Building a Linear Regression Model

In this notebook, I will be building and optimizing a Linear Regression Model in the hopes that it can accurately predict Mileage from various other variables--although the actual data is irrelevant, the point of this notebook is purely to showcase and improve my skills with building a model.

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
import seaborn as sns
import statsmodels.formula.api as smf
from sklearn.metrics import r2_score
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
```

Importing the data set

```
data = pd.read_csv("https://raw.githubusercontent.com/austinkirwin/public-projects/refs/heads/main/Python_projects/LinRegModelFromScratch/uae
data.head()
```

	Make	Model	Year	Price	Mileage	Body Type	Cylinders	Transmission	Fuel Type	Color	Location	Description
0	toyota	camry	2016	47819	156500	Sedan	4	Automatic Transmission	Gasoline	Black	Dubai	2016 toyota camry with Rear camera, Leather se...
1	kia	sorento	2013	61250	169543	SUV	4	Automatic Transmission	Gasoline	Grey	Abu Dhabi	2013 kia sorento with Sunroof, Adaptive cruise...

Basic data manipulation

```
# Description is useless for mileage so I will remove it

data = data.drop("Description", axis=1)
data.head()
```

	Make	Model	Year	Price	Mileage	Body Type	Cylinders	Transmission	Fuel Type	Color	Location
0	toyota	camry	2016	47819	156500	Sedan	4	Automatic Transmission	Gasoline	Black	Dubai
1	kia	sorento	2013	61250	169543	SUV	4	Automatic Transmission	Gasoline	Grey	Abu Dhabi
2	mini	cooper	2023	31861	221583	Soft Top Convertible	4	Automatic Transmission	Gasoline	Grey	Dubai
3	nissan	altima	2016	110322	69754	Sedan	4	Automatic Transmission	Gasoline	Red	Dubai
4	toyota	land-cruiser-76-series	2020	139994	71399	Pick Up Truck	4	Manual Transmission	Gasoline	White	Dubai

```
# Many categorical variables so One-Hot Encoding

transformed_data = pd.get_dummies(data, dtype = int)
transformed_data.head() # 616 columns is excessive, let's try dropping some

transformed_data = pd.get_dummies(data.drop('Location', axis=1), dtype = int)
transformed_data.head() # 600 columns

transformed_data = pd.get_dummies(data.drop(['Location','Color'], axis = 1), dtype = int)
transformed_data.head() # 583 columns

transformed_data = pd.get_dummies(data.drop(['Location','Color','Make','Model'], axis = 1), dtype = int)
transformed_data.head() # Only 30 columns!!
```

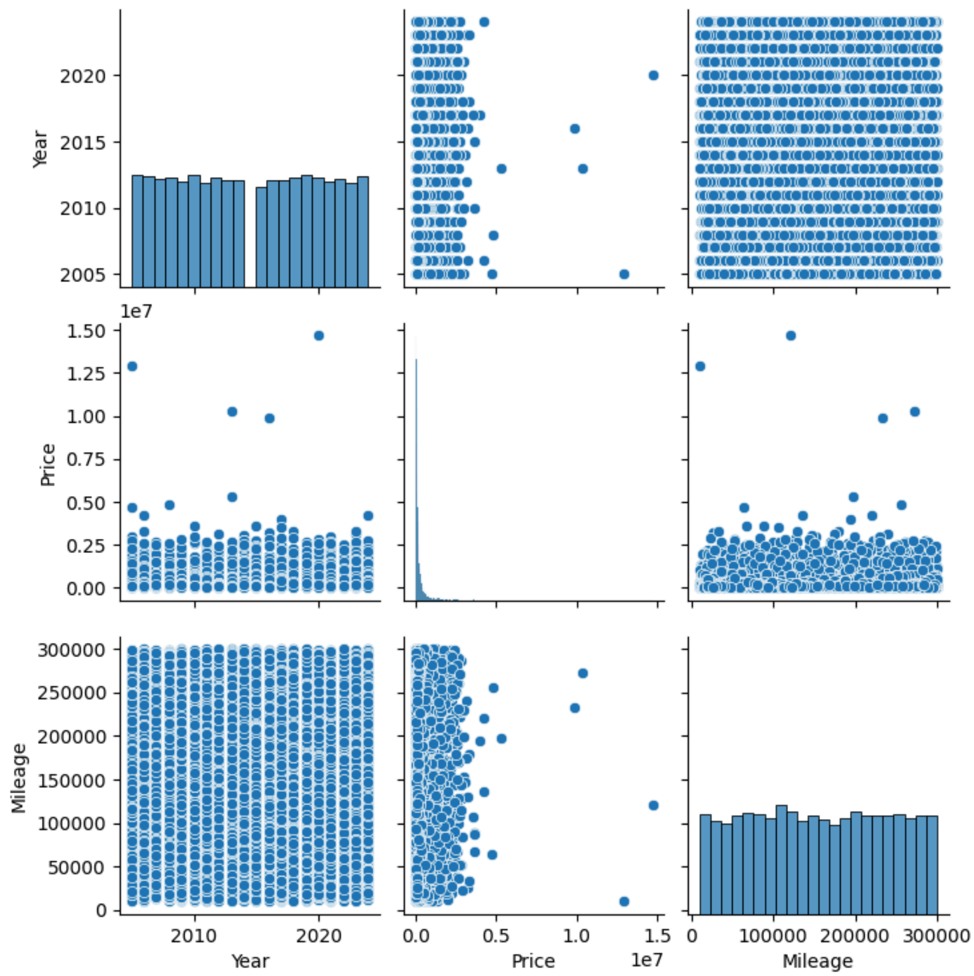
	Year	Price	Mileage	Body Type_Coupe	Body Type_Crossover	Body Type_Hard Top Convertible	Body Type_Hatchback	Body Type_Other	Body Type_Pick Up Truck	Body Type_SUV	...	Cylinders_5	Cyl
0	2016	47819	156500	0	0	0	0	0	0	0	...	0	
1	2013	61250	169543	0	0	0	0	0	0	1	...	0	
2	2023	31861	221583	0	0	0	0	0	0	0	...	0	
3	2016	110322	69754	0	0	0	0	0	0	0	...	0	
4	2020	139994	71399	0	0	0	0	0	1	0	...	0	

5 rows × 30 columns

Looking at pairwise data to see if there are any patterns

```
sns.pairplot(data)
```

```
<seaborn.axisgrid.PairGrid at 0x7f2267661810>
```



There do not seem to be any obvious relationships.

Building the Model

```
train, test = train_test_split(transformed_data, test_size=.2)

model = smf.ols(formula = 'Mileage ~ Price', data = train).fit()
model.summary()
```

OLS Regression Results

Dep. Variable:	Mileage	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	1.255
Date:	Tue, 04 Mar 2025	**Prob (F-statistic):**	0.263
Time:	21:47:19	**Log-Likelihood:**	-1.0206e+05
No. Observations:	8000	**AIC:**	2.041e+05
Df Residuals:	7998	**BIC:**	2.041e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.543e+05	1058.043	145.833	0.000	1.52e+05	1.56e+05
Price	0.0022	0.002	1.120	0.263	-0.002	0.006

Omnibus:	7689.209	**Durbin-Watson:**	1.953
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	489.066
Skew:	0.007	**Prob(JB):**	6.32e-107
Kurtosis:	1.789	**Cond. No.**	6.05e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.05e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

Checking for highly influential or high leverage points

```
# Get influence measures
influence = model.get_influence()

# Print Cook's distances
print("Cook's Distances:")
print(max(influence.cooks_distance[0]))

# Print leverage values
print("\nLeverage Values:")
print(max(influence.hat_matrix_diag))
```

```
Cook's Distances:
0.2240768497189483

Leverage Values:
0.11459555751536069
```

```
train_exp = train.drop('Mileage', axis = 1)
train_target = train['Mileage']
test_exp = test.drop('Mileage', axis = 1)
test_target = test['Mileage']

linreg = LinearRegression()
linreg.fit(train_exp, train_target)
linreg.score(test_exp, test_target) # obviously overfitted model
```

```
-0.009194744480062411
```

```
new_data = pd.get_dummies(data.drop(['Location','Color','Make','Model', 'Body Type'], axis = 1), dtype = int)
new_data.head()
```

	Year	Price	Mileage	Cylinders_10	Cylinders_12	Cylinders_3	Cylinders_4	Cylinders_5	Cylinders_6	Cylinders_8	Cylinders_Unknown
0	2016	47819	156500	0	0	0	1	0	0	0	0
1	2013	61250	169543	0	0	0	1	0	0	0	0
2	2023	31861	221583	0	0	0	1	0	0	0	0
3	2016	110322	69754	0	0	0	1	0	0	0	0
4	2020	139994	71399	0	0	0	1	0	0	0	0

Testing other models

```
new_train, new_test = train_test_split(new_data, test_size=.2)
new_train_exp = new_train.drop('Mileage', axis = 1)
new_train_target = new_train['Mileage']
new_test_exp = new_test.drop('Mileage', axis = 1)
new_test_target = new_test['Mileage']

new_linreg = LinearRegression()
new_linreg.fit(new_train_exp, new_train_target)
new_linreg.score(new_test_exp, new_test_target) # still overfit
```

```
-0.003463323851841782
```

```
AAAAA_data = data.drop(['Make','Model','Body Type','Cylinders','Transmission','Fuel Type','Color','Location'], axis = 1)
A_train, A_test = train_test_split(AAAAA_data, test_size=.2)
A_trainexp = A_train.drop('Mileage', axis = 1)
A_traintar = A_train['Mileage']
A_testexp = A_test.drop('Mileage', axis = 1)
A_testtar = A_test['Mileage']

Alinreg = LinearRegression()
Alinreg.fit(A_trainexp, A_traintar)
Alinreg.score(A_testexp, A_testtar)
```

```
-0.0019276961904044487
```

In conclusion all of these models have extremely low R^2 scores so Mileage is probably not able to be predicted by any of the variables in the dataset.