Car MPG Prediction Using Machine Learning

Objective: To predict the miles per gallon (MPG) of cars based on various features such as displacement, horsepower, weight, acceleration, model year, and origin.

Data Source: The dataset used for this project is sourced from the YBI Foundation Dataset Repository.

Import Library

```
import pandas as pd
```

```
import numpy as np
```

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

```
import seaborn as sns
```

Import Data

```
df = pd.read_csv('https://github.com/YBI-Foundation/Dataset/raw/main/MPG.csv')
```

```
df.head()
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	origin	name
0	18.0	8	307.0	130.0	3504	12.0	70	usa	chevrolet chevelle malibu
1	15.0	8	350.0	165.0	3693	11.5	70	usa	buick skylark 320
2	18.0	8	318.0	150.0	3436	11.0	70	usa	plymouth satellite
3	16.0	8	304.0	150.0	3433	12.0	70	usa	amc rebel sst
4	17.0	8	302.0	140.0	3449	10.5	70	usa	ford torino

```
df.nunique()
```

```
mpg             129
cylinders         5
displacement     82
horsepower       93
weight          351
acceleration     95
model_year       13
origin            3
name            305
dtype: int64
```

Data Preprocessing

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64
 2   displacement  398 non-null    float64
 3   horsepower    392 non-null    float64
 4   weight        398 non-null    int64
 5   acceleration  398 non-null    float64
 6   model_year    398 non-null    int64
 7   origin        398 non-null    object
 8   name          398 non-null    object
dtypes: float64(4), int64(3), object(2)
memory usage: 28.1+ KB
```

```
df.describe()
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year
count	398.000000	398.000000	398.000000	392.000000	398.000000	398.000000	398.000000
mean	23.514573	5.454774	193.425879	104.469388	2970.424623	15.568090	76.010050
std	7.815984	1.701004	104.269838	38.491160	846.841774	2.757689	3.697627
min	9.000000	3.000000	68.000000	46.000000	1613.000000	8.000000	70.000000
25%	17.500000	4.000000	104.250000	75.000000	2223.750000	13.825000	73.000000
50%	23.000000	4.000000	148.500000	93.500000	2803.500000	15.500000	76.000000
75%	29.000000	8.000000	262.000000	126.000000	3608.000000	17.175000	79.000000
max	46.600000	8.000000	455.000000	230.000000	5140.000000	24.800000	82.000000

Remove Missing Values

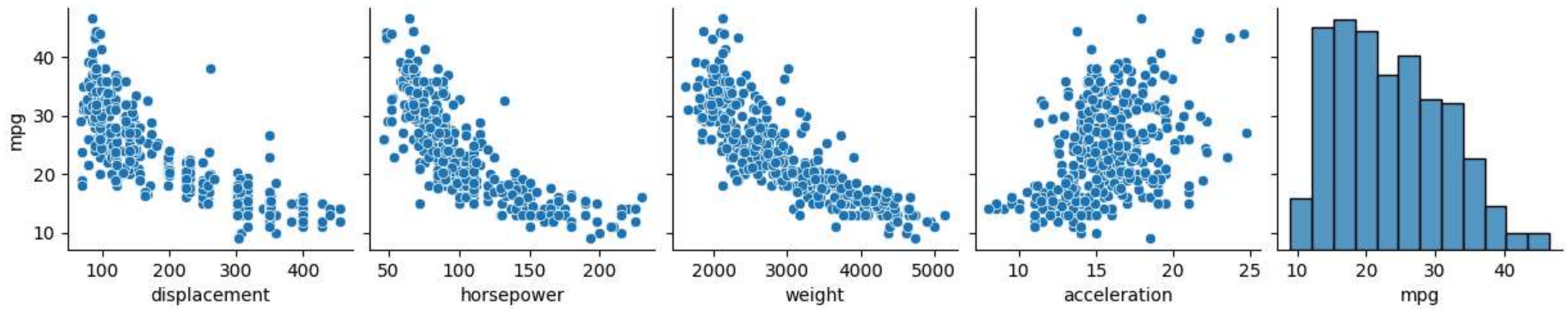
```
df = df.dropna()
```

```
df.info()
```

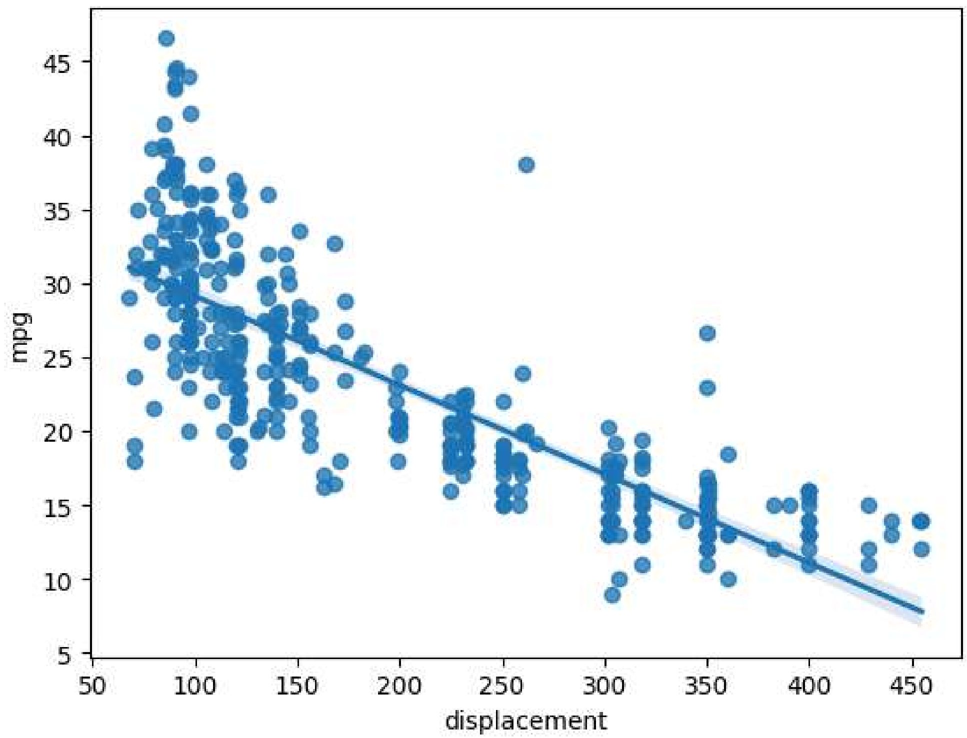
```
<class 'pandas.core.frame.DataFrame'>
Index: 392 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   mpg           392 non-null    float64
 1   cylinders     392 non-null    int64  
 2   displacement  392 non-null    float64
 3   horsepower    392 non-null    float64
 4   weight        392 non-null    int64  
 5   acceleration  392 non-null    float64
 6   model_year    392 non-null    int64  
 7   origin        392 non-null    object 
 8   name          392 non-null    object 
dtypes: float64(4), int64(3), object(2)
memory usage: 30.6+ KB
```

Data Visualization

```
sns.pairplot(df,x_vars= ['displacement','horsepower','weight','acceleration','mpg'],y_vars=['mpg']);
```




```
sns.regplot(x = "displacement", y = "mpg", data = df);
```



Define Target Variable Y and Feature X

```
df.columns
```

```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'model_year', 'origin', 'name'],
      dtype='object')
```

```
y = df['mpg']
```

```
y.shape
```

```
(392,)
```

```
x = df[['displacement','horsepower','weight','acceleration']]
```

```
x.shape
```

```
(392, 4)
```

```
x
```

	displacement	horsepower	weight	acceleration
0	307.0	130.0	3504	12.0
1	350.0	165.0	3693	11.5
2	318.0	150.0	3436	11.0
3	304.0	150.0	3433	12.0
4	302.0	140.0	3449	10.5
...	...	...	...	...
393	140.0	86.0	2790	15.6
394	97.0	52.0	2130	24.6
395	135.0	84.0	2295	11.6
396	120.0	79.0	2625	18.6
397	119.0	82.0	2720	19.4

392 rows × 4 columns

Scaling Data

```
from sklearn.preprocessing import StandardScaler

ss = StandardScaler()

x = ss.fit_transform(x)

x
```

```
array([[ 1.07728956,  0.66413273,  0.62054034, -1.285258  ],
       [ 1.48873169,  1.57459447,  0.84333403, -1.46672362],
       [ 1.1825422 ,  1.18439658,  0.54038176, -1.64818924],
       ...,
       [-0.56847897, -0.53247413, -0.80463202, -1.4304305 ],
       [-0.7120053 , -0.66254009, -0.41562716,  1.11008813],
       [-0.72157372, -0.58450051, -0.30364091,  1.40043312]])
```

```
pd.DataFrame(x).describe()
```

	0	1	2	3
count	3.920000e+02	3.920000e+02	3.920000e+02	3.920000e+02
mean	-7.250436e-17	-1.812609e-16	-1.812609e-17	4.350262e-16
std	1.001278e+00	1.001278e+00	1.001278e+00	1.001278e+00
min	-1.209563e+00	-1.520975e+00	-1.608575e+00	-2.736983e+00
25%	-8.555316e-01	-7.665929e-01	-8.868535e-01	-6.410551e-01
50%	-4.153842e-01	-2.853488e-01	-2.052109e-01	-1.499869e-02
75%	7.782764e-01	5.600800e-01	7.510927e-01	5.384714e-01
max	2.493416e+00	3.265452e+00	2.549061e+00	3.360262e+00

Train Test Split Data

```
from sklearn.model_selection import train_test_split
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size = 0.7, random_state = 2529)
```

```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

```
((274, 4), (118, 4), (274,), (118,))
```

Linear Regression Model

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

```
lr = LinearRegression()
```

```
lr.fit(x_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
lr.intercept_
```

```
23.485738559737584
```

```
lr.coef_
```

```
array([-1.05767743, -1.68734727, -4.10787617, -0.11495177])
```

Predict Test Data

```
y_pred = lr.predict(x_test)
```

```
y_pred
```

```
array([18.51865637, 15.09305675, 14.30128789, 23.6753321 , 29.7546115 ,
       23.68796629, 26.61066644, 24.56692437, 15.06260986, 11.94312046,
       24.08050053, 27.96518468, 31.66130278, 31.01309132, 18.32428976,
       19.32795009, 28.08847536, 32.1506879 , 31.15859692, 27.15792144,
       18.82433097, 22.54580176, 26.15598115, 32.36393869, 20.74377679,
        8.78027518, 22.19699435, 18.20614294, 25.00052718, 15.26421552,
       23.13441082, 17.10542257,  9.87180062, 30.00790415, 20.41204655,
       29.11860245, 24.4305187 , 21.72601835, 10.51174626, 13.12426391,
       21.41938406, 19.96113872,  6.19146626, 17.79025345, 22.5493033 ,
       29.34765021, 13.4861847 , 25.88852083, 29.40406946, 22.41841964,
       22.07684766, 16.46575802, 24.06290693, 30.12890046, 10.11318121,
        9.85011438, 28.07543852, 23.41426617, 20.08501128, 30.68234133,
       20.92026393, 26.78370281, 22.9078744 , 14.15936872, 24.6439883 ,
       26.95515832, 15.25709393, 24.11272087, 30.80980589, 14.9770217 ,
       27.67836372, 24.2372919 , 10.92177228, 30.22858779, 30.88687365,
       27.33992044, 31.18447082, 10.8873597 , 27.63510608, 16.49231363,
       25.63229888, 29.49776285, 14.90393439, 32.78670687, 30.37325244,
       30.9262743 , 14.71702373, 27.09633246, 26.69933806, 29.06424799,
       32.45810182, 29.44846898, 31.61239999, 31.57891837, 21.46542321,
       31.76739191, 26.28605476, 28.96419915, 31.09628395, 24.80549594,
       18.76490961, 23.28043777, 23.04466919, 22.14143162, 15.95854367,
       28.62870918, 25.58809869, 11.4040908 , 25.73334842, 30.83500051,
       21.94176255, 15.34532941, 30.37399213, 28.7620624 , 29.3639931 ,
       29.10476703, 20.44662365, 28.11466839])
```

Model Accuracy

```
from sklearn.metrics import mean_absolute_error,mean_absolute_percentage_error,r2_score
```

```
mean_absolute_error(y_test,y_pred)
```

```
3.3286968643244106
```

```
mean_absolute_percentage_error(y_test,y_pred)
```

```
0.14713035779536746
```

```
r2_score(y_test,y_pred)
```

```
0.7031250746717691
```

Polynomial Regression

```
from sklearn.preprocessing import PolynomialFeatures
```

```
poly = PolynomialFeatures(degree=2,interaction_only=True,include_bias=False)
```

```
x_train2 = poly.fit_transform(x_test)
```

```
x_test2 = poly.fit_transform(x_train)
```

```
lr.intercept_
```

```
23.485738559737584
```

```
lr.coef_
```

```
array([-1.05767743, -1.68734727, -4.10787617, -0.11495177])
```

Model Accuracy

```
from sklearn.metrics import mean_absolute_error,mean_absolute_percentage_error,r2_score
```

```
# Import the necessary libraries
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression

# Create a polynomial features object
poly_features = PolynomialFeatures(degree=2)

# Transform the input features
X_poly = poly_features.fit_transform(x_train)

# Train a linear regression model
lr = LinearRegression()
lr.fit(X_poly, y_train)

# Predict the output for the test data
y_pred_poly = lr.predict(poly_features.transform(x_test))

# Calculate the mean absolute error
mean_absolute_error(y_test, y_pred_poly)
```

```
3.0297164844490183
```

```
mean_absolute_percentage_error(y_test, y_pred_poly)
```

```
0.13669355401577676
```