Segun Adedipe Following

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Data Science Project: Using Machine Learning to Predict the Prices of Nigerian Cars

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In the automotive sector, pricing analytics play an essential role for both companies and individuals to assess the market price of a vehicle before putting it on sale or buying it. My goal with this Data Science Project is to estimate the price of Nigerian cars by taking into account a set of features, based on historical data. I'll be taking you through all the steps I took to achieve this objective so buckle up, it'll only get interesting from here connects buyers with sellers of used cars.

Firstly, let's import the important libraries

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

Now let's import our web scraped data of Nigerian car prices

```
data = pd.read_csv('Nigerian_Car_Prices.csv')
data
```

	Unnamed: 0	Make	Year of manufacture	Condition	Mileage	Engine Size	Fuel	Transmission	Price	Build
0	0	Toyota	2007.0	Nigerian Used	166418.0	2400.0	Petrol	Automatic	3,120,000	NaN
1	1	Lexus	NaN	NaN	138024.0	NaN	NaN	Automatic	5,834,000	NaN
2	2	Mercedes-Benz	2008.0	Nigerian Used	376807.0	3000.0	Petrol	Automatic	3,640,000	NaN
3	3	Lexus	NaN	NaN	213362.0	NaN	NaN	Automatic	3,594,000	NaN
4	4	Mercedes-Benz	NaN	NaN	106199.0	NaN	NaN	Automatic	8,410,000	NaN
...	...	...	...	...	...	...	...	...	...	...
4090	4090	Honda	2004.0	Nigerian Used	207446.0	3500.0	Petrol	Automatic	1,125,000	NaN
4091	4091	Toyota	2005.0	Nigerian Used	106914.0	1800.0	Petrol	Automatic	2,643,750	NaN
4092	4092	Honda	2006.0	Nigerian Used	247149.0	1800.0	Petrol	Automatic	1,462,500	NaN
4093	4093	Toyota	2007.0	Nigerian Used	249325.0	2500.0	Petrol	Automatic	2,475,000	NaN
4094	4094	Toyota	2013.0	Foreign Used	235184.0	2500.0	Petrol	Automatic	6,300,000	NaN

4095 rows × 10 columns

The data consists of 4095 cars and 10 features, one of which would be the dependent variable we will predict (price).

Methodology

EDA and data cleaning

To understand the data better and know how the numerical columns are distributed, let's use the describe method:

count	4095.000000	3617.000000	4.024000e+03	3584.000000
mean	2047.000000	2007.898535	1.825337e+05	3274.976562
std	1182.269005	4.300126	2.109233e+05	7693.489588
min	0.000000	1992.000000	1.000000e+00	3.000000
25%	1023.500000	2005.000000	1.020640e+05	2000.000000
50%	2047.000000	2008.000000	1.613525e+05	2500.000000
75%	3070.500000	2011.000000	2.319522e+05	3500.000000
max	4094.000000	2021.000000	9.976050e+06	371000.000000

From this, we can see that there is a large difference between the minimum and maximum values of our mileage and engine size. This indicates that there could be outliers which diminishes the effectiveness of linear models. We'll try to rectify that later

Now let's use the .info() method to gain more insights

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4095 entries, 0 to 4094
Data columns (total 10 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Unnamed: 0           4095 non-null   int64
 1   Make                 4095 non-null   object
 2   Year of manufacture  3617 non-null   float64
 3   Condition            3616 non-null   object
 4   Mileage              4024 non-null   float64
 5   Engine Size          3584 non-null   float64
 6   Fuel                 3607 non-null   object
 7   Transmission         4075 non-null   object
 8   Price                4095 non-null   object
 9   Build                1127 non-null   object
dtypes: float64(3), int64(1), object(6)
memory usage: 320.0+ KB
```

The First thing we can notice is that there are missing values in some of the columns which is not a surprise to us as some people listing their cars for sale may not know some technical details of their cars such as the engine size.

But if we look closely, an issue there we can't ignore is that the price column is seen as an object instead of an integer or float. I tried to prevent this issue when I was scraping the prices from the web by removing the naira sign, but I didn't know that the comma would be an issue. So, let's try to remove this by using the replace function in pandas to remove all commas. After doing that, we can now convert the column to an integer or

```
data['Price'].replace(to_replace=',', value='', regex=True, inplace=True)
```

```
data["Price"] = data["Price"].astype("float64")
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4095 entries, 0 to 4094
Data columns (total 10 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Unnamed: 0           4095 non-null   int64  
 1   Make                 4095 non-null   object 
 2   Year of manufacture  3617 non-null   float64
 3   Condition            3616 non-null   object 
 4   Mileage              4024 non-null   float64
 5   Engine Size          3584 non-null   float64
 6   Fuel                 3607 non-null   object 
 7   Transmission         4075 non-null   object 
 8   Price                4095 non-null   float64
 9   Build                1127 non-null   object 
dtypes: float64(4), int64(1), object(5)
memory usage: 320.0+ KB
```

We can now use the describe function to see the information of our data that includes the price

```
data.describe()
```

	Unnamed: 0	Year of manufacture	Mileage	Engine Size	Price
count	4095.000000	3617.000000	4.024000e+03	3584.000000	4.095000e+03
mean	2047.000000	2007.898535	1.825337e+05	3274.976562	4.271288e+06
std	1182.269005	4.300126	2.109233e+05	7693.489588	4.900064e+06
min	0.000000	1992.000000	1.000000e+00	3.000000	4.580000e+05
25%	1023.500000	2005.000000	1.020640e+05	2000.000000	1.872000e+06
50%	2047.000000	2008.000000	1.613525e+05	2500.000000	2.940000e+06
75%	3070.500000	2011.000000	2.319522e+05	3500.000000	4.725000e+06
max	4094.000000	2021.000000	9.976050e+06	371000.000000	5.880000e+07

From our new insights, we can see that the prices of our cars range from 458,000naira to 58,800,000naira, our mean is 4.2 million naira and our standard deviation is 4.9 million naira

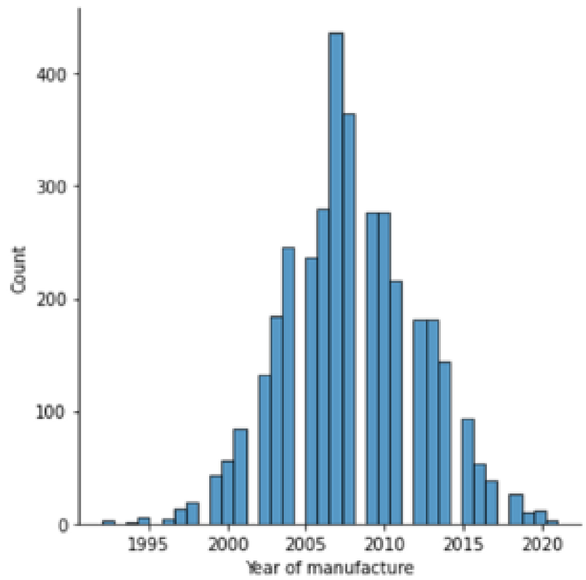
Now let's see how many missing values we have

```
Year of manufacture      478
Condition                479
Mileage                   71
Engine Size              511
Fuel                     488
Transmission              20
Price                      0
Build                   2968
dtype: int64
```

From this, only 3 columns do not have missing values. We'll try to rectify this issue later on but for now, let's perform an explanatory data analysis of our features. we'll plot the probability density functions of the continuous variable's columns. Let's start with the year the cars were produced

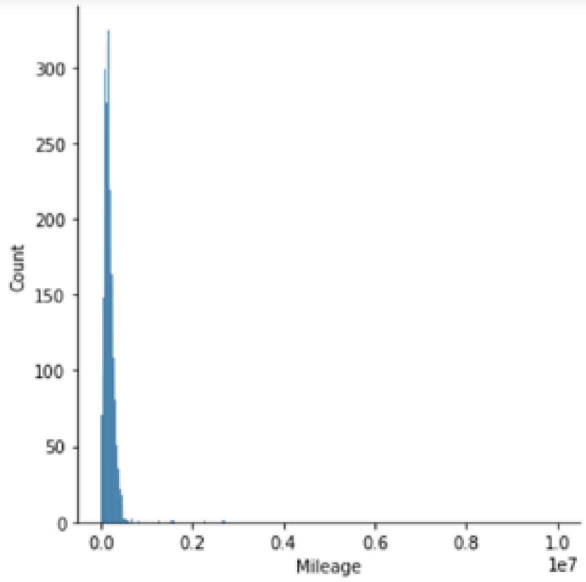
```
sns.displot(data['Year of manufacture'])
```

```
<seaborn.axisgrid.FacetGrid at 0x24efc65bfd0>
```



This is a normal distribution which is the most desirable distribution.

Now let's see the PDF (Probability Density Function) of the mileage column

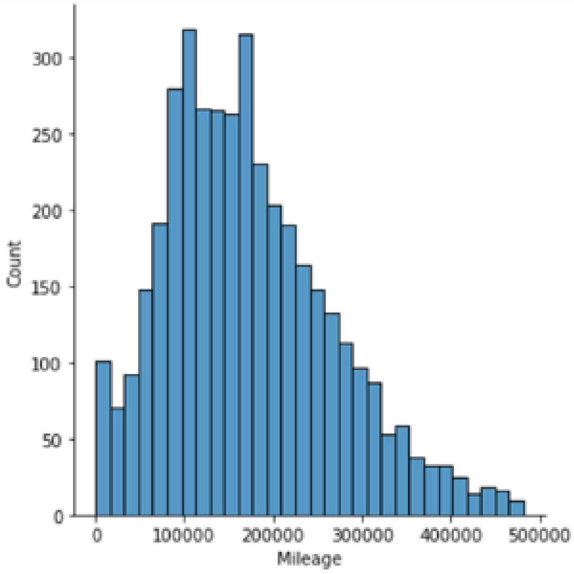


From the PDF we observe that there are outliers in the column and it could affect the efficiency of certain machine learning models such as the ordinary least squares model which is sensitive to outliers.

Let’s try to fix this by making sure all the values fall within the 99 percentile of the ‘mileage’ variable. This way, we’ll have effectively removed the top 1% of the data about mileage

```
q = data['Mileage'].quantile(0.99)
data = data[data['Mileage']<q]
```

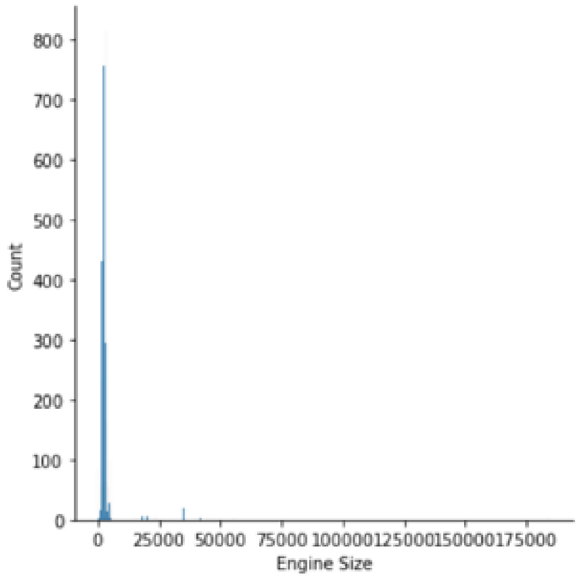
Now let’s see the new distribution



This is much better and it now looks like a normal distribution.

Now let's see the PDF of the Engine size

```
sns.displot(x=data['Engine Size'])
<seaborn.axisgrid.FacetGrid at 0x24efdd1dca0>
```



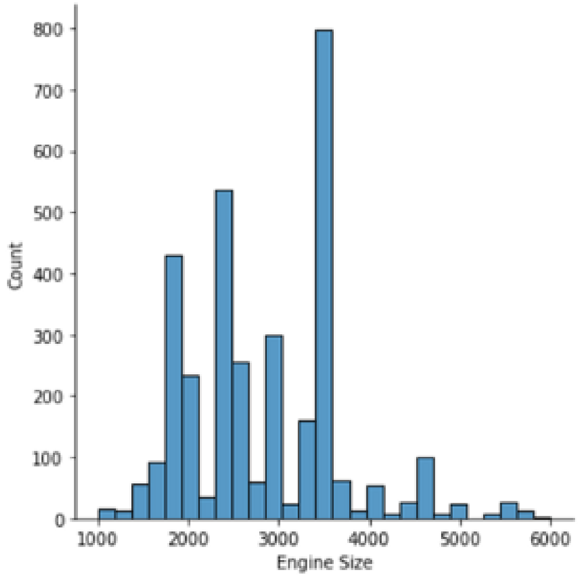
It is similar to the PDF of the mileage column. To try to fix this one, I checked for the biggest car engine size and I discovered that the biggest one is 8382cc and the smallest car engine size is 624cc

So, let's remove data that are above and below those thresholds

Now let's see the PDF

```
sns.displot(x=data['Engine Size'])
```

```
<seaborn.axisgrid.FacetGrid at 0x24efdfe1940>
```



This is more desirable.

Since we've removed some data points, let's see how many missing values we still have

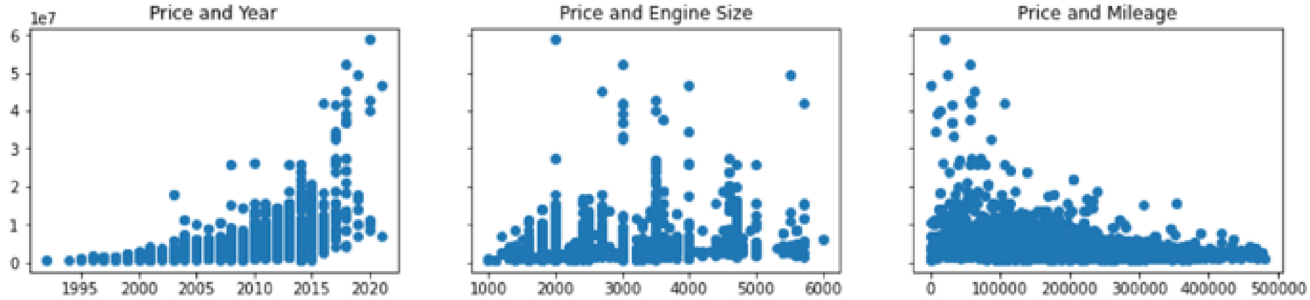
```
data.isnull().sum()
```

```
Unnamed: 0               0
Make                     0
Year of manufacture      0
Condition                0
Mileage                  0
Engine Size              0
Fuel                     6
Transmission             2
Price                    0
Build                 2307
dtype: int64
```

It has reduced significantly. It is likely that those who left a lot of empty values when listing their cars also exaggerated the values of the mileage and engine sizes

Now let's see how the prices of the cars are related to the mileage, engine size and year manufactured

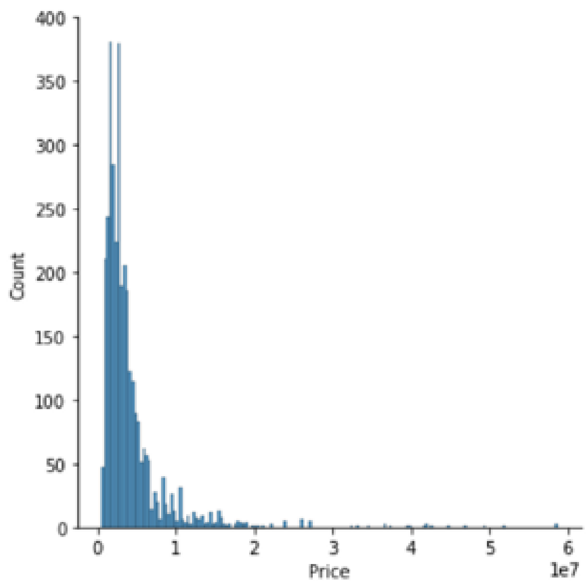
```
ax2.scatter(data['Engine Size'],data['Price'])
ax2.set_title('Price and Engine Size')
ax3.scatter(data['Mileage'],data['Price'])
ax3.set_title('Price and Mileage')
plt.show()
```



We can notice that cars manufactured more recently costs more than older cars (no s**t sherlock), and cars with lower mileage also cost more than those with bigger mileage. But the main issue that should draw our attention here is the fact that it forms an exponential distribution

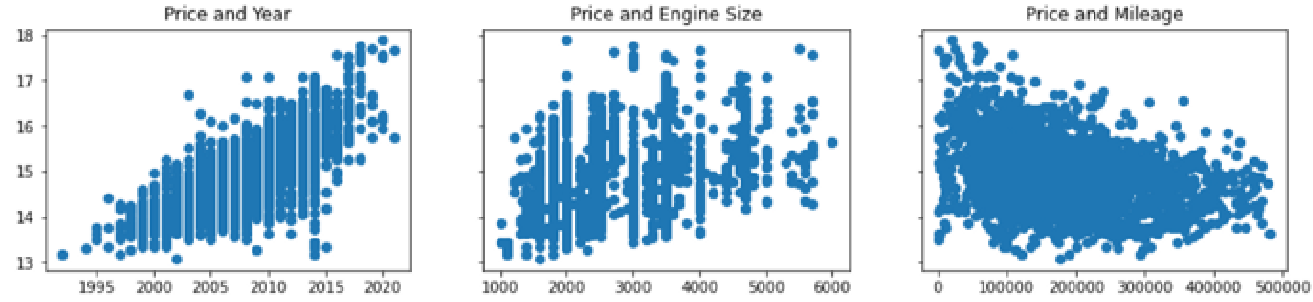
```
sns.displot(x=data['Price'])
```

<seaborn.axisgrid.FacetGrid at 0x24efee15970>



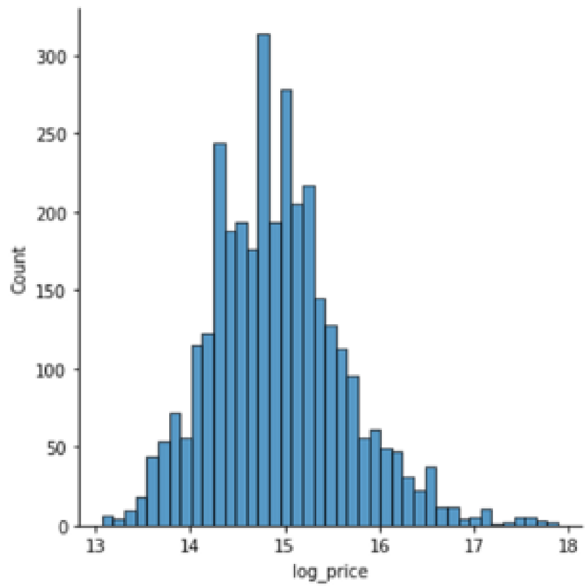
The long tail makes it quite difficult for us to see the distribution, but it has an even stronger effect on a model. such distribution can greatly confuse the model, so it won't learn well enough. One way to solve this problem is log transformation. If we apply the log function to the prices, it removes the undesired effect.

```
f, (ax1, ax2, ax3) = plt.subplots(1, 3, sharey=True, figsize =(15,3))
ax1.scatter(data['Year of manufacture'],data['log_price'])
ax1.set_title('Price and Year')
ax2.scatter(data['Engine Size'],data['log_price'])
ax2.set_title('Price and Engine Size')
ax3.scatter(data['Mileage'],data['log_price'])
ax3.set_title('Price and Mileage')
plt.show()
```



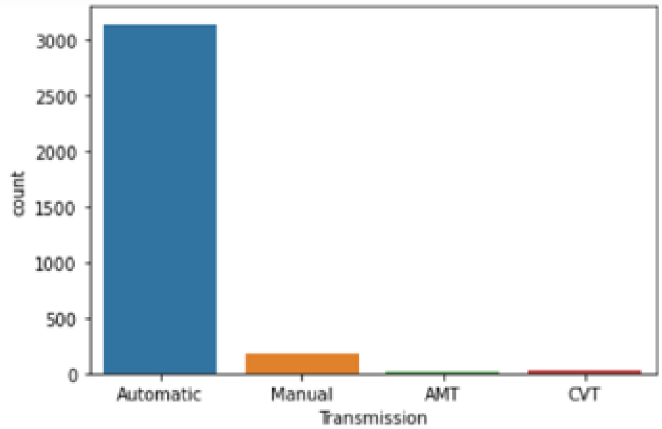

```
sns.displot(x=data['log_price'])
```

```
<seaborn.axisgrid.FacetGrid at 0x24efd6f9e50>
```



As we see, this transformation removes the long tail, and now the distribution resembles a bell-shaped curve. Generally, it’s good when the target distribution looks like the normal distribution. Under this condition, models such as linear regression perform well.

Now let’s visualize the categorical columns

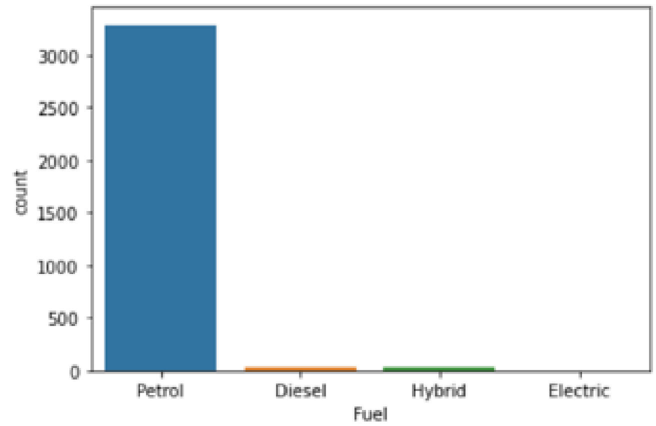


The automatic cars listed are more than the other cars listed(combined). In Nigeria, the majority of the cars are automatic except maybe pickup trucks and taxis. I didn't know there were transmission types such as AMT (Automated Manual Transmission) and CVT (Constantly Variable Transmission) until I started this project. If you're just like me who just learned about the CVT and AMT transmission, you should know that there's another one that wasn't listed on the site and it's the DCT (Dual Clutch Transmission).

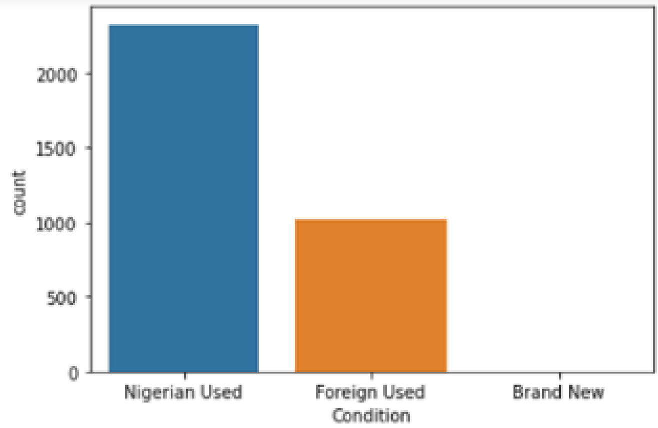
Now let's visualize the fuel type

```
sns.countplot(x=data['Fuel'])
```

```
<AxesSubplot:xlabel='Fuel', ylabel='count'>
```



If you're a Nigerian, this shouldn't be a surprise to you. Diesel is way more expensive than petrol. And I'm even surprised electric cars are even listed because I haven't physically seen an electric car charging station in Nigeria. So, it makes sense for



It also isn't a surprise to see that the number of brand-new cars are very few. It is because the website was designed for the sales of used cars

Now let's see the most listed car brand and the total number of car brands on our data sets

```
data['Make'].value_counts().head(7)
```

```
Toyota           1324
Lexus             384
Honda             356
Mercedes-Benz     293
Ford              163
Hyundai           142
Nissan            134
Name: Make, dtype: int64
```

Maybe Toyota owes Nigeria more assembly plants.

```
data['Make'].nunique()
```

```
40
```

40 different brands is a lot. Although I would have liked to include that feature in the predictive model but encoding the 40 brands would make the model more complex and could be detrimental to the efficiency of the model

So, let's drop that column and the 'Unmarked: 0' column which offers nothing to our dataset

```
data.drop(['Unnamed: 0','Make'], axis=1, inplace=True)
```

Now let's prepare our data for training. We'll start with dealing with the missing values of the Build column. I also wanted to remove that column right from when I was scraping the data but I felt that SUVs are more expensive than regular cars and it could improve the predictability of our model.

```
data['Build'] = data['Build'].fillna('other')
```

Now let's define our dependent and independent variables

```
X = data.drop(['Price','log_price'], axis=1)
y = data['log_price']
```

```
X
```

	Year of manufacture	Condition	Mileage	Engine Size	Fuel	Transmission	Build
0	2007.0	Nigerian Used	166418.0	2400.0	Petrol	Automatic	other
2	2008.0	Nigerian Used	376807.0	3000.0	Petrol	Automatic	other
30	2008.0	Foreign Used	301265.0	3500.0	Petrol	Automatic	other
32	2011.0	Nigerian Used	105546.0	4600.0	Petrol	Automatic	SUV
43	2011.0	Foreign Used	211917.0	3500.0	Petrol	Automatic	other
...	...	...	...	...	...	...	...
4090	2004.0	Nigerian Used	207446.0	3500.0	Petrol	Automatic	other
4091	2005.0	Nigerian Used	106914.0	1800.0	Petrol	Automatic	other
4092	2006.0	Nigerian Used	247149.0	1800.0	Petrol	Automatic	other
4093	2007.0	Nigerian Used	249325.0	2500.0	Petrol	Automatic	other
4094	2013.0	Foreign Used	235184.0	2500.0	Petrol	Automatic	other

Now to import libraries we'll use for filling the remaining missing values, encoding the categorical columns, and scaling the numerical columns. Thereafter, we'll split the data into the training and test set. We'll put 80% of the data in the training set and the remaining 20% in the test.

```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.impute import SimpleImputer
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Let's get our categorical and numerical columns

Defining our pre-processing pipeline

```
cat_pipeline = Pipeline([('impute', SimpleImputer(strategy='most_frequent')),('encode', OneHotEncoder())])
num_pipeline = Pipeline([('scale', MinMaxScaler())])

full_pipeline = ColumnTransformer([('cat', cat_pipeline, cat), ('num', num_pipeline, num)])


prepared = full_pipeline.fit_transform(X_train)
```

Training

Now we're done with the pre-processing let's fit a bunch of machine learning models on the training set using cross-validation and find out which one works best for our data. We'll use the RMSE (Root Mean Squared Error) to estimate how good our model is.

```
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import SGDRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import BaggingRegressor
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import StackingRegressor
from sklearn.ensemble import VotingRegressor
from xgboost import XGBRegressor


models = [('sgd',SGDRegressor()),('svm',SVR()),('forest',RandomForestRegressor()),
         ('ada', AdaBoostRegressor()),('bag',BaggingRegressor()),('extree',ExtraTreesRegressor()),
          ('grad',GradientBoostingRegressor()),('xgb',XGBRegressor())]

for i,j in models:
    scores = cross_val_score(j, prepared, y_train, scoring='neg_mean_squared_error', cv=10)
    rmse = np.sqrt(-scores.mean())
    print(i,rmse)
```

```
sgd 0.436058371022116O3
svm 0.37289738429987157
forest 0.32979885580895296
ada 0.4102180814278946
bag 0.34356886320164887
extree 0.3433478317732058
grad 0.3436416459362274
xgb 0.3276902712777479
```

Although not a surprise, we can see that xgboost performs the best. Although random

```
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV

xgb = XGBRegressor()
param_grid = [{'n_estimators':[100,300,400], 'max_depth':[4,5,6],'learning_rate':[0.1,0.3,0.5],
              'colsample_bylevel':[0.7,1]}]

grid_search = GridSearchCV(xgb, param_grid, cv=5, scoring='neg_mean_squared_error', return_train_score=True,
                           n_jobs=-1)
grid_search.fit(prepared, y_train)
```

```
GridSearchCV(cv=5,
             estimator=XGBRegressor(base_score=None, booster=None,
                                    colsample_bylevel=None,
                                    colsample_bynode=None,
                                    colsample_bytree=None, gamma=None,
                                    gpu_id=None, importance_type='gain',
                                    interaction_constraints=None,
                                    learning_rate=None, max_delta_step=None,
                                    max_depth=None, min_child_weight=None,
                                    missing=nan, monotone_constraints=None,
                                    n_estimators=100, n_jobs=...
                                    num_parallel_tree=None, random_state=None,
                                    reg_alpha=None, reg_lambda=None,
                                    scale_pos_weight=None, subsample=None,
                                    tree_method=None, validate_parameters=None,
                                    verbosity=None),
             n_jobs=-1,
```

Now to see the best parameters and use them when creating the xgboost object

```
grid_search.best_params_
```

```
{'colsample_bylevel': 0.7,
 'learning_rate': 0.1,
 'max_depth': 6,
 'n_estimators': 300}
```

```
xgb = XGBRegressor(learning_rate= 0.1, max_depth= 6, n_estimators= 300, colsample_bylevel=0.7)
xgb.fit(prepared,y_train)
```

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=0.7,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.1, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=300, n_jobs=4, 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)
```

We’ve trained the model. Now to test it we have to make our test data look like the training data. Note that we would only transform the data instead of using fit transform to prevent data leakage

```
test = full_pipeline.transform(X_test)
```

```
y_pred = xgb.predict(test)
```

```
y_test = y_test.values
```

```
t = np.exp(y_test)
p = np.exp(y_pred)
```

```
mse = mean_squared_error(p,t)
rmse = np.sqrt(mse)
print(rmse)
```

```
1691715.9972830664
```

An error of 1.69 million is good considering the range of our prices is from 458,000 to 58.8 million naira.

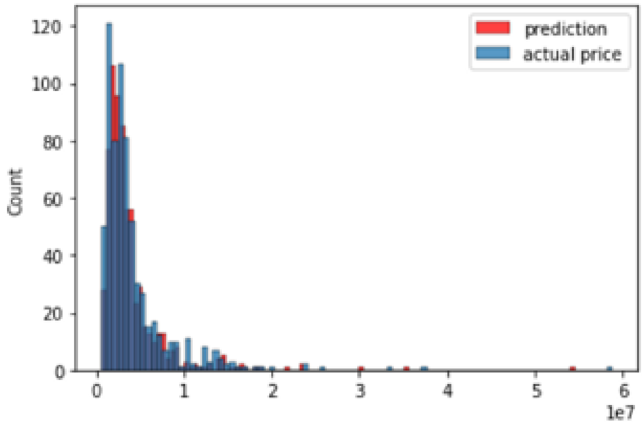
Result

For this project, I used the Xgboost regressor to predict the prices of cars in Nigeria. It showed excellent performance by having a root mean squared error of 1.69 million naira.

Let's look at the distribution of our predicted prices and the actual prices

```
sns.histplot(p, label='prediction',color='red')
sns.histplot(t, label='actual price')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x24e8b0736d0>
```



We can see that our model was good at imitating the price.

Let's see some of our best predictions

```
pd.set_option('display.float_format', lambda x: '%.2f' % x)
df_pred = df_pred.sort_values(by=['Difference%'])
df_pred
```

	Prediction	Target	Difference%
547	3151450.00	3150000.00	0.05
16	3597689.25	3600000.00	0.06
498	3995010.50	3990000.00	0.13
209	1467248.25	1462500.00	0.32
334	1467498.75	1462500.00	0.34
...	...	...	...

With this, we can say our goal to create a model that was able to estimate the price of cars has been achieved.

Conclusion

With this project, we have built a model that can predict the price of cars, given a set of features. This information can have an enormous value for both companies and individuals when trying to understand how to estimate the value of their vehicles.

The art of pricing is not an easy task and is sometimes only done by experts in the field, but with the study of historical data, it is possible to find patterns using machine learning that lead to results just as good. Acquiring this knowledge can provide you with a comparative advantage before putting a vehicle on sale or buying it on the market.

To view the web scraping code of this project please visit: segun7/nigerian-cars-price-prediction (github.com)

Thank you for reading.