In [ ]:

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Exercise Set 26: Regression Models

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ENGR 1330 Exercise Set 26 - Homework

Exercise:

In the http://54.243.252.9/engr-1330-webroot/4-Databases/CarsDF.csv file, you will find a dataset with information about cars and motorcycles including their age, kilometers driven (mileage), fuel economy, enginer power, engine volume, and selling price. Follow the steps and answer the questions.

- Step1: Read the "CarsDF.csv" file as a dataframe. Explore the dataframe and in a markdown cell briefly describe it in your own words.
- Step2: Calculate and compare the correlation coefficient of the "selling price" with all the other parameters (execpt for "name", of course!). In a markdown cell, explain the results and state which parameters have the strongest and weakest relationship with "selling price" of a vehicle.
- Step3: Use linear regression modeling in primitive python and VISUALLY assess the quality of a linear fit with Age as the predictor, and selling price as outcome. Explain the result of this analysis in a markdown cell.
- Step4: Use linear regression modeling with statsmodels and VISUALLY assess the quality of a linear fit with fuel economy as the predictor, and selling price as outcome. Explain the result of this analysis in a markdown cell.
- Step5: Use linear regression modeling with statsmodels and VISUALLY assess the quality of a linear fit with engine volume as the predictor, and selling price as outcome. Explain the result of this analysis in a markdown cell.
- Step6: In a markdown cell, explain which of the three predictors in steps 3,4, and 5, was a better predictor (resulted in a better fit) for selling price?
- Step7: Use multiple linear regression modeling with scikit-learn and use all the parameters (execpt for "name", of course!) to predict selling price. Then, use this model to predict the selling price of a car that has the following charactristics and decide whether this prediction is reliable in your opinion:
  - 2 years old
  - has gone 17000 km
  - has fuel economy measure of 24.2 kmpl
  - has an engine power of 74 bhp

- has en engine volume of 1260 CC

In [38]:

```
# code here
# Step1:
import requests # Module to process http/https requests
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
from sklearn.linear_model import LinearRegression



remote_url="http://54.243.252.9/engr-1330-webroot/4-Databases/CarsDF.csv"  # set the ur
rget = requests.get(remote_url, allow_redirects=True)  # get the remote resource, follo
open('CarsDF.csv','wb').write(rget.content); # extract from the remote the contents, as
# Step1B
# make into a dataframe
# whats in the dataframe
dfd = pd.read_csv('CarsDF.csv')
dfd.head()
```

Out[38]:

	name	Age	km_driven	FuelEconomy_kmpl	engine_p	engine_v	selling_price
0	Maruti Swift Dzire VDI	6	145500	23.4	74.0	1248	450000
1	Skoda Rapid 1.5 TDI Ambition	6	120000	21.1	103.0	1498	370000
2	Honda City 2017-2020 EXi	14	140000	17.7	78.0	1497	158000
3	Hyundai i20 Sportz Diesel	10	127000	23.0	90.0	1396	225000
4	Maruti Swift VXI BSIII	13	120000	16.1	88.0	1298	130000

In [39]:

```
dfd.describe()
```

Out[39]:

	Age	km_driven	FuelEconomy_kmpl	engine_p	engine_v	selling_price
count	7905.000000	7.905000e+03	7905.000000	7905.000000	7905.000000	7.905000e+03
mean	6.015939	6.918350e+04	19.397293	79.227577	1458.735484	6.498295e+05
std	3.863924	5.679403e+04	4.034584	23.035056	503.919358	8.136330e+05
min	0.000000	1.000000e+00	0.000000	32.000000	624.000000	2.999900e+04
25%	3.000000	3.500000e+04	16.700000	67.000000	1197.000000	2.700000e+05
50%	5.000000	6.000000e+04	19.300000	81.000000	1248.000000	4.500000e+05
75%	8.000000	9.520000e+04	22.300000	88.000000	1582.000000	6.900000e+05
max	26.000000	2.360457e+06	42.000000	280.000000	3604.000000	1.000000e+07

On Step1:

The dataframe is filled with 7 colums and describes the

vehicle Names, age, km driven, fueleconomy, enginep, enginey, and

it includes the selling price of the vehicle.

It is also filled with 7905 rows and the purpose is to compare the vehicles

to see which is ideal.

In [40]:
```
# Step2:.
dfd.corr()
```

Out[40]:

	Age	km_driven	FuelEconomy_kmpl	engine_p	engine_v	selling_price
Age	1.000000	0.428541	-0.327189	-0.096420	-0.018250	-0.412299
km_driven	0.428541	1.000000	-0.173003	-0.010078	0.206078	-0.222152
FuelEconomy_kmpl	-0.327189	-0.173003	1.000000	-0.143632	-0.577973	-0.127844
engine_p	-0.096420	-0.010078	-0.143632	1.000000	0.282820	0.278393
engine_v	-0.018250	0.206078	-0.577973	0.282820	1.000000	0.455679
selling_price	-0.412299	-0.222152	-0.127844	0.278393	0.455679	1.000000

On Step2:

According to selling price the only variables that have a positive correlation are

Engine power and Enginer volume and Engine volume has the highest positive corr.

with selling price. The rest are all negative so the main driving factors of

selling price are engine power and engine volume.

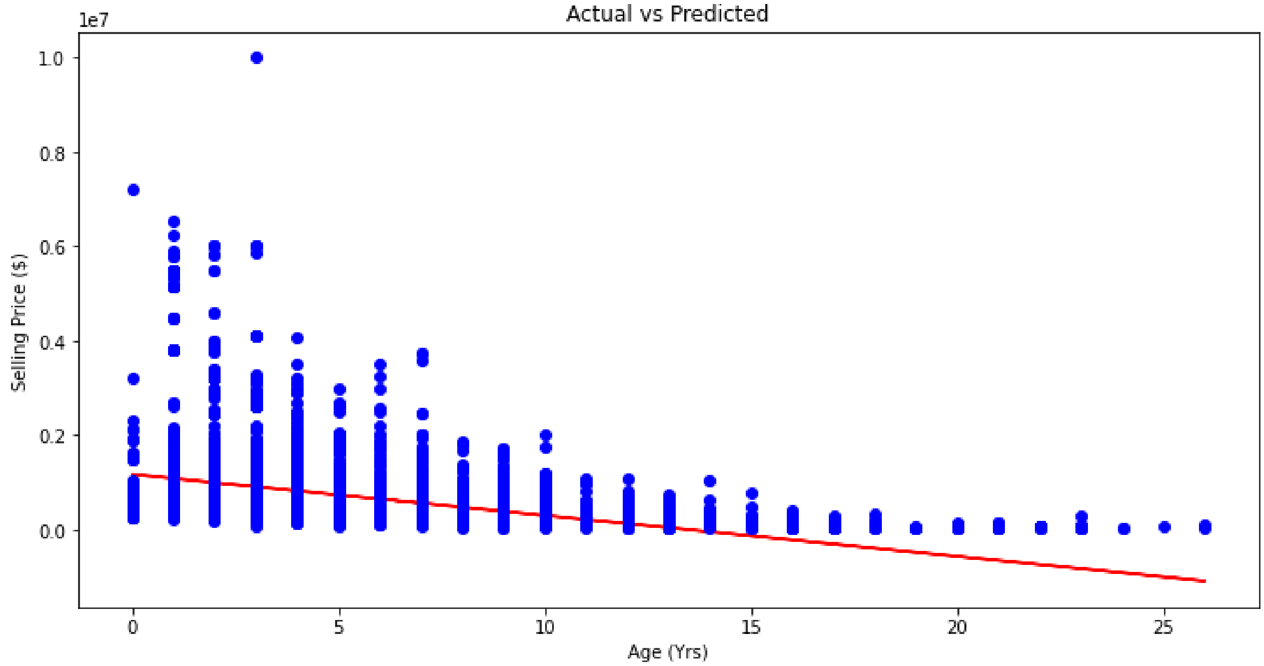
In [41]:
```
#Step3:
a = dfd['Age']
sp = dfd['selling_price']

meanA = np.mean(a)
meanSp = np.mean(sp)
print(meanA, meanSp)

dfd['xycov'] = (dfd['Age'] - meanA) * (dfd['selling_price'] - meanSp)
dfd['xvar'] = (dfd['Age'] - meanA)**2
print('===========================')

b = dfd['xycov'].sum() / dfd['xvar'].sum()
alpha = meanSp - (b * meanA)

print('Beta =',b)
print('Alpha=',alpha)
```

```
6.015939278937381 649829.510056926
===========================
Beta = -86818.48239180523
Alpha= 1172124.2284155204
```

In [42]:
```
X = np.array(a)

ypred = alpha + b * X
print(ypred)
```

```
[651213.33406469 651213.33406469 -43334.52506975 ... 217120.92210566
 564394.85167288 564394.85167288]
```

In [43]:
```
plt.figure(figsize=(12, 6))
plt.plot(X, ypred, color="red")
plt.plot(a, sp, 'ro', color="blue")
plt.title('Actual vs Predicted')
plt.xlabel('Age (Yrs)')
plt.ylabel('Selling Price ($)')

plt.show();
```



On Step3:

The older the car the lower the selling price becomes.

Higher Age = Lower Selling Price

Due to car damage, inflation, car wearing down, etc

In [53]:

```
# Step4:
f = dfd['FuelEconomy_kmpl']

model = smf.ols('sp ~ f', data = dfd)
model = model.fit()
model.params
```

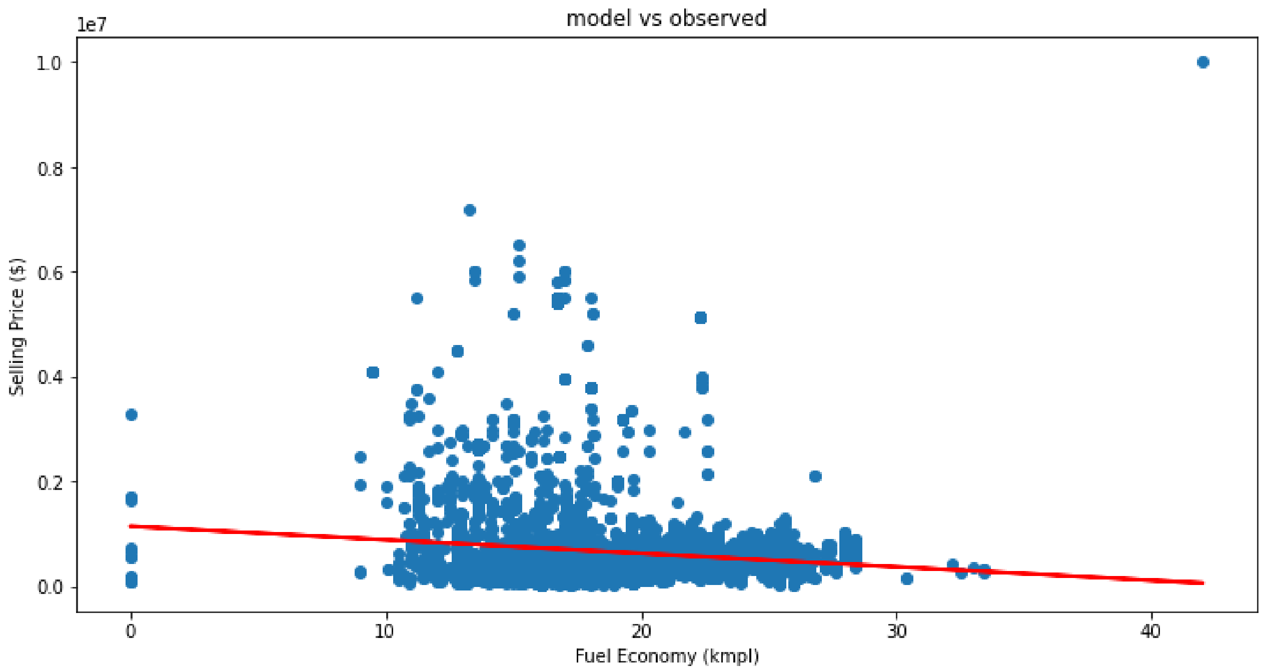
Out[53]:

```
Intercept    1.149923e+06
f           -2.578159e+04
dtype: float64
```

In [54]:

```
sp_p = model.predict()

plt.figure(figsize=(12, 6))
plt.plot(f, sp, 'o')

plt.plot(f, sp_p, 'r', linewidth=2)
plt.xlabel('Fuel Economy (kmpl)')
plt.ylabel('Selling Price ($)')
```

```
plt.title('model vs observed')

plt.show();
```



On Step4:

According to the plot as fuel economy continues to grow

The selling price begins to lower.

Fuel economy increases = Selling Price lowers

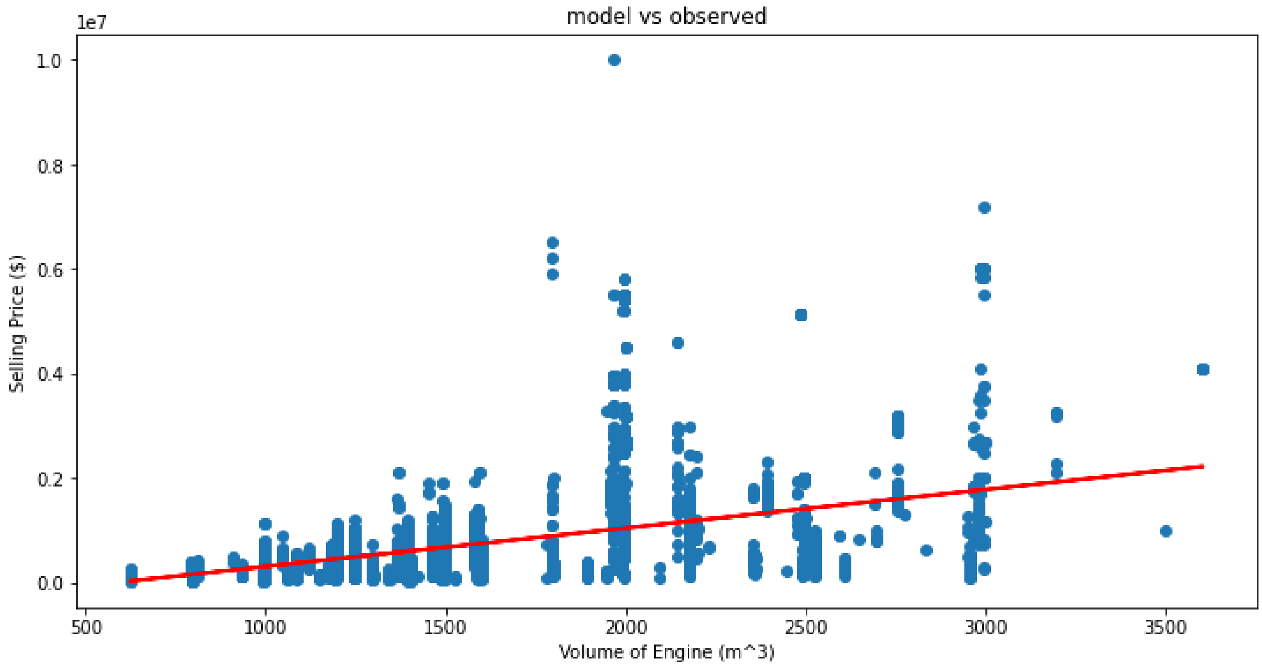
Although it is a low correlation.

In [46]:
```
# Step5:
e = dfd['engine_v']

model = smf.ols('sp ~ e', data = dfd)

model = model.fit()
model.params
```

Out[46]:
```
Intercept   -423426.822869
e               735.744311
dtype: float64
```

In [47]:
```
sepP = model.predict()
```

```
plt.figure(figsize=(12, 6))
plt.plot(e, sp, 'o')
plt.plot(e, sepP, 'r', linewidth=2)
plt.xlabel('Volume of Engine (m^3)')
plt.ylabel('Selling Price ($)')
plt.title('model vs observed')

plt.show();
```



On Step5:

As the engine volume increased the selling price also increased

Engine Volume Increase = Selling Price Increase

People tend to enjoy cars with a bigger engine.


```
In [48]: # Step6:
```

On Step6:

As a whole it seems as though step5 has the best fit

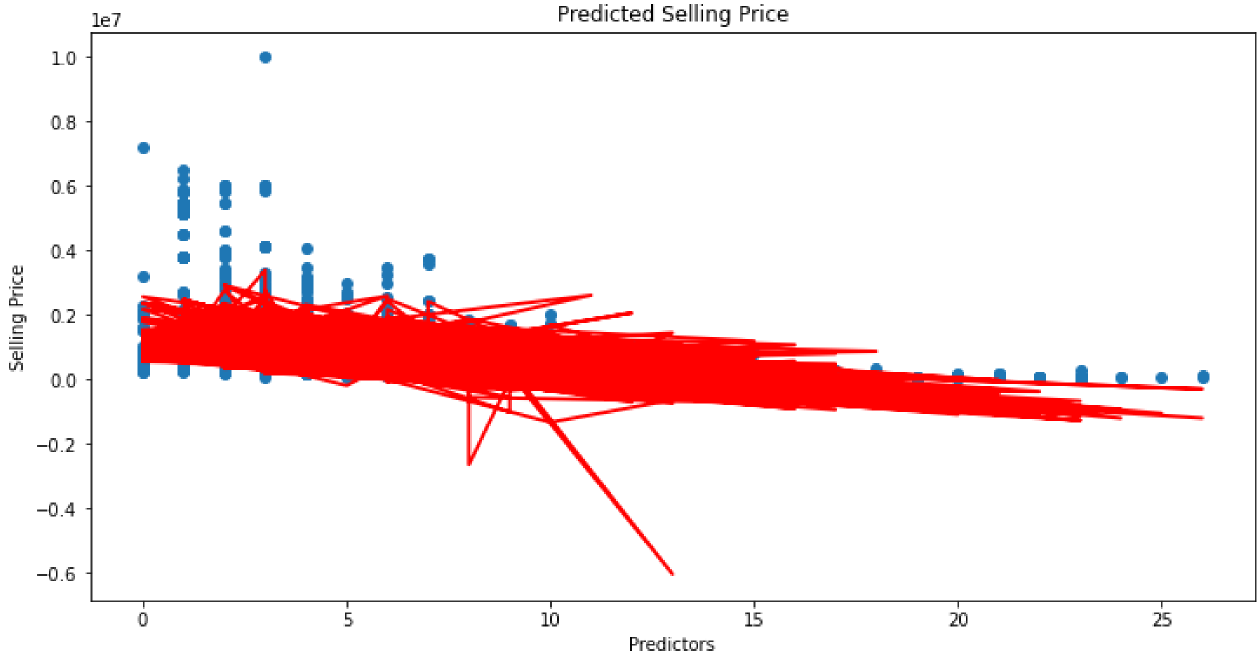
Step 3 has a decent fit as well, but not as great as step5s

Meaning Engine Volume being the predictor will lease to the best fit in terms of selling price.

In [55]:
```
#Step7:
predictors = ['Age', 'km_driven', 'FuelEconomy_kmpl','engine_p','engine_v']
X = dfd[predictors]
y = dfd['selling_price']
lm = LinearRegression()
model = lm.fit(X, y)
print(f'alpha = {model.intercept_}')
print(f'betas = {model.coef_}')
```

```
alpha = -349182.43008742994
betas = [-6.39699185e+04 -2.61785873e+00  6.27862738e+03  4.17269445e+03
  7.62703638e+02]
```

In [56]:
```
fitted = model.predict(X)


plt.figure(figsize=(12, 6))
plt.plot(dfd['Age'], dfd['selling_price'], 'o')
plt.plot(dfd['Age'], fitted, 'r', linewidth=2)
plt.xlabel('Predictors')
plt.ylabel('Selling Price')
plt.title('Predicted Selling Price')

plt.show();
```



In [57]:
```
final = [[2,17000,24.2,74,1260]]
finals =model.predict(final)
print('The Final Prediction for those parameters is:',finals)
```

```
The Final Prediction for those parameters is: [900102.89014124]
```