Linear Regression on Automobile Dataset

Hamdi Braiek*

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1 Linear Regression on Automobile Dataset

1.1 Dataset

This data set contains information on various attributes / features of vehicles, including their specifications and prices. Each row represents a different vehicle.

Description of the columns in the dataset:

1. **make**: The make or brand of the vehicle.
2. **fuel_type**: The type of fuel used by the vehicle (e.g., gas, diesel).
3. **aspiration**: The type of aspiration system in the engine (e.g., std, turbo).
4. **num_of_doors**: The number of doors on the vehicle.
5. **body_style**: The style or type of body of the vehicle (e.g., sedan, hatchback).
6. **drive_wheels**: The type of drive wheels (e.g., fwd, rwd, 4wd).
7. **engine_location**: The location of the engine in the vehicle (e.g., front, rear).
8. **length**: The length of the vehicle.
9. **width**: The width of the vehicle.
10. **height**: The height of the vehicle.
11. **engine_type**: The type of engine (e.g., ohc, ohcf).
12. **num_of_cylinders**: The number of cylinders in the engine.
13. **engine_size**: The size of the engine (in cubic centimeters).
14. **compression_ratio**: The compression ratio of the engine.
15. **horsepower**: The horsepower of the vehicle.
16. **peak_rpm**: The peak revolutions per minute of the engine.
17. **city_mpg**: The city miles per gallon (fuel efficiency) of the vehicle.
18. **highway_mpg**: The miles travelled per gallon (fuel efficiency) of the vehicle.
19. **price**: The price of the vehicle.

1.2 The Objective

The objective is to perform exploratory data analysis (EDA) and build a simple linear regression model to understand the relationship between predictor variables (such as `horsepower`) and the target variable (`price`) in the automotive data set.

During this notebook, our aim is to:

*ResearchGate: https://www.researchgate.net/profile/Hamdi-Braiek,
LinkedIn: https://www.linkedin.com/in/hamdi-braiek/,
Notebook on Kaggle: https://www.kaggle.com/code/hamdi20/simple-linear-regression-on-automobile-datasets

1. Load the dataset and inspect its structure, including the organization of data, column names, and data types.
2. Explore the data set through descriptive statistics, data visualisation, and correlation analysis to gain insight into the relationships between variables.
3. Build a simple linear regression model to predict the vehicle price based on one predictor variable (e.g., `horsepower`).
4. Evaluate the performance of the linear regression model using metrics such as R-squared and adjusted R-squared.
5. Visualize the relationship between the predictor variable and the target variable using scatter plots and regression lines.
6. Use the trained regression model to make predictions for new data points (e.g., predicting the price for a given horsepower value).

Show the directory where the datasets or notebook is currently located

```python
import numpy as np
import pandas as pd

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/autoscars/autos.txt
```

1.3 Loading and Manipulating Data

1. Import the dataset

```python
df = pd.read_csv('/kaggle/input/autoscars/autos.txt', sep='\t')
```

2. Show the first five rows of the dataframe `df`

```python
df.head()
```

[5]:

```
          make fuel_type aspiration num_of_doors   body_style drive_wheels  \
0  alfa-romeo       gas        std          two  convertible          rwd
1  alfa-romeo       gas        std          two  convertible          rwd
2  alfa-romeo       gas        std          two    hatchback          rwd
3        audi       gas        std         four        sedan          fwd
4        audi       gas        std         four        sedan          4wd

  engine_location  length  width  height engine_type num_of_cylinders  \
0           front   168.8   64.1    48.8        dohc             four
1           front   168.8   64.1    48.8        dohc             four
2           front   171.2   65.5    52.4        ohcv              six
3           front   176.6   66.2    54.3         ohc             four
4           front   176.6   66.4    54.3         ohc             five

   engine_size  compression_ratio  horsepower  peak_rpm  city_mpg  \
```

```
0          130                   9.0      111.0    5000.0        21
1          130                   9.0      111.0    5000.0        21
2          152                   9.0      154.0    5000.0        19
3          109                  10.0      102.0    5500.0        24
4          136                   8.0      115.0    5500.0        18

   highway_mpg  price
0           27  13495
1           27  16500
2           26  16500
3           30  13950
4           22  17450
```

- The first line represent the column names or headers of the dataset, which include various attributes such as :

```
df.column
```

```
[6]: Index(['make', 'fuel_type', 'aspiration', 'num_of_doors', 'body_style',
       'drive_wheels', 'engine_location', 'length', 'width', 'height',
       'engine_type', 'num_of_cylinders', 'engine_size', 'compression_ratio',
       'horsepower', 'peak_rpm', 'city_mpg', 'highway_mpg', 'price'],
      dtype='object')
```

- The separator between columns is a tab character ().
- The decimal point used in numerical values is a dot (.) like :

```
df['length'][0]
```

```
[8]: 168.8
```

- The shape of the data (the number of the observations and the features)

```
df.shape
```

```
[9]: (205, 19)
```

3. Display the list of variables and their types

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   make               205 non-null    object
 1   fuel_type          205 non-null    object
 2   aspiration         205 non-null    object
```

```
 3   num_of_doors       205 non-null    object
 4   body_style         205 non-null    object
 5   drive_wheels       205 non-null    object
 6   engine_location    205 non-null    object
 7   length             205 non-null    float64
 8   width              205 non-null    float64
 9   height             205 non-null    float64
 10  engine_type        205 non-null    object
 11  num_of_cylinders   205 non-null    object
 12  engine_size        205 non-null    int64
 13  compression_ratio  205 non-null    float64
 14  horsepower         205 non-null    float64
 15  peak_rpm           205 non-null    float64
 16  city_mpg           205 non-null    int64
 17  highway_mpg        205 non-null    int64
 18  price              205 non-null    int64
dtypes: float64(6), int64(4), object(9)
memory usage: 30.6+ KB
```

From this output:

- The total number of rows is 205.
- The total number of variables is 19.
- There are 6 columns with floating-point (`float64`) data type.
- There are 4 columns with integer (`int64`) data type.
- There are 9 columns with object data type (`object`), which represents strings.
- The count for each column is 205, indicating that there are no missing values in the dataframe.

1.4 Exploratory Data Analysis

4. Descriptive statistics for each numerical column in `df`

```python
description = df.describe()
description
```

[12]:

```
           length       width      height  engine_size  compression_ratio  \
count  205.000000  205.000000  205.000000   205.000000         205.000000
mean   174.049268   65.907805   53.724878   126.907317          10.142439
std     12.337289    2.145204    2.443522    41.642693           3.972060
min    141.100000   60.300000   47.800000    61.000000           7.000000
25%    166.300000   64.100000   52.000000    97.000000           8.600000
50%    173.200000   65.500000   54.100000   120.000000           9.000000
75%    183.100000   66.900000   55.500000   141.000000           9.400000
max    208.100000   72.300000   59.800000   326.000000          23.000000

       horsepower     peak_rpm    city_mpg  highway_mpg         price
count  205.000000   205.000000  205.000000   205.000000    205.000000
mean   104.256195  5125.369465   25.219512    30.751220  13207.126829
std     39.519211   476.979093    6.542142     6.886443   7868.768212
```

```
min     48.000000  4150.000000   13.000000    16.000000    5118.000000
25%     70.000000  4800.000000   19.000000    25.000000    7788.000000
50%     95.000000  5200.000000   24.000000    30.000000   10595.000000
75%    116.000000  5500.000000   30.000000    34.000000   16500.000000
max    288.000000  6600.000000   49.000000    54.000000   45400.000000
```

From this output:

- The mean, standard deviation, minimum, maximum, and percentiles are provided for each numerical column, giving an overview of the distribution of values.
- The numerical columns must be scaled to a standard range.

5. Calculate the mean and standard deviation of the variable `price`

```python
mn = df['price'].mean()
sd = df['price'].std()
print(f'The mean of the price variable is {mn}')
print(f'The standard deviation of the price variable is {sd}')
```

```
The mean of the price variable is 13207.126829268293
The standard deviation of the price variable is 7868.76821236424
```

Anothor method the show the mean and std of the price feature is to use the `df.describe()` as :

- `description['price']['mean']`
- `description['price']['std']`

6. Calculate the frequency of vehicles according to `fuel_type`

```python
fuel_type_frequency = df['fuel_type'].value_counts()
fuel_type_frequency
```

```
[24]: fuel_type
gas       185
diesel     20
Name: count, dtype: int64
```

7. Calculate the frequency of vehicles according to `aspiration`

```python
aspiration_frequency = df['aspiration'].value_counts()
aspiration_frequency
```

```
[25]: aspiration
std      168
turbo     37
Name: count, dtype: int64
```

8. Display the frequency of vehicles according to `fuel_type` and `aspiration`

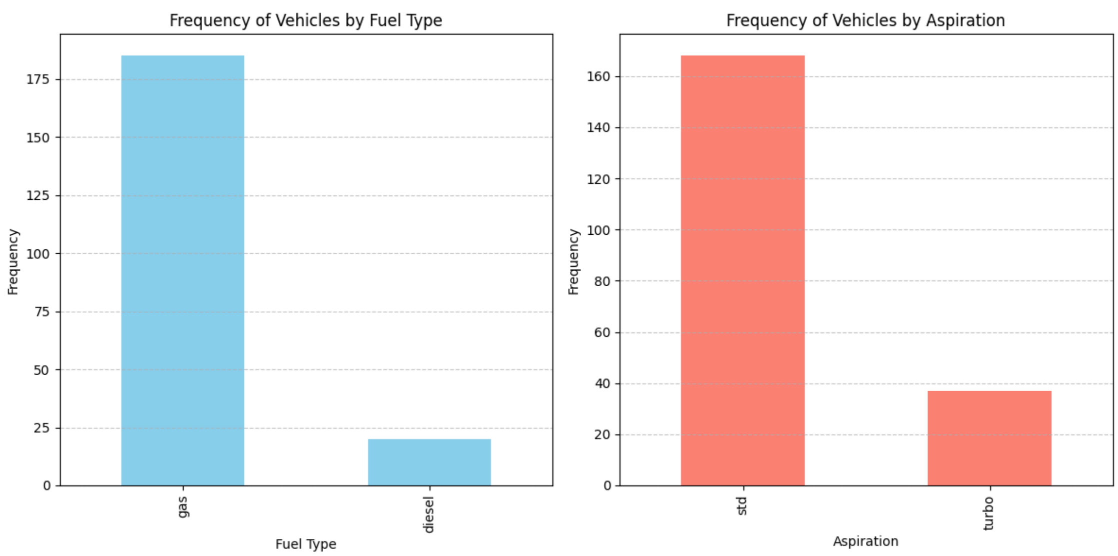
```python
import matplotlib.pyplot as plt
```

```
fig, axes = plt.subplots(1, 2, figsize=(12, 6))

fuel_type_frequency.plot(kind='bar', color='skyblue', ax=axes[0])
axes[0].set_title('Frequency of Vehicles by Fuel Type')
axes[0].set_xlabel('Fuel Type')
axes[0].set_ylabel('Frequency')
axes[0].grid(axis='y', linestyle='--', alpha=0.7)

aspiration_frequency.plot(kind='bar', color='salmon', ax=axes[1])
axes[1].set_title('Frequency of Vehicles by Aspiration')
axes[1].set_xlabel('Aspiration')
axes[1].set_ylabel('Frequency')
axes[1].grid(axis='y', linestyle='--', alpha=0.7)

plt.tight_layout()
plt.show()
```



9. Show the number of vehicles with `fuel_type = gas` and `aspiration = std`

From the `value_counts()` of `fuel_type` and `aspiration`: - Number of vehicles with `fuel_type = gas`: 185 - Number of vehicles with `aspiration = std`: 168

We can get the same result using - `df[df['fuel_type'] == 'gas'].shape[0]` - `df[df['aspiration'] == 'std'].shape[0]`

If we want to show in same time the number of vehicles with `fuel_type = gas` and `aspiration = std` we can use

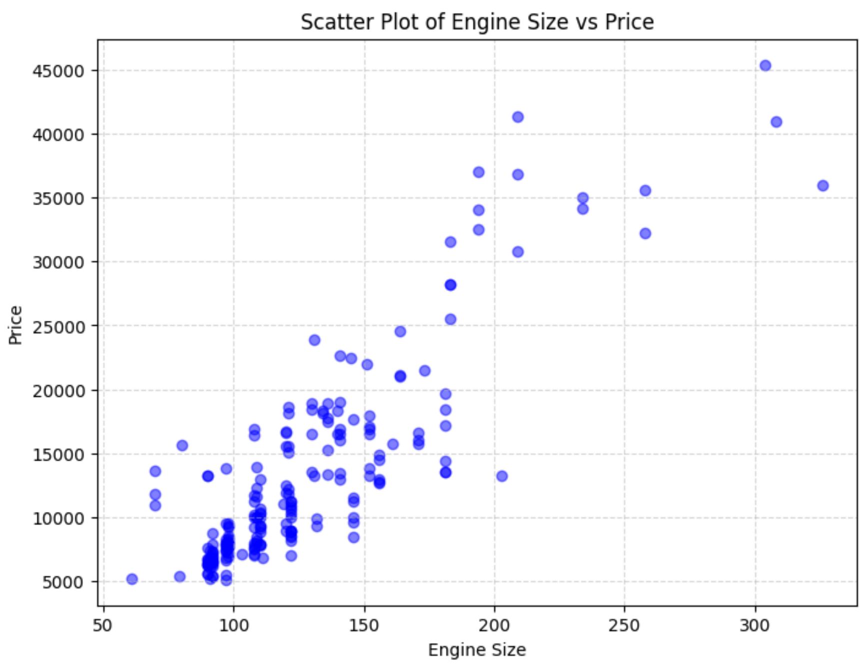
```
df[(df['fuel_type'] == 'gas') & (df['aspiration'] == 'std')].shape[0]
```

[37]: 161

1.5 Correlation

10. Create a scatter plot with `engine_size` on the x-axis and `price` on the y-axis

```
plt.figure(figsize=(8, 6))
plt.scatter(df['engine_size'], df['price'], color='blue', alpha=0.5)
plt.title('Scatter Plot of Engine Size vs Price')
plt.xlabel('Engine Size')
plt.ylabel('Price')
plt.grid(True, linestyle='--', alpha=0.5)
plt.show()
```



Observations:

- As the engine size increases, there seems to be a general trend of higher prices.
- However, the relationship is perfectly linear, as there are variations in price for a given engine size.

11. Calculate the correlation coefficient between the `engine_size` and `price`

```
df['engine_size'].corr(df['price'])
```

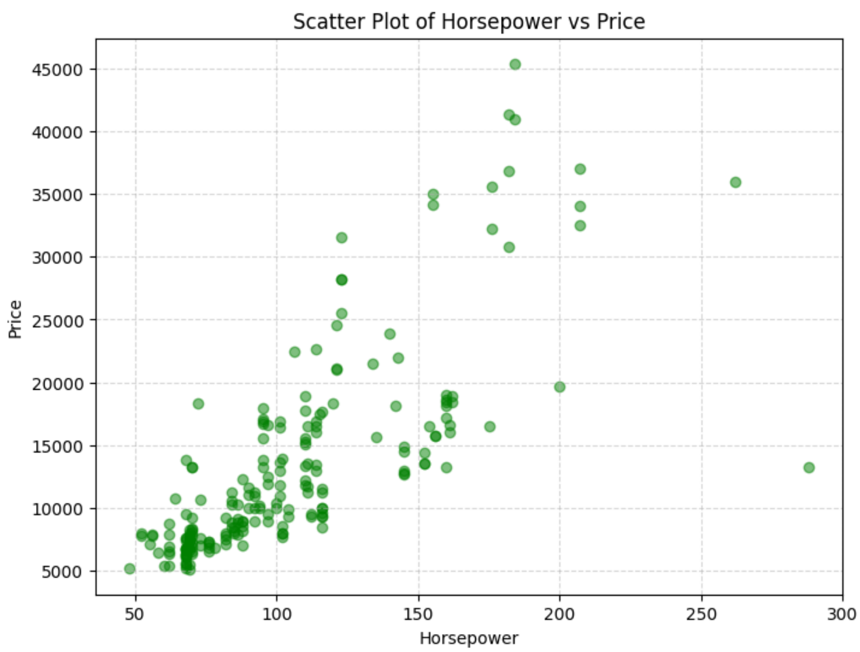
[39]: 0.861752231355783

The correlation coefficient is 0.86 which is close to 1 suggests that there is a strong linear relationship between `engine_size` and `price`. This indicates a strong positive correlation between `engine_size` and `price`.

1.6 Linear Regression

12. Create the scatter plot between `horsepower` (x-axis) and `price` (y-axis)

```
plt.figure(figsize=(8, 6))
plt.scatter(df['horsepower'], df['price'], color='green', alpha=0.5)
plt.title('Scatter Plot of Horsepower vs Price')
plt.xlabel('Horsepower')
plt.ylabel('Price')
plt.grid(True, linestyle='--', alpha=0.5)
plt.show()
```



Observations:

- As horsepower increases, there seems to be a general trend of higher prices.
- However, the relationship is not perfectly linear, as there are variations in price for a given horsepower.
- There may be some outliers where vehicles have unusually high or low prices for their horsepower.

```
df['horsepower'].corr(df['price'])
```

[41]: 0.7579161672743434

13. Identify the brand of the outlier and drop them from the DataFrame

Based on previous graph, we can drop all rows with `horsepower > 100 & price > 14000`

```python
outlier_brand = df[(df['horsepower'] > 100) & (df['price'] > 14000)]
outlier_make = outlier_brand['make'].unique()
print("brand of the outlier:", outlier_make)
df_cleaned = df.drop(outlier_brand.index)
df_cleaned.shape
```

```
brand of the outlier: ['alfa-romeo' 'audi' 'bmw' 'jaguar' 'mazda' 'mercedes-benz' 'mercury' 'mitsubishi' 'nissan' 'peugot' 'porsche' 'saab' 'toyota' 'volvo']
```

[85]: (147, 19)

It isn't the good way to identify the outliers. The good method is to use the `IQR`

```python
Q1_price = df['price'].quantile(0.25)
Q3_price = df['price'].quantile(0.75)
IQR_price = Q3_price - Q1_price
lower_bound_price = Q1_price - 1.5 * IQR_price
upper_bound_price = Q3_price + 1.5 * IQR_price
Q1_horsepower = df['horsepower'].quantile(0.25)
Q3_horsepower = df['horsepower'].quantile(0.75)
IQR_horsepower = Q3_horsepower - Q1_horsepower
lower_bound_horsepower = Q1_horsepower - 1.5 * IQR_horsepower
upper_bound_horsepower = Q3_horsepower + 1.5 * IQR_horsepower
outliers = df[(df['price'] < lower_bound_price) | (df['price'] > upper_bound_price) |
(df['horsepower'] < lower_bound_horsepower) | (df['horsepower'] > upper_bound_horsepower)]
df_cleaned = df[~df.index.isin(outliers.index)]
print("Number of observations after removing outliers:", df_cleaned.shape[0])
```

```
Number of observations after removing outliers: 189
```

14. Linear regression of "price" (Y) on "horsepower" (X)

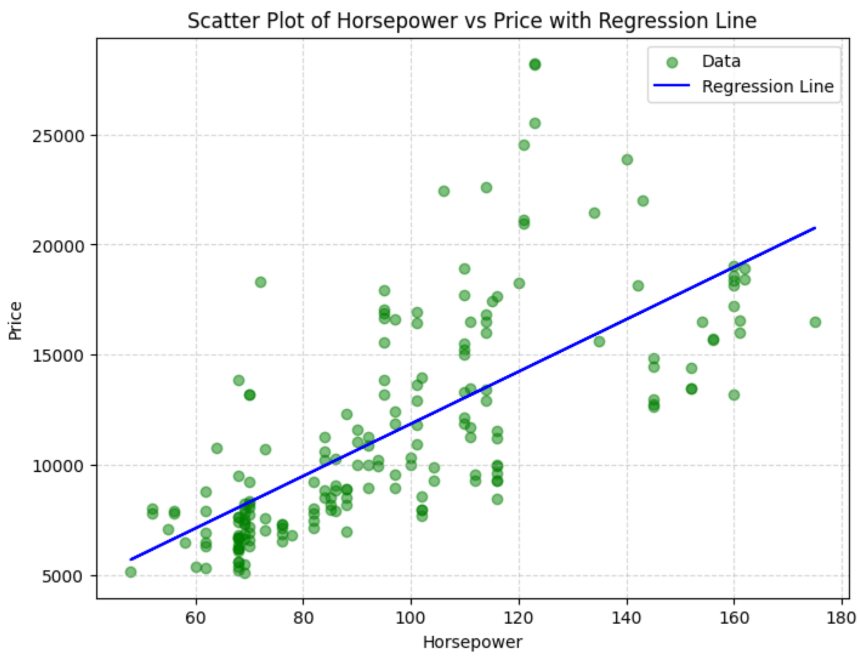
```python
from sklearn.linear_model import LinearRegression
```

```python
X = df_cleaned[['horsepower']]
Y = df_cleaned['price']
model = LinearRegression()
model.fit(X, Y)
a = model.coef_[0]
b = model.intercept_
print("Coefficient a:", a)
print("Coefficient b:", b)
```

```
Coefficient a: 118.60031791677316
Coefficient b: 1.7529567395740742
```

15. create a scatter plot between "horsepower" (x-axis) and "price" (y-axis) and add the regression line to the plot

```python
plt.figure(figsize=(8, 6))
plt.scatter(X, Y, color='green', alpha=0.5, label='Data')
plt.plot(X, model.predict(X), color='blue', label='Regression Line')
plt.title('Scatter Plot of Horsepower vs Price with Regression Line')
plt.xlabel('Horsepower')
plt.ylabel('Price')
plt.legend()
plt.grid(True, linestyle='--', alpha=0.5)
plt.show()
```



16. Calculate the coefficient of determination (R2) and R2-adjasted

```python
from sklearn.metrics import r2_score
R_squared = r2_score(Y, model.predict(X))
k = 1 # We have only one predictor, which is 'horsepower'
R_squared_adj = 1 - (1 - R_squared) * (len(Y) - 1) / (len(Y) - k - 1)
print("R-squared (R²):", R_squared)
print("Adjusted R-squared (R²_adj):", R_squared_adj)
```

```
R-squared (R²): 0.5006871119966264
Adjusted R-squared (R²_adj): 0.49801698960088636
```

1.7 Predictions

17. Predict the value of "price" for a given value of "horsepower" = 100 using the linear regression model

```python
X_new = pd.DataFrame({'horsepower': [100]})
model.predict(X_new)
```

[100]: `array([11861.78474842])`

Another method is to use the coefficients a and b

```python
horsepower = 100
predicted_price = a * horsepower + b
print("Predicted price for horsepower = 100:", predicted_price)
```

```
Predicted price for horsepower = 100: 11861.78474841689
```

18. Reconstruct the scatter plot of "horsepower" vs "price" with the regression line and the predicted point

```python
plt.figure(figsize=(8, 6))
plt.scatter(X, Y, color='green', label='Data')
plt.plot(X, model.predict(X), color='blue', label='Regression Line')
plt.scatter(100, model.predict(X_new), color='red', label='Predicted Point')
plt.title('Scatter Plot of Horsepower vs Price with Regression Line and Predicted Point')
plt.xlabel('Horsepower')
plt.ylabel('Price')
plt.legend()
plt.grid(True, linestyle='--', alpha=0.5)
plt.show()
```