ML PROJECT 2 - VEHICLE PRICE PREDICTION

our algorithm will take vehicle details like mileage,engin type, no of doors, lenght,width,height,engine capacity,etc.... and our algorithm will predict PRICE of the vehicle

step 1 - load the data

In [1]:

```
import pandas as pd

auto_data = pd.read_csv('auto.txt')
auto_data.head()
```

Out[1]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...
0	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...
1	3	?	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...
2	1	?	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...

5 rows × 26 columns

step 2 - clean data

In [2]:
```python
# you can observe there are some columns with values ? lets clean these.
import numpy as np
auto_data = auto_data.replace('?',np.nan)
auto_data.head()
```

Out[2]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	.
0	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	.
1	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	.
2	1	NaN	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	.
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	.
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	.

5 rows × 26 columns

In [3]:
```python
auto_data['price'].describe() # Let see what is the data type of price colum
```

Out[3]:
```
count      201
unique     186
top       8921
freq         2
Name: price, dtype: object
```

In [4]:
```python
# we have to convert this column to float type
auto_data['price'] = pd.to_numeric(auto_data['price'], errors='coerce') #coe
auto_data['price'].describe() #now type is converted to float
```

Out[4]:
```
count      201.000000
mean     13207.129353
std       7947.066342
min       5118.000000
25%       7775.000000
50%      10295.000000
75%      16500.000000
max      45400.000000
Name: price, dtype: float64
```

In [5]:
```python
# Let us remove unwanted columns --  which are not useful
```

In [6]:
```
auto_data = auto_data.drop('normalized-losses', axis=1)
auto_data.head()
```

Out[6]:

	symboling	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	...	en
0	3	alfa-romero	gas	std	two	convertible	rwd	front	88.6	168.8	...	
1	3	alfa-romero	gas	std	two	convertible	rwd	front	88.6	168.8	...	
2	1	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	171.2	...	
3	2	audi	gas	std	four	sedan	fwd	front	99.8	176.6	...	
4	2	audi	gas	std	four	sedan	4wd	front	99.4	176.6	...	

5 rows × 25 columns

In [7]:
```
auto_data.columns
```

Out[7]:
```
Index(['symboling', 'make', 'fuel-type', 'aspiration', 'num-of-doors',
       'body-style', 'drive-wheels', 'engine-location', 'wheel-base', 'length',
       'width', 'height', 'curb-weight', 'engine-type', 'num-of-cylinders',
       'engine-size', 'fuel-system', 'bore', 'stroke', 'compression-ratio',
       'horsepower', 'peak-rpm', 'city-mpg', 'highway-mpg', 'price'],
      dtype='object')
```

In [8]:
```
auto_data['horsepower'].describe()
```

Out[8]:
```
count     203
unique     59
top        68
freq       19
Name: horsepower, dtype: object
```

In [9]:
```
auto_data['horsepower'] = pd.to_numeric(auto_data['horsepower'], errors='coe
auto_data['horsepower'].describe()
```

Out[9]:
```
count    203.000000
mean     104.256158
std       39.714369
min       48.000000
25%       70.000000
50%       95.000000
75%      116.000000
max      288.000000
Name: horsepower, dtype: float64
```

In [10]:
```
auto_data.columns
```

Out[10]:
```
Index(['symboling', 'make', 'fuel-type', 'aspiration', 'num-of-doors',
       'body-style', 'drive-wheels', 'engine-location', 'wheel-base', 'length',
       'width', 'height', 'curb-weight', 'engine-type', 'num-of-cylinders',
       'engine-size', 'fuel-system', 'bore', 'stroke', 'compression-ratio',
       'horsepower', 'peak-rpm', 'city-mpg', 'highway-mpg', 'price'],
      dtype='object')
```

In [11]:
```
auto_data['bore']
```

Out[11]:
```
0      3.47
1      3.47
2      2.68
3      3.19
4      3.19
       ...
200    3.78
201    3.78
202    3.58
203    3.01
204    3.78
Name: bore, Length: 205, dtype: object
```

In [12]:
```
auto_data['bore'] = pd.to_numeric(auto_data['bore'], errors='coerce')#cnvrt
auto_data['bore'].describe()
```

Out[12]:
```
count    201.000000
mean       3.329751
std        0.273539
min        2.540000
25%        3.150000
50%        3.310000
75%        3.590000
max        3.940000
Name: bore, dtype: float64
```

In [13]:
```
auto_data['stroke'] = pd.to_numeric(auto_data['stroke'], errors='coerce')#cn
auto_data['stroke'].describe()
```

Out[13]:
```
count    201.000000
mean       3.255423
std        0.316717
min        2.070000
25%        3.110000
50%        3.290000
75%        3.410000
max        4.170000
Name: stroke, dtype: float64
```

In [14]:
```python
auto_data['peak-rpm'] = pd.to_numeric(auto_data['peak-rpm'], errors='coerce'
auto_data['peak-rpm'].describe()
```

Out[14]:
```
count     203.000000
mean     5125.369458
std       479.334560
min      4150.000000
25%      4800.000000
50%      5200.000000
75%      5500.000000
max      6600.000000
Name: peak-rpm, dtype: float64
```

In [15]:
```python
auto_data['num-of-cylinders']
```

Out[15]:
```
0      four
1      four
2       six
3      four
4      five
       ...
200    four
201    four
202     six
203     six
204    four
Name: num-of-cylinders, Length: 205, dtype: object
```

In [16]:

```
cylinders_dict = {
    'two':2,
    'three':3,
    'four':4,
    'five':5,
    'six':6,
    'eight':8,
    'twelve':12
}
auto_data['num-of-cylinders'].replace(cylinders_dict, inplace = True)
auto_data.head()
```

Out[16]:

	symboling	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	...
0	3	alfa-romero	gas	std	two	convertible	rwd	front	88.6	168.8	...
1	3	alfa-romero	gas	std	two	convertible	rwd	front	88.6	168.8	...
2	1	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	171.2	...
3	2	audi	gas	std	four	sedan	fwd	front	99.8	176.6	...
4	2	audi	gas	std	four	sedan	4wd	front	99.4	176.6	...

5 rows × 25 columns

In [17]:

```
auto_data['num-of-cylinders'].head()
```

Out[17]:

```
0    4
1    4
2    6
3    4
4    5
Name: num-of-cylinders, dtype: int64
```

In [18]:

```python
a = {'1bbl':1, '2bbl':2, '4bbl':4, 'idi':5, 'mfi':6, 'mpfi':7,
               'spdi':8, 'spfi':9}
auto_data['fuel-system'].replace(a, inplace = True)

b = {'dohc':1, 'dohcv':2, 'l':3, 'ohc':4, 'ohcf':5, 'ohcv':6,
              'rotor':7}
auto_data['engine-type'].replace(b, inplace = True)

c = {'front':1, 'rear':2}
auto_data['engine-location'].replace(c, inplace = True)

d = {'4wd':1, 'fwd':2, 'rwd':3}
auto_data['drive-wheels'].replace(d, inplace = True)

e = {
    'alfa-romero' : 1,'audi' : 2,'bmw': 3,'chevrolet' :4,'dodge':5,
        'honda':6, 'isuzu':7,'jaguar':8, 'mazda':9, 'mercedes-benz':10,
        'mercury':11,'mitsubishi':12, 'nissan':13, 'peugot':14,
        'plymouth':15,'porsche':16, 'renault':17, 'saab':18, 'subaru':19,
       'toyota':20, 'volkswagen':21, 'volvo':22
}
auto_data['make'].replace(e, inplace = True)

f = {'convertible':1,'hardtop':2, 'hatchback':3, 'sedan':4, 'wagon':5}
auto_data['body-style'].replace(f, inplace = True)

g = {'four':4, 'two':2}
auto_data['num-of-doors'].replace(g, inplace = True)

h = {'std':0, 'turbo':1}
auto_data['aspiration'].replace(h, inplace = True)



auto_data.head(10)
```

Out[18]:

	symboling	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	...	eng
0	3	1	gas	0	2.0	1	3	1	88.6	168.8	...	
1	3	1	gas	0	2.0	1	3	1	88.6	168.8	...	
2	1	1	gas	0	2.0	3	3	1	94.5	171.2	...	
3	2	2	gas	0	4.0	4	2	1	99.8	176.6	...	
4	2	2	gas	0	4.0	4	1	1	99.4	176.6	...	
5	2	2	gas	0	2.0	4	2	1	99.8	177.3	...	
6	1	2	gas	0	4.0	4	2	1	105.8	192.7	...	
7	1	2	gas	0	4.0	5	2	1	105.8	192.7	...	
8	1	2	gas	1	4.0	4	2	1	105.8	192.7	...	
9	0	2	gas	1	2.0	3	1	1	99.5	178.2	...	

10 rows × 25 columns

In [19]:

```
i = {'gas':0, 'diesel':1}
auto_data['fuel-type'].replace(i,inplace = True)

auto_data.head(10)
```

Out[19]:

	symboling	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	...	engine-size
0	3	1	0	0	2.0	1	3	1	88.6	168.8	...	130
1	3	1	0	0	2.0	1	3	1	88.6	168.8	...	130
2	1	1	0	0	2.0	3	3	1	94.5	171.2	...	152
3	2	2	0	0	4.0	4	2	1	99.8	176.6	...	109
4	2	2	0	0	4.0	4	1	1	99.4	176.6	...	136
5	2	2	0	0	2.0	4	2	1	99.8	177.3	...	136
6	1	2	0	0	4.0	4	2	1	105.8	192.7	...	136
7	1	2	0	0	4.0	5	2	1	105.8	192.7	...	136
8	1	2	0	1	4.0	4	2	1	105.8	192.7	...	131
9	0	2	0	1	2.0	3	1	1	99.5	178.2	...	131

10 rows × 25 columns

In [20]:
```
auto_data.isnull()
```

Out[20]:

	symboling	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	...	engi si
0	False	False	False	False	False	False	False	False	False	False	...	Fal
1	False	False	False	False	False	False	False	False	False	False	...	Fal
2	False	False	False	False	False	False	False	False	False	False	...	Fal
3	False	False	False	False	False	False	False	False	False	False	...	Fal
4	False	False	False	False	False	False	False	False	False	False	...	Fal
...	...	...	...	...	...	...	...	...	...	...	...	
200	False	False	False	False	False	False	False	False	False	False	...	Fal
201	False	False	False	False	False	False	False	False	False	False	...	Fal
202	False	False	False	False	False	False	False	False	False	False	...	Fal
203	False	False	False	False	False	False	False	False	False	False	...	Fal
204	False	False	False	False	False	False	False	False	False	False	...	Fal

205 rows × 25 columns

In [21]:
```
auto_data.isna().sum()
```

Out[21]:
```
symboling            0
make                 0
fuel-type            0
aspiration           0
num-of-doors         2
body-style           0
drive-wheels         0
engine-location      0
wheel-base           0
length               0
width                0
height               0
curb-weight          0
engine-type          0
num-of-cylinders     0
engine-size          0
fuel-system          0
bore                 4
stroke               4
compression-ratio    0
horsepower           2
peak-rpm             2
city-mpg             0
highway-mpg          0
price                4
dtype: int64
```

In [22]:
```
# horsepower
# curb-weight
# peak-rpm
del auto_data['horsepower']
del auto_data['curb-weight']
del auto_data['peak-rpm']

```

In [ ]:
```

```

In [23]:
```
# lets clean up our data
auto_data = auto_data.dropna()
```

step 3 -train test split

In [24]:

```python
from sklearn.model_selection import train_test_split
# lets feed our data to machine learning model
x = auto_data.drop('price', axis=1)

y = auto_data['price']

# split data into 80% for training, 20% for testing
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.2, ra
```

step 4 - train the algorithm

In [25]:

```python
from sklearn.linear_model import LinearRegression

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

Out[25]:

```
LinearRegression()
```

In [26]:

```python
linear_model.score(x_train, y_train) # traing data accuracy
```

Out[26]:

```
0.8977925747050544
```

In [27]:

```python
linear_model.coef_
```

Out[27]:

```
array([  -667.83607138,   -201.03840036, -11877.75594957,   3267.45664655,
         -341.88511643,   -275.67970494,    534.24818935,  12457.43964247,
          -27.57274928,     13.49191389,    735.2578018 ,    331.25941981,
         -633.39734035,    167.85881525,    149.24314962,    266.08507362,
        -3020.67818985,  -4381.08882035,    866.25626477,   -280.79536587,
          314.52728571])
```

In [28]:
```
predictors = x_train.columns #see the weights associcated with perticuler fe
coef = pd.Series(linear_model.coef_,predictors).sort_values()
print(coef)
```

```
fuel-type           -11877.755950
stroke               -4381.088820
bore                 -3020.678190
symboling             -667.836071
engine-type           -633.397340
num-of-doors          -341.885116
city-mpg              -280.795366
body-style            -275.679705
make                  -201.038400
wheel-base             -27.572749
length                  13.491914
engine-size            149.243150
num-of-cylinders       167.858815
fuel-system            266.085074
highway-mpg            314.527286
height                 331.259420
drive-wheels           534.248189
width                  735.257802
compression-ratio      866.256265
aspiration            3267.456647
engine-location      12457.439642
dtype: float64
```

step 5 - test the algorithm

In [29]:
```
# lets predict using linear regression model
y_predict = linear_model.predict(x_test)
```

In [30]:

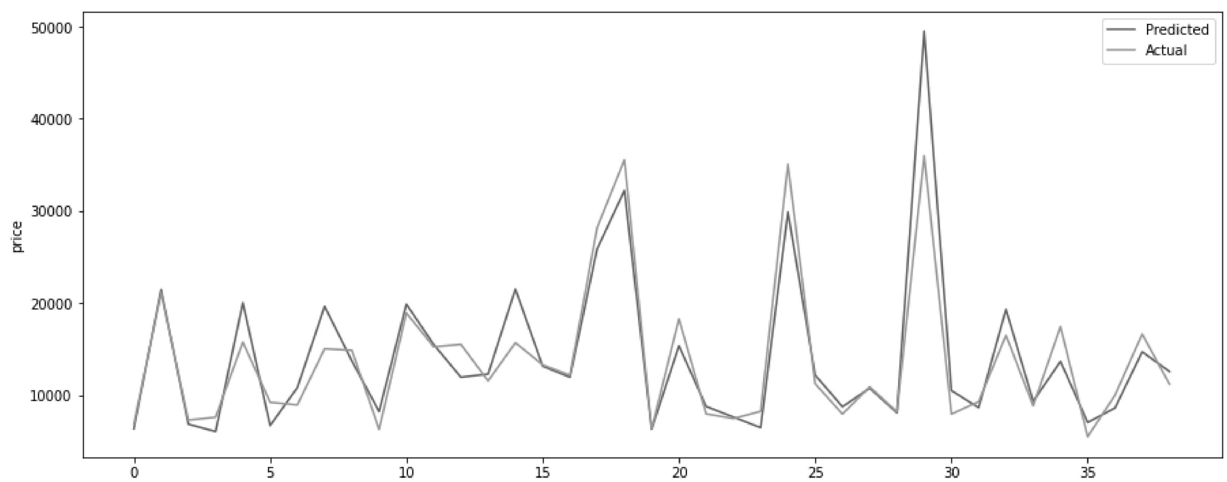
```
# lets plot the prediction using matplot lib
%pylab inline
pylab.rcParams['figure.figsize'] = (15,6)

plt.plot(y_predict, label='Predicted')
plt.plot(y_test.values, label='Actual')

plt.ylabel('price')
plt.legend()
plt.show()
```

```
Populating the interactive namespace from numpy and matplotlib

C:\Users\91918\AppData\Local\Programs\Python\Python39\lib\site-packages\IPython
\core\magics\pylab.py:159: UserWarning: pylab import has clobbered these variab
les: ['f', 'e']
`%matplotlib` prevents importing * from pylab and numpy
  warn("pylab import has clobbered these variables: %s"  % clobbered +
```



In [31]:

```
# how well our regression model works on our test data
score = linear_model.score(x_test, y_test)
score
```

Out[31]: 0.8409940243694667

step 6 - find the error(how much is the error in the output)

MEAN SQUARED ERROR --- ### this will tell us how much error is there in the given output.

In [32]:
```python
from sklearn.metrics import mean_squared_error

linear_model_mse = mean_squared_error(y_predict, y_test) #predicted y and ac
linear_model_mse # its coming out to be 26 millions
```

Out[32]: 9848274.421919573

In [33]:
```python
import math
math.sqrt(linear_model_mse)
```

Out[33]: 3138.1960458071408

conclusion for linear regression algorithm - accuracy is 84% and error is 3,138 dollars

step 7 : improvies, let us test other algorithms

In [34]:
```python
# implementing lasso and ridge regression models.
from sklearn.linear_model import Lasso

lasso_model = Lasso(alpha=0.5, normalize=True) #alpha is regularization para
lasso_model.fit(x_train, y_train)
```

```
C:\Users\91918\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn
\linear_model\_base.py:141: FutureWarning: 'normalize' was deprecated in versio
n 1.0 and will be removed in 1.2.
If you wish to scale the data, use Pipeline with a StandardScaler in a preproce
ssing stage. To reproduce the previous behavior:

from sklearn.pipeline import make_pipeline

model = make_pipeline(StandardScaler(with_mean=False), Lasso())

If you wish to pass a sample_weight parameter, you need to pass it as a fit par
ameter to each step of the pipeline as follows:

kwargs = {s[0] + '__sample_weight': sample_weight for s in model.steps}
model.fit(X, y, **kwargs)

Set parameter alpha to: original_alpha * np.sqrt(n_samples).
  warnings.warn(
```

Out[34]: Lasso(alpha=0.5, normalize=True)

In [35]:

```
coef = pd.Series(lasso_model.coef_, predictors).sort_values()
print(coef)
```

```
fuel-type            -7268.421633
stroke               -4024.350234
bore                 -2191.378272
engine-type           -648.687296
symboling             -603.255536
body-style            -294.850287
num-of-doors          -271.787484
city-mpg              -216.952356
make                  -196.387898
wheel-base             -20.796517
length                  11.544332
engine-size            135.243830
highway-mpg            260.129778
fuel-system            261.962291
height                 319.023898
compression-ratio      525.214813
num-of-cylinders       579.079765
drive-wheels           614.931666
width                  743.132522
aspiration            2861.847142
engine-location      12747.200906
dtype: float64
```

In [36]:

```
y_predict = lasso_model.predict(x_test)
score = lasso_model.score(x_test,y_test)
print('accuracy of lassoo model is  ....',score)
lasso_model_mse = mean_squared_error(y_predict,y_test)
print('error of lasso model is...', math.sqrt(lasso_model_mse))
```

```
accuracy of lassoo model is  .... 0.8549364877465662
error of lasso model is... 2997.4534137729383
```

conclusion for lasso - accuracy is 85% and error is 2997 dollars

In [38]:

```
from sklearn.linear_model import Ridge

ridge_model = Ridge(alpha = 0.5, normalize = True)
ridge_model.fit(x_train, y_train)
y_predict = ridge_model.predict(x_test)
score = ridge_model.score(x_test, y_test)
print('accuracy of ridge model is...', score)
ridge_model_mse = mean_squared_error(y_predict, y_test)
print('error of ridge model is ...',math.sqrt(ridge_model_mse))

```

```
accuracy of ridge model is... 0.9036806546176769
error of ridge model is ... 2442.4748979913443
```

```
C:\Users\91918\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn
\linear_model\_base.py:141: FutureWarning: 'normalize' was deprecated in versio
n 1.0 and will be removed in 1.2.
If you wish to scale the data, use Pipeline with a StandardScaler in a preproce
ssing stage. To reproduce the previous behavior:

from sklearn.pipeline import make_pipeline

model = make_pipeline(StandardScaler(with_mean=False), Ridge())

If you wish to pass a sample_weight parameter, you need to pass it as a fit par
ameter to each step of the pipeline as follows:

kwargs = {s[0] + '__sample_weight': sample_weight for s in model.steps}
model.fit(X, y, **kwargs)

Set parameter alpha to: original_alpha * n_samples.
  warnings.warn(
```

conclusion for ridge algorithm - accuracy is 90% and error is 2440 dollars

final conclusion - i am recommending ridge algorithm for vehicle price prediction project

In [ ]:

```

```