losses"].fillna(npmean, inplace=True)
df["normalized-losses"].value_counts()
```

Out[9]:

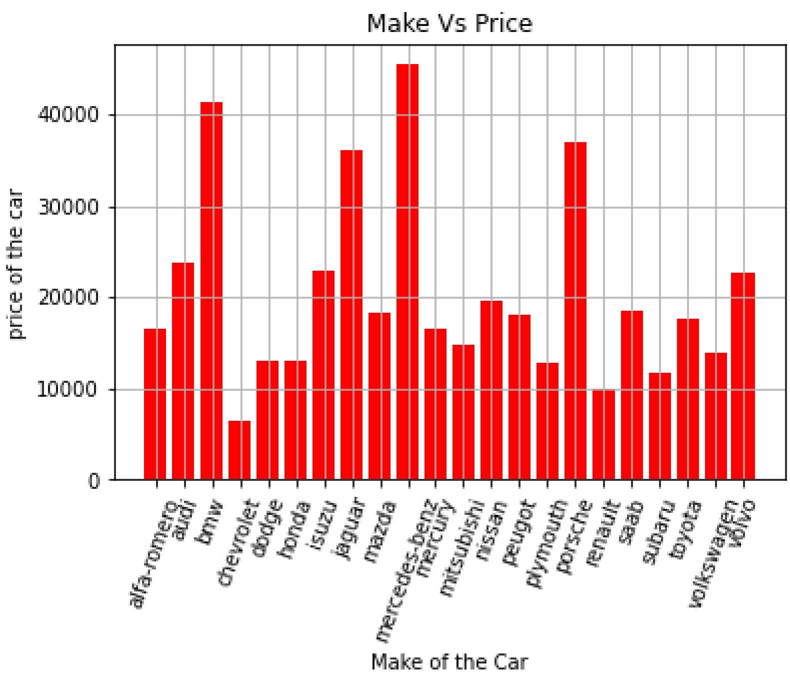
```
122.0    45
161.0    11
91.0      8
150.0     7
134.0     6
104.0     6
128.0     6
103.0     5
102.0     5
74.0      5
65.0      5
168.0     5
85.0      5
95.0      5
94.0      5
118.0     4
93.0      4
106.0     4
148.0     4
101.0     3
115.0     3
125.0     3
83.0      3
154.0     3
137.0     3
108.0     2
145.0     2
188.0     2
81.0      2
158.0     2
129.0     2
197.0     2
153.0     2
192.0     2
164.0     2
194.0     2
110.0     2
113.0     2
89.0      2
119.0     2
87.0      2
256.0     1
90.0      1
142.0     1
78.0      1
186.0     1
231.0     1
107.0     1
98.0      1
121.0     1
```

```
77.0      1
Name: normalized-losses, dtype: int64
```

Visualization of the Data

In [10]:

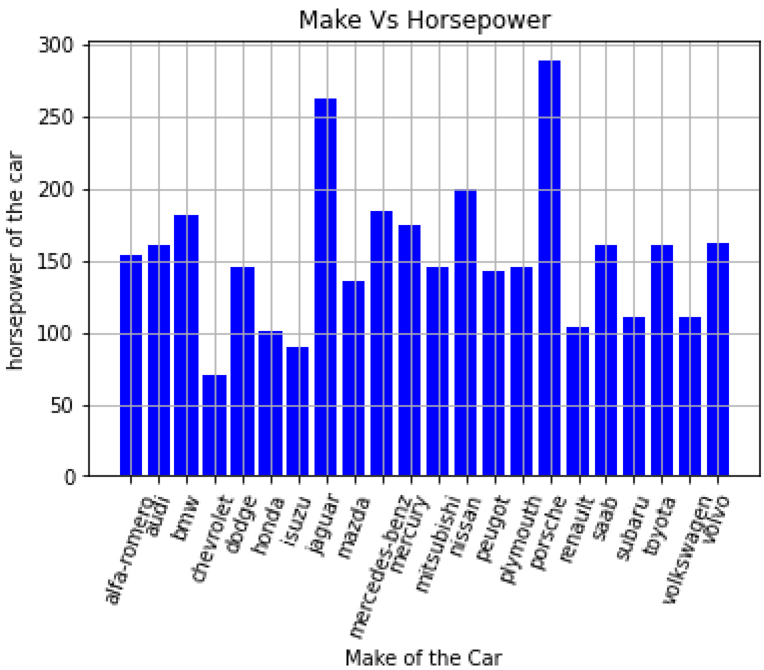
```python
plt.bar("make","price", data = df, color = "red")
plt.xticks(rotation=70)
plt.xlabel("Make of the Car")
plt.ylabel("price of the car")
plt.title("Make Vs Price")
plt.grid()
plt.show()
```



- By the above visualtization it is seen that Mercedes Benz has the highest price above $45000.
- BMW, Audi and Porsche comes after that

In [11]:

```
plt.bar("make","horsepower", data = df, color = "blue")
plt.xticks(rotation=70)
plt.xlabel("Make of the Car")
plt.ylabel("horsepower of the car")
plt.title("Make Vs Horsepower")
plt.grid()
plt.show()
```

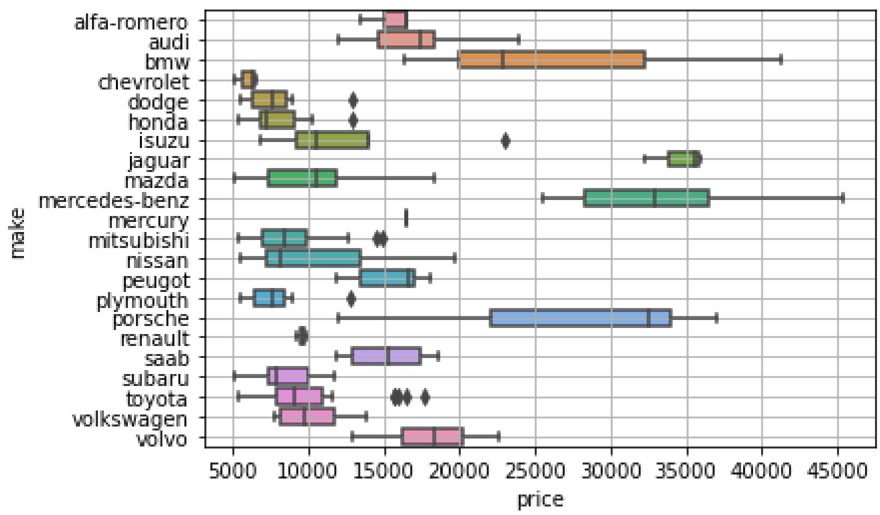


- By this Visulaization it shows that the Brand with Highest Horsepower are Porshce, Jaguar and BMWW

Handling the Outlier

In [12]:

```
sns.boxplot(data = df, x = "price", y = "make")
plt.grid(True)
```



In [13]:

```
df[(df["make"]=="dodge") & (df["price"]>11000)]
```

Out[13]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type
29	3	145.0	dodge	gas	hatchback	fwd	front	66.3	50.2	ohc

In [14]:

```
df[(df["make"]=="honda") & (df["price"]>11000)]
```

Out[14]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type	engi s
41	0	85.0	honda	gas	sedan	fwd	front	65.2	54.1	ohc	

In [15]:

```
df[(df["make"]=="mitsubishi") & (df["price"]>13000)]
```

Out[15]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine typ
83	3	122.0	mitsubishi	gas	hatchback	fwd	front	66.3	50.2	oh
84	3	122.0	mitsubishi	gas	hatchback	fwd	front	66.3	50.2	oh

In [16]:

```
df[(df["make"]=="isuzu") & (df["price"]>15000)]
```

Out[16]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type	engi s
45	0	122.0	isuzu	gas	sedan	fwd	front	63.6	52.0	ohc	

In [17]:

```
df[(df["make"]=="plymouth") & (df["price"]>10000)]
```

Out[17]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine typ
124	3	122.0	plymouth	gas	hatchback	rwd	front	66.3	50.2	oh

In [18]:

```
df[(df["make"]=="toyota") & (df["price"]>12000)]
```

Out[18]:

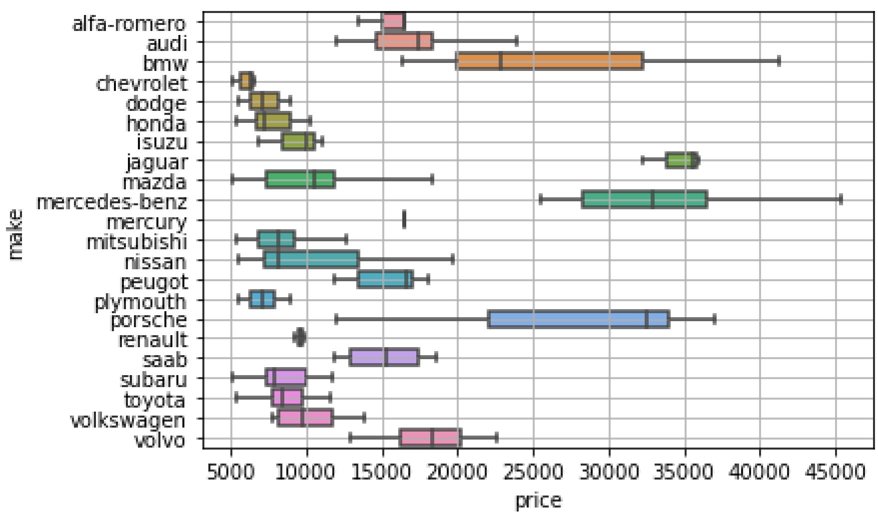
	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type
172	2	134.0	toyota	gas	convertible	rwd	front	65.6	53.0	ohc
178	3	197.0	toyota	gas	hatchback	rwd	front	67.7	52.0	dohc
179	3	197.0	toyota	gas	hatchback	rwd	front	67.7	52.0	dohc
180	-1	90.0	toyota	gas	sedan	rwd	front	66.5	54.1	dohc
181	-1	122.0	toyota	gas	wagon	rwd	front	66.5	54.1	dohc

In [19]:

```
df.drop([29,41,83,84,45,124,172,178,179,180,181], inplace = True)
```

In [20]:

```
sns.boxplot(data = df, x = "price", y = "make")
plt.grid(True)
```



In [21]:

```
df.head()
```

Out[21]:

	symboling	normalized-losses	make	fuel-type	body-style	drive-wheels	engine-location	width	height	engine-type
0	3	122.0	alfa-romero	gas	convertible	rwd	front	64.1	48.8	dohc
1	3	122.0	alfa-romero	gas	convertible	rwd	front	64.1	48.8	dohc
2	1	122.0	alfa-romero	gas	hatchback	rwd	front	65.5	52.4	ohcv
3	2	164.0	audi	gas	sedan	fwd	front	66.2	54.3	ohc
4	2	164.0	audi	gas	sedan	4wd	front	66.4	54.3	ohc

Label encoding the Data

In [22]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 194 entries, 0 to 204
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          194 non-null    int64  
 1   normalized-losses  194 non-null    float64
 2   make               194 non-null    object 
 3   fuel-type          194 non-null    object 
 4   body-style         194 non-null    object 
 5   drive-wheels       194 non-null    object 
 6   engine-location    194 non-null    object 
 7   width              194 non-null    float64
 8   height             194 non-null    float64
 9   engine-type        194 non-null    object 
 10  engine-size        194 non-null    int64  
 11  horsepower         194 non-null    float64
 12  city-mpg           194 non-null    int64  
 13  highway-mpg        194 non-null    int64  
 14  price              194 non-null    int64  
dtypes: float64(4), int64(5), object(6)
memory usage: 28.3+ KB
```

In [23]:

```
df_cat = df.select_dtypes(object)
df_num = df.select_dtypes(["int64","float64"])
```

In [24]:

```
1 df_cat
```

Out[24]:

	make	fuel-type	body-style	drive-wheels	engine-location	engine-type
0	alfa-romero	gas	convertible	rwd	front	dohc
1	alfa-romero	gas	convertible	rwd	front	dohc
2	alfa-romero	gas	hatchback	rwd	front	ohcv
3	audi	gas	sedan	fwd	front	ohc
4	audi	gas	sedan	4wd	front	ohc
...	...	...	...	...	...	...
200	volvo	gas	sedan	rwd	front	ohc
201	volvo	gas	sedan	rwd	front	ohc
202	volvo	gas	sedan	rwd	front	ohcv
203	volvo	diesel	sedan	rwd	front	ohc
204	volvo	gas	sedan	rwd	front	ohc

194 rows × 6 columns

In [25]:

```
1 df_num
```

Out[25]:

	symboling	normalized-losses	width	height	engine-size	horsepower	city-mpg	highway-mpg	price
0	3	122.0	64.1	48.8	130	111.0	21	27	13495
1	3	122.0	64.1	48.8	130	111.0	21	27	16500
2	1	122.0	65.5	52.4	152	154.0	19	26	16500
3	2	164.0	66.2	54.3	109	102.0	24	30	13950
4	2	164.0	66.4	54.3	136	115.0	18	22	17450
...	...	...	...	...	...	...	...	...	...
200	-1	95.0	68.9	55.5	141	114.0	23	28	16845
201	-1	95.0	68.8	55.5	141	160.0	19	25	19045
202	-1	95.0	68.9	55.5	173	134.0	18	23	21485
203	-1	95.0	68.9	55.5	145	106.0	26	27	22470
204	-1	95.0	68.9	55.5	141	114.0	19	25	22625

194 rows × 9 columns

In [26]:

```
df_cat["fuel-type"]
```

Out[26]:

```
0         gas
1         gas
2         gas
3         gas
4         gas
        ...
200       gas
201       gas
202       gas
203    diesel
204       gas
Name: fuel-type, Length: 194, dtype: object
```

In [27]:

```
pd.get_dummies(df_cat["fuel-type"])
```

Out[27]:

	diesel	gas
0	0	1
1	0	1
2	0	1
3	0	1
4	0	1
...	...	...
200	0	1
201	0	1
202	0	1
203	1	0
204	0	1

194 rows × 2 columns

In [28]:

```
df["make"].nunique()
```

Out[28]:

```
22
```

In [29]:

```
pd.get_dummies(df_cat["make"])
```

Out[29]:

	alfa-romero	audi	bmw	chevrolet	dodge	honda	isuzu	jaguar	mazda	mercedes-benz	...	nissa
0	1	0	0	0	0	0	0	0	0	0	...	
1	1	0	0	0	0	0	0	0	0	0	...	
2	1	0	0	0	0	0	0	0	0	0	...	
3	0	1	0	0	0	0	0	0	0	0	...	
4	0	1	0	0	0	0	0	0	0	0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
200	0	0	0	0	0	0	0	0	0	0	...	
201	0	0	0	0	0	0	0	0	0	0	...	
202	0	0	0	0	0	0	0	0	0	0	...	
203	0	0	0	0	0	0	0	0	0	0	...	
204	0	0	0	0	0	0	0	0	0	0	...	

194 rows × 22 columns

In [30]:

```
df_cat
```

	make	fuel-type	body-style	drive-wheels	engine-location	engine-type
0	alfa-romero	gas	convertible	rwd	front	dohc
1	alfa-romero	gas	convertible	rwd	front	dohc
2	alfa-romero	gas	hatchback	rwd	front	ohcv
3	audi	gas	sedan	fwd	front	ohc
4	audi	gas	sedan	4wd	front	ohc
...	...	...	...	...	...	...
200	volvo	gas	sedan	rwd	front	ohc
201	volvo	gas	sedan	rwd	front	ohc
202	volvo	gas	sedan	rwd	front	ohcv
203	volvo	diesel	sedan	rwd	front	ohc
204	volvo	gas	sedan	rwd	front	ohc

In [31]:

```
from sklearn.preprocessing import LabelEncoder

```

In [32]:

```
for col in df_cat:
    le = LabelEncoder()
    df_cat[col] = le.fit_transform(df_cat[col])
```

In [33]:

```
df_cat
```

Out[33]:

	make	fuel-type	body-style	drive-wheels	engine-location	engine-type
0	0	1	0	2	0	0
1	0	1	0	2	0	0
2	0	1	2	2	0	5
3	1	1	3	1	0	3
4	1	1	3	0	0	3
...	...	...	...	...	...	...
200	21	1	3	2	0	3
201	21	1	3	2	0	3
202	21	1	3	2	0	5
203	21	0	3	2	0	3
204	21	1	3	2	0	3

194 rows × 6 columns

In [34]:

```
df = pd.concat([df_cat, df_num], axis=1)
```

In [35]:

```
df
```

Out[35]:

	make	fuel-type	body-style	drive-wheels	engine-location	engine-type	symboling	normalized-losses	width	height	eng
0	0	1	0	2	0	0	3	122.0	64.1	48.8	
1	0	1	0	2	0	0	3	122.0	64.1	48.8	
2	0	1	2	2	0	5	1	122.0	65.5	52.4	
3	1	1	3	1	0	3	2	164.0	66.2	54.3	
4	1	1	3	0	0	3	2	164.0	66.4	54.3	
...	...	...	...	...	...	...	...	...	...	...	
200	21	1	3	2	0	3	-1	95.0	68.9	55.5	
201	21	1	3	2	0	3	-1	95.0	68.8	55.5	
202	21	1	3	2	0	5	-1	95.0	68.9	55.5	
203	21	0	3	2	0	3	-1	95.0	68.9	55.5	
204	21	1	3	2	0	3	-1	95.0	68.9	55.5	

194 rows × 15 columns

Dividing the Data into x and y

In [36]:

```
x = df.iloc[:,:-1].values
y = df.iloc[:,-1].values
```

Preprocessing

In [37]:

```
from sklearn.model_selection import train_test_split, cross_val_score
xtrain,xtest,ytrain,ytest = train_test_split(x,y, test_size = 0.25, random_state = 0)
```

In [38]:

```
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR

from sklearn.metrics import r2_score, mean_squared_error,mean_absolute_error

```

In [39]:

```
def mymodel(model):
    model.fit(xtrain, ytrain)
    ypred = model.predict(xtest)
    ac = r2_score(ytest, ypred)
    mse = mean_squared_error(ytest, ypred)
    rmse = np.sqrt(mse)
    mae = mean_absolute_error(ytest, ypred)
    print(f"Accuracy -: {ac}\n\nMSE -:\n{mse}\n\nRMSE -:\n{rmse}\n\nMAE -: {mae}")
```

In [40]:

```
models = []

models.append(("Linreg          -: ", LinearRegression()))
models.append(("KNN             -: ", KNeighborsRegressor()))
models.append(("SVM-l           -: ", SVR(kernel="linear")))
models.append(("SVM-r           -: ", SVR(kernel="rbf")))


for name, model in models:
    print(name)
    mymodel(model)
    print("\n\n")
```

```
Linreg          -:
Accuracy -: 0.773730267617807

MSE -:
17164264.09263911

RMSE -:
4142.97768430378

MAE -: 2862.978078671882



KNN             -:
Accuracy -: 0.7354891230067488

MSE -:
20065143.04979592

RMSE -:
4479.413248383757

MAE -: 2706.922448979592



SVM-l           -:
Accuracy -: 0.7093560754688115

MSE -:
22047531.612173293

RMSE -:
4695.479912870813

MAE -: 2890.666286906662



SVM-r           -:
Accuracy -: -0.2003478916136967

MSE -:
91055431.92979647

RMSE -:
```

```
9542.296994424167

MAE -: 5634.141088793915
```

Hyperparameter Tuning

In [41]:

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

In [42]:

```
l2 = Ridge(alpha=10)
l2.fit(xtrain, ytrain)
ypred = l2.predict(xtest)
print(r2_score(ytest, ypred))
```

```
0.72866626766047
```

In [43]:

```
l2.coef_
```

Out[43]:

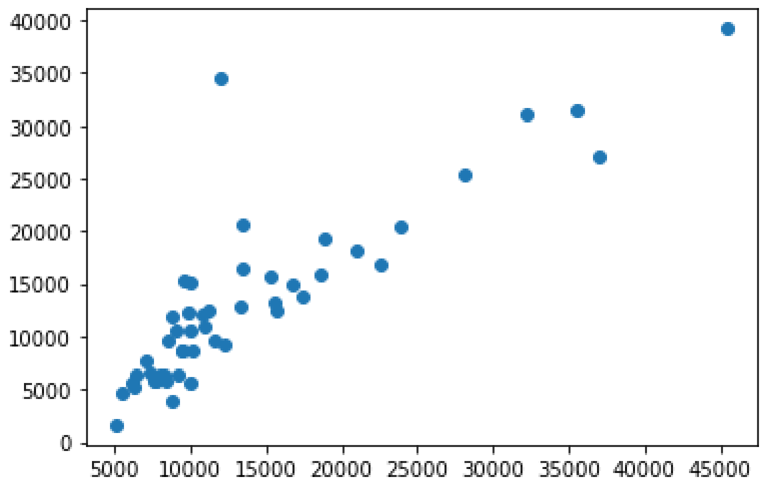
```
array([ -161.67047158, -1091.95994427,  -246.0053102 ,  1914.71315327,
        1301.48308582,   138.14429355,   329.09419219,   -13.78251147,
         691.31719053,   327.07563574,    80.726493  ,    60.81704185,
         -32.4908748 ,    38.91463197])
```

In [44]:

```
plt.scatter(ytest, ypred)
```

Out[44]:

```
<matplotlib.collections.PathCollection at 0xb121803160>
```



In [45]:

```
l1 = Lasso(alpha=10)
l1.fit(xtrain, ytrain)
ypred = l1.predict(xtest)
print(r2_score(ytest, ypred))
```

```
0.7699917962869316
```

In [46]:

```
l1.coef_
```

Out[46]:

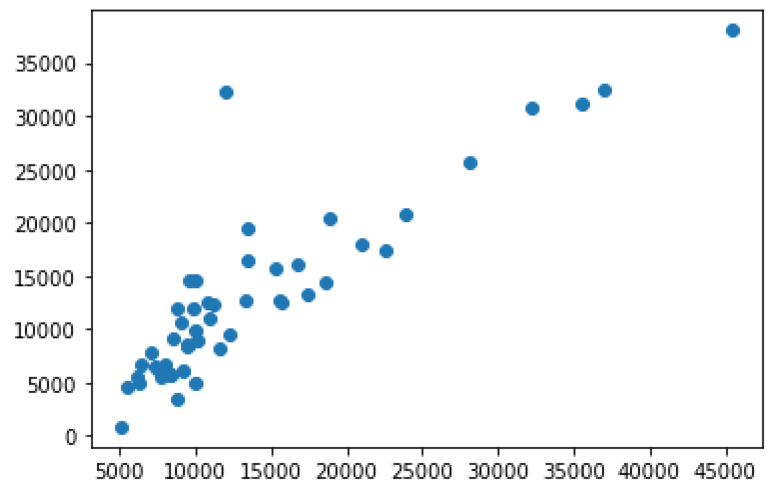
```
array([-1.82882236e+02, -1.37192271e+03,  0.00000000e+00,  2.34944314e+03,
        9.60029642e+03,  1.18880452e+02,  2.46574540e+02, -1.50827921e+01,
        8.61970657e+02,  2.20130885e+02,  7.63189726e+01,  4.18553427e+01,
       -3.22662797e+01, -6.55632273e-01])
```

In [47]:

```
plt.scatter(ytest, ypred)
```

Out[47]:

```
<matplotlib.collections.PathCollection at 0xb121871a60>
```



In [48]:

```
for i in range(100):
    l2 = Ridge(alpha=i)
    l2.fit(xtrain, ytrain)
    print(f"{i} -: {l2.score(xtest, ytest)}")
```

```
0 -: 0.7737302676178046
1 -: 0.7518429340867678
2 -: 0.742041130679302
3 -: 0.7368470556772466
4 -: 0.7337956083458914
5 -: 0.7318874901164595
6 -: 0.7306478376489106
7 -: 0.7298247335534228
8 -: 0.7292735249807932
9 -: 0.7289060949022612
10 -: 0.72866626766047
11 -: 0.7285169219002868
12 -: 0.7284328085314543
13 -: 0.7283963430433417
14 -: 0.7283950366881593
15 -: 0.7284198732095152
16 -: 0.7284642526981494
17 -: 0.7285232870611238
18 -: 0.7285933198013379
19 -: 0.7286715924905208
20 -: 0.7287560092842165
21 -: 0.7288449682307082
22 -: 0.7289372388654709
23 -: 0.729031872369603
24 -: 0.7291281349518193
25 -: 0.7292254579964018
26 -: 0.7293234004494682
27 -: 0.7294216202283965
28 -: 0.7295198523446351
29 -: 0.7296178920629219
30 -: 0.7297155818674592
31 -: 0.7298128013256695
32 -: 0.7299094591713355
33 -: 0.7300054870975232
34 -: 0.7301008348736873
35 -: 0.7301954664932812
36 -: 0.7302893571268732
37 -: 0.7303824907074551
38 -: 0.7304748580137008
39 -: 0.730566455146755
40 -: 0.7306572823189402
41 -: 0.73074734289034
42 -: 0.7308366426028301
43 -: 0.7309251889716829
44 -: 0.7310129908031402
45 -: 0.7311000578128213
46 -: 0.7311864003249158
47 -: 0.7312720290361475
48 -: 0.7313569548316801
49 -: 0.7314411886426517
50 -: 0.7315247413370864
51 -: 0.7316076236374853
52 -: 0.7316898460597525
53 -: 0.7317714188691146
```

```
54 -: 0.731852352049531
55 -: 0.7319326552837777
56 -: 0.7320123379419254
57 -: 0.7320914090763702
58 -: 0.7321698774219316
59 -: 0.7322477513998271
60 -: 0.7323250391245606
61 -: 0.7324017484129535
62 -: 0.7324778867947026
63 -: 0.732553461523975
64 -: 0.7326284795916513
65 -: 0.7327029477379087
66 -: 0.7327768724649046
67 -: 0.732850260049378
68 -: 0.7329231165550272
69 -: 0.7329954478445551
70 -: 0.7330672595913075
71 -: 0.7331385572904479
72 -: 0.7332093462696369
73 -: 0.7332796316991876
74 -: 0.7333494186016976
75 -: 0.7334187118611335
76 -: 0.733487516231415
77 -: 0.733555836344458
78 -: 0.7336236767177338
79 -: 0.7336910417613379
80 -: 0.7337579357846
81 -: 0.7338243630022505
82 -: 0.7338903275401653
83 -: 0.7339558334407138
84 -: 0.734020884667731
85 -: 0.7340854851111358
86 -: 0.7341496385912114
87 -: 0.7342133488625817
88 -: 0.7342766196178858
89 -: 0.7343394544911861
90 -: 0.7344018570611182
91 -: 0.7344638308538001
92 -: 0.7345253793455276
93 -: 0.7345865059652559
94 -: 0.7346472140968923
95 -: 0.7347075070814149
96 -: 0.7347673882188213
97 -: 0.7348268607699286
98 -: 0.7348859279580308
99 -: 0.7349445929704248
```

In [49]:

```
l2 = Ridge(alpha=0)
l2.fit(xtrain, ytrain)
ypred = l2.predict(xtest)

print(r2_score(ytest, ypred))
```

```
0.7737302676178046
```

In [50]:

```
for i in range(0,1000,50):
    l1 = Lasso(alpha=i)
    l1.fit(xtrain, ytrain)
    print(f"{i} -: {l1.score(xtest, ytest)}")
```

```
0 -: 0.7737302676178069
50 -: 0.7506461701495694
100 -: 0.7189785263379442
150 -: 0.7163098206915988
200 -: 0.720759175685989 7
250 -: 0.7211609660172624
300 -: 0.7207342085673817
350 -: 0.7217125685528865
400 -: 0.7222711582449708
450 -: 0.7218732080868915
500 -: 0.7212772634035048
550 -: 0.7220728998633944
600 -: 0.723172604920933
650 -: 0.7242078927282716
700 -: 0.7251752855488806
750 -: 0.7260748167816642
800 -: 0.7269135026336293
850 -: 0.7276826592903824
900 -: 0.7283856994270395
950 -: 0.7290228559971043
```

In [51]:

```
l1 = Lasso(alpha=0)
l1.fit(xtrain, ytrain)
ypred = l1.predict(xtest)
print(r2_score(ytest, ypred))
```

```
0.7737302676178069
```

In [52]:

```
cvs = cross_val_score(l2, x,y,cv=4)
cvs
```

Out[52]:

```
array([ 7.51352795e-01,  8.57869101e-01, -1.61916999e+27,  3.81584948e-01])
```

In [53]:

```
cvs.mean()
```

Out[53]:

```
-4.0479249637304396e+26
```

In [54]:

```
cvs1 = cross_val_score(l1, x,y,cv=4)
cvs1
```

Out[54]:

```
array([0.75135279, 0.8578691 , 0.37303229, 0.38158495])
```

In [55]:

```
cvs1.mean()
```

Out[55]:

```
0.590959782108395
```

CONCLUSION

- As we can deduce the best fit model for this Dataset is LinearRegression
- The accuracy of this model is 77%

In [ ]:

```

```