Predicting used car price

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

```
car_df = pd.read_csv("/data/workspace_files/cars_data.csv")
```

```
car_df.head()
```

	Make	Model	Type	Origin	DriveTrain	MSRP	Invoice	EngineSize	Cylinders	Horsepower	MPG_City	MPG_Highway	Weight
0	Acura	MDX	SUV	Asia	All	$36,945	$33,337	3.5	6.0	265	17	23	4451
1	Acura	RSX Type S 2dr	Sedan	Asia	Front	$23,820	$21,761	2.0	4.0	200	24	31	2778
2	Acura	TSX 4dr	Sedan	Asia	Front	$26,990	$24,647	2.4	4.0	200	22	29	3230
3	Acura	TL 4dr	Sedan	Asia	Front	$33,195	$30,299	3.2	6.0	270	20	28	3575
4	Acura	3.5 RL 4dr	Sedan	Asia	Front	$43,755	$39,014	3.5	6.0	225	18	24	3880

```
car_df.tail()
```

	Make	Model	Type	Origin	DriveTrain	MSRP	Invoice	EngineSize	Cylinders	Horsepower	MPG_City	MPG_Highway
423	Volvo	C70 LPT convertible 2dr	Sedan	Europe	Front	$40,565	$38,203	2.4	5.0	197	21	28
424	Volvo	C70 HPT convertible 2dr	Sedan	Europe	Front	$42,565	$40,083	2.3	5.0	242	20	26
425	Volvo	S80 T6 4dr	Sedan	Europe	Front	$45,210	$42,573	2.9	6.0	268	19	26
426	Volvo	V40	Wagon	Europe	Front	$26,135	$24,641	1.9	4.0	170	22	29
427	Volvo	XC70	Wagon	Europe	All	$35,145	$33,112	2.5	5.0	208	20	27

```
car_df.columns
```

```
Index(['Make', 'Model', 'Type', 'Origin', 'DriveTrain', 'MSRP', 'Invoice',
'EngineSize', 'Cylinders', 'Horsepower', 'MPG_City', 'MPG_Highway',
'Weight', 'Wheelbase', 'Length'],
dtype='object')
```

```
car_df.shape
```

```
(428, 15)
```

```
car_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 428 entries, 0 to 427
Data columns (total 15 columns):
# Column Non-Null Count Dtype
--- ------ -------------- -----
0 Make 428 non-null object
1 Model 428 non-null object
2 Type 428 non-null object
3 Origin 428 non-null object
4 DriveTrain 428 non-null object
5 MSRP 428 non-null object
6 Invoice 428 non-null object
7 EngineSize 428 non-null float64
8 Cylinders 426 non-null float64
9 Horsepower 428 non-null int64
10 MPG_City 428 non-null int64
11 MPG_Highway 428 non-null int64
12 Weight 428 non-null int64
13 Wheelbase 428 non-null int64
14 Length 428 non-null int64
dtypes: float64(2), int64(6), object(7)
memory usage: 50.3+ KB
```

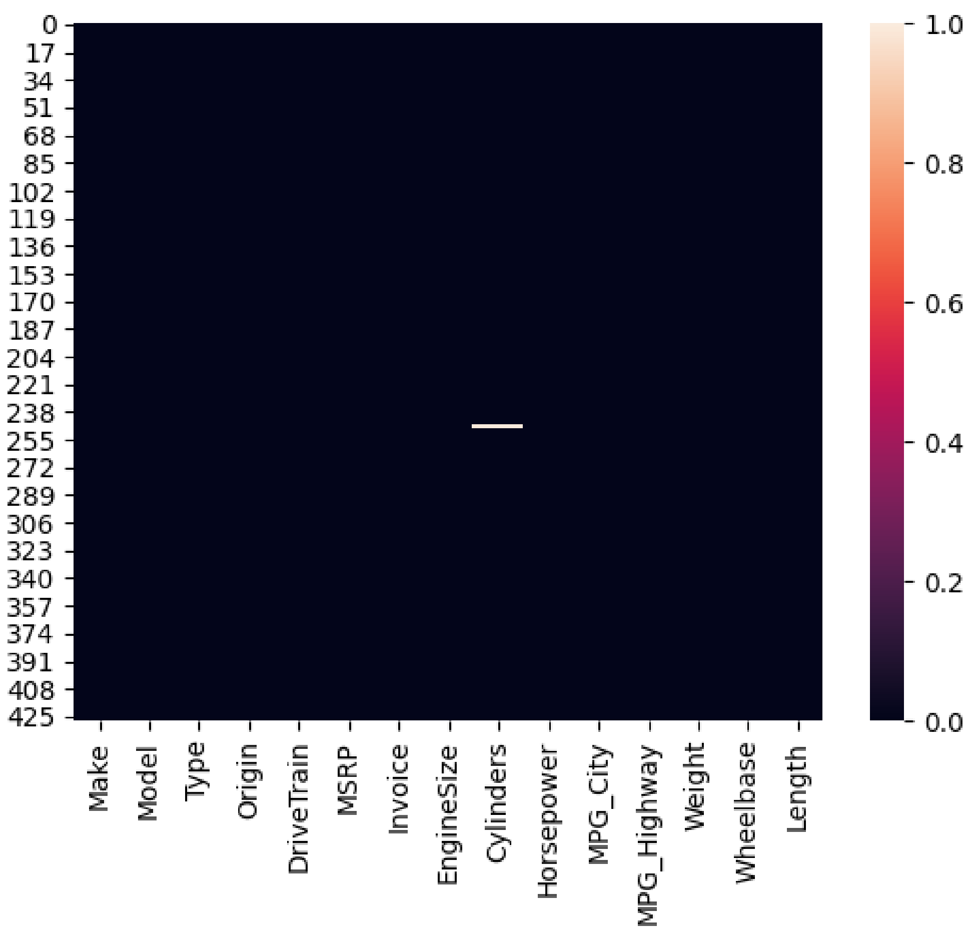
```
car_df.describe()
```

	EngineSize	Cylinders	Horsepower	MPG_City	MPG_Highway	Weight	Wheelbase	Length
count	428.000000	426.000000	428.000000	428.000000	428.000000	428.000000	428.000000	428.000000
mean	3.196729	5.807512	215.885514	20.060748	26.843458	3577.953271	108.154206	186.362150
std	1.108595	1.558443	71.836032	5.238218	5.741201	758.983215	8.311813	14.357991
min	1.300000	3.000000	73.000000	10.000000	12.000000	1850.000000	89.000000	143.000000
25%	2.375000	4.000000	165.000000	17.000000	24.000000	3104.000000	103.000000	178.000000
50%	3.000000	6.000000	210.000000	19.000000	26.000000	3474.500000	107.000000	187.000000
75%	3.900000	6.000000	255.000000	21.250000	29.000000	3977.750000	112.000000	194.000000
max	8.300000	12.000000	500.000000	60.000000	66.000000	7190.000000	144.000000	238.000000

```
# Check if there are any missing elements
car_df.isnull().sum()
```

```
Make 0
Model 0
Type 0
Origin 0
DriveTrain 0
MSRP 0
Invoice 0
EngineSize 0
Cylinders 2
Horsepower 0
MPG_City 0
MPG_Highway 0
Weight 0
Wheelbase 0
Length 0
dtype: int64
```

```
sns.heatmap(car_df.isnull())
plt.show()
```




```
car_df[car_df['Cylinders'].isnull()]
```

	Make	Model	Type	Origin	DriveTrain	MSRP	Invoice	EngineSize	Cylinders	Horsepower	MPG_City	MPG_Highway	V
247	Mazda	RX-8 4dr automatic	Sports	Asia	Rear	$25,700	$23,794	1.3	NaN	197	18	25	3
248	Mazda	RX-8 4dr manual	Sports	Asia	Rear	$27,200	$25,179	1.3	NaN	238	18	24	3

```
car_df.dropna(inplace=True)
```

```
car_df.isnull().sum()
```

```
Make 0
Model 0
Type 0
Origin 0
DriveTrain 0
MSRP 0
Invoice 0
EngineSize 0
Cylinders 0
Horsepower 0
MPG_City 0
MPG_Highway 0
Weight 0
Wheelbase 0
Length 0
dtype: int64
```

We can see that from the calculation above as well as the heatmap that there are a few(2) missing values in the cylinders column

```
car_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 426 entries, 0 to 427
Data columns (total 15 columns):
# Column Non-Null Count Dtype
--- ------ -------------- -----
0 Make 426 non-null object
1 Model 426 non-null object
2 Type 426 non-null object
3 Origin 426 non-null object
4 DriveTrain 426 non-null object
5 MSRP 426 non-null object
6 Invoice 426 non-null object
7 EngineSize 426 non-null float64
8 Cylinders 426 non-null float64
9 Horsepower 426 non-null int64
10 MPG_City 426 non-null int64
11 MPG_Highway 426 non-null int64
12 Weight 426 non-null int64
13 Wheelbase 426 non-null int64
```

```
14 Length 426 non-null int64
dtypes: float64(2), int64(6), object(7)
memory usage: 53.2+ KB
```

```
# Converting Invoice to int and removing $ and , from values

car_df["Invoice"] = car_df["Invoice"].str.replace("$", "")
car_df["Invoice"] = car_df["Invoice"].str.replace(",", "")
car_df["Invoice"] = car_df["Invoice"].astype(int)
```

```
<ipython-input-74-721ce763c947-SdwxTcY3dyrvmFXDrzAJsV>:3: FutureWarning:

The default value of regex will change from True to False in a future version. In addition, single
character regular expressions will*not* be treated as literal strings when regex=True.
```

```
# Converting MSRP to int and removing $ and , from values

car_df["MSRP"] = car_df["MSRP"].str.replace("$", "")
car_df["MSRP"] = car_df["MSRP"].str.replace(",", "")
car_df["MSRP"] = car_df["MSRP"].astype(int)
```

```
<ipython-input-75-8e65e3ee98e1-vGzkd3TfMyBYQVZdjgoUYV>:3: FutureWarning:

The default value of regex will change from True to False in a future version. In addition, single
character regular expressions will*not* be treated as literal strings when regex=True.
```

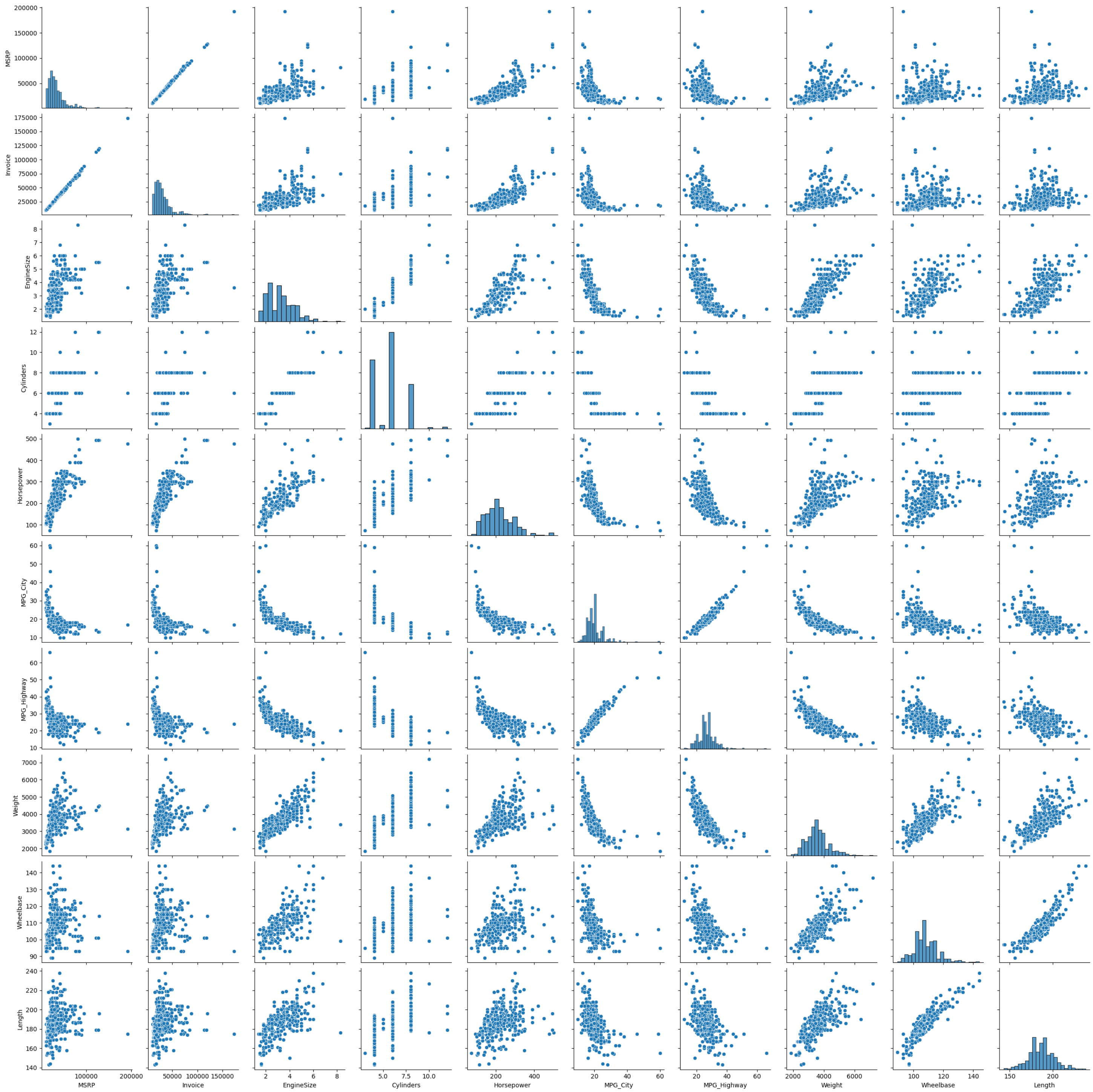
```
car_df.head()
```

	Make	Model	Type	Origin	DriveTrain	MSRP	Invoice	EngineSize	Cylinders	Horsepower	MPG_City	MPG_Highway	Weight	Wh
0	Acura	MDX	SUV	Asia	All	36945	33337	3.5	6.0	265	17	23	4451	106
1	Acura	RSX Type S 2dr	Sedan	Asia	Front	23820	21761	2.0	4.0	200	24	31	2778	101
2	Acura	TSX 4dr	Sedan	Asia	Front	26990	24647	2.4	4.0	200	22	29	3230	105
3	Acura	TL 4dr	Sedan	Asia	Front	33195	30299	3.2	6.0	270	20	28	3575	108
4	Acura	3.5 RL 4dr	Sedan	Asia	Front	43755	39014	3.5	6.0	225	18	24	3880	115

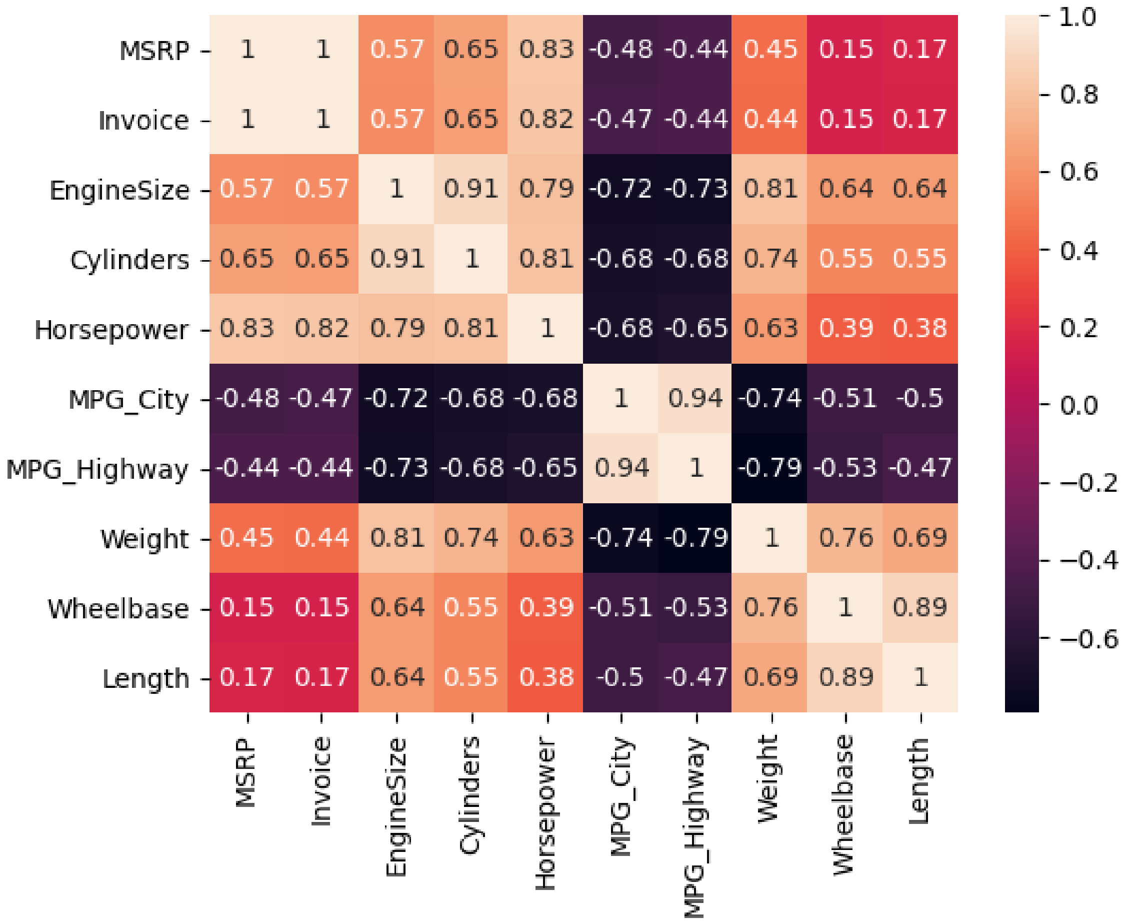
```
car_df.describe()
```

	MSRP	Invoice	EngineSize	Cylinders	Horsepower	MPG_City	MPG_Highway	Weight	Wheelb
count	426.000000	426.000000	426.000000	426.000000	426.000000	426.000000	426.000000	426.000000	426.00
mean	32804.549296	30040.654930	3.205634	5.807512	215.877934	20.070423	26.854460	3580.474178	108.164
std	19472.460825	17679.430122	1.103520	1.558443	71.991040	5.248616	5.752335	759.870073	8.3300
min	10280.000000	9875.000000	1.400000	3.000000	73.000000	10.000000	12.000000	1850.000000	89.000
25%	20324.750000	18836.000000	2.400000	4.000000	165.000000	17.000000	24.000000	3111.250000	103.000
50%	27807.500000	25521.500000	3.000000	6.000000	210.000000	19.000000	26.000000	3476.000000	107.000
75%	39225.000000	35754.750000	3.900000	6.000000	255.000000	21.750000	29.000000	3979.250000	112.000
max	192465.000000	173560.000000	8.300000	12.000000	500.000000	60.000000	66.000000	7190.000000	144.000

```
sns.pairplot(car_df)
plt.show()
```



```
# checking correlation
sns.heatmap(car_df.corr(), annot=True)
plt.show()
```



From the above histogram plots, we can see that almost all features depict the skewness to the right. Hence, we can say that there are more outliers to the right except for the length of the car which looks that it is normally distributed.

Secondly we can see strong positive correlation between engine size and horsepower, which seems pretty obvious as the engine size increases the horse power increases. Also the increase in weight can be because of the increase in size of an engine.

On the other hand the mileage decreases as it seems the higher capacity engines could be of some type of a high performance car

We can see the skewness to the right for almost every feature which depicts that those outliers could be these high performance cars as the engine size, horse power and cylinders histogram skew towards right.

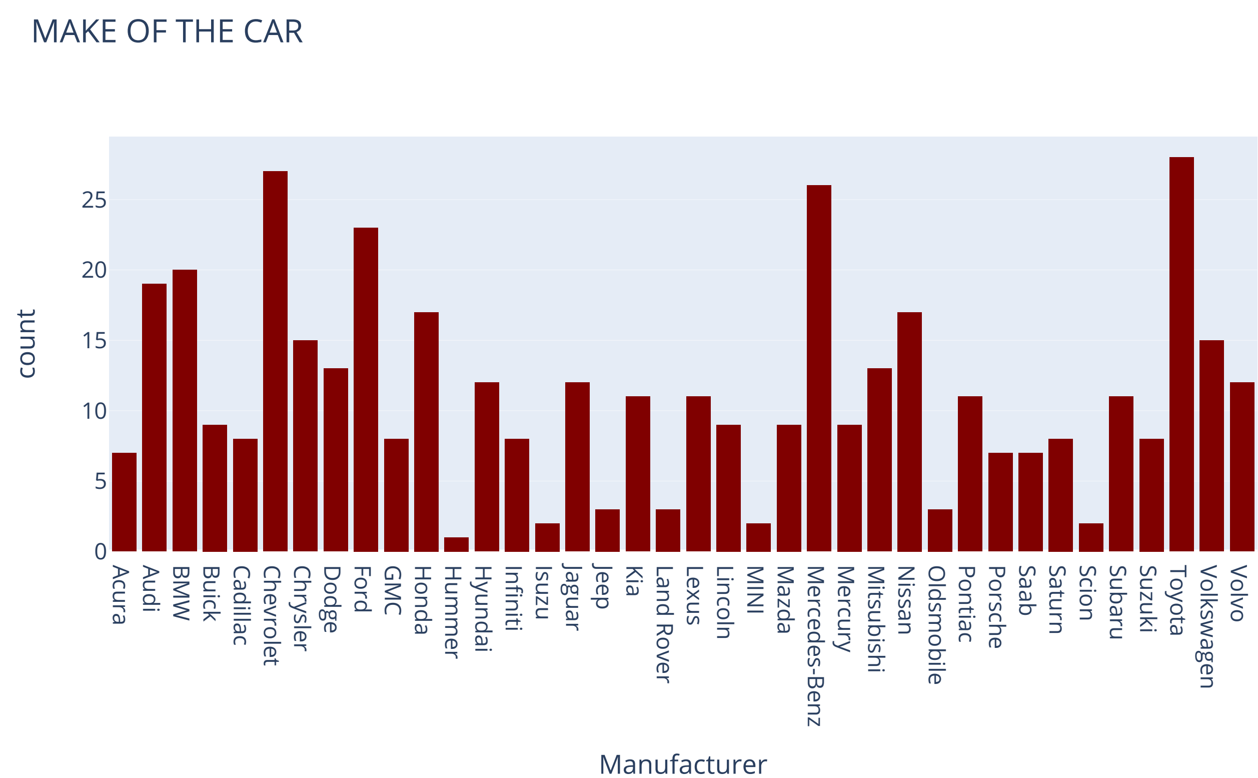
While exploring the correlation between MSRP and other features, we can see that there is a strong positive correlation between MSRP and the horsepower.

```
# Lets see all the companies in car_df

car_df.Make.unique()
```

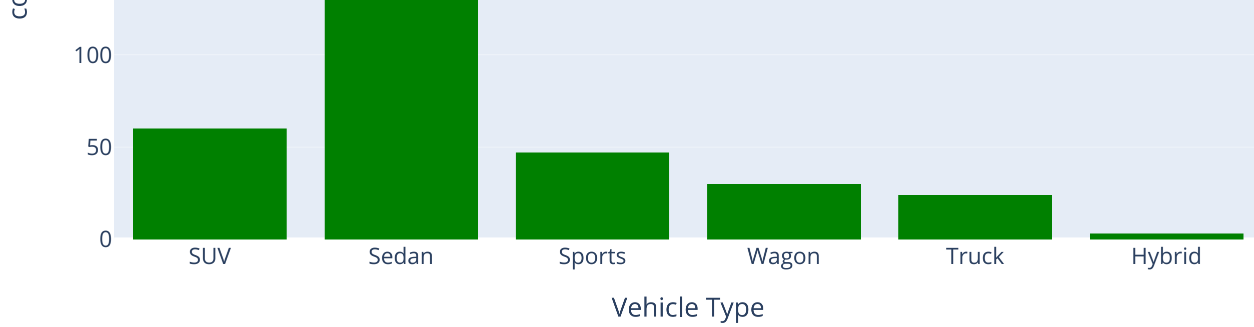
```
array(['Acura', 'Audi', 'BMW', 'Buick', 'Cadillac', 'Chevrolet', 'Chrysler', 'Dodge', 'Ford',
'GMC', 'Honda', 'Hummer', 'Hyundai', 'Infiniti', 'Isuzu', 'Jaguar', 'Jeep', 'Kia', 'Land Rover',
'Lexus', 'Lincoln', 'MINI', 'Mazda', 'Mercedes-Benz', 'Mercury', 'Mitsubishi', 'Nissan',
'Oldsmobile', 'Pontiac', 'Porsche', 'Saab', 'Saturn', 'Scion', 'Subaru', 'Suzuki', 'Toyota',
'Volkswagen', 'Volvo'], dtype=object)
```

```python
import plotly as px
```

```python
fig = px.hist_series(car_df, x = "Make",
                   labels = {"Make": "Manufacturer"},
                   title = "MAKE OF THE CAR",
                   color_discrete_sequence = ["maroon"])

fig.show()
```

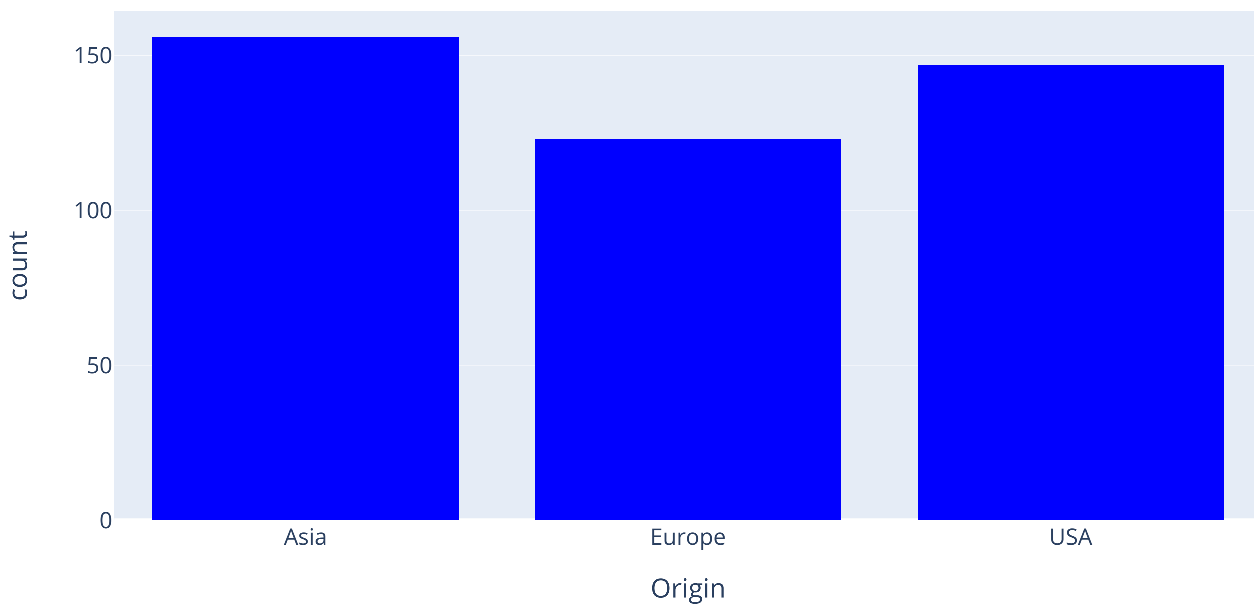



```python
fig = px.hist_series(car_df, x = "Type",
                   labels = {"Type": "Vehicle Type"},
                   title = "Type of Vehicle",
                   color_discrete_sequence = ["green"])

fig.show()
```



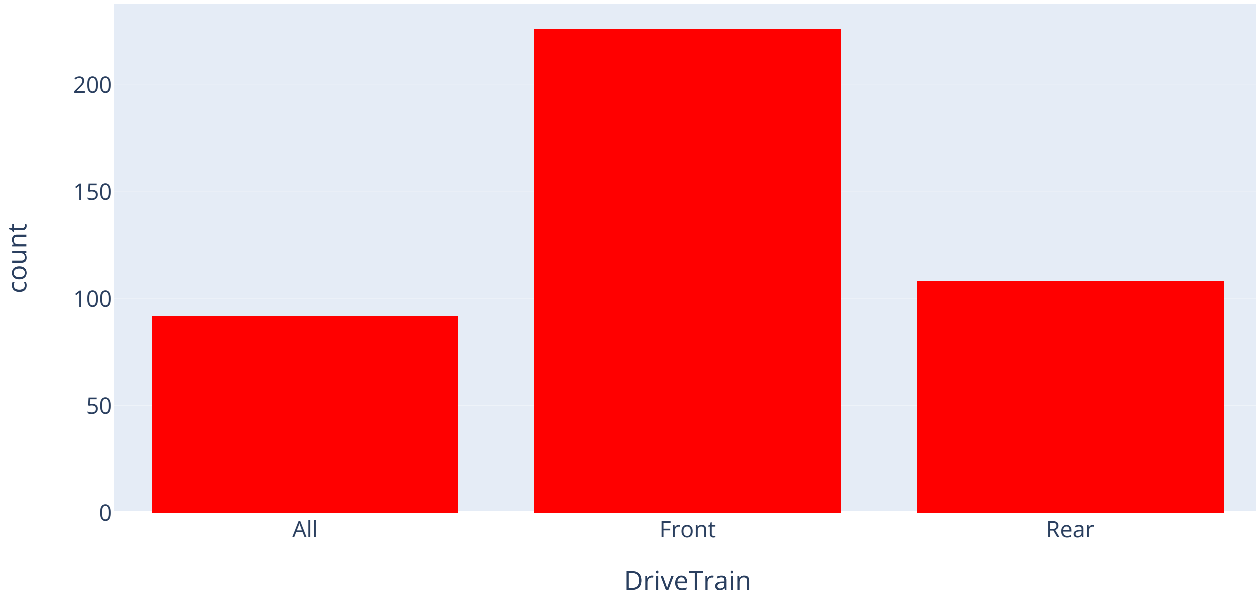

```
fig = px.hist_series(car_df, x = "Origin",
                   labels = {"Type": "Location"},
                   title = "Origin of company",
                   color_discrete_sequence = ["blue"])

fig.show()
```

Origin of company

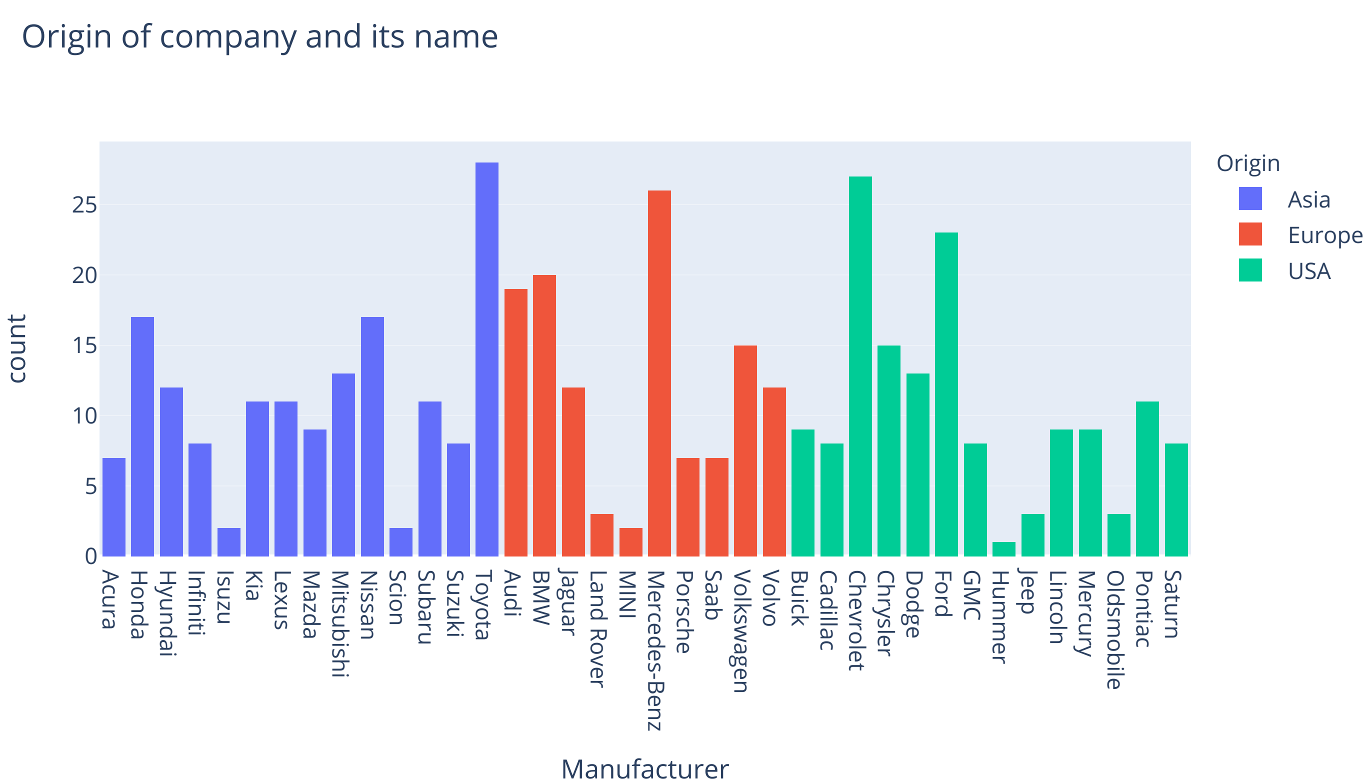



```
fig = px.hist_series(car_df, x = "DriveTrain",
                   labels = {"Type": "Drive Train"},
                   title = "Drive Trainy",
                   color_discrete_sequence = ["red"])

fig.show()
```

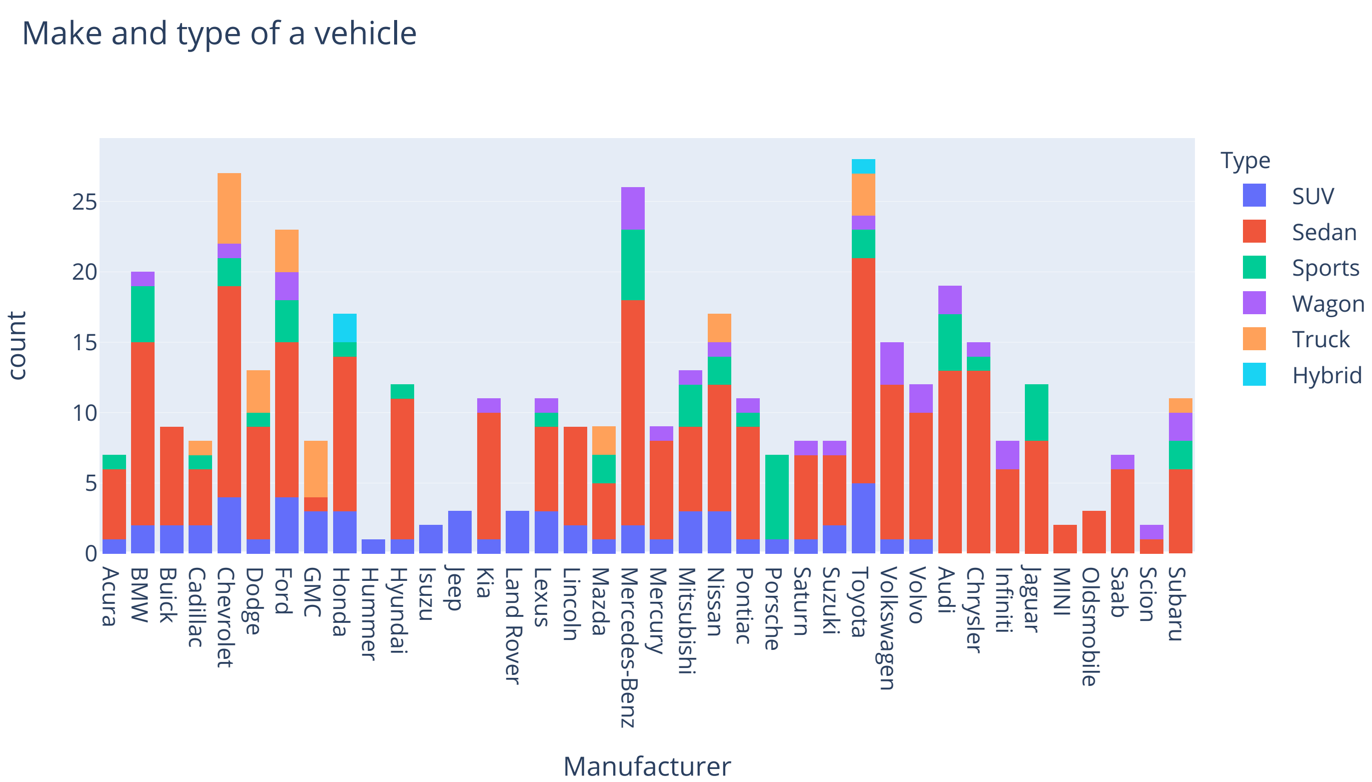
Drive Trainy




```
fig = px.hist_series(car_df, x = "Make",
                     color = "Origin",
                   labels = {"Make": "Manufacturer"},
                   title = "Origin of company and its name",
                    )

fig.show()
```



```python
fig = px.hist_series(car_df, x = "Make",
                     color = "Type",
                   labels = {"Make": "Manufacturer"},
                   title = "Make and type of a vehicle",
                    )

fig.show()
```



Above chart depict that all the green color segments could be the outliers as the green color in the bar represents the "sports" type and the make Porsche makes highest number of sports car and only Toyota and Honda makes the hybrid cars.

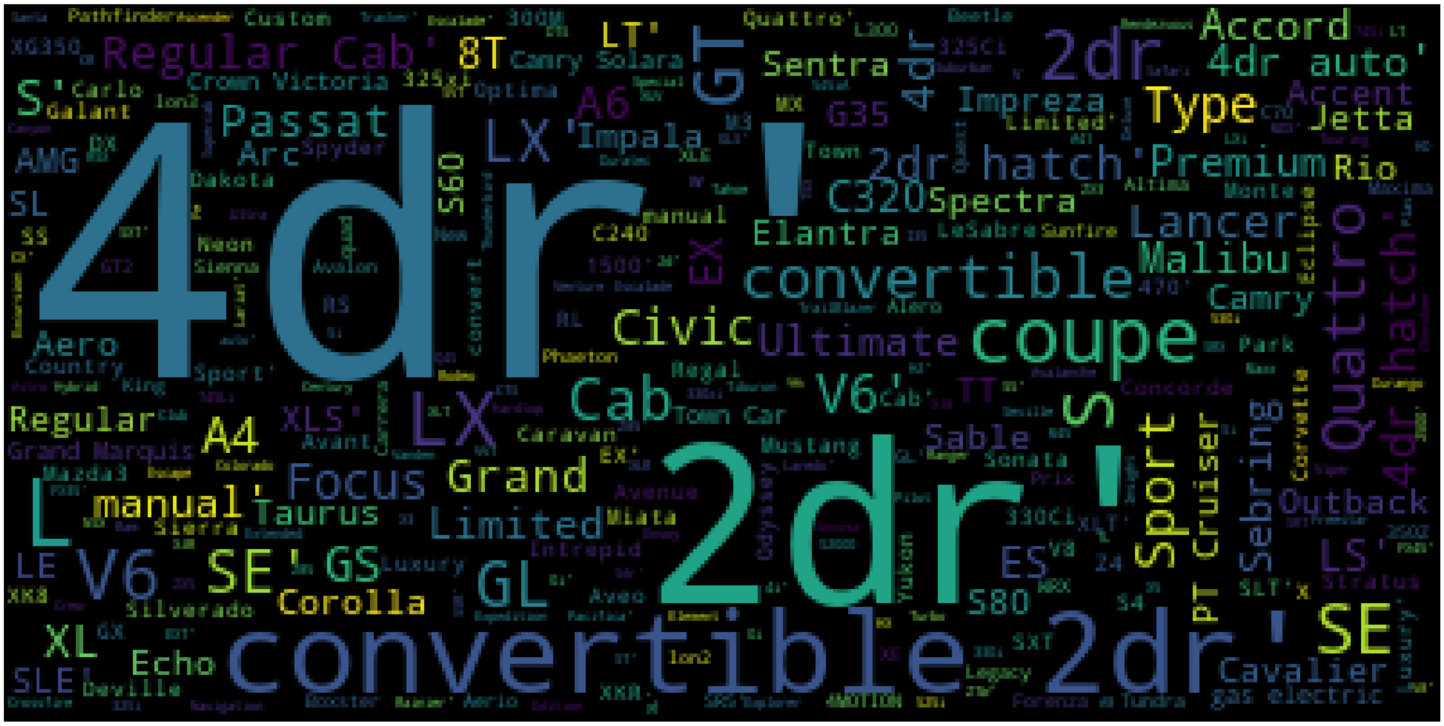
```python
# Visualisation using wordcloud

from wordcloud import WordCloud, STOPWORDS
```

```python
text = car_df.Model.values
```

```python
stopwords = set(STOPWORDS)
```

```
wc = WordCloud(background_color='black', max_words= 2000, max_font_size= 100, random_state=3, stopwor
               contour_width=3).generate(str(text))
```

```
fig = plt.figure(figsize = (25,15))
plt.imshow(wc)
plt.axis("off")
plt.show()
```



Cleaning and preparing the data for training

```
df_dum = pd.get_dummies(car_df, columns = ['Make', 'Model', 'Type', 'Origin', 'DriveTrain'], drop_fir
```

```
df_dum
```

	MSRP	Invoice	EngineSize	Cylinders	Horsepower	MPG_City	MPG_Highway	Weight	Wheelbase	Length	Make_Audi	Make_BM
0	36945	33337	3.5	6.0	265	17	23	4451	106	189	0	0
1	23820	21761	2.0	4.0	200	24	31	2778	101	172	0	0
2	26990	24647	2.4	4.0	200	22	29	3230	105	183	0	0
3	33195	30299	3.2	6.0	270	20	28	3575	108	186	0	0
4	43755	39014	3.5	6.0	225	18	24	3880	115	197	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
423	40565	38203	2.4	5.0	197	21	28	3450	105	186	0	0
424	42565	40083	2.3	5.0	242	20	26	3450	105	186	0	0
425	45210	42573	2.9	6.0	268	19	26	3653	110	190	0	0
426	26135	24641	1.9	4.0	170	22	29	2822	101	180	0	0
427	35145	33112	2.5	5.0	208	20	27	3823	109	186	0	0

426 rows × 478 columns

```
df_data = df_dum.drop(['Invoice'], axis=1)
```

```
df_data.shape
```

```
(426, 477)
```

```
# Splitting the data

X = df_data.drop(['MSRP'], axis=1)
y = df_data['MSRP']
```

```
# Converting the data into an array

X = np.array(X)
y = np.array(y)
```

```
# Training the data

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)
```

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((340, 476), (86, 476), (340,), (86,))
```

Now we will predict the continuous variable MSRP through Linear Regression

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, accuracy_score, r2_score
from math import sqrt
```

```
linearRegression_model = LinearRegression()
linearRegression_model.fit(X_train, y_train)
```

```
LinearRegression()
```

```
accuracy_linearRegression = linearRegression_model.score(X_test, y_test)
print(accuracy_linearRegression)
```

```
0.7842981779789897
```

Train and Evaluate Decision tree and Random forest Models

```
from sklearn.tree import DecisionTreeRegressor
DecisionTree_model = DecisionTreeRegressor()
DecisionTree_model.fit(X_train, y_train)
```

```
DecisionTreeRegressor()
```

```
accuracy_DecisionTree = DecisionTree_model.score(X_test, y_test)
print(accuracy_DecisionTree)
```

```
0.7314227537745278
```

```
from sklearn.ensemble import RandomForestRegressor
RandomForest_model = RandomForestRegressor(n_estimators=5, max_depth=5)
RandomForest_model.fit(X_train, y_train)
```

```
RandomForestRegressor(max_depth=5, n_estimators=5)
```

```
accuracy_RandomForest = RandomForest_model.score(X_test, y_test)
print(accuracy_RandomForest)
```

```
0.7376270961437256
```

NOw we will use XGBOOST

```
from xgboost import XGBRegressor
model = XGBRegressor()
model.fit(X_train, y_train)
```

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
importance_type='gain', interaction_constraints='',
learning_rate=0.300000012, max_delta_step=0, max_depth=6,
min_child_weight=1, missing=nan, monotone_constraints='()',
n_estimators=100, n_jobs=2, num_parallel_tree=1, random_state=0,
reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
tree_method='exact', validate_parameters=1, verbosity=None)
```

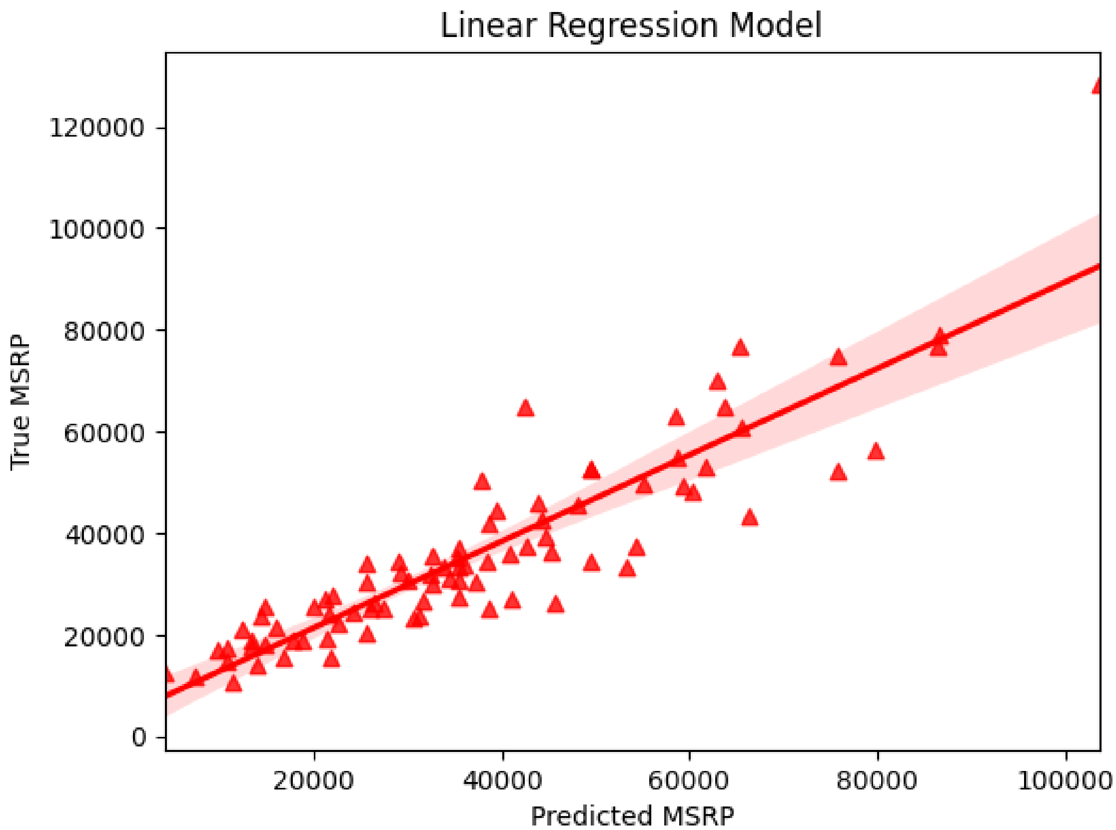
```
accuracy_XGBoost = model.score(X_test, y_test)
print(accuracy_XGBoost)
```

```
0.8547854569198877
```

Compare models and calculate regression KPI's

```
# Linear

y_predict_linear = linearRegression_model.predict(X_test)

#plotting against y_test

fig = sns.regplot(y_predict_linear, y_test, color='r', marker='^')
fig.set(title = "Linear Regression Model", xlabel= "Predicted MSRP", ylabel= "True MSRP")
```

```
[Text(0.5, 1.0, 'Linear Regression Model'),
Text(0.5, 23.52222222222222, 'Predicted MSRP'),
Text(12.097222222222216, 0.5, 'True MSRP')]
```



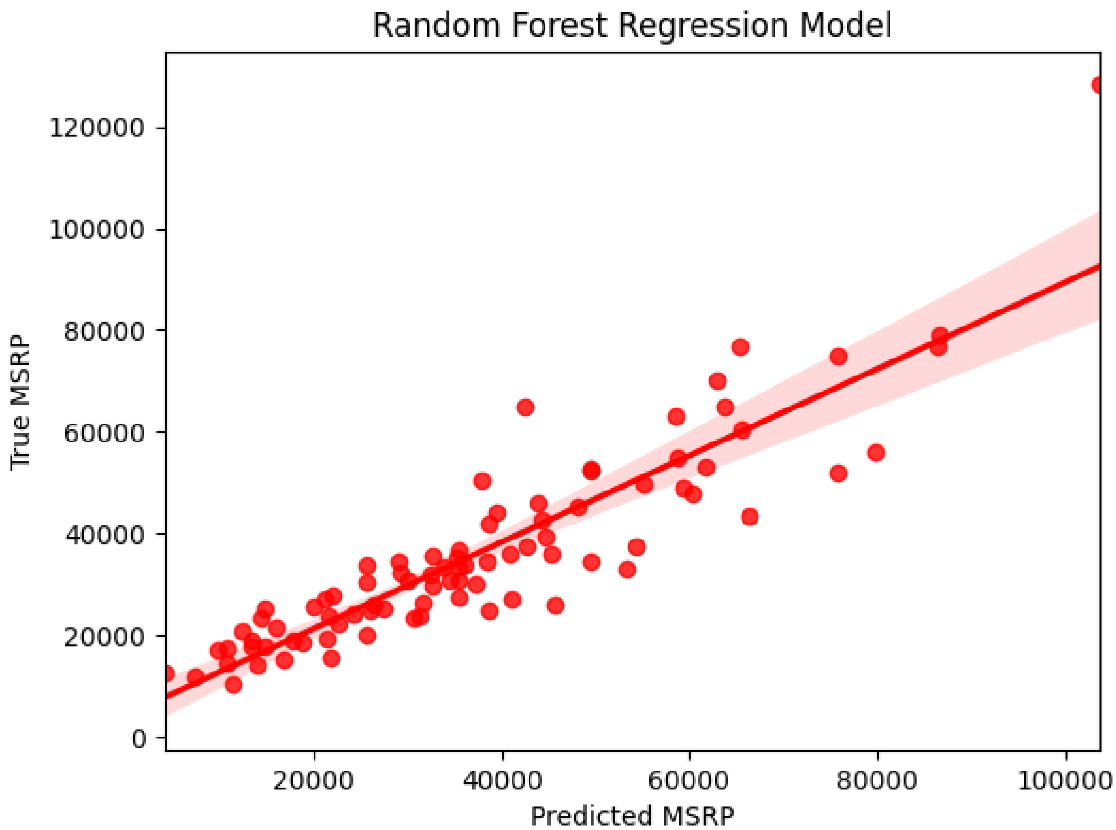

```
/opt/python/envs/default/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning:

Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an explicit keyword will result in an
error or misinterpretation.
```

```
r2 = r2_score(y_test, y_predict_linear)
MAE = mean_absolute_error(y_test, y_predict_linear)
MSE = mean_squared_error(y_test, y_predict_linear)
RMSE = np.sqrt(MSE)

print('r2 = ' ,r2, 'MAE = ',MAE, 'MSE = ',MSE, 'RMSE = ',RMSE)
```

```
r2 = 0.7842981779789897 MAE = 6555.734560048513 MSE = 79105471.10929047 RMSE = 8894.125651759732
```

```
# Random forest

y_predict_RandomForest = RandomForest_model.predict(X_test)

#plotting against y_test

fig = sns.regplot(y_predict_linear, y_test, color='r', marker='o')
fig.set(title = "Random Forest Regression Model", xlabel= "Predicted MSRP", ylabel= "True MSRP")
```

```
[Text(0.5, 1.0, 'Random Forest Regression Model'),
Text(0.5, 23.52222222222222, 'Predicted MSRP'),
Text(12.097222222222216, 0.5, 'True MSRP')]
```



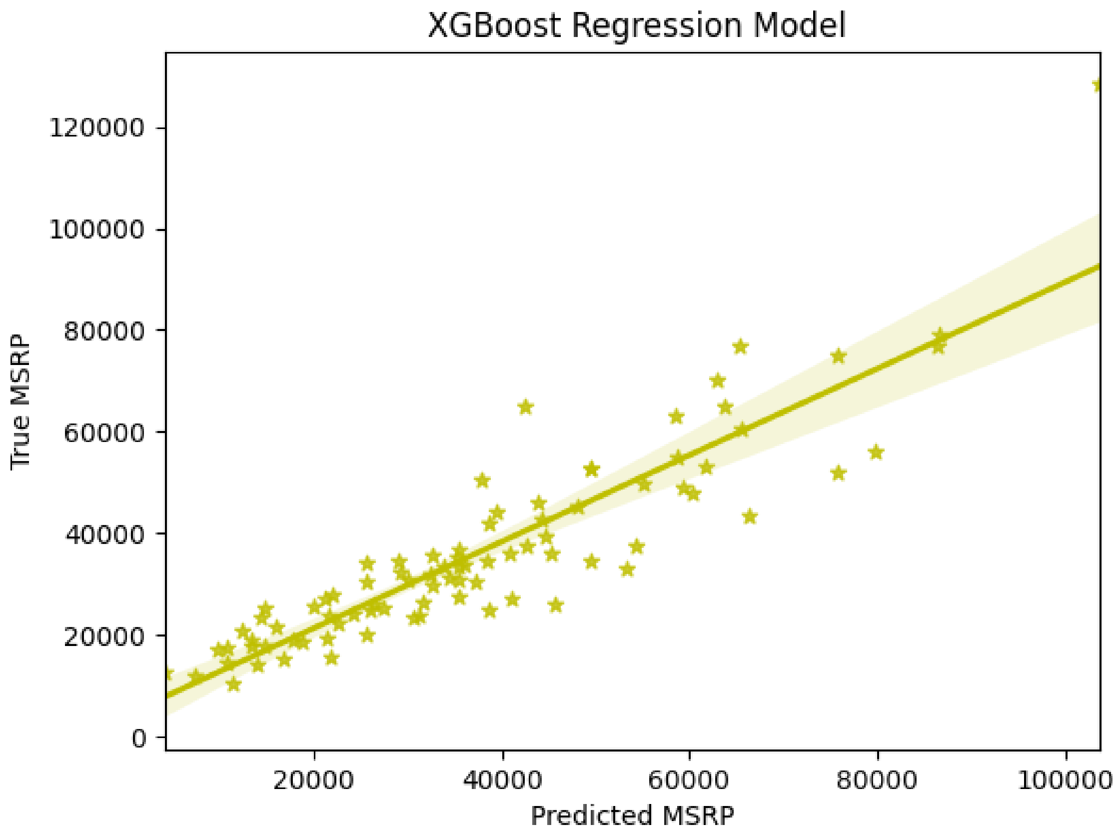

```
/opt/python/envs/default/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning:

Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an explicit keyword will result in an
error or misinterpretation.
```

```
r2 = r2_score(y_test, y_predict_linear)
MAE = mean_absolute_error(y_test, y_predict_linear)
MSE = mean_squared_error(y_test, y_predict_linear)
RMSE = np.sqrt(MSE)

print('r2 = ' ,r2, 'MAE = ',MAE, 'MSE = ',MSE, 'RMSE = ',RMSE)
```

```
r2 = 0.7842981779789897 MAE = 6555.734560048513 MSE = 79105471.10929047 RMSE = 8894.125651759732
```

```
# XGBoost
y_predict_XGBoost = model.predict(X_test)

#plotting against y_test

fig = sns.regplot(y_predict_linear, y_test, color='y', marker='*')
fig.set(title = " XGBoost Regression Model", xlabel= "Predicted MSRP", ylabel= "True MSRP")
```

```
[Text(0.5, 1.0, ' XGBoost Regression Model'),
Text(0.5, 23.52222222222222, 'Predicted MSRP'),
Text(12.097222222222216, 0.5, 'True MSRP')]
```



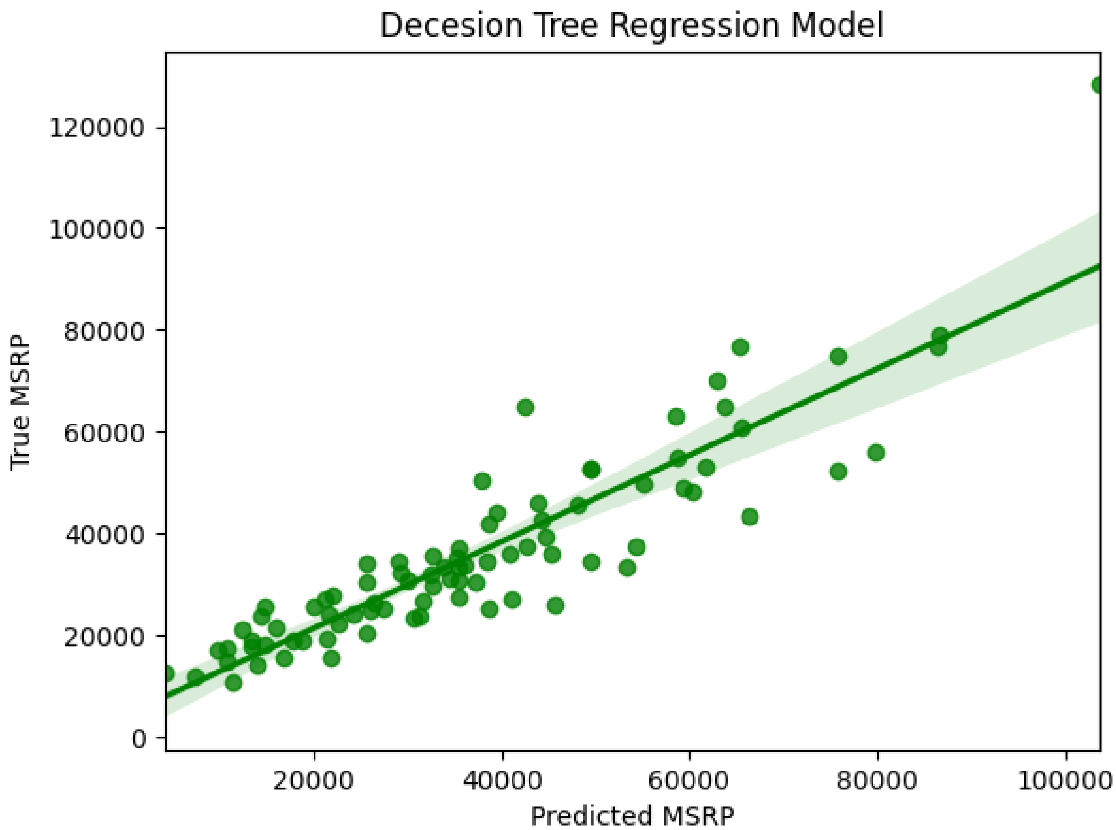

```
/opt/python/envs/default/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning:

Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an explicit keyword will result in an
error or misinterpretation.
```

```
r2 = r2_score(y_test, y_predict_linear)
MAE = mean_absolute_error(y_test, y_predict_linear)
MSE = mean_squared_error(y_test, y_predict_linear)
RMSE = np.sqrt(MSE)

print('r2 = ' ,r2, 'MAE = ',MAE, 'MSE = ',MSE, 'RMSE = ',RMSE)
```

```
r2 = 0.7842981779789897 MAE = 6555.734560048513 MSE = 79105471.10929047 RMSE = 8894.125651759732
```

```
y_predict_DecesionTree = DecisionTree_model.predict(X_test)

#plotting against y_test

fig = sns.regplot(y_predict_linear, y_test, color='g', marker='o')
fig.set(title = "Decesion Tree Regression Model", xlabel= "Predicted MSRP", ylabel= "True MSRP")
```

```
[Text(0.5, 1.0, 'Decesion Tree Regression Model'),
Text(0.5, 23.52222222222222, 'Predicted MSRP'),
Text(12.097222222222216, 0.5, 'True MSRP')]
```

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