#Importing necessary python library

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split from
sklearn.linear_model import LinearRegression from
sklearn.metrics import r2_score
```

#Uploading Automobile Dataset

```
from google.colab import files uploaded
= files.upload()
<IPython.core.display.HTML object>
Saving Automobile_data.csv to Automobile_data.csv
```

#Load the dataset

```
df = pd.read_csv('Automobile_data.csv')
```

#Univariate Analysis Numeric Variables Preparing Data

```
df = df.replace('?', pd.NA)

# convert data types
df['normalized-losses'] = pd.to_numeric(df['normalized-losses'],
errors='coerce')
df['bore'] = pd.to_numeric(df['bore'], errors='coerce')
df['stroke'] = pd.to_numeric(df['stroke'], errors='coerce')
df['horsepower'] = pd.to_numeric(df['horsepower'], errors='coerce')
df['peak-rpm'] = pd.to_numeric(df['peak-rpm'], errors='coerce')
df['price'] = pd.to_numeric(df['price'], errors='coerce')

# drop rows with missing values
df = df.dropna()

# reset index
df = df.reset_index(drop=True)

# display the first few rows
print(df.head())
   symboling  normalized-losses  make fuel-type aspiration num-of-
doors  \

0          2              164.0  audi       gas        std
four
1     2                   164.0   audi        gas          std          four
2     1                   158.0   audi        gas          std          four
```

```
3     1                 158.0  audi        gas      turbo          four
4     2                 192.0   bmw        gas        std           two

  body-style drive-wheels engine-location  wheel-base  ...  enginesize
\
0      sedan          fwd           front        99.8  ...
109
1      sedan          4wd           front        99.4  ...
136
2      sedan          fwd           front       105.8  ...
136
3      sedan          fwd           front       105.8  ...
131
4      sedan          rwd           front       101.2  ...
108

   fuel-system  bore  stroke compression-ratio horsepower  peak-rpm
city-mpg  \
0         mpfi  3.19     3.4              10.0      102.0    5500.0
24
1         mpfi  3.19     3.4               8.0      115.0    5500.0
18
2         mpfi  3.19     3.4               8.5      110.0    5500.0
19
3         mpfi  3.13     3.4               8.3      140.0    5500.0
17
4         mpfi  3.50     2.8               8.8      101.0    5800.0
23

   highway-mpg    price  0
30  13950.0
1           22  17450.0
2           25  17710.0
3           20  23875.0
4           29  16430.0

[5 rows x 26 columns]
```

```
df.describe()
```

```
        symboling  normalized-losses  wheel-base      length
width  \
count  159.000000         159.000000  159.000000  159.000000
159.000000
mean     0.735849         121.132075   98.264151  172.413836
65.607547
std      1.193086          35.651285    5.167416   11.523177
1.947883
min     -2.000000          65.000000   86.600000  141.100000
```

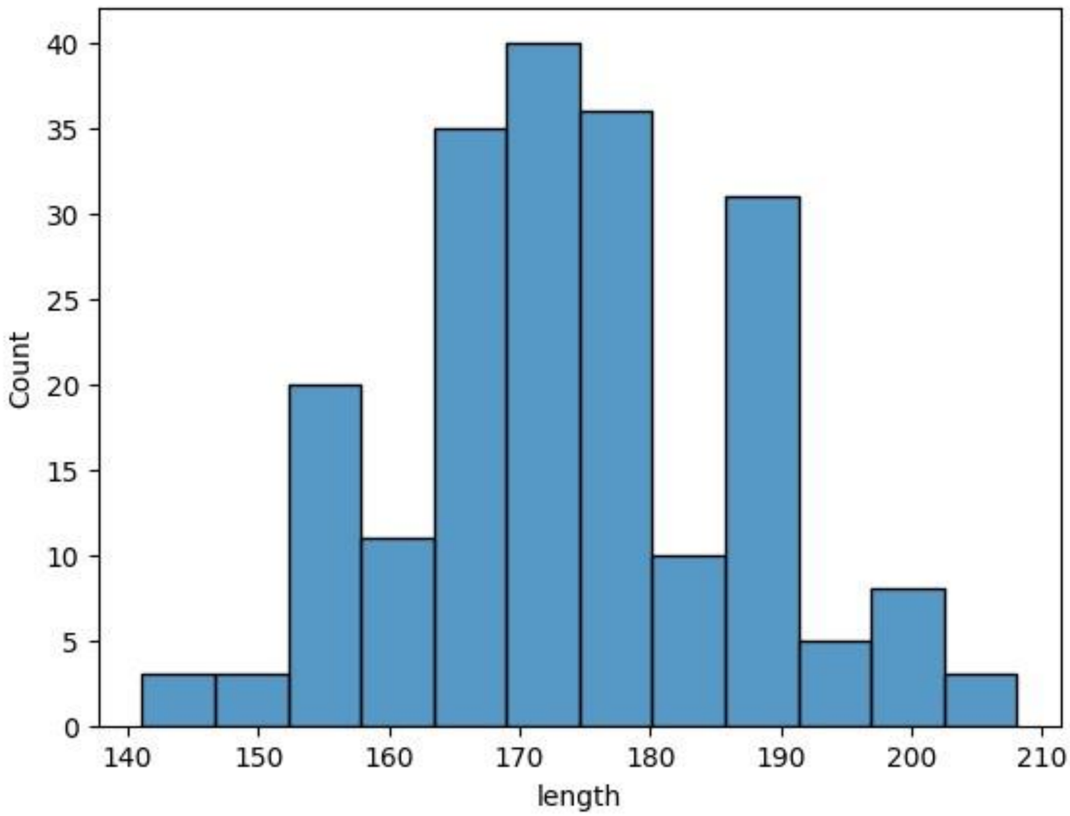
```
60.300000
25%      0.000000          94.000000   94.500000  165.650000
64.000000
50%      1.000000         113.000000   96.900000  172.400000
65.400000
75%      2.000000         148.000000  100.800000  177.800000
66.500000
max      3.000000         256.000000  115.600000  202.600000
71.700000

           height  curb-weight  engine-size        bore      stroke  \
count  159.000000   159.000000   159.000000  159.000000  159.000000
mean    53.899371  2461.138365   119.226415    3.300126    3.236352
std      2.268761   481.941321    30.460791    0.267336    0.294888
min     49.400000  1488.000000    61.000000    2.540000    2.070000
25%     52.250000  2065.500000    97.000000    3.050000    3.105000
50%     54.100000  2340.000000   110.000000    3.270000    3.270000
75%     55.500000  2809.500000   135.000000    3.560000    3.410000
max     59.800000  4066.000000   258.000000    3.940000    4.170000

       compression-ratio  horsepower     peak-rpm    city-mpg
highway-mpg  \
count         159.000000  159.000000   159.000000  159.000000
159.000000
mean           10.161132   95.836478  5113.836478   26.522013
32.081761
std             3.889475   30.718583   465.754864    6.097142
6.459189
min             7.000000   48.000000  4150.000000   15.000000
18.000000
25%             8.700000   69.000000  4800.000000   23.000000
28.000000
50%             9.000000   88.000000  5200.000000   26.000000
32.000000
75%             9.400000  114.000000  5500.000000   31.000000
37.000000
max            23.000000  200.000000  6600.000000   49.000000
54.000000

              price
count    159.000000
mean   11445.729560
std     5877.856195
min     5118.000000
```

```
25%      7372.000000
50%      9233.000000
75%     14719.500000
max     35056.000000
```

#Categorical Variables

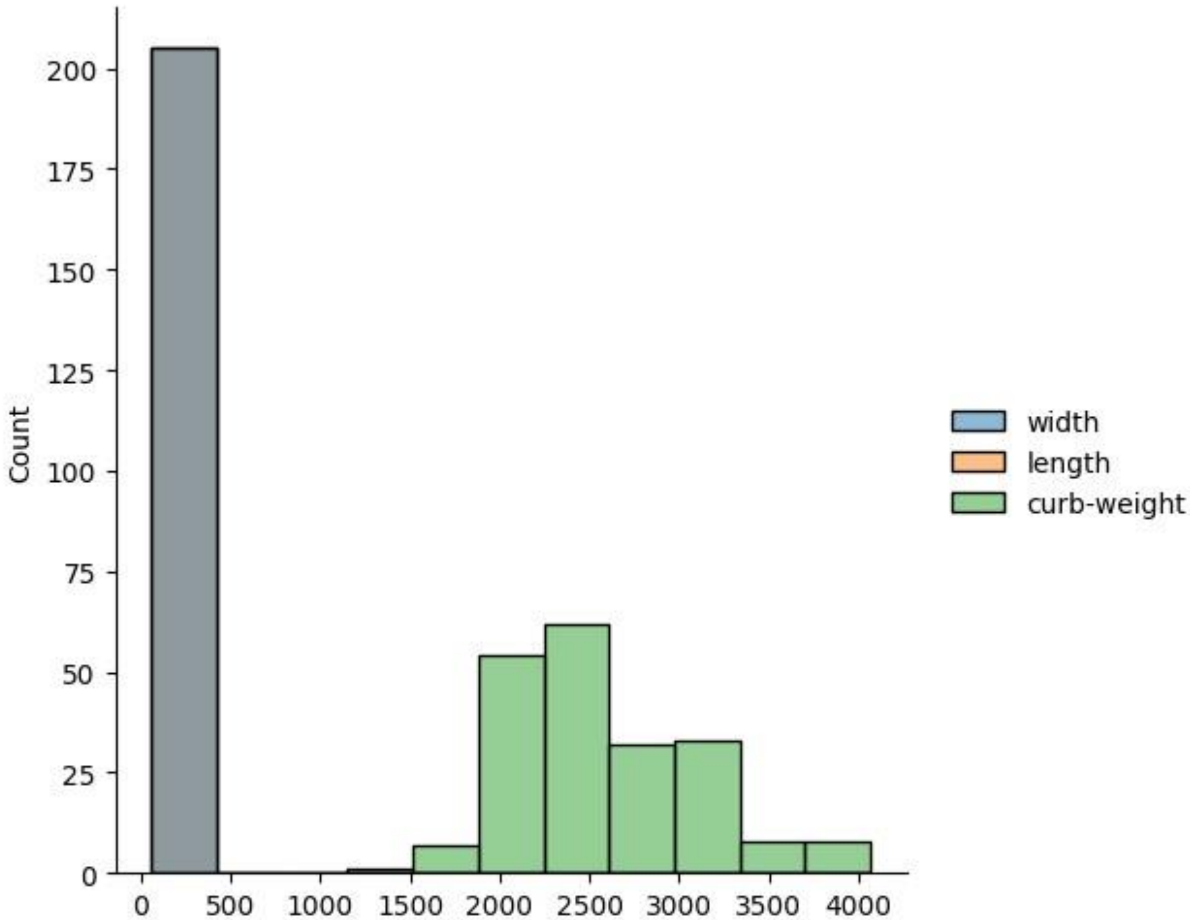
```
sns.histplot(x='length',data=df)
```

```
<Axes: xlabel='length', ylabel='Count'>
```



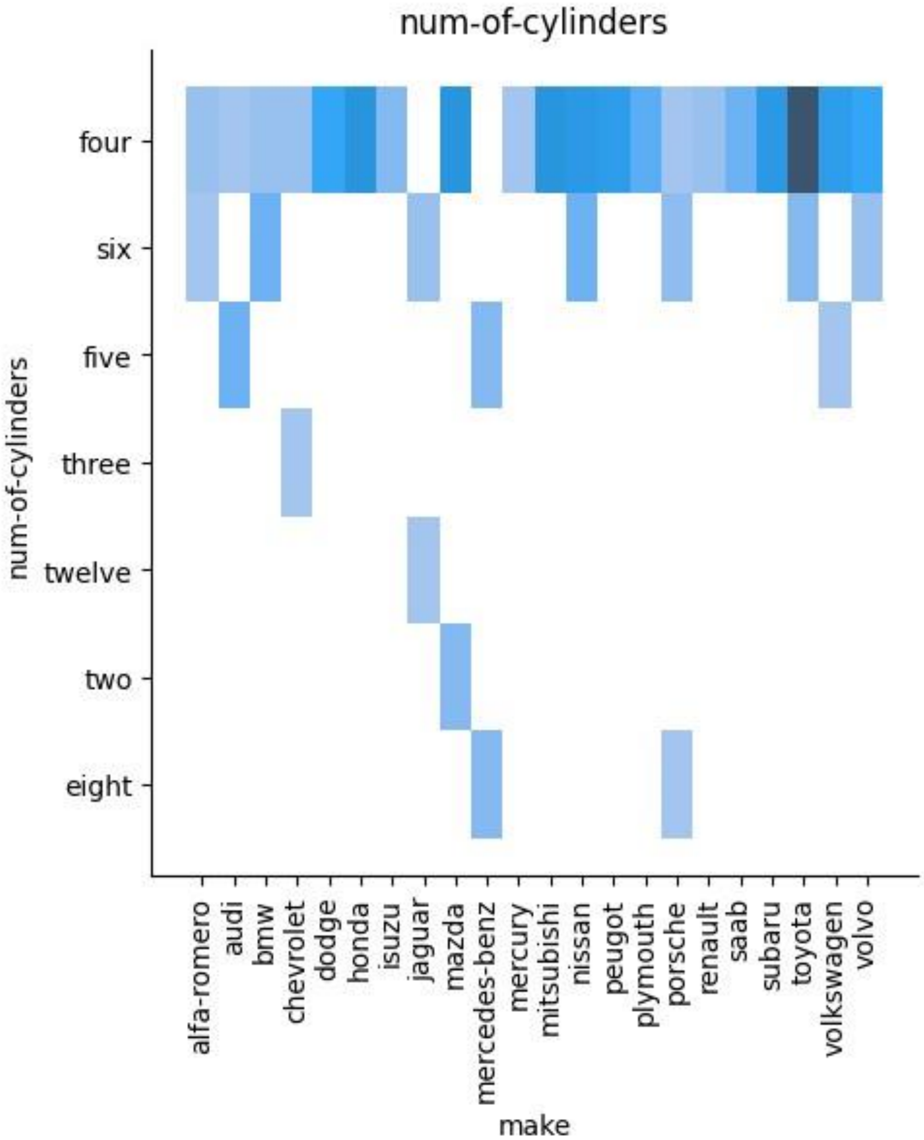
#Bi-Variate Analysis Numerical Variables

```
sns.displot(df[['price', 'width', 'length', 'curb-weight']])
plt.show()
```



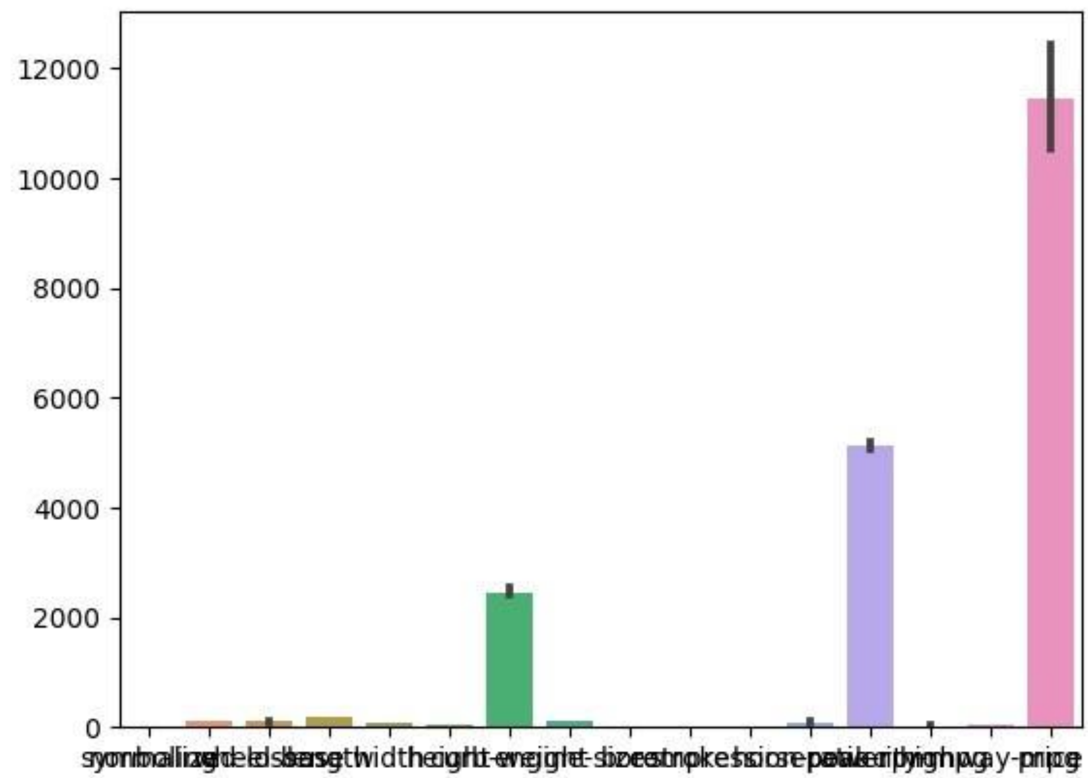
#Categorical Variables

```
plt.figure(figsize=(10, 8))
sns.displot(x='make', y='num-of-cylinders', data=df)
plt.xticks(rotation=90) plt.title('num-of-
cylinders') plt.show()

<Figure size 1000x800 with 0 Axes>
```



#Muliti-Variate Analysis

```
sns.barplot(df)
plt.show()
```



#Task 4: Perform data preprocessing handling missing values

```
df.replace('?', np.nan, inplace=True)
df.dropna(inplace=True)
```

#Handling categorical values

```
le = LabelEncoder()
df['make'] = le.fit_transform(df['make']) df['fuel-type']
= le.fit_transform(df['fuel-type']) df['aspiration'] =
le.fit_transform(df['aspiration']) df['num-of-doors'] =
le.fit_transform(df['num-of-doors']) df['body-style'] =
le.fit_transform(df['body-style']) df['drive-wheels'] =
le.fit_transform(df['drive-wheels']) df['engine-location']
= le.fit_transform(df['engine-location']) df['engine-
type'] = le.fit_transform(df['engine-type']) df['num-of-
cylinders'] = le.fit_transform(df['num-of-cylinders'])
df['fuel-system'] = le.fit_transform(df['fuel-system'])
```

#perform scaling

```
scaler = StandardScaler()
df_scaled =
pd.DataFrame(scaler.fit_transform(df.drop('price',
```

```
axis=1)), columns=df.columns[:-1]) df_scaled['price'] =
df['price']
```

#Task 5: Build Machine Learning Model

```
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer import
numpy as np

# Load the dataset
df = pd.read_csv("Automobile_data.csv")

# Handling missing values
df.replace('?', np.nan, inplace=True)  # replace '?' with NaN
df['normalized-losses'].fillna(df['normalized-losses'].median(),
inplace=True) # replace missing values with median
df['num-of-doors'].fillna(df['num-of-doors'].mode()[0], inplace=True)
# replace missing values with mode

# Encode categorical variables
df = pd.get_dummies(df, columns=['make', 'fuel-type', 'aspiration',
'num-of-doors', 'body-style',
                                 'drive-wheels', 'engine-location',
'engine-type', 'num-of-cylinders',
                                 'fuel-system'])

# Handle missing values
imputer = SimpleImputer(strategy='mean')
df = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)

# Perform scaling scaler
= StandardScaler()
df_scaled = scaler.fit_transform(df)

# Convert numpy array to DataFrame
df_scaled = pd.DataFrame(df_scaled, columns=df.columns)

# Split data into train and test sets
X = df_scaled.drop('price', axis=1) y
= df_scaled['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Build and fit the linear regression model
lr = LinearRegression() lr.fit(X_train,
y_train)

LinearRegression()
```

#Task 6: Evaluating Machine Learing Model

```
y_pred = lr.predict(X_test)
print('R-squared score:', r2_score(y_test, y_pred))
```

```
R-squared score: -1.7804692480809753e+23
```