Second-hand Cars reselling Price Analysis Report

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Introduction

In this analysis, the dataset will be preprocessed by identifying the null values, outliers, and multicollinearity and cleaning them. The preprocessed data is then scaled and split into test and training parts to create a linear regression model to predict the price. We will be modeling the price of second-hand cars based on the features in the dataset.

Dataset description

- **Shape:** (4345, 9)
- **Columns:** Brand, Price, Body, Mileage, Engine V, Engine Type, Registration, Year, Model

    Brand- The brand name of the second-hand car
    Price- Price of the second-hand car
    Body- Body type of the car
    Mileage- Mileage of the car
    EngineV- Engine capacity of the car
    Registration - Registration information of the car
    Year - Year od the purchase of the car
    Model-Model name of the car
- **Dependent Variable:** Price
- **Independent variable:** Brand, Body, Mileage, Engine V, Engine Type, Registration, Year, Model

Steps involved in the Analysis

1. Connecting google drive to google colab

In this step, Google Drive was connected to the Google colab in order to import the dataset into the colab.

Before this step, the dataset was uploaded to Google Drive.

```
[1] #connecting googledrive
    from google.colab import drive
    drive.mount("/content/drive")

    Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

2. Importing libraries

The following image shows the libraries imported to carry out the analysis. The libraries are as follows:

- NumPy
- Pandas
- Matplotlib
- Seaborn
- Statsmodels
- Math
- Warnings

```
[ ] import numpy as np #numpy used for mathematical codes in python
    import pandas as pd #pandas used to deal with datasets(clean, treat null values and analyse)
    import matplotlib.pyplot as plt  #used for visualising data
    import seaborn as sns #visualisng data
    import statsmodels.api as sm  #used to explore data ,estimate statistical models and perform statistical tests
    import os #importing python
    sns.set() #setting theme in seaborn

    from math import * #import all mathematical function
    import warnings
    warnings.filterwarnings("ignore")
```

3. Loading the dataset

The dataset is loaded into Google Colab, then the first five rows and the last five rows of the dataset are loaded. Using the *.shape* function, the number of rows and columns is displayed.

Loading the Raw Data

```
[ ] data= pd.read_csv("/content/drive/MyDrive/ML 02/Week 1/Second hand cars reselling price.csv")
```

```
data.head()
```

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year	Model
0	BMW	4200.0	sedan	277	2.0	Petrol	yes	1991	320
1	Mercedes-Benz	7900.0	van	427	2.9	Diesel	yes	1999	Sprinter 212
2	Mercedes-Benz	13300.0	sedan	358	5.0	Gas	yes	2003	S 500
3	Audi	23000.0	crossover	240	4.2	Petrol	yes	2007	Q7
4	Toyota	18300.0	crossover	120	2.0	Petrol	yes	2011	Rav 4

```
data.tail()
```

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year	Model
4340	Mercedes-Benz	125000.0	sedan	9	3.0	Diesel	yes	2014	S 350
4341	BMW	6500.0	sedan	1	3.5	Petrol	yes	1999	535
4342	BMW	8000.0	sedan	194	2.0	Petrol	yes	1985	520
4343	Toyota	14200.0	sedan	31	NaN	Petrol	yes	2014	Corolla
4344	Volkswagen	13500.0	van	124	2.0	Diesel	yes	2013	T5 (Transporter)

```
[ ] data.shape

(4345, 9)
```

4. Displaying the summary of the statistics for the dataset

Using the *.describe* function, we display the summary of the statistics for every column.

```
#getting statistical values for each column
data.describe(include= "all")
```

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year	Model
count	4345	4173.000000	4345	4345.000000	4195.000000	4345	4345	4345.000000	4345
unique	7	NaN	6	NaN	NaN	4	2	NaN	312
top	Volkswagen	NaN	sedan	NaN	NaN	Diesel	yes	NaN	E-Class
freq	936	NaN	1649	NaN	NaN	2019	3947	NaN	199
mean	NaN	19418.746935	NaN	161.237284	2.790734	NaN	NaN	2006.550058	NaN
std	NaN	25584.242620	NaN	105.705797	5.066437	NaN	NaN	6.719097	NaN
min	NaN	600.000000	NaN	0.000000	0.600000	NaN	NaN	1969.000000	NaN
25%	NaN	6999.000000	NaN	86.000000	1.800000	NaN	NaN	2003.000000	NaN
50%	NaN	11500.000000	NaN	155.000000	2.200000	NaN	NaN	2008.000000	NaN
75%	NaN	21700.000000	NaN	230.000000	3.000000	NaN	NaN	2012.000000	NaN
max	NaN	300000.000000	NaN	980.000000	99.990000	NaN	NaN	2016.000000	NaN

5. Displaying the number of null values

The number of null values in each column is displayed using the *isnull().sum()* function. It was evident that there were null values present only in the "Price" column and the "EngineV" column.

```
#finding the number of null values in each column
data.isnull().sum()
```

```
Brand             0
Price           172
Body              0
Mileage           0
EngineV         150
Engine Type       0
Registration      0
Year              0
Model             0
dtype: int64
```

6. Determining the variables of interest

The variables that we need for the analysis are decided in this step.

- Since the column "Model" has more than one value for a given "Brand", the column "Model" is dropped using the .drop() function. The column "Brand" can be used for analysis purposes as a result.
- The null values from the "Price" and "EngineV" columns were then dropped using the.dropna() function.
- In both instances, the axis parameter is used. When a column is removed, the axis parameter will be 1, and when a row is removed, the axis parameter will be 0.

```python
# dropping it because there are different types of model for a given brand hence we can deak with a brand instead of the model for now
data1= data.drop(["Model"], axis=1)
data1
```

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year
0	BMW	4200.0	sedan	277	2.0	Petrol	yes	1991
1	Mercedes-Benz	7900.0	van	427	2.9	Diesel	yes	1999
2	Mercedes-Benz	13300.0	sedan	358	5.0	Gas	yes	2003
3	Audi	23000.0	crossover	240	4.2	Petrol	yes	2007
4	Toyota	18300.0	crossover	120	2.0	Petrol	yes	2011
...	...	...	...	...	...	...	...	...
4340	Mercedes-Benz	125000.0	sedan	9	3.0	Diesel	yes	2014
4341	BMW	6500.0	sedan	1	3.5	Petrol	yes	1999
4342	BMW	8000.0	sedan	194	2.0	Petrol	yes	1985
4343	Toyota	14200.0	sedan	31	NaN	Petrol	yes	2014
4344	Volkswagen	13500.0	van	124	2.0	Diesel	yes	2013

4345 rows × 8 columns

```python
#removing null values from Price and Engine V column

data_no_mv= data1.dropna(axis=0)  #axis= 0 is because we remove rows, if we need to remove the column it should be axis=1
```

```python
[13] data_no_mv
```

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year
0	BMW	4200.0	sedan	277	2.0	Petrol	yes	1991
1	Mercedes-Benz	7900.0	van	427	2.9	Diesel	yes	1999
2	Mercedes-Benz	13300.0	sedan	358	5.0	Gas	yes	2003
3	Audi	23000.0	crossover	240	4.2	Petrol	yes	2007
4	Toyota	18300.0	crossover	120	2.0	Petrol	yes	2011
...	...	...	...	...	...	...	...	...
4339	Toyota	17900.0	sedan	35	1.6	Petrol	yes	2014
4340	Mercedes-Benz	125000.0	sedan	9	3.0	Diesel	yes	2014
4341	BMW	6500.0	sedan	1	3.5	Petrol	yes	1999
4342	BMW	8000.0	sedan	194	2.0	Petrol	yes	1985
4344	Volkswagen	13500.0	van	124	2.0	Diesel	yes	2013

4025 rows × 8 columns

- Now we have the dataset with no null/missing values *(data_no_mv)*

```python
0s
data_no_mv.isnull().sum()
```

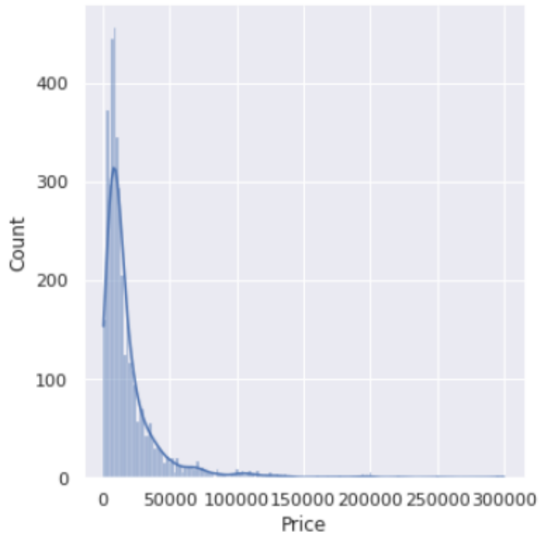
```
Brand           0
Price           0
Body            0
Mileage         0
EngineV         0
Engine Type     0
Registration    0
Year            0
dtype: int64
```

7. Identifying outliers and removing them

- **“Price” column**

  The outliers are identified by plotting a graph.

```
sns.displot(data_no_mv["Price"], kde =True ) #plotting to see the outliers
plt.show()
```

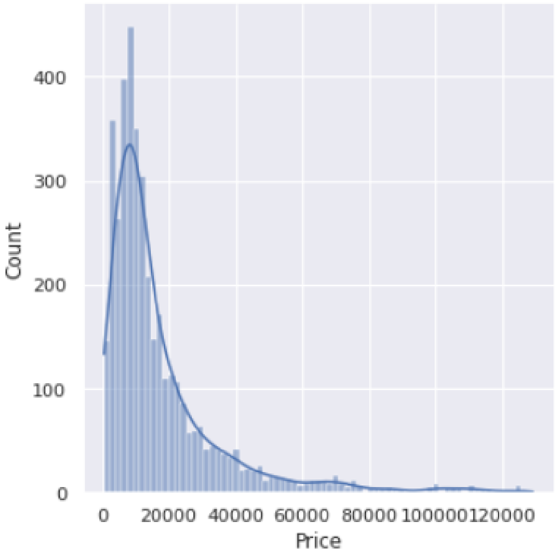


It was evident that "Price" has a right-skewed distribution; therefore, we will use 99% of the distribution on the left for analysis by removing the outliers on the right.

```
q=data_no_mv["Price"].quantile(0.99) #using quantile method to remove the outliers
data_1= data_no_mv[data_no_mv["Price"]< q] #
data_1.describe()
```

	Price	Mileage	EngineV	Year
count	3984.000000	3984.000000	3984.000000	3984.000000
mean	17837.117460	165.116466	2.743770	2006.292922
std	18976.268315	102.766126	4.956057	6.672745
min	600.000000	0.000000	0.600000	1969.000000
25%	6980.000000	93.000000	1.800000	2002.750000
50%	11400.000000	160.000000	2.200000	2007.000000
75%	21000.000000	230.000000	3.000000	2011.000000
max	129222.000000	980.000000	99.990000	2016.000000

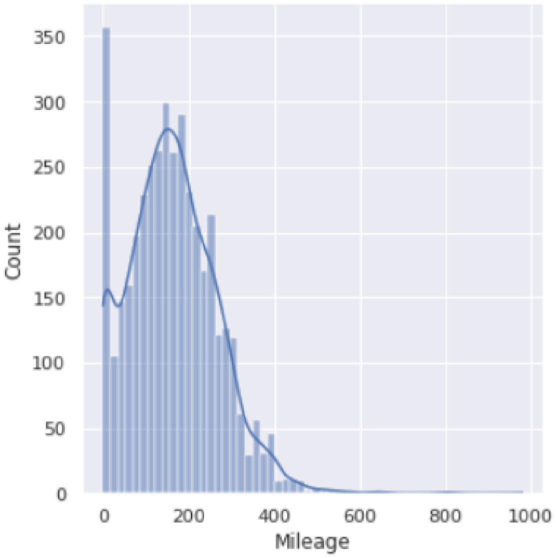
```
[17] sns.displot(data_1["Price"], kde =True) #plotting to see the outliers
     plt.show()
```



- **"Mileage" column**
  The outliers are identified by plotting a graph.

```
[18] #dealing with mileage column

     sns.displot(data_no_mv["Mileage"], kde =True) #plotting to see the outliers
     plt.show()
```

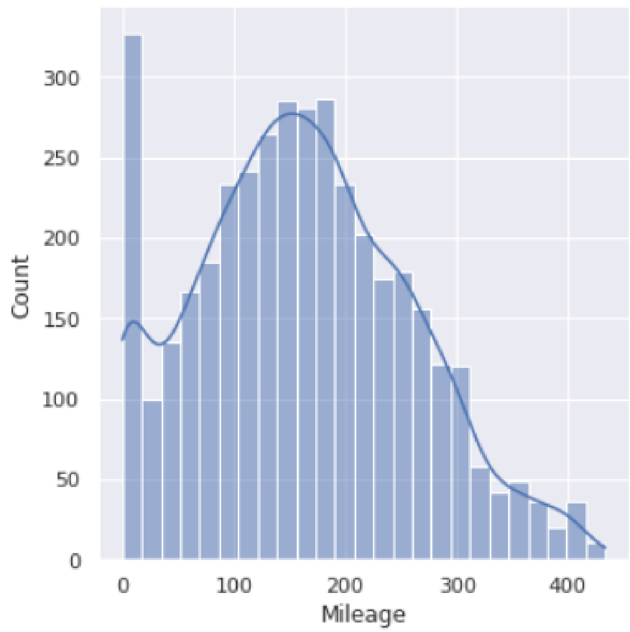


It was evident that "Mileage" is a right-skewed distribution; therefore, we will use 99% of the distribution on the left for analysis by removing the outliers on the right.

```
q1=data_no_mv["Mileage"].quantile(0.99) #using quantile method to remove the outliers
data_2= data_1[data_1["Mileage"]< q1] #
data_2.describe()
```

	Price	Mileage	EngineV	Year
count	3943.000000	3943.000000	3943.000000	3943.000000
mean	17936.780614	161.414659	2.747497	2006.393102
std	19009.750360	95.940408	4.981033	6.593870
min	600.000000	0.000000	0.600000	1969.000000
25%	7000.000000	92.000000	1.800000	2003.000000
50%	11500.000000	158.000000	2.200000	2007.000000
75%	21417.500000	230.000000	3.000000	2011.000000
max	129222.000000	433.000000	99.990000	2016.000000

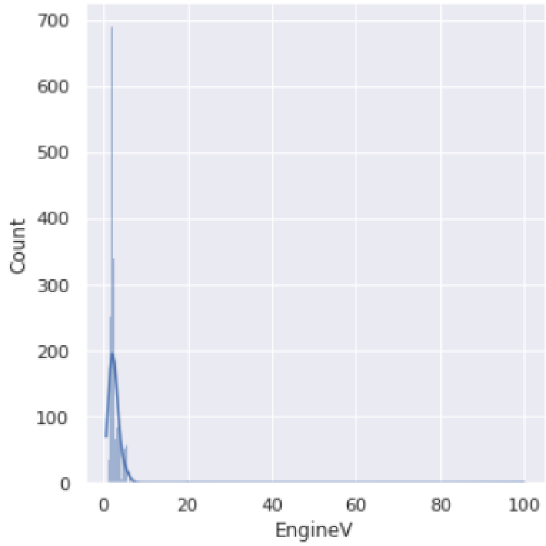
```
[21] sns.displot(data_2["Mileage"], kde =True) #plotting to see the outliers
     plt.show()
```



- **“EngineV” Column**
  The outliers are identified by plotting a graph.

```
#dealing with EngineV column

sns.displot(data_no_mv["EngineV"], kde =True) #plotting to see the outliers
plt.show()
```



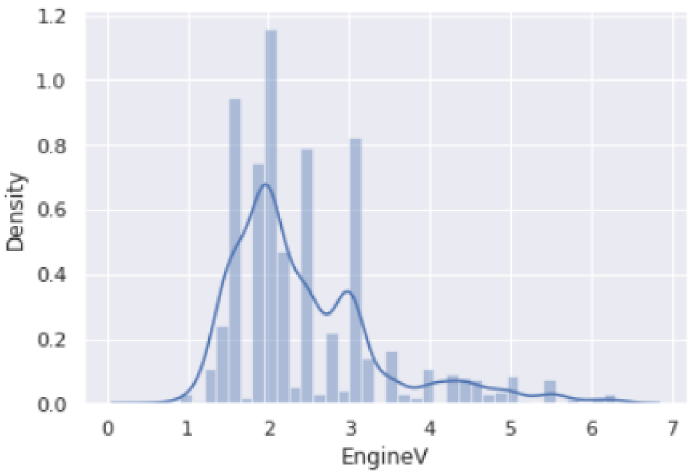
Normally, the engine capacity would be between 0.5 and 6.5. Since in this dataset, as is evident, we have values that are greater than 6.5, which is not correct, we are taking the data that are less than 6.5 for analysis purposes.

```
data_3 =data_2[data_2['EngineV'] < 6.5]
data_3
```

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year
0	BMW	4200.0	sedan	277	2.0	Petrol	yes	1991
1	Mercedes-Benz	7900.0	van	427	2.9	Diesel	yes	1999
2	Mercedes-Benz	13300.0	sedan	358	5.0	Gas	yes	2003
3	Audi	23000.0	crossover	240	4.2	Petrol	yes	2007
4	Toyota	18300.0	crossover	120	2.0	Petrol	yes	2011
...	...	...	...	...	...	...	...	...
4339	Toyota	17900.0	sedan	35	1.6	Petrol	yes	2014
4340	Mercedes-Benz	125000.0	sedan	9	3.0	Diesel	yes	2014
4341	BMW	6500.0	sedan	1	3.5	Petrol	yes	1999
4342	BMW	8000.0	sedan	194	2.0	Petrol	yes	1985
4344	Volkswagen	13500.0	van	124	2.0	Diesel	yes	2013

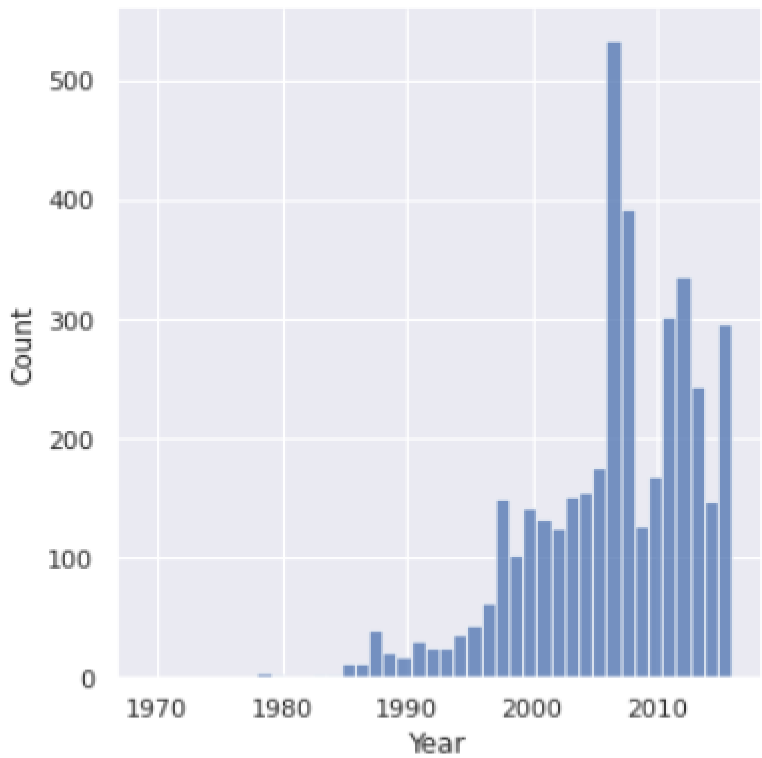
3920 rows × 8 columns

```
[24] sns.distplot(data_3["EngineV"]) #plotting to see the outliers
     plt.show()
```



- **“Year” column**
  The outliers are identified by plotting a graph.

```
[25] sns.displot(data_no_mv["Year"])
     plt.show()
```

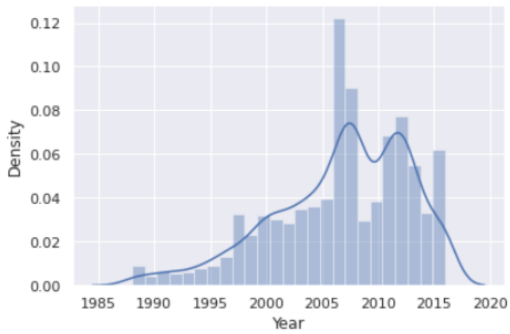


It was evident that "Year" has a left-skewed distribution; therefore, we will use the 99% of the distribution on the right for analysis by removing the outliers on the left.

```
q4=data_3["Year"].quantile(0.01) #since this is left skewed we remove first 1% if data to remove outliers
data_4=data_3[data_3["Year" ]> q4] #
data_4.describe()
```

	Price	Mileage	EngineV	Year
count	3866.000000	3866.000000	3866.000000	3866.000000
mean	18197.480629	160.471547	2.450246	2006.713140
std	19087.396949	95.543697	0.949413	6.101235
min	800.000000	0.000000	0.600000	1988.000000
25%	7200.000000	91.000000	1.800000	2003.000000
50%	11700.000000	157.000000	2.200000	2008.000000
75%	21700.000000	225.000000	3.000000	2012.000000
max	129222.000000	433.000000	6.300000	2016.000000

```
[27] sns.distplot(data_4["Year"])
plt.show()
```



8. Dropping the Index

When a dataset is loaded as a Python data frame, it will automatically get an index. As we have dropped many rows due to various reasons, we need to reset the initial index. This is accomplished by calling function.reset_index(drop=True).

We will have the cleaned dataset after this step.

Before resetting the index

```
data_4
```

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year
0	BMW	4200.0	sedan	277	2.0	Petrol	yes	1991
1	Mercedes-Benz	7900.0	van	427	2.9	Diesel	yes	1999
2	Mercedes-Benz	13300.0	sedan	358	5.0	Gas	yes	2003
3	Audi	23000.0	crossover	240	4.2	Petrol	yes	2007
4	Toyota	18300.0	crossover	120	2.0	Petrol	yes	2011
...	...	...	...	...	...	...	...	...
4338	Volkswagen	11500.0	van	163	2.5	Diesel	yes	2008
4339	Toyota	17900.0	sedan	35	1.6	Petrol	yes	2014
4340	Mercedes-Benz	125000.0	sedan	9	3.0	Diesel	yes	2014
4341	BMW	6500.0	sedan	1	3.5	Petrol	yes	1999
4344	Volkswagen	13500.0	van	124	2.0	Diesel	yes	2013

3866 rows × 8 columns

After resetting the index

```
#current index will be deleted. This is to remove the index that comes automatically from the dataset
data_cleaned= data_4.reset_index(drop=True)
data_cleaned
```

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year
0	BMW	4200.0	sedan	277	2.0	Petrol	yes	1991
1	Mercedes-Benz	7900.0	van	427	2.9	Diesel	yes	1999
2	Mercedes-Benz	13300.0	sedan	358	5.0	Gas	yes	2003
3	Audi	23000.0	crossover	240	4.2	Petrol	yes	2007
4	Toyota	18300.0	crossover	120	2.0	Petrol	yes	2011
...	...	...	...	...	...	...	...	...
3861	Volkswagen	11500.0	van	163	2.5	Diesel	yes	2008
3862	Toyota	17900.0	sedan	35	1.6	Petrol	yes	2014
3863	Mercedes-Benz	125000.0	sedan	9	3.0	Diesel	yes	2014
3864	BMW	6500.0	sedan	1	3.5	Petrol	yes	1999
3865	Volkswagen	13500.0	van	124	2.0	Diesel	yes	2013

3866 rows × 8 columns

9. Summarising the statistics for the cleaned data

```
[29] data_cleaned.describe(include="all")
```

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year
count	3866	3866.000000	3866	3866.000000	3866.000000	3866	3866	3866.000000
unique	7	NaN	6	NaN	NaN	4	2	NaN
top	Volkswagen	NaN	sedan	NaN	NaN	Diesel	yes	NaN
freq	848	NaN	1466	NaN	NaN	1807	3504	NaN
mean	NaN	18197.480629	NaN	160.471547	2.450246	NaN	NaN	2006.713140
std	NaN	19087.396949	NaN	95.543697	0.949413	NaN	NaN	6.101235
min	NaN	800.000000	NaN	0.000000	0.600000	NaN	NaN	1988.000000
25%	NaN	7200.000000	NaN	91.000000	1.800000	NaN	NaN	2003.000000
50%	NaN	11700.000000	NaN	157.000000	2.200000	NaN	NaN	2008.000000
75%	NaN	21700.000000	NaN	225.000000	3.000000	NaN	NaN	2012.000000
max	NaN	129222.000000	NaN	433.000000	6.300000	NaN	NaN	2016.000000

10. Checking the OLS (Ordinary Least Square) assumptions

The dependent variable is plotted against all the independent variables.

```
#plotting independant variables against all the dependant variable (Price)

f, (ax1, ax2, ax3)= plt.subplots(1,3,sharey=True, figsize = (20,9))

ax1.scatter(data_cleaned ["Year"], data_cleaned['Price'])
ax1.set_title("Price and Year")

ax2.scatter(data_cleaned ["EngineV"], data_cleaned['Price'])
ax2.set_title("Price and EngineV")

ax3.scatter(data_cleaned ["Mileage"], data_cleaned['Price'])
ax3.set_title("Price and Mileage")

plt.show()
```

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11. Log Transformation

It is evident that the above data is skewed; therefore, we will transform the "Price" value to log values in order to normalize the data.

▾ Log Tranformation

```
[31] #normalising the skewed data

     log_price= np.log(data_cleaned['Price']) #Log transformation is done for DEPENDANT Variable
     data_cleaned['log_price']= log_price
     data_cleaned
```

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year	log_price
0	BMW	4200.0	sedan	277	2.0	Petrol	yes	1991	8.342840
1	Mercedes-Benz	7900.0	van	427	2.9	Diesel	yes	1999	8.974618
2	Mercedes-Benz	13300.0	sedan	358	5.0	Gas	yes	2003	9.495519
3	Audi	23000.0	crossover	240	4.2	Petrol	yes	2007	10.043249
4	Toyota	18300.0	crossover	120	2.0	Petrol	yes	2011	9.814656
...	...	...	...	...	...	...	...	...	...
3861	Volkswagen	11500.0	van	163	2.5	Diesel	yes	2008	9.350102
3862	Toyota	17900.0	sedan	35	1.6	Petrol	yes	2014	9.792556
3863	Mercedes-Benz	125000.0	sedan	9	3.0	Diesel	yes	2014	11.736069
3864	BMW	6500.0	sedan	1	3.5	Petrol	yes	1999	8.779557
3865	Volkswagen	13500.0	van	124	2.0	Diesel	yes	2013	9.510445

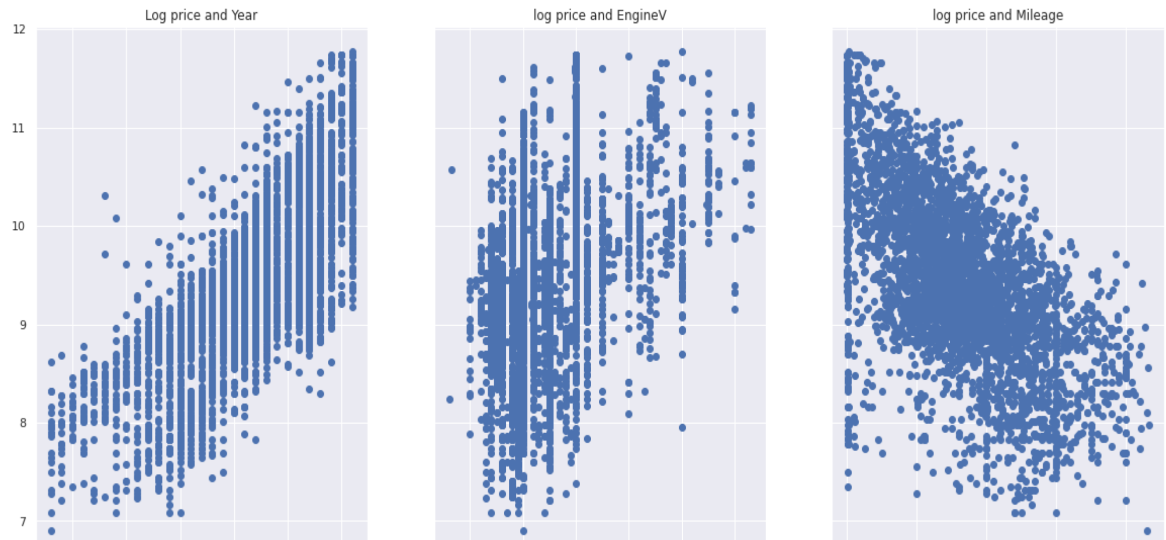
3866 rows × 9 columns

.

12. Plotting graphs after normalizing the data

The data has now been normalized, and the graphs demonstrate that they are linear.

```
[32] #plotting all independant variables against all the dependant variable (Price)

     f, (ax1, ax2, ax3)= plt.subplots(1,3,sharey=True, figsize = (20,9))


     ax1.scatter(data_cleaned ["Year"], data_cleaned['log_price'])
     ax1.set_title("Log price and Year")

     ax2.scatter(data_cleaned ["EngineV"], data_cleaned['log_price'])
     ax2.set_title("log price and EngineV")

     ax3.scatter(data_cleaned ["Mileage"], data_cleaned['log_price'])
     ax3.set_title("log price and Mileage")

     plt.show()
```



✓ 0s completed at 19:19

13. Removing the “Price” column

As we have transformed the “Price” column to log values (log_price), we will drop the “Price” column. The “Log_price” column will be used for analysis purposes.

```
[33] data_cleaned= data_cleaned.drop(['Price'], axis=1) #removing price from the dataset
```

14. Identifying the column which has the highest multicollinearity

Multicollinearity is when multiple independent variables are correlated to each other. When independent variables are multicollinear, statistical assumptions that are made become less reliable.

```
from statsmodels.stats.outliers_influence import variance_inflation_factor

variables = data_cleaned [['Mileage','Year','EngineV']]
vif=pd.DataFrame()
vif['VIF']=[variance_inflation_factor(variables.values, i) for i in range(variables.shape[1])]
vif["features"]= variables.columns

vif
```

	VIF	features
0	3.794319	Mileage
1	10.360888	Year
2	7.660317	EngineV

15. Dropping the column with High multicollinearity

From the VIF data frame, we can see that the year has a high multicollinearity; therefore, we drop the "Year" column.

```
[35] data_no_mc= data_cleaned.drop(['Year'], axis=1)
     data_no_mc.head()
```

	Brand	Body	Mileage	EngineV	Engine Type	Registration	log_price
0	BMW	sedan	277	2.0	Petrol	yes	8.342840
1	Mercedes-Benz	van	427	2.9	Diesel	yes	8.974618
2	Mercedes-Benz	sedan	358	5.0	Gas	yes	9.495519
3	Audi	crossover	240	4.2	Petrol	yes	10.043249
4	Toyota	crossover	120	2.0	Petrol	yes	9.814656

16. Creating dummies

Since most of the data we have are categorical variables in the dataset, we are changing them to numerical variables for analysis purposes.

```
[ ] # changing the data to numerical since most of them are categorical, this is done for analysis purpose

    data_with_dummies=pd.get_dummies(data_no_mc, drop_first= True)
    data_with_dummies.head()
```

	Mileage	EngineV	log_price	Brand_BMW	Brand_Mercedes-Benz	Brand_Mitsubishi	Brand_Renault	Brand_Toyota
0	277	2.0	8.342840	1	0	0	0	0
1	427	2.9	8.974618	0	1	0	0	0
2	358	5.0	9.495519	0	1	0	0	0
3	240	4.2	10.043249	0	0	0	0	0
4	120	2.0	9.814656	0	0	0	0	1

17. Rearranging columns

```
data_with_dummies.columns

Index(['Mileage', 'EngineV', 'log_price', 'Brand_BMW', 'Brand_Mercedes-Benz',
       'Brand_Mitsubishi', 'Brand_Renault', 'Brand_Toyota', 'Brand_Volkswagen',
       'Body_hatch', 'Body_other', 'Body_sedan', 'Body_vagon', 'Body_van',
       'Engine Type_Gas', 'Engine Type_Other', 'Engine Type_Petrol',
       'Registration_yes'],
      dtype='object')
```

```
[38] cols= ['log_price','Mileage','EngineV','Brand_BMW','Brand_Mercedes-Benz',
       'Brand_Mitsubishi', 'Brand_Renault', 'Brand_Toyota', 'Brand_Volkswagen',
       'Body_hatch', 'Body_other', 'Body_sedan', 'Body_vagon', 'Body_van',
       'Engine Type_Gas', 'Engine Type_Other', 'Engine Type_Petrol',
       'Registration_yes']
```

```
[ ] data_preprocessed=data_with_dummies[cols]
    data_preprocessed.head()
```

	log_price	Mileage	EngineV	Brand_BMW	Brand_Mercedes-Benz
0	8.342840	277	2.0	1	0
1	8.974618	427	2.9	0	1
2	9.495519	358	5.0	0	1
3	10.043249	240	4.2	0	0
4	9.814656	120	2.0	0	0

18. Downloading the preprocessed data

```
[40] data_preprocessed.to_csv('data_preprocessed.csv')
     data_preprocessed= pd.read_csv('data_preprocessed.csv')
```

19. Determining target and input variables for Linear regression model

The target variable is the variable whose values are modeled and predicted by other variables. The variables that are used to predict the target variable are called the input variables.

Linear Regression Model

```
targets= data_preprocessed['log_price']
inputs= data_preprocessed.drop(['log_price'],axis=1)
```

20. Scaling the data

Scaling is used to generalize data points so that the distance between them is reduced.

Scaling the data

```
[ ] import sklearn as sk
    from sklearn.preprocessing import StandardScaler
```

```
[ ] scalar= StandardScaler()
    scalar.fit(inputs)

    StandardScaler()
```

```
[ ] inputs_scaled= scalar.transform(inputs)
```

21. Test and train split

Using the test_train_split function, the dataset will be split into two parts, where one is used to train the model and the other is used to test the model. When we use the same dataset to train and test the model, it would be helpful for us to reduce the impacts of the data discrepancies and better understand the characteristics of the model.

Test Train split

```
[ ] from sklearn.model_selection import train_test_split

    x_train, x_test, y_train, y_test= train_test_split(inputs_scaled,targets,test_size=0.25, random_state= 365)
```

```
x_train
```

```
array([[-1.34406430e-03,  1.41612724e-01, -2.63613631e-01, ...,
        -1.62113726e-01, -7.50101044e-01,  3.21419511e-01],
       [ 1.50131983e+00,  2.56758184e-01, -2.63613631e-01, ...,
        -1.62113726e-01, -7.50101044e-01,  3.21419511e-01],
       [ 6.98465416e-01,  1.93160124e+00, -5.79639358e-01, ...,
        -1.62113726e-01, -7.50101044e-01, -3.11119881e+00],
       ...,
       [-1.01387251e+00,  6.44065640e-01,  3.21266937e+00, ...,
        -1.62113726e-01,  1.33315372e+00,  3.21419511e-01],
       [ 7.23554617e-01, -1.29247164e+00,  5.79121641e-01, ...,
        -1.62113726e-01, -7.50101044e-01,  3.21419511e-01],
       [ 1.55329031e+00,  8.53421022e-01, -2.63613631e-01, ...,
        -1.62113726e-01, -7.50101044e-01,  3.21419511e-01]])
```

```
[ ] y_train
```

```
1931     9.341369
3608     9.464983
2712     8.318742
1229     9.449357
1734    10.273325
          ...
428     11.074421
859     10.434116
801      9.928180
2740    10.609057
3666     8.824678
Name: log_price, Length: 2899, dtype: float64
```

22. Creating Linear Regression

Linear regression is used to predict the variable's value based on the value of another variable. The "fit" method trains the algorithm on the training data.

The "predict" method allows for predicting the output values once the model is trained.

Creating Regression

```
[ ] from sklearn.linear_model import LinearRegression
    reg=LinearRegression()
    reg.fit(x_train,y_train)
```

```
LinearRegression()
```

```
[ ] yhat= reg.predict(x_train)
```

```
plt.scatter(y_train,yhat)
plt.xlabel('Targets(y_train)',fontsize= 20)
plt.ylabel('Prediction(yhat)',fontsize= 20)
plt.xlim(8,12)
plt.ylim(8,12)
plt.show()

#This is optimised model since the curve of the graph in on the linear regression
```

23. Getting the Residual

In linear regression, the residual is the difference between the real value and the predicted value from the model for any given point. Residual analysis is used to check the accuracy of the linear regression model by getting the residuals and examining the residual plot graphs.

```
sns.distplot(y_train-yhat)
plt.title("Residuals PDF", size= 20)
plt.show()
```

Conclusion

The dataset was downloaded from Kaggle.com. The shape of the dataset is (4345, 9), that is, there are 4345 rows and 9 columns in the dataset. The analysis was started by connecting the drive to the Google Colab, loading the dataset, analyzing the shape and size of the dataset, and identifying the null values.

The missing values were dropped because they represented less than 5% of the total number of data points. Then, the outliers were treated. Once that is done, the dependent variable is plotted against all the independent variables. It was evident that all the graphs were skewed; hence, the log transformation was applied in order to get a linear relationship between the variables.

Then, the presence of multicollinearity was checked, and it was removed in order to avoid any misleading predictions. Once the multicollinearity was removed, the categorical variables were changed to numerical values for analysis purposes.

After preprocessing the data, the data was scaled and split into test and training parts, followed by creating the linear regression model.

Learning Outcome

- Able to connect Google Drive to Google Colab
- Able to clean the raw dataset by removing null values, outliers, and multicollinearity
- Able to convert categorical variables to numerical variables for analysis purposes
- Able to download the preprocessed datasets to Google Drive
- Able split the preprocessed dataset to Test and train sets.
- Able to create a linear regression model
- Able to use Residual Analysis to check the model's accuracy