

Mini Project 8: Predictive Analytics

▼ Step 1: Import library

```
import pandas as pd
```

```
import numpy as np
```

```
import seaborn as sns
```

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

▼ Step 2: Import Data

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

```
df
```

Saved successfully!



	displacement	horsepower	weight	acceleration	model_year	origin	name
0	18.0	8	307.0	130.0	3504	usa	chevrolet chevelle malibu
1	15.0	8	350.0	165.0	3693	usa	buick skylark 320
2	18.0	8	318.0	150.0	3436	usa	plymouth satellite
3	16.0	8	304.0	150.0	3433	usa	amc rebel sst
4	17.0	8	302.0	140.0	3449	usa	ford torino
...
393	27.0	4	140.0	86.0	2790	usa	ford mustang gl
394	44.0	4	97.0	52.0	2130	europe	vw pickup

```
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 8 columns):

```

Saved successfully!



int 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

```
df.corr()
```

Saved successfully!



	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year
mpg	1.000000	-0.775396	-0.804203	-0.778427	-0.831741	0.420289	0.579267
cylinders	-0.775396	1.000000	0.950721	0.842983	0.896017	-0.505419	-0.348746
displacement	-0.804203	0.950721	1.000000	0.897257	0.932824	-0.543684	-0.370164
horsepower	-0.778427	0.842983	0.897257	1.000000	0.864538	-0.689196	-0.416361
weight	-0.831741	0.896017	0.932824	0.864538	1.000000	-0.417457	-0.306564

```
df.shape
```

```
(398, 9)
```

```
df.columns
```

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

▼ Auxillary Step: Remove Missing Value Rows

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

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 392 entries, 0 to 397
Data columns (total 9 columns):
#   Column      Non-Null Count  Dtype
---  -
0   mpg         392 non-null    float64
                                int64
```

Saved successfully!



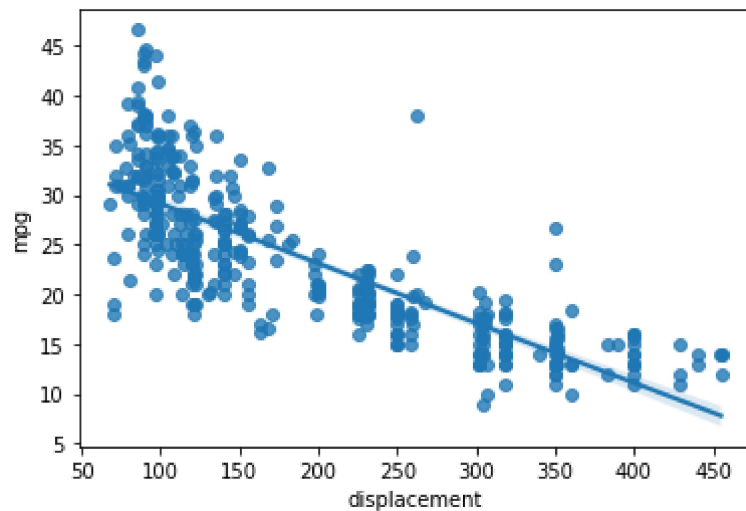
```
float64
float64
4  weight      392 non-null  int64
5  acceleration 392 non-null  float64
6  model_year   392 non-null  int64
7  origin       392 non-null  object
8  name         392 non-null  object
dtypes: float64(4), int64(3), object(2)
memory usage: 30.6+ KB
```

▼ Data Visualisation

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

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f90a89cc090>
```



▼ Step 3: Define y and X

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

```
y.shape
```

```
(392,)
```

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

```
X.shape
```

```
(392, 4)
```

▼ Auxillary Step: Data Scaling

```
from sklearn.preprocessing import StandardScaler  
s=StandardScaler()  
X=s.fit_transform(X)
```

```
pd.DataFrame(X).describe()
```

Saved successfully!



	1	2	3
count	3.920000e+02	3.920000e+02	3.920000e+02
mean	-2.537653e-16	-4.392745e-16	5.607759e-17

▼ Step 4: Splitting Data

```
from sklearn.model_selection import train_test_split

75% 7.782764e-01 5.600800e-01 7.510927e-01 5.384714e-01
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,))
```

▼ Step 5: Create a Model

```
from sklearn.linear_model import LinearRegression

model=LinearRegression()
```

▼ Step 6: Train a Model

```
model.fit(X_train,y_train)
```

Saved successfully!



```
model.intercept_
```

```
23.485738559737584
```

```
model.coef_
```

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

▼ Step 7: Predict Model

```
y_pred=model.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,
       22.15210122, 20.11216203, 31.61239999, 31.57891837, 21.46542321,
```


Saved successfully!



```
, 28.96419915, 31.09628395, 24.80549594,  
, 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])
```

▼ Step 8: Accuracy

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

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

```
0.14713035779536746
```

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

```
3.3286968643244106
```

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

```
0.7031250746717692
```

▼ Polynomial Regression

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

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

Saved successfully!



```
X_test1=p.fit_transform(X_test)
```

```
model.fit(X_train1,y_train)
```

```
LinearRegression()
```

```
model.intercept_
```

```
21.27336450063766
```

```
model.coef_
```

```
array([-2.76070596, -5.00559628, -1.36884133, -0.81225214,  1.24596571,  
       -0.12475017, -0.90542822,  1.35064048, -0.17337823,  1.41680398])
```

```
y_pred_p=model.predict(X_test1)
```

▼ Accuracy

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

```
mean_absolute_percentage_error(y_test,y_pred_p)
```

```
0.1207401834293869
```

```
mean_absolute_error(y_test,y_pred_p)
```

```
2.7887147720295977
```

Saved successfully!



0.7461731314563803

Link of the same:

[https://colab.research.google.com/drive/1J2SCi7MflqCZxEZPoRpyh6KIf5EtKbsE?
usp=sharing](https://colab.research.google.com/drive/1J2SCi7MflqCZxEZPoRpyh6KIf5EtKbsE?usp=sharing)

