Problem Statement

The objective of this project is to develop a supervised linear regression model for predicting car mileage based on various features and attributes. The dataset consists of historical data about different cars, including factors such as engine size, horsepower, weight, and other relevant specifications. The goal is to create an accurate and reliable model that can estimate the mileage (fuel efficiency) of a car given its characteristics.

Dataset Download Link

http://courses.washington.edu/hcde511/s14/datasets/cars.xls

Importing Packages

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Loading the Data

In [2]:
```
cars_data = pd.read_excel("D:\\Self Made Learning Projects\\Linear Regression\\Predict Car Mileage\\Datasets\\Cars Dataset.xlsx")
```

Understanding the Data

The dataset comprises details about various car models, encompassing their corresponding fuel efficiency (MPG) values. The features encompass cylinders, engine displacement, horsepower, weight, acceleration, manufacturing year, and the origin of the car.

In [3]:
```
cars_data.shape
```

Out[3]:
```
(394, 9)
```

In [4]:
```
cars_data.columns
```

Out[4]:
```
Index(['Model', 'MPG', 'Cylinders', 'Displacement', 'Horsepower', 'Weight',
       'Acceleration', 'Year', 'Origin'],
      dtype='object')
```

In [5]:
```
cars_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 394 entries, 0 to 393
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Model         394 non-null    object 
 1   MPG           394 non-null    float64
 2   Cylinders     394 non-null    int64  
 3   Displacement  394 non-null    float64
 4   Horsepower    392 non-null    float64
 5   Weight        394 non-null    int64  
 6   Acceleration  394 non-null    float64
 7   Year          394 non-null    int64  
 8   Origin        394 non-null    object 
dtypes: float64(4), int64(3), object(2)
memory usage: 27.8+ KB
```

Data Preprocessing

In [6]:
```
cars_data.head()
```

Out[6]:

	Model	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Year	Origin
0	chevrolet chevelle malibu	18.0	8	307.0	130.0	3504	12.0	70	US
1	buick skylark 320	15.0	8	350.0	165.0	3693	11.5	70	US
2	plymouth satellite	18.0	8	318.0	150.0	3436	11.0	70	US
3	amc rebel sst	16.0	8	304.0	150.0	3433	12.0	70	US
4	ford torino	17.0	8	302.0	140.0	3449	10.5	70	US

In [7]:
```
cars_data.isnull().sum()
```

Out[7]:
```
Model           0
MPG             0
Cylinders       0
Displacement    0
Horsepower      2
Weight          0
Acceleration    0
Year            0
Origin          0
dtype: int64
```

In [8]:
```
cars_data.describe()
```

Out[8]:

	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Year
count	394.000000	394.000000	394.000000	392.000000	394.000000	394.000000	394.000000
mean	23.472843	5.464467	194.062183	104.469388	2976.060914	15.554569	76.007614
std	7.805051	1.704658	104.508345	38.491160	847.891143	2.763179	3.695461
min	9.000000	3.000000	68.000000	46.000000	1613.000000	8.000000	70.000000
25%	17.125000	4.000000	105.000000	75.000000	2226.500000	13.800000	73.000000
50%	23.000000	4.000000	151.000000	93.500000	2803.500000	15.500000	76.000000
75%	29.000000	8.000000	265.750000	126.000000	3612.000000	17.075000	79.000000
max	46.600000	8.000000	455.000000	230.000000	5140.000000	24.800000	82.000000

In [9]:

```
cars_data.loc[~cars_data.Horsepower.apply(np.isreal)]
```

Out[9]:

Model	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Year	Origin

In [10]:

```
cars_data['Horsepower'].replace(0, np.nan, inplace =True)
```

In [11]:

```
cars_data['Horsepower'] = cars_data['Horsepower'].fillna(cars_data['Horsepower'].mean())
```

Replacing Null Values of Horsepower with Mean Value

In [12]:

```
cars_data.isnull().sum()
```

Out[12]:

```
Model           0
MPG             0
Cylinders       0
Displacement    0
Horsepower      0
Weight          0
Acceleration    0
Year            0
Origin          0
dtype: int64
```

In [13]:

```
cars_data.dtypes
```

Out[13]:

```
Model            object
MPG             float64
Cylinders         int64
Displacement    float64
Horsepower      float64
Weight            int64
Acceleration    float64
Year              int64
Origin           object
dtype: object
```

In [14]:

```
cars_data["Horsepower"] = cars_data["Horsepower"].astype('int64')
```

In [15]:

```
cars_data.dtypes
```

Out[15]:
```
Model            object
MPG             float64
Cylinders         int64
Displacement    float64
Horsepower        int64
Weight            int64
Acceleration    float64
Year              int64
Origin           object
dtype: object
```

Non-Graphical Univariate Analysis

In [16]:
```
cars_data['Origin'].unique()
```

Out[16]:
```
array(['US', 'Japan', 'Europe'], dtype=object)
```

In [17]:
```
cars_data['Cylinders'].value_counts()
```

Out[17]:
```
4    201
8    103
6     83
3      4
5      3
Name: Cylinders, dtype: int64
```

In [18]:
```
data_4cylinder = cars_data[(cars_data['Cylinders']==4)]
```

In [19]:
```
data_4cylinder.head()
```

Out[19]:

	Model	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Year	Origin
14	toyota corona mark ii	24.0	4	113.0	95	2372	15.0	70	Japan
18	datsun pl510	27.0	4	97.0	88	2130	14.5	70	Japan
19	volkswagen 1131 deluxe sedan	26.0	4	97.0	46	1835	20.5	70	Europe
20	peugeot 504	25.0	4	110.0	87	2672	17.5	70	Europe
21	audi 100 ls	24.0	4	107.0	90	2430	14.5	70	Europe

In [20]:
```
data_4cylinder.describe()
```

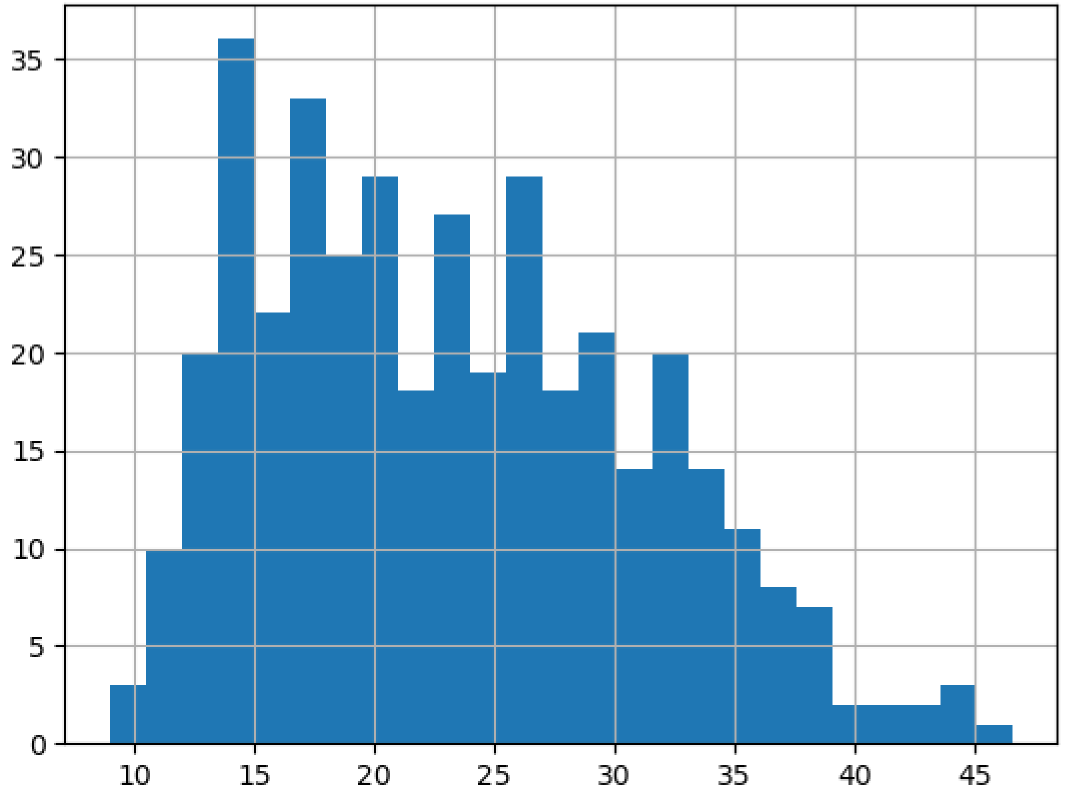
Out[20]:

	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Year
count	201.000000	201.0	201.000000	201.000000	201.00000	201.000000	201.000000
mean	29.278607	4.0	109.828358	78.537313	2308.81592	16.597512	77.074627
std	5.671595	0.0	21.479796	14.675144	345.01703	2.387958	3.745584
min	18.000000	4.0	68.000000	46.000000	1613.00000	11.600000	70.000000
25%	25.000000	4.0	91.000000	68.000000	2050.00000	14.800000	74.000000
50%	28.400000	4.0	105.000000	78.000000	2234.00000	16.200000	78.000000
75%	33.000000	4.0	121.000000	89.000000	2565.00000	18.000000	80.000000
max	46.600000	4.0	156.000000	115.000000	3270.00000	24.800000	82.000000

Graphical Univariate Analysis

In [21]:
```
cars_data['MPG'].hist(bins=25)
```

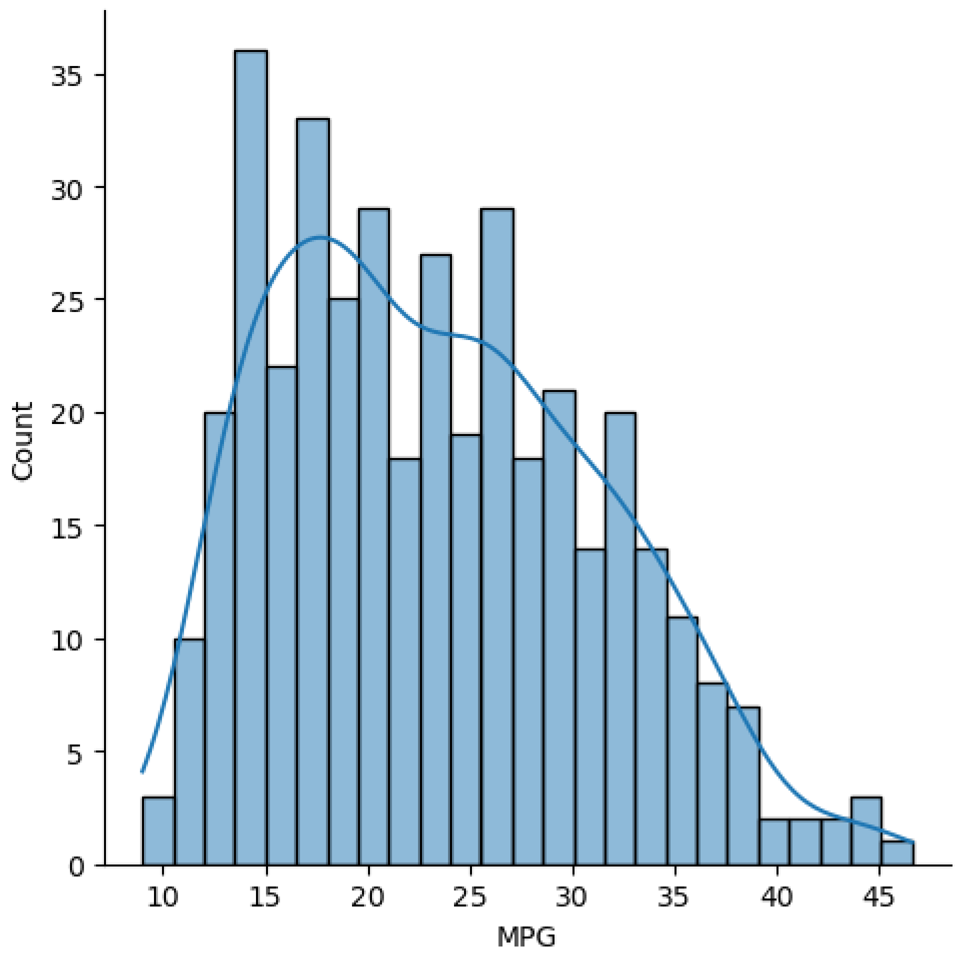
Out[21]: <Axes: >



In [22]:
```
plt.tight_layout()
sns.displot(cars_data['MPG'], bins=25, kde=True)
```

Out[22]: <seaborn.axisgrid.FacetGrid at 0x1ec389a0f10>

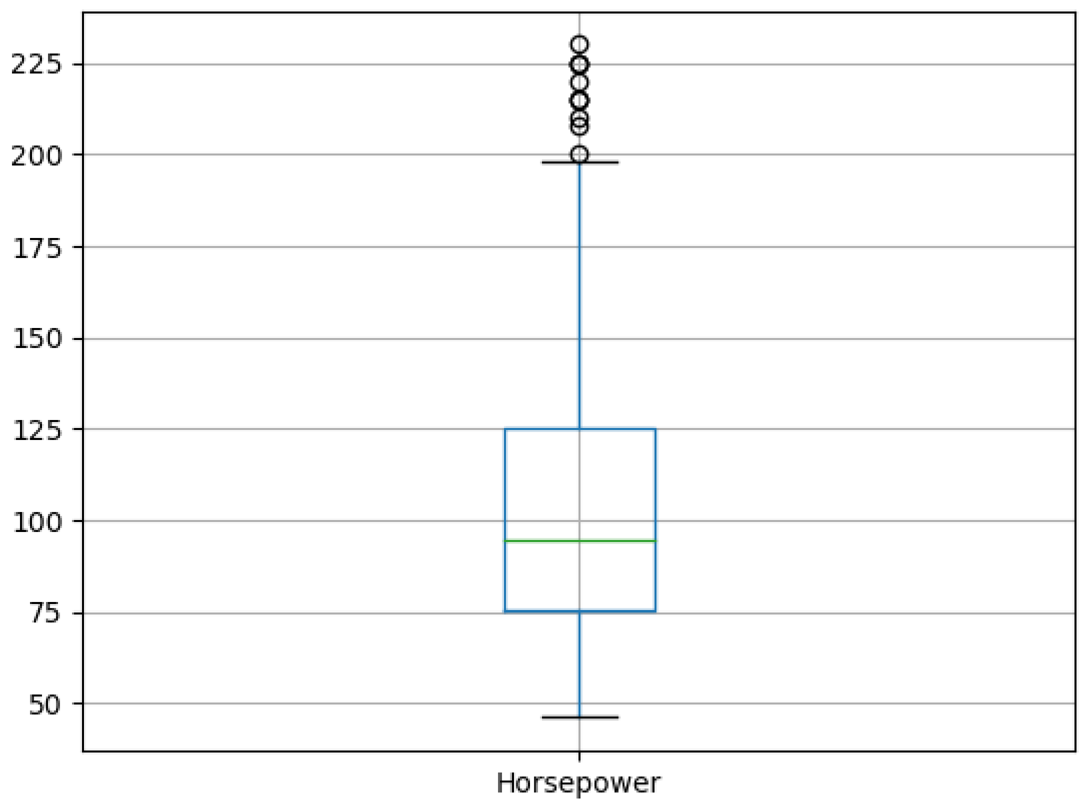
<Figure size 640x480 with 0 Axes>



Box Plots

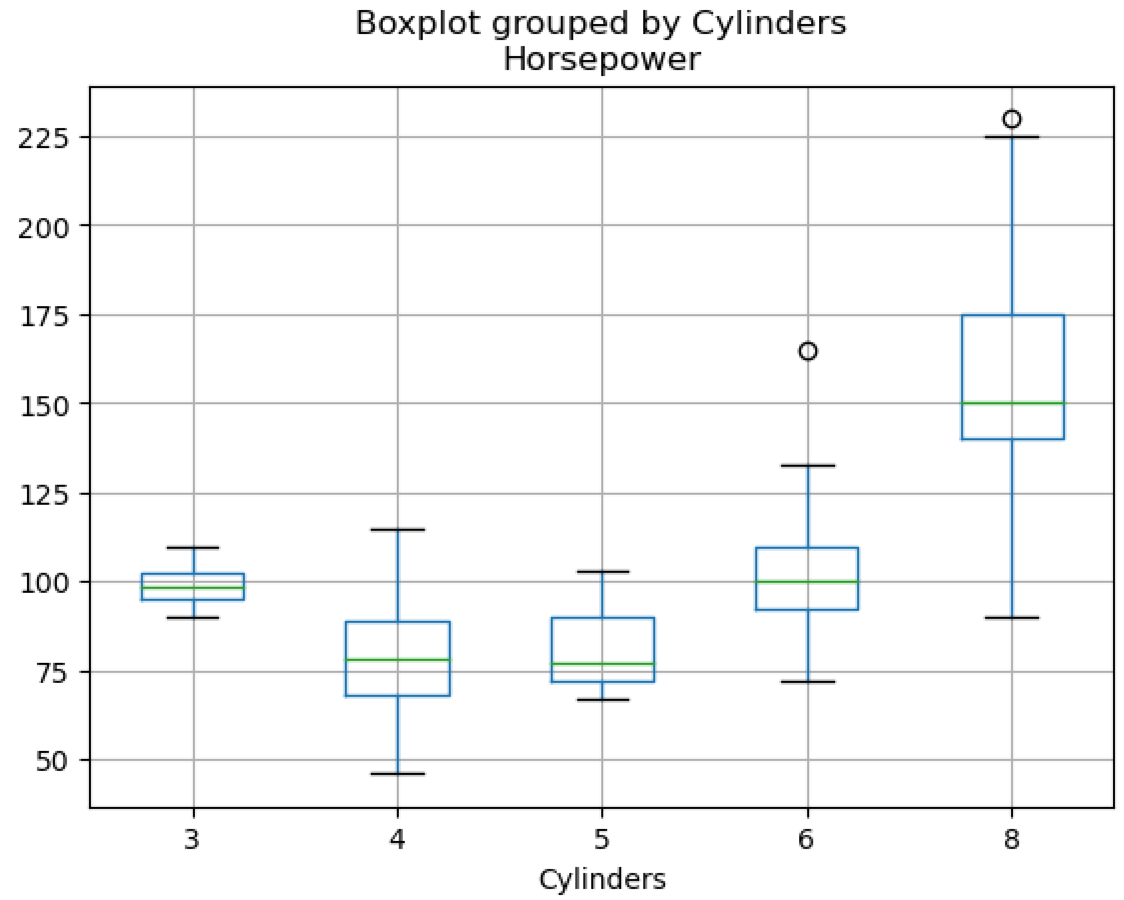
In [23]:
```
cars_data.boxplot(column="Horsepower")
```

Out[23]:
```
<Axes: >
```



In [24]:
```
cars_data.boxplot(column="Horsepower", by="Cylinders")
```

Out[24]:
```
<Axes: title={'center': 'Horsepower'}, xlabel='Cylinders'>
```



Dealing with Outliers

1. Removing the Outliers

In [25]:
```
upper_value = cars_data["Horsepower"].quantile(1-0.2)
upper_value
```

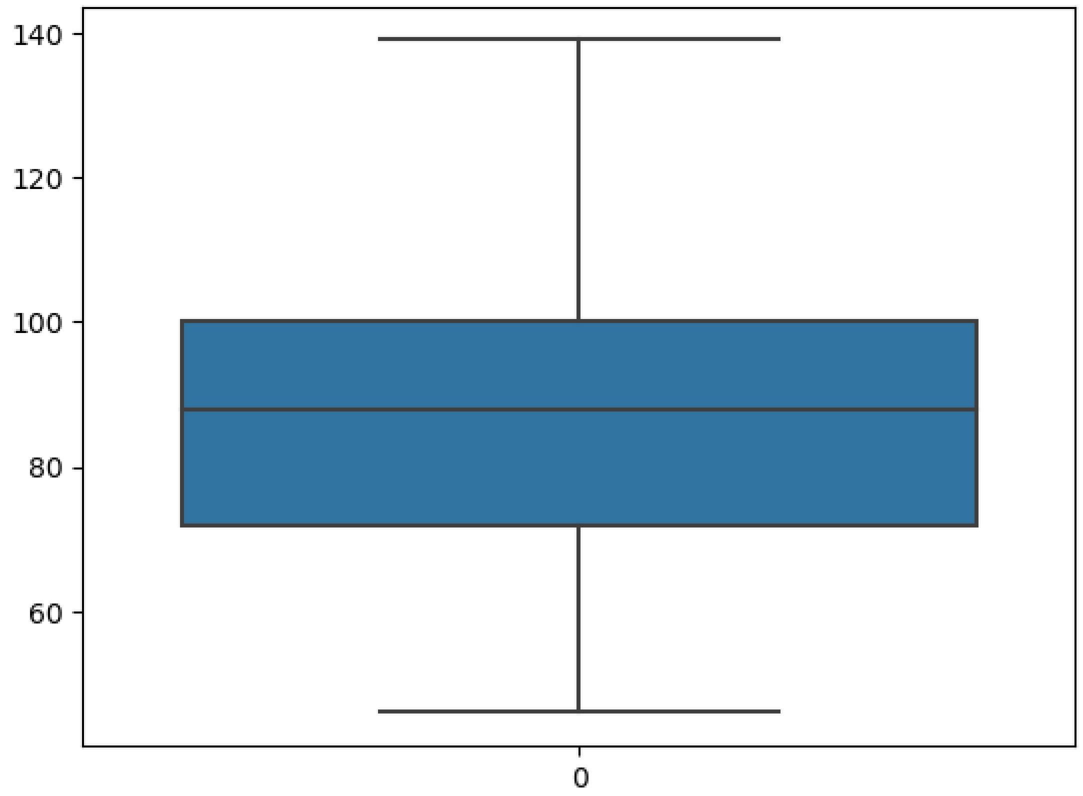
Out[25]:
```
140.0
```

In [26]:
```
mask = (cars_data["Horsepower"]<upper_value)
masked_cardata = cars_data[mask]
```

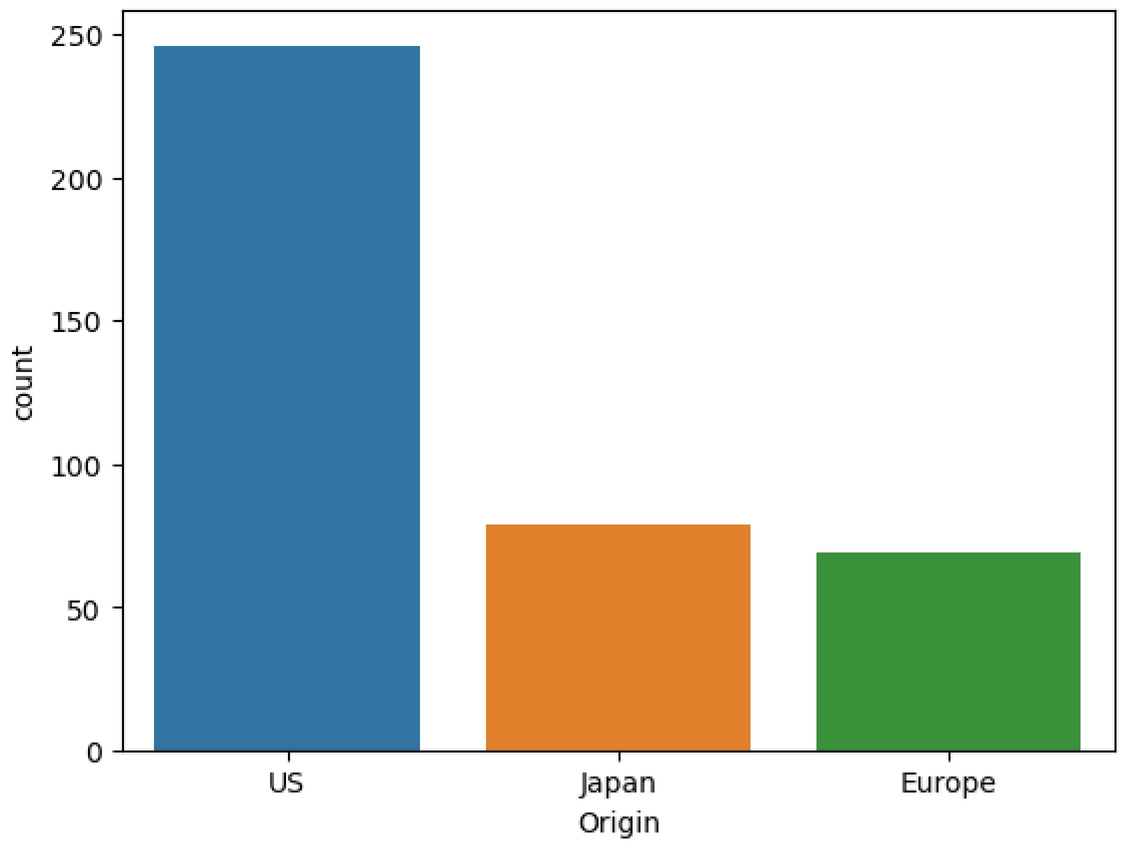
In [27]:
```
masked_cardata.head()
```

Out[27]:

	Model	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Year	Origin
0	chevrolet chevelle malibu	18.0	8	307.0	130	3504	12.0	70	US
14	toyota corona mark ii	24.0	4	113.0	95	2372	15.0	70	Japan
15	plymouth duster	22.0	6	198.0	95	2833	15.5	70	US
16	amc hornet	18.0	6	199.0	97	2774	15.5	70	US
17	ford maverick	21.0	6	200.0	85	2587	16.0	70	US

In [28]:
```
masked_cardata.shape
```
Out[28]:
```
(310, 9)
```
In [29]:
```
sns.boxplot(masked_cardata["Horsepower"])
```
Out[29]:
```
<Axes: >
```


In [30]:
```
sns.countplot(x='Origin', data=cars_data)
plt.show()
```



Non-Graphical Bivariate Analysis

In [31]:
```
correlation_matrix = cars_data.corr()
correlation_matrix['MPG'].sort_values()
```

```
C:\Users\sengu\AppData\Local\Temp\ipykernel_20060\3560153460.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to Fals
e. Select only valid columns or specify the value of numeric_only to silence this warning.
  correlation_matrix = cars_data.corr()
```

Out[31]:
```
Weight         -0.832279
Displacement   -0.805249
Cylinders      -0.777138
Horsepower     -0.776481
Acceleration    0.420574
Year            0.580384
MPG             1.000000
Name: MPG, dtype: float64
```

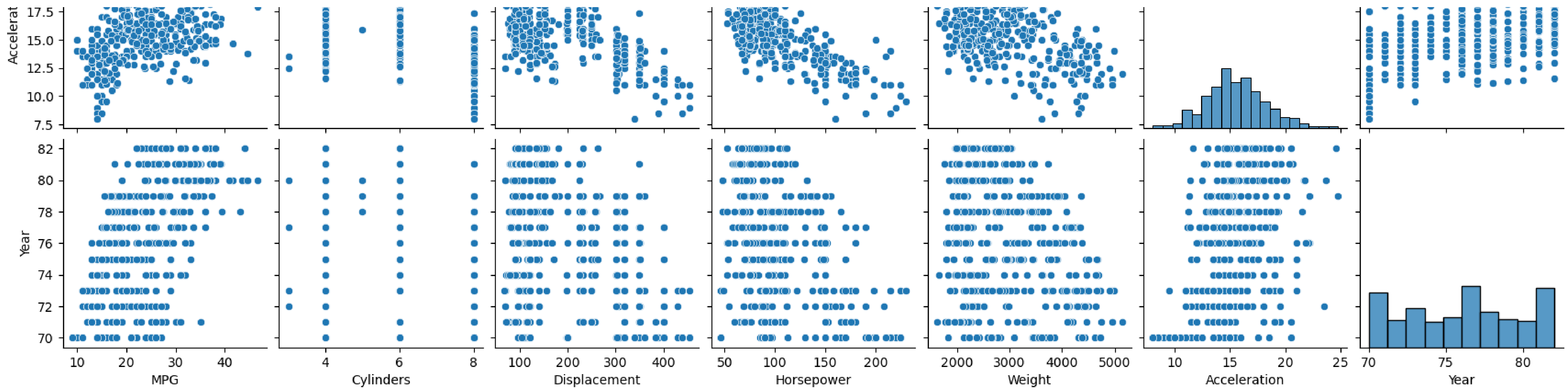
Graphical Bivariate Analysis

Pair-Plot

In [32]:
```
sns.pairplot(cars_data)
```

Out[32]:
```
<seaborn.axisgrid.PairGrid at 0x1ec391fbf10>
```


MPG
Cylinders
Displacement
Horsepower
Weight



Feature Selection

In [33]:
```
cars_data=pd.get_dummies(cars_data, columns=['Origin'])
```

In [34]:
```
cars_data.columns
```

Out[34]:
```
Index(['Model', 'MPG', 'Cylinders', 'Displacement', 'Horsepower', 'Weight',
       'Acceleration', 'Year', 'Origin_Europe', 'Origin_Japan', 'Origin_US'],
      dtype='object')
```

In [35]:
```
feature_variables = ['Cylinders', 'Displacement', 'Horsepower', 'Weight',
       'Acceleration', 'Year', 'Origin_Europe', 'Origin_Japan', 'Origin_US']
```

In [36]:
```
X = cars_data[feature_variables]
Y = cars_data['MPG']
```

Spliting the dataset for Training and Testing

In [37]:
```
from sklearn.model_selection import train_test_split
```

In [38]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,
                                                    test_size= 0.3,
                                                    random_state=10)
```

In [39]:
```
X_train
```

Out[39]:

	Cylinders	Displacement	Horsepower	Weight	Acceleration	Year	Origin_Europe	Origin_Japan	Origin_US
20	4	110.0	87	2672	17.5	70	1	0	0
189	6	225.0	100	3233	15.4	76	0	0	1
59	4	140.0	90	2408	19.5	72	0	0	1
333	4	107.0	72	2290	17.0	80	0	1	0
37	8	350.0	165	4209	12.0	71	0	0	1
...	...	...	...	...	...	...	...	...	...
369	4	140.0	92	2865	16.4	82	0	0	1
320	4	86.0	65	2110	17.9	80	0	1	0
15	6	198.0	95	2833	15.5	70	0	0	1
125	6	232.0	100	2901	16.0	74	0	0	1
265	4	134.0	95	2560	14.2	78	0	1	0

275 rows × 9 columns

In [40]:

```
X_test
```

Out[40]:

	Cylinders	Displacement	Horsepower	Weight	Acceleration	Year	Origin_Europe	Origin_Japan	Origin_US
149	4	79.0	67	2000	16.0	74	1	0	0
188	8	351.0	152	4215	12.8	76	0	0	1
227	8	400.0	180	4220	11.1	77	0	0	1
294	4	121.0	80	2670	15.0	79	0	0	1
78	4	96.0	69	2189	18.0	72	1	0	0
...	...	...	...	...	...	...	...	...	...
25	8	360.0	215	4615	14.0	70	0	0	1
392	4	120.0	79	2625	18.6	82	0	0	1
212	8	302.0	130	3870	15.0	76	0	0	1
357	6	168.0	116	2900	12.6	81	0	1	0
163	8	262.0	110	3221	13.5	75	0	0	1

119 rows × 9 columns

In [41]:

```
Y_train
```

Out[41]:
```
20     25.0
189    22.0
59     20.0
333    32.4
37     14.0
       ...
369    24.0
320    46.6
15     22.0
125    19.0
265    27.5
Name: MPG, Length: 275, dtype: float64
```

In [42]:
```python
Y_test
```

Out[42]:
```
149    31.0
188    14.5
227    16.0
294    27.4
78     26.0
       ...
25     10.0
392    28.0
212    13.0
357    25.4
163    20.0
Name: MPG, Length: 119, dtype: float64
```

Training the Model

In [43]:
```python
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

In [44]:
```python
ln = LinearRegression()
```

In [45]:
```python
ln.fit(X_train, Y_train)
```

Out[45]:
```
▾ LinearRegression
LinearRegression()
```

In [46]:
```python
coeff = ln.coef_
```

In [47]:
```python
coeffdf = pd.DataFrame(coeff, X.columns,
                       columns=["Co-Efficients"])
coeffdf
```

Out[47]:

	Co-Efficients
Cylinders	-0.493838
Displacement	0.025440
Horsepower	-0.020734
Weight	-0.006950
Acceleration	0.049351
Year	0.818052
Origin_Europe	0.880814
Origin_Japan	0.894203
Origin_US	-1.775017

Predictions

In [48]:
```
prediction = ln.predict(X_test)
```

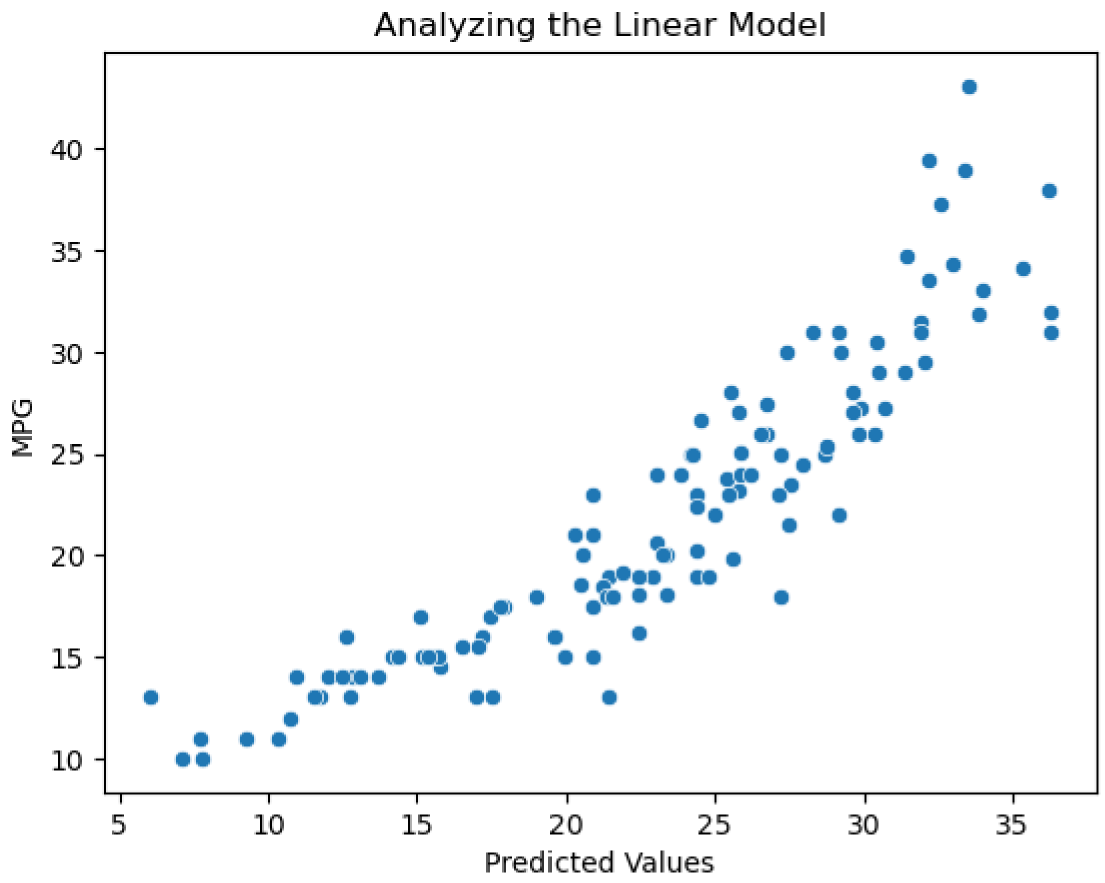
In [49]:
```
prediction
```

Out[49]:
```
array([29.18262228, 15.79164501, 17.15704225, 26.70983944, 26.72259894,
       21.40495071,  7.75830966, 15.07516303, 30.49437741, 25.39379474,
       17.07220938, 12.72865958, 12.6342293 , 20.88465563, 27.55839656,
       30.37168738, 31.448893  , 25.887413  , 32.02214172, 26.70897959,
       16.98393018, 27.95256004, 10.94007209, 26.16891105, 10.34852404,
       12.84267302, 20.28956799, 21.24936639, 14.15231872, 32.16235654,
       20.90699709, 23.00828211, 22.42567748, 27.2384076 , 10.74277248,
       24.38997498, 16.48947427, 17.8981937 , 11.77490079,  9.24949466,
       20.50752088,  6.0024281 , 21.36096919, 31.92339585, 19.00917984,
       20.89743933, 30.45227008, 27.16409749, 23.39171008, 22.89047395,
       31.89497647, 33.86692081, 24.36105573, 22.44236522, 24.54264752,
       25.8814901 , 27.48550487, 33.38197543, 27.18072665, 24.19496343,
       29.17501554, 15.16398393, 36.27415997, 32.20043741, 33.50430035,
       29.85217773, 14.39146525, 32.56897713, 24.39603231, 15.56892763,
       28.30560665, 29.90478529, 29.60812391, 21.43459164, 13.10631143,
        7.71507722, 25.82644395, 23.38266809, 21.56413578, 30.71450257,
       23.02904513, 19.60309561, 23.21253554, 25.56202102, 27.39360077,
       36.23961405, 11.52455033, 19.96867125, 36.31244135, 15.7176882 ,
       24.97541754, 12.0189876 , 17.48914246, 24.39818214, 25.54710197,
       24.26537822, 13.68827395, 25.46300624, 34.01586546, 21.91323448,
       29.20897767, 28.6723059 , 12.47043488, 22.42161657, 25.78677519,
       17.81976848, 26.50450544, 24.78574956, 35.31117128, 20.89200495,
       15.36690139, 33.00422295, 23.85549459, 31.38540493,  7.08510277,
       29.64972235, 17.50771544, 28.75968998, 20.52355314])
```

Graphical Evaluations

In [50]:
```
sns.scatterplot(x=prediction, y=Y_test)
plt.xlabel("Predicted Values")
plt.title("Analyzing the Linear Model")
```

Out[50]:
```
Text(0.5, 1.0, 'Analyzing the Linear Model')
```



Error Analysis

In [51]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
import math
```

In [52]:
```
Absolute_error = mean_absolute_error(Y_test, prediction)
Absolute_error
```

Out[52]:
```
2.606724713349901
```

In [53]:
```
Squared_error = mean_squared_error(Y_test, prediction)
Squared_error
```

Out[53]:
```
10.835678787219592
```

In [54]:
```
Root_Squared = math.sqrt(Squared_error)
Root_Squared
```

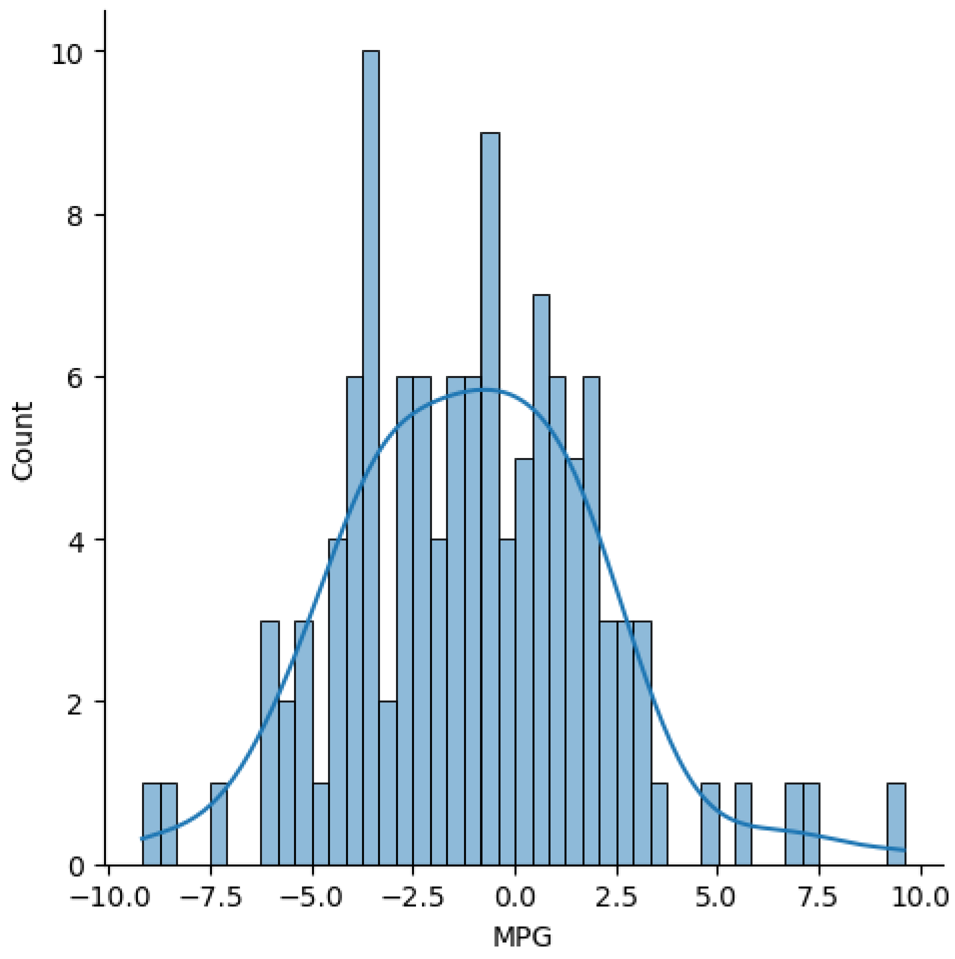
Out[54]:
```
3.2917592237616033
```

Residual Analysis

In [55]:
```
residuals = Y_test - prediction
```

In [56]:
```
sns.displot(residuals, bins=45, kde=True)
```

Out[56]:
```
<seaborn.axisgrid.FacetGrid at 0x1ec3d778ed0>
```



Interpretation and Context for Model Evaluation Metrics

Mean Absolute Error (MAE):

The Mean Absolute Error (MAE) is a measure of the average absolute differences between the predicted and actual values. In the context of this linear regression model predicting car mileage, the MAE represents the average absolute discrepancy in miles per gallon (MPG) between the actual and predicted values. For example, if the MAE is 2, it implies that, on average, the model's predictions are off by 2 MPG.

Mean Squared Error (MSE):

The Mean Squared Error (MSE) measures the average squared differences between predicted and actual values. In the context of this car mileage prediction model, MSE gives more weight to large errors compared to MAE. If the MSE is, for instance, 10, it implies that, on average, the squared difference between predicted and actual MPG is 10.

Root Mean Squared Error (RMSE):

The Root Mean Squared Error (RMSE) is the square root of the MSE and provides an interpretable metric in the same units as the target variable. It is particularly useful for understanding the magnitude of prediction errors. A RMSE of 3, for instance, means that, on average, the model's predictions deviate by 3 MPG from the actual values.

Contextual Interpretation:

- **MAE**: A lower MAE indicates that the model's predictions are, on average, closer to the actual MPG values. It is easily interpretable but might not penalize large errors significantly.
- **MSE**: MSE considers larger errors more seriously. A lower MSE is desirable, but it may be sensitive to outliers.
- **RMSE**: Similar to MSE but provides a more interpretable scale as it is in the same units as the target variable. A lower RMSE suggests better predictive performance.

Residual Analysis:

The residual analysis involves studying the distribution of residuals (the differences between actual and predicted values). A symmetric and approximately normal distribution of residuals indicates that the model is capturing the underlying patterns well. Any patterns or trends in the residual plot may highlight areas where the model performs poorly or fails to capture certain characteristics.

Graphical Evaluations:

The scatter plot of predicted vs. actual values provides a visual representation of how well the model predictions align with the true values. A perfect model would have all points lying on a diagonal line (y=x). Deviations from this line suggest areas where the model is making errors.

In conclusion, evaluating these metrics alongside graphical analyses provides a comprehensive understanding of the model's performance. Keep in mind that the choice of metric depends on the specific goals of the prediction task and the importance of different types of errors.

Conclusions

The linear regression model demonstrated its ability to predict car mileage based on the selected features. The project involved thorough data exploration, preprocessing, and model training, providing valuable insights into the relationships within the dataset. Further refinements and optimizations can be explored to enhance the model's performance and robustness.