Importing Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.formula.api as smf
```

Importing Dataset

```
import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage.
It includes your credentials.
# You might want to remove those credentials before you share the
notebook.
cos_client = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='eASimw06bTq5Rjts5iIC_g7P6axTb0h5x736EBNISkSM',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.private.us.cloud-object-
storage.appdomain.cloud')

bucket = 'mlbasedvehicleperformanceanalyser-donotdelete-pr-
0isa20q1npyfgm'
object_key = 'car performance.csv'

body = cos_client.get_object(Bucket=bucket,Key=object_key)['Body']
# add missing __iter__ method, so pandas accepts body as file-like
object
if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType(
__iter__, body )

dataset = pd.read_csv(body)
dataset.head(7)
```

```
    mpg  cylinders  displacement horsepower  weight  acceleration
model year  \
0  18.0          8         307.0        130    3504          12.0
70
1  15.0          8         350.0        165    3693          11.5
```

```
70
2  18.0          8         318.0         150    3436            11.0
70
3  16.0          8         304.0         150    3433            12.0
70
4  17.0          8         302.0         140    3449            10.5
70
5  15.0          8         429.0         198    4341            10.0
70
6  14.0          8         454.0         220    4354             9.0
70

   origin                  car name
0       1  chevrolet chevelle malibu
1       1          buick skylark 320
2       1         plymouth satellite
3       1              amc rebel sst
4       1                ford torino
5       1           ford galaxie 500
6       1           chevrolet impala
```

Finding missing data

```
dataset.isnull().any()
```

```
mpg             False
cylinders       False
displacement    False
horsepower      False
weight          False
acceleration    False
model year      False
origin          False
car name        False
dtype: bool
```

There are no null characters in the columns but there is a special character '?' in the 'horsepower' column. So we we replaced '?' with nan and replaced nan values with mean of the column.

```
dataset['horsepower']=dataset['horsepower'].replace('?',np.nan)
```

```
dataset['horsepower'].isnull().sum()
```

```
6
```

```
dataset['horsepower']=dataset['horsepower'].astype('float64')
```

```
dataset['horsepower'].fillna((dataset['horsepower'].mean()),inplace=True)
```

```
dataset.isnull().any()
```

```
mpg             False
cylinders       False
displacement    False
horsepower      False
weight          False
acceleration    False
model year      False
origin          False
car name        False
dtype: bool
```

```
dataset.info() #Pandas dataframe.info() function is used to get a
quick overview of the dataset.
```

```
<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    398 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    int64
 8   car name      398 non-null    object
dtypes: float64(4), int64(4), object(1)
memory usage: 28.1+ KB
```

```
dataset.describe() #Pandas describe() is used to view some basic
statistical details of a data frame or a series of numeric values.
```

```
              mpg   cylinders  displacement  horsepower
weight  \
count  398.000000  398.000000    398.000000  398.000000   398.000000

mean    23.514573    5.454774    193.425879  104.469388  2970.424623

std      7.815984    1.701004    104.269838   38.199187   846.841774

min      9.000000    3.000000     68.000000   46.000000  1613.000000

25%     17.500000    4.000000    104.250000   76.000000  2223.750000

50%     23.000000    4.000000    148.500000   95.000000  2803.500000

75%     29.000000    8.000000    262.000000  125.000000  3608.000000
```

```
max     46.600000    8.000000    455.000000  230.000000  5140.000000


       acceleration  model year      origin
count    398.000000  398.000000  398.000000
mean      15.568090   76.010050    1.572864
std        2.757689    3.697627    0.802055
min        8.000000   70.000000    1.000000
25%       13.825000   73.000000    1.000000
50%       15.500000   76.000000    1.000000
75%       17.175000   79.000000    2.000000
max       24.800000   82.000000    3.000000
```

There is no use with car name attribute so drop it

```
dataset=dataset.drop('car name',axis=1) #dropping the unwanted column.
```

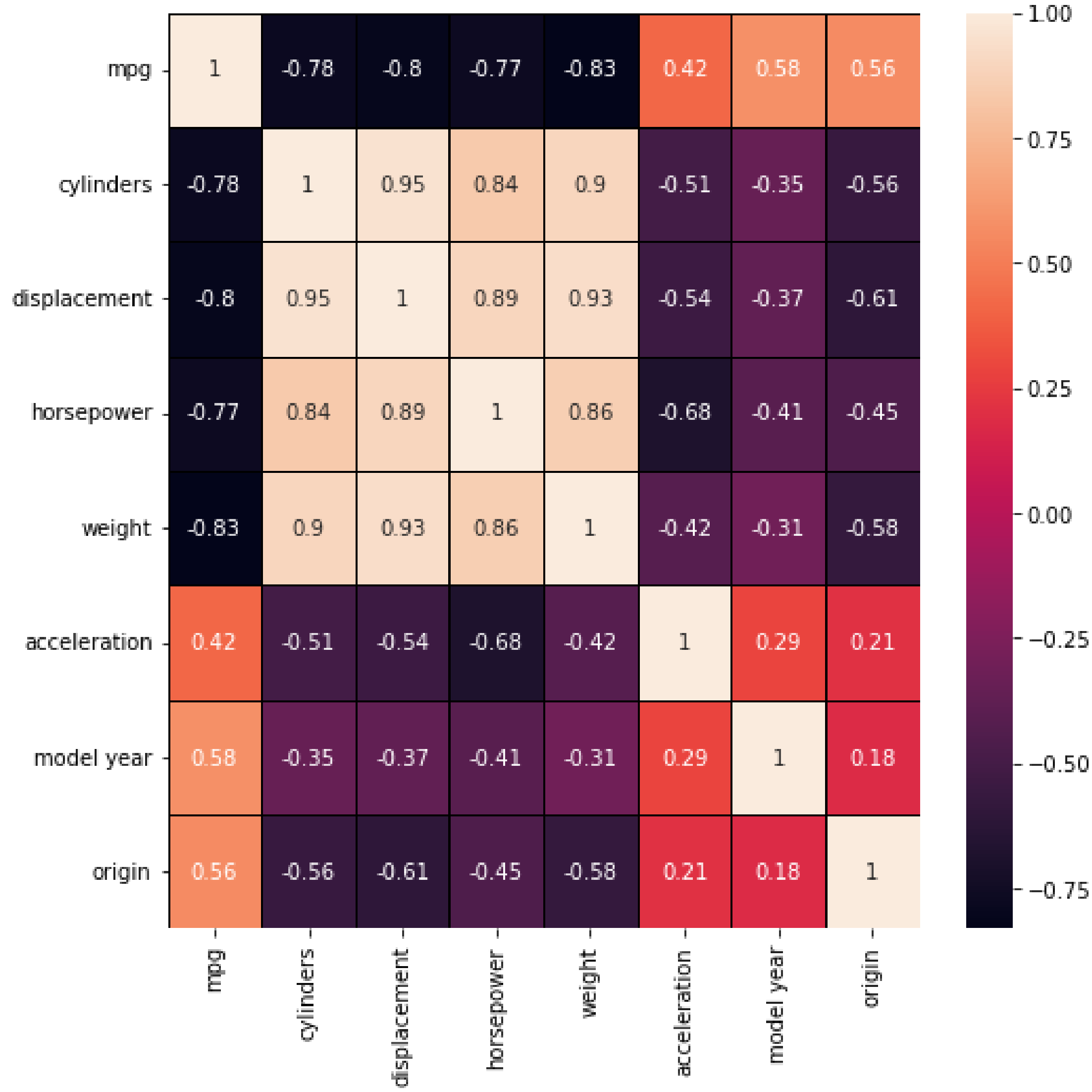
```
corr_table=dataset.corr()#Pandas dataframe.corr() is used to find the 
pairwise correlation of all columns in the dataframe.
corr_table
```

```
                   mpg  cylinders  displacement  horsepower    weight  
\
mpg           1.000000  -0.775396     -0.804203   -0.771437 -0.831741   

cylinders    -0.775396   1.000000      0.950721    0.838939  0.896017   

displacement -0.804203   0.950721      1.000000    0.893646  0.932824   

horsepower   -0.771437   0.838939      0.893646    1.000000  0.860574   

weight       -0.831741   0.896017      0.932824    0.860574  1.000000   

acceleration  0.420289  -0.505419     -0.543684   -0.684259 -0.417457   

model year    0.579267  -0.348746     -0.370164   -0.411651 -0.306564   

origin        0.563450  -0.562543     -0.609409   -0.453669 -0.581024   


              acceleration  model year    origin  
mpg               0.420289    0.579267  0.563450  
cylinders        -0.505419   -0.348746 -0.562543  
displacement     -0.543684   -0.370164 -0.609409  
horsepower       -0.684259   -0.411651 -0.453669  
weight           -0.417457   -0.306564 -0.581024  
acceleration      1.000000    0.288137  0.205873  
model year        0.288137    1.000000  0.180662  
origin            0.205873    0.180662  1.000000  
```

Data Visualizations

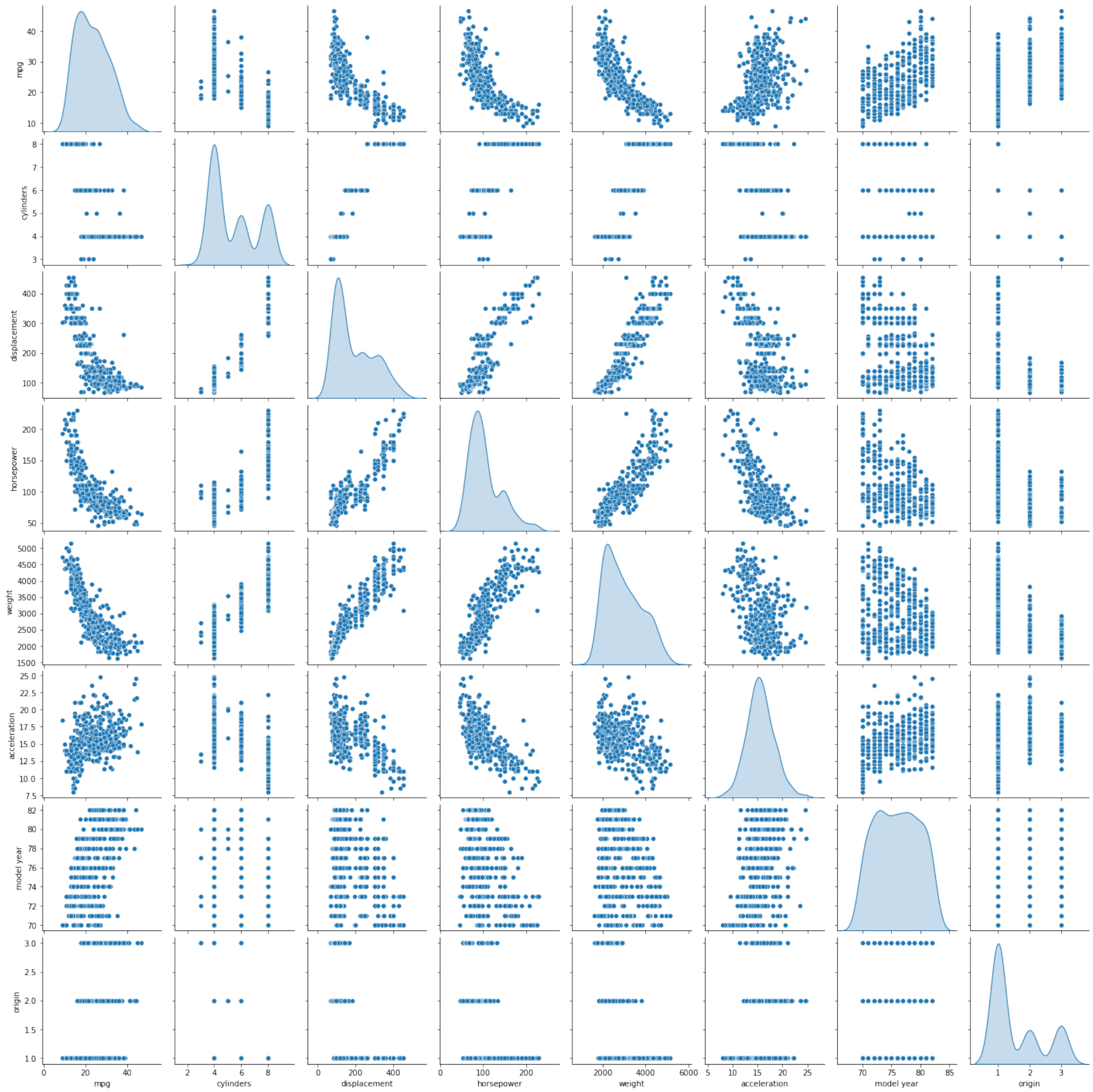
Heatmap : which represents correlation between attributes

```
sns.heatmap(dataset.corr(),annot=True,linecolor ='black', linewidths =
1)#Heatmap is a way to show some sort of matrix plot,annot is used for
correlation.
fig=plt.gcf()
fig.set_size_inches(8,8)
```



Visualizations of each attributes w.r.t rest of all attributes

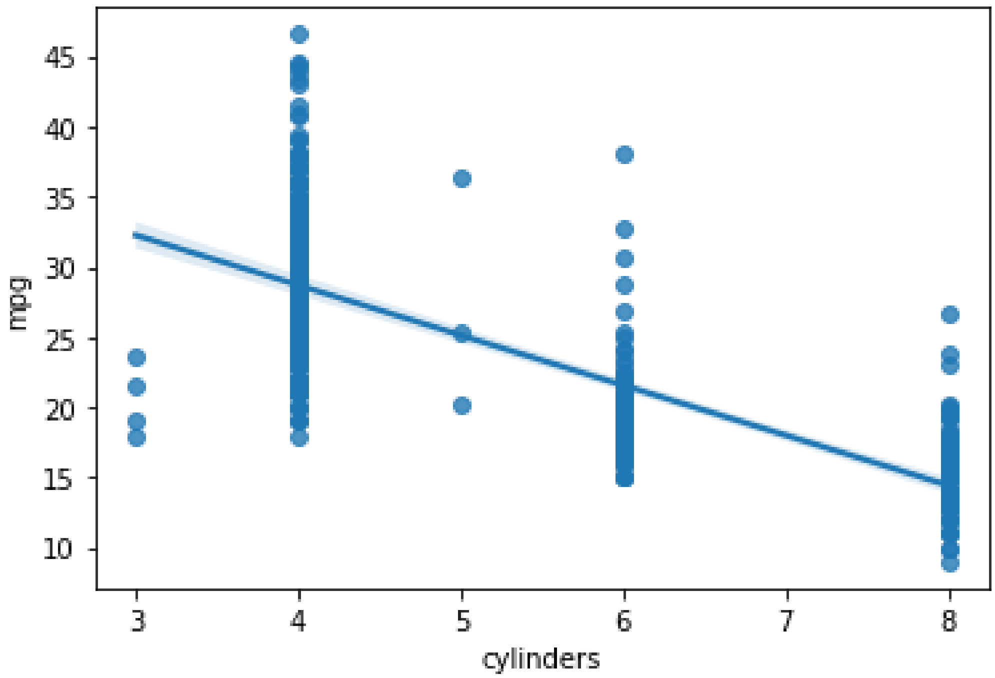
```
sns.pairplot(dataset,diag_kind='kde') #pairplot represents pairwise
relation across the entire dataframe.
plt.show()
```



Regression plots(regplot()) creates a regression line between 2 parameters and helps to visualize their linear relationships.

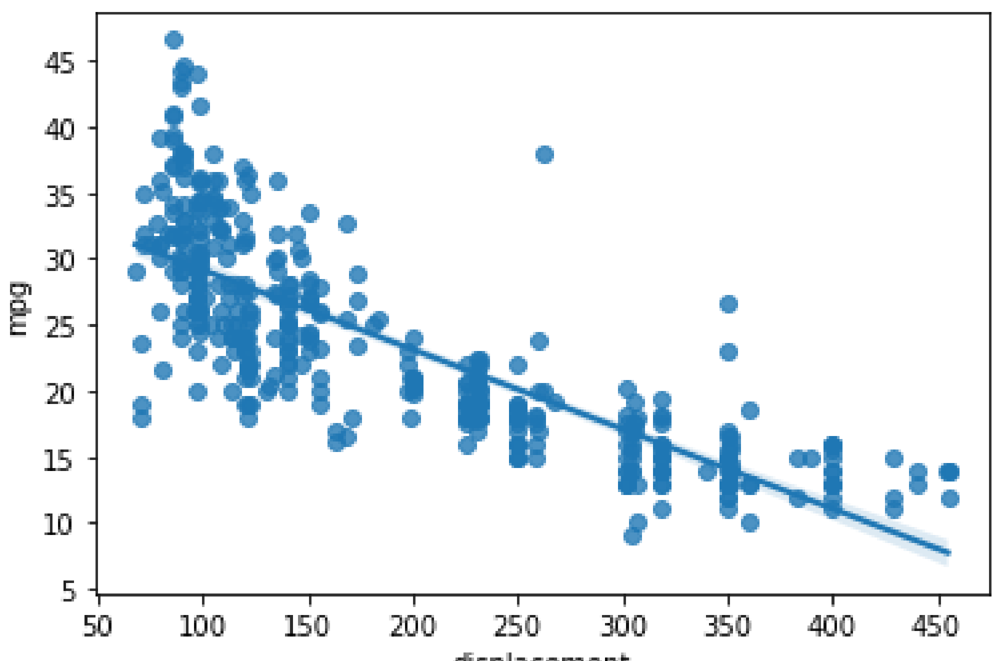
```
sns.regplot(x="cylinders", y="mpg", data=dataset)
```

```
<AxesSubplot:xlabel='cylinders', ylabel='mpg'>
```



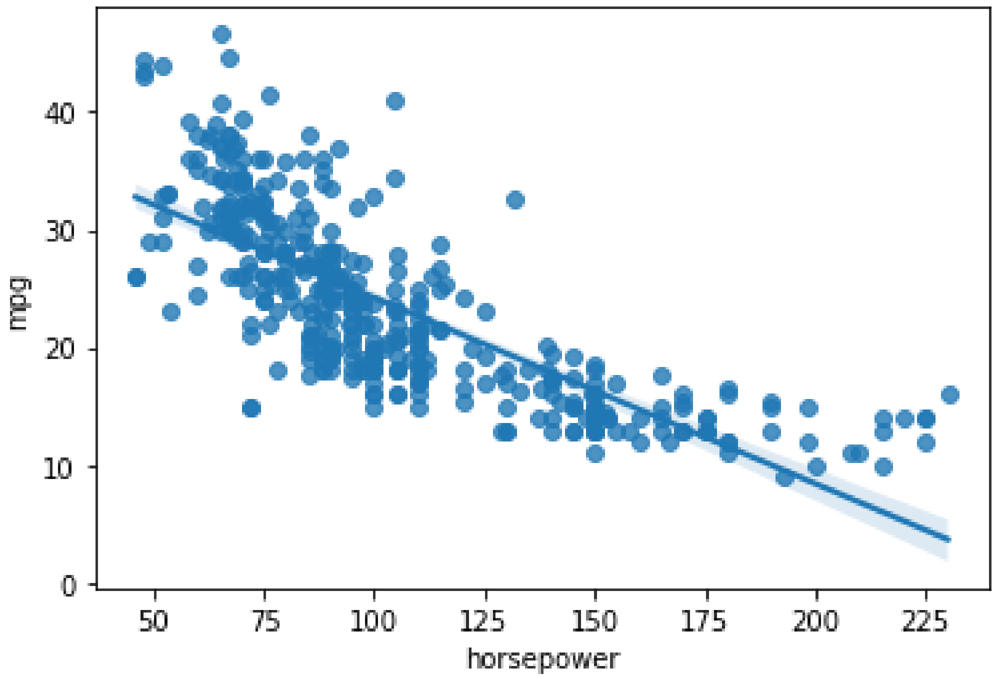

```
sns.regplot(x="displacement", y="mpg", data=dataset)
```

```
<AxesSubplot:xlabel='displacement', ylabel='mpg'>
```



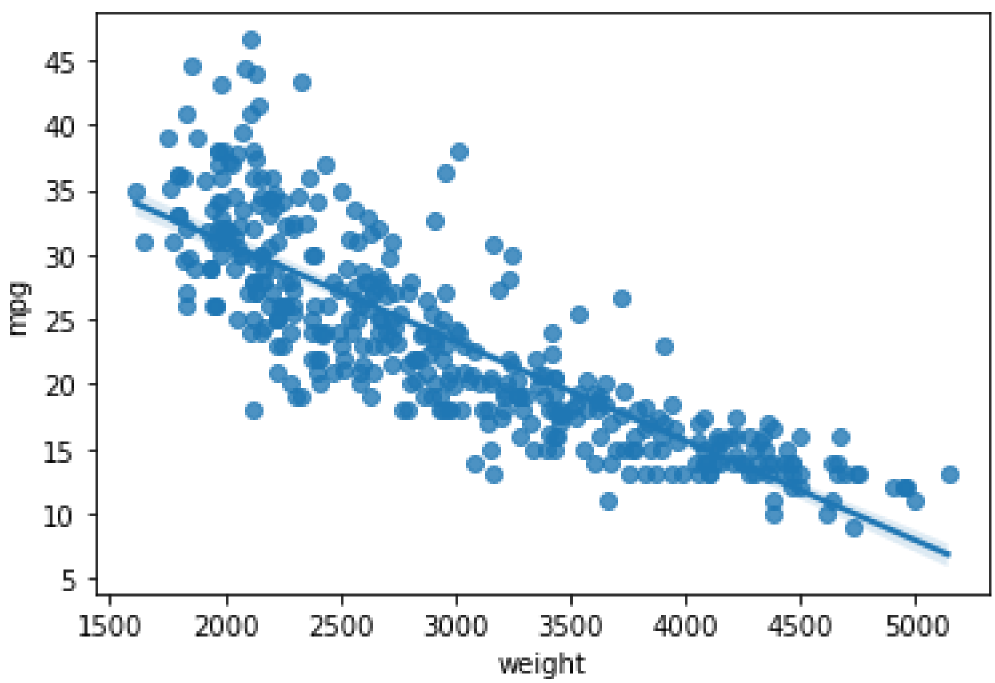

```
sns.regplot(x="horsepower", y="mpg", data=dataset)
```

```
<AxesSubplot:xlabel='horsepower', ylabel='mpg'>
```



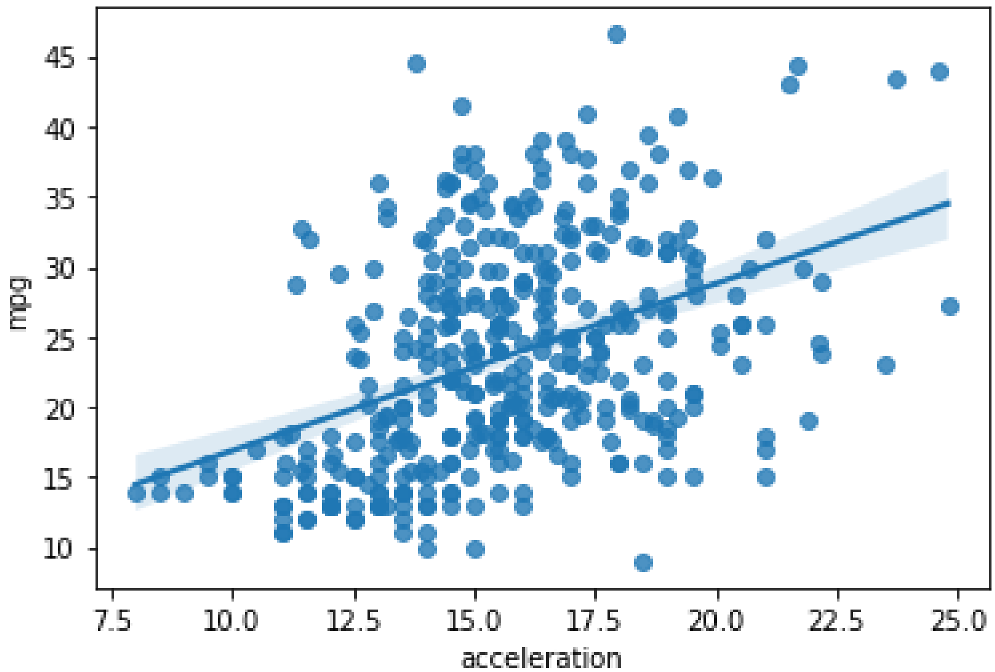

```
sns.regplot(x="weight", y="mpg", data=dataset)
```

```
<AxesSubplot:xlabel='weight', ylabel='mpg'>
```



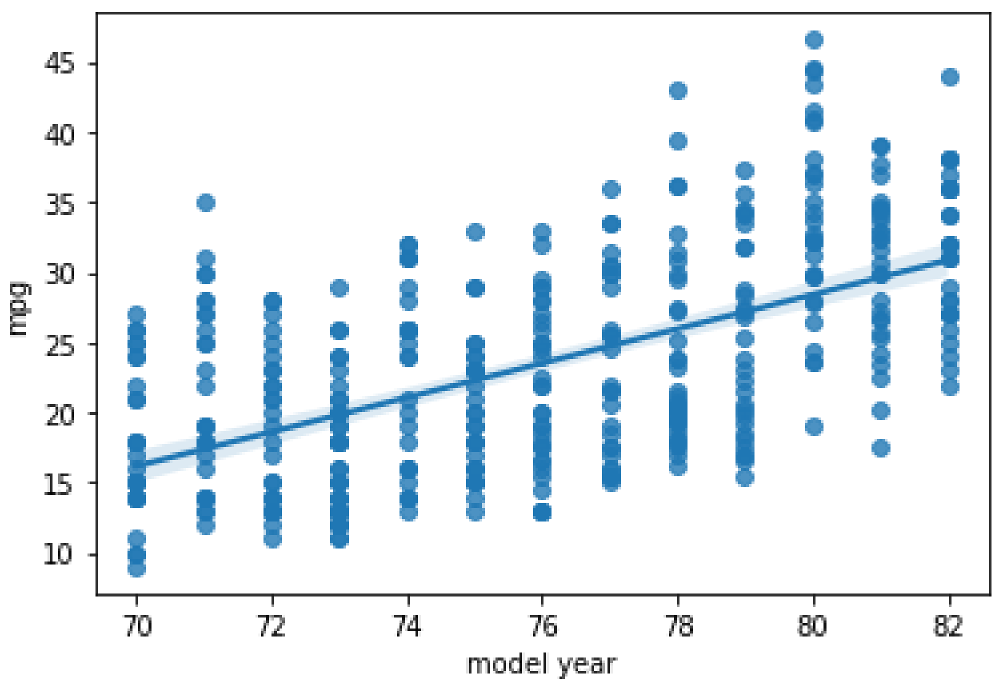

```
sns.regplot(x="acceleration", y="mpg", data=dataset)
```

```
<AxesSubplot:xlabel='acceleration', ylabel='mpg'>
```



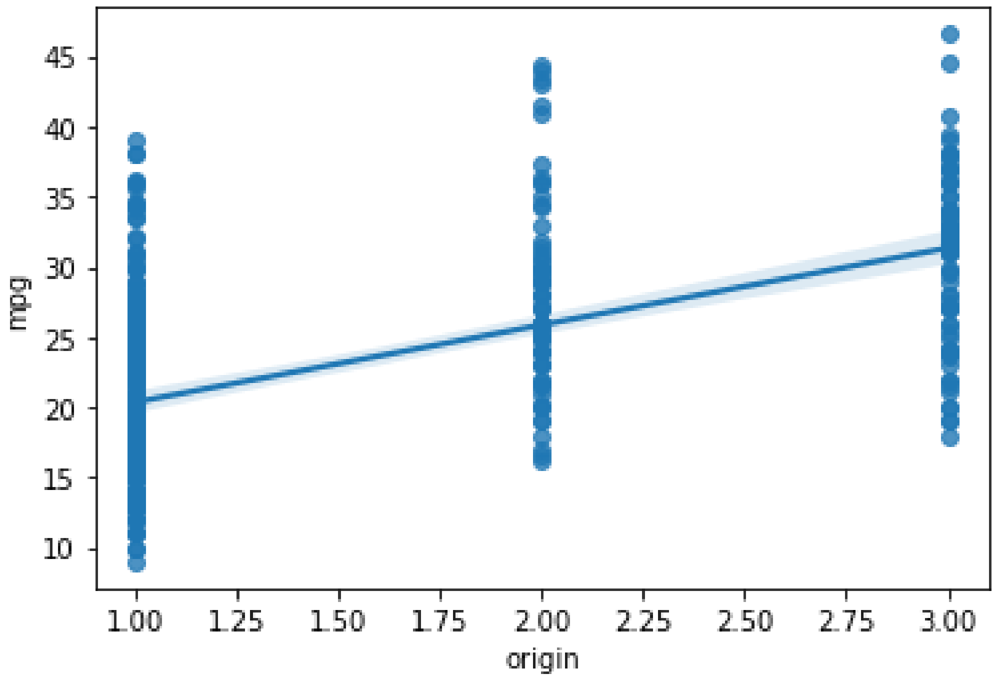

```
sns.regplot(x="model year", y="mpg", data=dataset)
```

```
<AxesSubplot:xlabel='model year', ylabel='mpg'>
```



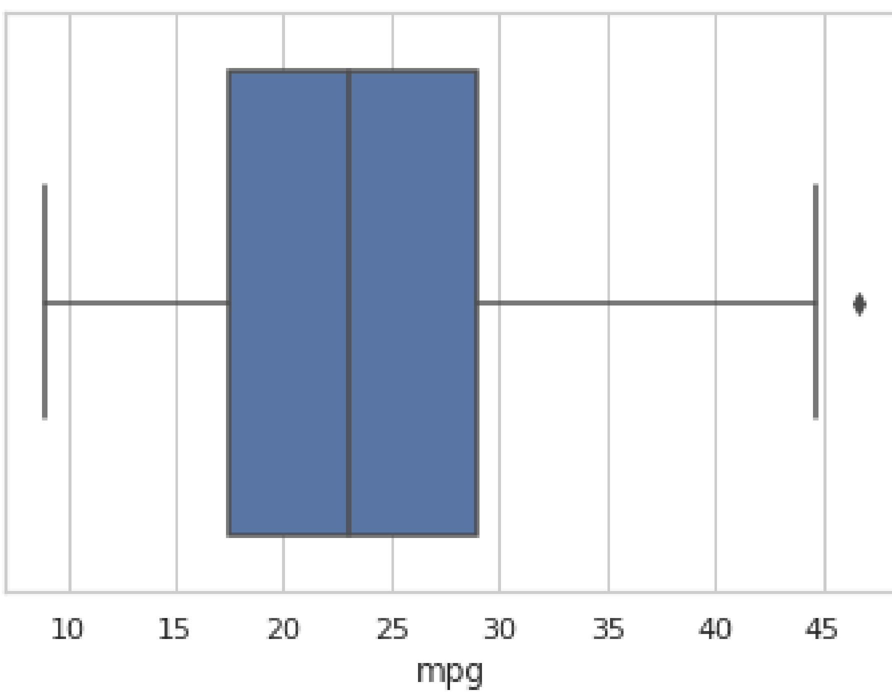

```
sns.regplot(x="origin", y="mpg", data=dataset)
```

```
<AxesSubplot:xlabel='origin', ylabel='mpg'>
```




```
sns.set(style="whitegrid")
sns.boxplot(x=dataset["mpg"])
```

<AxesSubplot:xlabel='mpg'>



Finding quartiles for mgp

The P-value is the probability value that the correlation between these two variables is statistically significant.

Normally, we choose a significance level of 0.05, which means that we are 95% confident that the correlation between the variables is significant.

By convention, when the p-value is ¿ 0.001: we say there is strong evidence that the correlation is significant. the p-value is ¿ 0.05: there is moderate evidence that the correlation is significant. the p-value is ¿ 0.1: there is weak evidence that the correlation is significant. the p-value is ¿ 0.1: there is no evidence that the correlation is significant.

```
from scipy import stats
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'Cylinders' and 'mpg'.

```
pearson_coef, p_value = stats.pearsonr(dataset['cylinders'], 
dataset['mpg'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a 
P-value of P =", p_value)
```

```
The Pearson Correlation Coefficient is -0.7753962854205542  with a P-
value of P = 4.503992246177055e-81
```

Since the p-value is ¿ 0.001, the correlation between cylinders and mpg is statistically significant, and the coefficient of ~ -0.775 shows that the relationship is negative and moderately strong.

Let's calculate the Pearson Correlation Coefficient and P-value of 'Displacement' and 'mpg'.

```
pearson_coef, p_value = stats.pearsonr(dataset['displacement'], 
dataset['mpg'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a 
P-value of P =", p_value)
```

```
The Pearson Correlation Coefficient is -0.8042028248058978  with a P-
value of P = 1.6558889101930157e-91
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'horsepower' and 'mpg'.

```
pearson_coef, p_value = stats.pearsonr(dataset['horsepower'], 
dataset['mpg'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a 
P-value of P =", p_value)
```

```
The Pearson Correlation Coefficient is -0.7714371350025526  with a P-
value of P = 9.255477533166725e-80
```

Since the p-value is ¿ 0.001, the correlation between horsepower and mpg is statistically significant, and the coefficient of ~ -0.771 shows that the relationship is negative and moderately strong.

Let's calculate the Pearson Correlation Coefficient and P-value of 'weight' and 'mpg'.

```
pearson_coef, p_value = stats.pearsonr(dataset['weight'],
dataset['mpg'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a
P-value of P =", p_value)
```

```
The Pearson Correlation Coefficient is -0.831740933244335  with a P-
value of P = 2.9727995640500577e-103
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'Acceleration' and 'mpg'.

```
pearson_coef, p_value = stats.pearsonr(dataset['acceleration'],
dataset['mpg'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a
P-value of P =", p_value)
```

```
The Pearson Correlation Coefficient is 0.4202889121016507  with a P-
value of P = 1.823091535078553e-18
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'Model year' and 'mpg'.

```
pearson_coef, p_value = stats.pearsonr(dataset['model year'],
dataset['mpg'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a
P-value of P =", p_value)
```

```
The Pearson Correlation Coefficient is 0.5792671330833096  with a P-
value of P = 4.844935813365483e-37
```

Let's calculate the Pearson Correlation Coefficient and P-value of 'Origin' and 'mpg'.

```
pearson_coef, p_value = stats.pearsonr(dataset['origin'],
dataset['mpg'])
print("The Pearson Correlation Coefficient is", pearson_coef, " with a
P-value of P =", p_value)
```

```
The Pearson Correlation Coefficient is 0.5634503597738431  with a P-
value of P = 1.0114822102336483e-34
```

Ordinary Least Squares Statistics

```
test=smf.ols('mpg~cylinders+displacement+horsepower+weight+acceleratio
n+origin',dataset).fit()
test.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:                    mpg   R-squared:
```

```
0.717
Model:                            OLS   Adj. R-squared:
0.713
Method:                 Least Squares   F-statistic:
165.5
Date:                Sat, 19 Nov 2022   Prob (F-statistic):
4.84e-104
Time:                        19:13:46   Log-Likelihood:
-1131.1
No. Observations:                 398   AIC:
2276.
Df Residuals:                     391   BIC:
2304.
Df Model:                           6

Covariance Type:            nonrobust

======================================================================
==========
                   coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
----------
Intercept       42.7111      2.693     15.861      0.000      37.417
48.005
cylinders       -0.5256      0.404     -1.302      0.194      -1.320
0.268
displacement     0.0106      0.009      1.133      0.258      -0.008
0.029
horsepower      -0.0529      0.016     -3.277      0.001      -0.085
-0.021
weight          -0.0051      0.001     -6.441      0.000      -0.007
-0.004
acceleration     0.0043      0.120      0.036      0.972      -0.232
0.241
origin           1.4269      0.345      4.136      0.000       0.749
2.105
======================================================================
========
Omnibus:                       32.659   Durbin-Watson:
0.886
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
43.338
Skew:                           0.624   Prob(JB):
3.88e-10
Kurtosis:                       4.028   Cond. No.
3.99e+04
======================================================================
========
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.99e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

Inference as in the above summary the p value of the accelaration is maximum(i.e 0.972) so we can remove the acc variable from the dataset

Seperating into Dependent and Independent variables

Independent variables

```
x=dataset[['cylinders','displacement','horsepower','weight','model year','origin']].values
x
```

```
array([[8.000e+00, 3.070e+02, 1.300e+02, 3.504e+03, 7.000e+01, 1.000e+00],
       [8.000e+00, 3.500e+02, 1.650e+02, 3.693e+03, 7.000e+01, 1.000e+00],
       [8.000e+00, 3.180e+02, 1.500e+02, 3.436e+03, 7.000e+01, 1.000e+00],
       ...,
       [4.000e+00, 1.350e+02, 8.400e+01, 2.295e+03, 8.200e+01, 1.000e+00],
       [4.000e+00, 1.200e+02, 7.900e+01, 2.625e+03, 8.200e+01, 1.000e+00],
       [4.000e+00, 1.190e+02, 8.200e+01, 2.720e+03, 8.200e+01, 1.000e+00]])
```

Dependent variables

```
y=dataset.iloc[:,0:1].values
y
```

```
array([[18. ],
       [15. ],
       [18. ],
       [16. ],
       [17. ],
       [15. ],
       [14. ],
       [14. ],
       [14. ],
       [15. ],
       [15. ],
       [14. ],
```

```
[15. ],
[14. ],
[24. ],
[22. ],
[18. ],
[21. ],
[27. ],
[26. ],
[25. ],
[24. ],
[25. ],
[26. ],
[21. ],
[10. ],
[10. ],
[11. ],
[ 9. ],
[27. ],
[28. ],
[25. ],
[25. ],
[19. ],
[16. ],
[17. ],
[19. ],
[18. ],
[14. ],
[14. ],
[14. ],
[14. ],
[12. ],
[13. ],
[13. ],
[18. ],
[22. ],
[19. ],
[18. ],
[23. ],
[28. ],
[30. ],
[30. ],
[31. ],
[35. ],
[27. ],
[26. ],
[24. ],
[25. ],
[23. ],
[20. ],
[21. ],
```

```
[13. ],
[14. ],
[15. ],
[14. ],
[17. ],
[11. ],
[13. ],
[12. ],
[13. ],
[19. ],
[15. ],
[13. ],
[13. ],
[14. ],
[18. ],
[22. ],
[21. ],
[26. ],
[22. ],
[28. ],
[23. ],
[28. ],
[27. ],
[13. ],
[14. ],
[13. ],
[14. ],
[15. ],
[12. ],
[13. ],
[13. ],
[14. ],
[13. ],
[12. ],
[13. ],
[18. ],
[16. ],
[18. ],
[18. ],
[23. ],
[26. ],
[11. ],
[12. ],
[13. ],
[12. ],
[18. ],
[20. ],
[21. ],
[22. ],
[18. ],
```

```
[19. ],
[21. ],
[26. ],
[15. ],
[16. ],
[29. ],
[24. ],
[20. ],
[19. ],
[15. ],
[24. ],
[20. ],
[11. ],
[20. ],
[21. ],
[19. ],
[15. ],
[31. ],
[26. ],
[32. ],
[25. ],
[16. ],
[16. ],
[18. ],
[16. ],
[13. ],
[14. ],
[14. ],
[14. ],
[29. ],
[26. ],
[26. ],
[31. ],
[32. ],
[28. ],
[24. ],
[26. ],
[24. ],
[26. ],
[31. ],
[19. ],
[18. ],
[15. ],
[15. ],
[16. ],
[15. ],
[16. ],
[14. ],
[17. ],
[16. ],
```

```
[15. ],
[18. ],
[21. ],
[20. ],
[13. ],
[29. ],
[23. ],
[20. ],
[23. ],
[24. ],
[25. ],
[24. ],
[18. ],
[29. ],
[19. ],
[23. ],
[23. ],
[22. ],
[25. ],
[33. ],
[28. ],
[25. ],
[25. ],
[26. ],
[27. ],
[17.5],
[16. ],
[15.5],
[14.5],
[22. ],
[22. ],
[24. ],
[22.5],
[29. ],
[24.5],
[29. ],
[33. ],
[20. ],
[18. ],
[18.5],
[17.5],
[29.5],
[32. ],
[28. ],
[26.5],
[20. ],
[13. ],
[19. ],
[19. ],
[16.5],
```

```
[16.5],
[13. ],
[13. ],
[13. ],
[31.5],
[30. ],
[36. ],
[25.5],
[33.5],
[17.5],
[17. ],
[15.5],
[15. ],
[17.5],
[20.5],
[19. ],
[18.5],
[16. ],
[15.5],
[15.5],
[16. ],
[29. ],
[24.5],
[26. ],
[25.5],
[30.5],
[33.5],
[30. ],
[30.5],
[22. ],
[21.5],
[21.5],
[43.1],
[36.1],
[32.8],
[39.4],
[36.1],
[19.9],
[19.4],
[20.2],
[19.2],
[20.5],
[20.2],
[25.1],
[20.5],
[19.4],
[20.6],
[20.8],
[18.6],
[18.1],
```

```
[19.2],
[17.7],
[18.1],
[17.5],
[30. ],
[27.5],
[27.2],
[30.9],
[21.1],
[23.2],
[23.8],
[23.9],
[20.3],
[17. ],
[21.6],
[16.2],
[31.5],
[29.5],
[21.5],
[19.8],
[22.3],
[20.2],
[20.6],
[17. ],
[17.6],
[16.5],
[18.2],
[16.9],
[15.5],
[19.2],
[18.5],
[31.9],
[34.1],
[35.7],
[27.4],
[25.4],
[23. ],
[27.2],
[23.9],
[34.2],
[34.5],
[31.8],
[37.3],
[28.4],
[28.8],
[26.8],
[33.5],
[41.5],
[38.1],
[32.1],
```

```
[37.2],
[28. ],
[26.4],
[24.3],
[19.1],
[34.3],
[29.8],
[31.3],
[37. ],
[32.2],
[46.6],
[27.9],
[40.8],
[44.3],
[43.4],
[36.4],
[30. ],
[44.6],
[40.9],
[33.8],
[29.8],
[32.7],
[23.7],
[35. ],
[23.6],
[32.4],
[27.2],
[26.6],
[25.8],
[23.5],
[30. ],
[39.1],
[39. ],
[35.1],
[32.3],
[37. ],
[37.7],
[34.1],
[34.7],
[34.4],
[29.9],
[33. ],
[34.5],
[33.7],
[32.4],
[32.9],
[31.6],
[28.1],
[30.7],
[25.4],
```

```
       [24.2],
       [22.4],
       [26.6],
       [20.2],
       [17.6],
       [28. ],
       [27. ],
       [34. ],
       [31. ],
       [29. ],
       [27. ],
       [24. ],
       [23. ],
       [36. ],
       [37. ],
       [31. ],
       [38. ],
       [36. ],
       [36. ],
       [36. ],
       [34. ],
       [38. ],
       [32. ],
       [38. ],
       [25. ],
       [38. ],
       [26. ],
       [22. ],
       [32. ],
       [36. ],
       [27. ],
       [27. ],
       [44. ],
       [32. ],
       [28. ],
       [31. ]])
```

Splitting into train and test data.

```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.1,rando
m_state=0)
```

we are splitting as 90% train data and 10% test data

Normalisation

```
from sklearn.preprocessing import StandardScaler
sd = StandardScaler()
```

```
x_train = sd.fit_transform(x_train)
x_test = sd.fit_transform(x_test)
y_train = sd.fit_transform(y_train)
y_test = sd.fit_transform(y_test)
```

```
x_train
```

```
array([[ 1.46858608,  2.48230464,  2.97856512,  1.62455076, -
1.61295698,
        -0.71873488],
       [ 1.46858608,  1.48729292,  1.55429873,  0.84358808, -
1.61295698,
        -0.71873488],
       [-0.86550411, -0.70364636, -0.64684023, -0.36507278,
0.82235108,
        -0.71873488],
       ...,
       [-0.86550411, -1.21071964, -1.44960856, -1.31380657, -
0.80118763,
         0.53032865],
       [ 0.30154098,  0.53055088, -0.12892518,  0.35799706, -1.3423672
,
        -0.71873488],
       [-0.86550411, -1.00023639, -0.87990201, -0.89319732, -
0.26000806,
         0.53032865]])
```

decision tree regressor

```
from sklearn.tree import DecisionTreeRegressor
dt=DecisionTreeRegressor(random_state=0,criterion="mae")
dt.fit(x_train,y_train)
```

```
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/sklearn/tree/
_classes.py:366: FutureWarning: Criterion 'mae' was deprecated in v1.0
and will be removed in version 1.2. Use `criterion='absolute_error'`
which is equivalent.
  warnings.warn(
```

```
DecisionTreeRegressor(criterion='mae', random_state=0)
```

```
import pickle
pickle.dump(dt,open('decision_model.pkl','wb'))
```

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

```
array([-1.21248604,  0.40341575, -1.21248604, -0.56612532, -
0.82466961,
        0.98514039,  2.07102639, -0.17830889, -1.08321389,
0.20950753,
```

```
        1.43759289,  2.74324153, -0.43685318,  0.33877968, -
0.95394175,
        1.41173846,  0.41634296,  0.33877968, -0.82466961,
1.39881125,
       -0.95394175, -0.04903675, -0.24294497, -0.56612532,
1.33417517,
        0.20950753,  0.79123218,  0.98514039,  0.98514039, -
0.43685318,
       -0.88930568,  1.50222896, -1.08321389,  1.04977646, -
0.54027089,
       -0.39807154, -1.08321389, -0.95394175,  0.79123218, -
1.60030246])
```

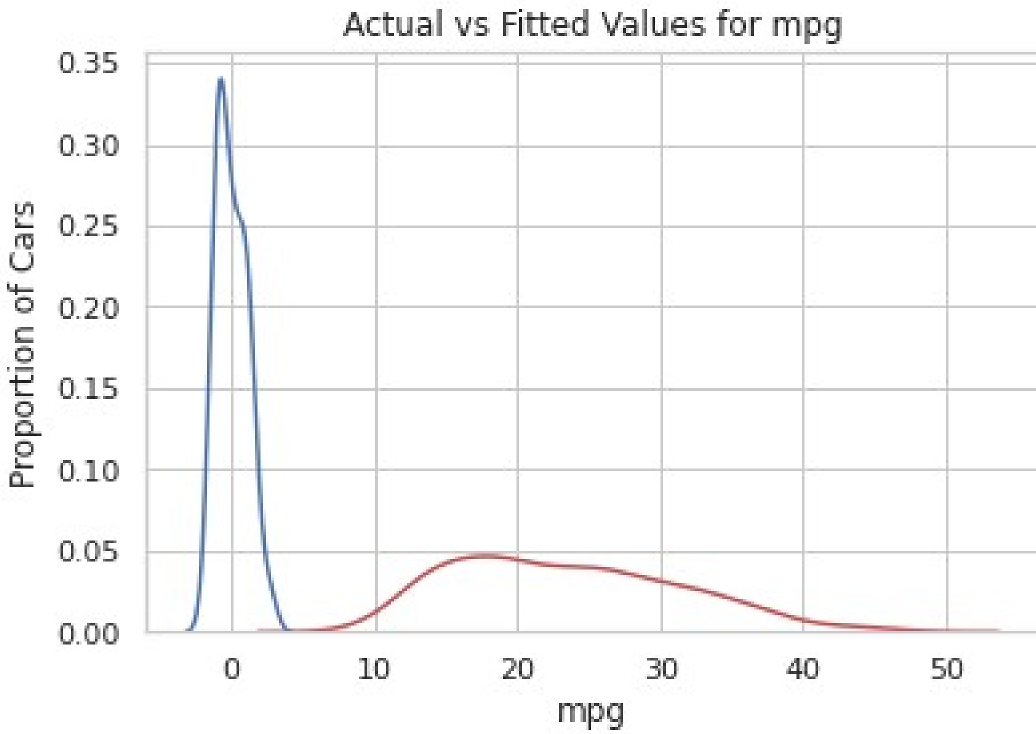
```
y_test
```

```
array([[-1.29002284],
       [ 0.03307751],
       [-1.41030469],
       [-0.44804989],
       [-0.80889544],
       [ 1.23589601],
       [ 1.12764234],
       [-0.56833174],
       [-1.16974099],
       [-0.14734527],
       [ 1.94555892],
       [ 1.50051608],
       [-0.80889544],
       [-0.20748619],
       [-1.10960007],
       [ 1.3200933 ],
       [ 0.75476861],
       [ 0.27364121],
       [-0.80889544],
       [ 1.51254426],
       [-1.10960007],
       [-0.20748619],
       [-0.08720434],
       [-0.80889544],
       [ 1.17575508],
       [ 0.08119025],
       [ 1.36820604],
       [ 1.11561416],
       [ 0.63448676],
       [-1.04945914],
       [-0.73672633],
       [ 1.47645971],
       [-1.16974099],
       [ 1.05547323],
       [-0.2796553 ],
       [-0.08720434],
```

```
       [-0.68861359],
       [-0.94120548],
       [ 0.86302227],
       [-1.53058654]])
```

```
ax1 = sns.distplot(dataset['mpg'], hist=False, color="r",
label="Actual Value")
sns.distplot(y_pred, hist=False, color="b", label="Fitted Values" ,
ax=ax1)


plt.title('Actual vs Fitted Values for mpg')
plt.xlabel('mpg')
plt.ylabel('Proportion of Cars')

plt.show()
plt.close()
```

```
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/seaborn/
distributions.py:2619: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `kdeplot` (an axes-level function for kernel density
plots).
  warnings.warn(msg, FutureWarning)
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/seaborn/distrib
utions.py:2619: FutureWarning: `distplot` is a deprecated function and
will be removed in a future version. Please adapt your code to use
either `displot` (a figure-level function with similar flexibility) or
`kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



We can see that the fitted values are reasonably close to the actual values, since the two distributions overlap a bit. However, there is definitely some room for improvement.

R-squared R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determination for multiple regression.

R-squared = Explained variation / Total variation

Mean Squared Error (MSE)

```
from sklearn.metrics import r2_score,mean_squared_error
```

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

```
0.8693935947768933
```

```
mean_squared_error(y_test,y_pred)
```

```
0.1306064052231067
```

```
np.sqrt(mean_squared_error(y_test,y_pred))
```

```
0.36139508190221226
```

random forest regressor

```
from sklearn.ensemble import RandomForestRegressor
```

```
rf=
RandomForestRegressor(n_estimators=10,random_state=0,criterion='mae')
rf.fit(x_train,y_train)
```

```
/tmp/wsuser/ipykernel_209/4164760693.py:2: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change
the shape of y to (n_samples,), for example using ravel().
  rf.fit(x_train,y_train)
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/sklearn/ensembl
e/_forest.py:403: FutureWarning: Criterion 'mae' was deprecated in
v1.0 and will be removed in version 1.2. Use
`criterion='absolute_error'` which is equivalent.
  warn(
```

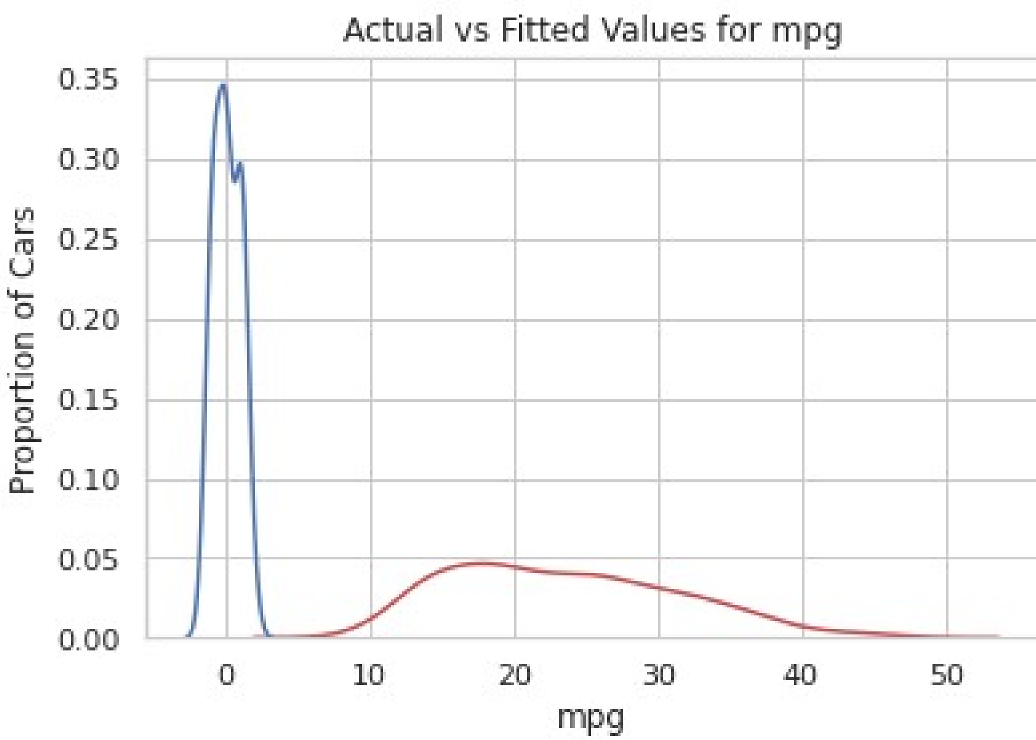
```
RandomForestRegressor(criterion='mae', n_estimators=10,
random_state=0)
```

```
y_pred2=rf.predict(x_test)
y_pred2
```

```
array([-1.22541325,  0.04145375, -1.27712211, -0.21321237, -
0.73417911,
        0.94635875,  1.42983656,  0.05438096, -1.08321389,
0.09057716,
        1.36778593,  1.89133811, -0.52734368,  0.26380183, -
0.95394175,
        1.04460558,  0.5818113 ,  0.23406924, -0.86991486,
1.10794893,
       -0.97333257,  0.19140943,  0.03757558, -0.29982471,
0.86879546,
       -0.02318232,  1.1066562 ,  1.07563089,  1.09760715, -
0.87767119,
       -0.39677881,  1.0278002 , -0.82596233,  0.97221318, -
0.18735794,
       -0.03610954, -0.59844336, -0.92808732,  1.28375904, -
1.47103032])
```

```
ax1 = sns.distplot(dataset['mpg'], hist=False, color="r",
label="Actual Value")
sns.distplot(y_pred2, hist=False, color="b", label="Fitted Values" ,
ax=ax1)



plt.title('Actual vs Fitted Values for mpg')
plt.xlabel('mpg')
plt.ylabel('Proportion of Cars')

plt.show()
plt.close()
```

```
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/seaborn/
distributions.py:2619: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `kdeplot` (an axes-level function for kernel density
plots).
  warnings.warn(msg, FutureWarning)
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/seaborn/distrib
utions.py:2619: FutureWarning: `distplot` is a deprecated function and
will be removed in a future version. Please adapt your code to use
either `displot` (a figure-level function with similar flexibility) or
`kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



We can see that the fitted values are reasonably close to the actual values, since the two distributions overlap a bit. However, there is definitely some room for improvement.

```
from sklearn.metrics import r2_score,mean_squared_error
```

```
r2_score(y_test,y_pred2)
```

```
0.9172449209441422
```

```
mean_squared_error(y_test,y_pred2)
```

```
0.08275507905585772
```

```
np.sqrt(mean_squared_error(y_test,y_pred2))
```

```
0.28767182527292745
```

linear regression

```
from sklearn.linear_model import LinearRegression
mr=LinearRegression()
mr.fit(x_train,y_train)
```

```
LinearRegression()
```

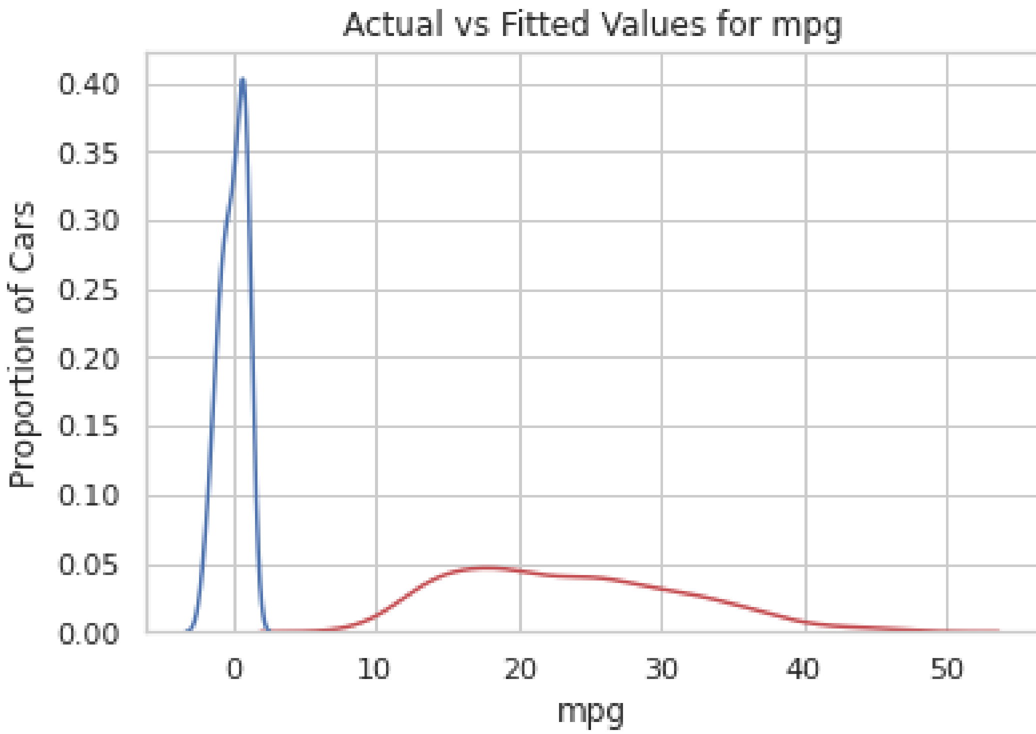
```
y_pred3=mr.predict(x_test)
y_pred3
```

```
array([[-1.48354417],
       [ 0.02018821],
       [-1.68903988],
       [-0.42532853],
       [-0.85893857],
       [ 0.68603096],
       [ 1.21891251],
       [-0.13204094],
       [-1.23799478],
       [ 0.3208166 ],
       [ 1.05032664],
       [ 1.27944186],
       [-0.35801006],
       [ 0.22377607],
       [-1.07318175],
       [ 0.84489227],
       [ 0.55090001],
       [ 0.59162161],
       [-0.86938749],
       [ 0.90060746],
       [-1.19252105],
       [ 0.06263748],
       [ 0.34334107],
       [-0.49842421],
       [ 0.7257113 ],
       [ 0.5306685 ],
       [ 0.90224828],
       [ 0.75809371],
       [ 0.75230078],
       [-0.81562435],
       [-0.51790152],
       [ 0.92628973],
       [-0.41719037],
       [ 1.02755713],
       [-0.05714634],
       [ 0.26677556],
       [-0.37496781],
```

```
       [-1.01152038],
       [ 1.04592662],
       [-2.01630218]])
```

```
ax1 = sns.distplot(dataset['mpg'], hist=False, color="r",
label="Actual Value")
sns.distplot(y_pred3, hist=False, color="b", label="Fitted Values" ,
ax=ax1)


plt.title('Actual vs Fitted Values for mpg')
plt.xlabel('mpg')
plt.ylabel('Proportion of Cars')

plt.show()
plt.close()
```

```
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/seaborn/
distributions.py:2619: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `kdeplot` (an axes-level function for kernel density
plots).
  warnings.warn(msg, FutureWarning)
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/seaborn/distrib
utions.py:2619: FutureWarning: `distplot` is a deprecated function and
will be removed in a future version. Please adapt your code to use
either `displot` (a figure-level function with similar flexibility) or
`kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



We can see that the fitted values are not as close to the actual values, since the two distributions overlap a bit. However, there is definitely some room for improvement.

```
from sklearn.metrics import r2_score,mean_squared_error
r2_score(y_test,y_pred3)
```

```
0.8631101197005312
```

```
mean_squared_error(y_test,y_pred3)
```

```
0.13688988029946877
```

```
np.sqrt(mean_squared_error(y_test,y_pred3))
```

```
0.3699863244762822
```

Conclusion: When comparing models, the model with the higher R-squared value is a better fit for the data. When comparing models, the model with the smallest MSE value is a better fit for the data.

Comparing these three models, we conclude that the DecisionTree model is the best model to be able to predict mpg from our dataset. But We use Random Forest Regressor

```
from ibm_watson_machine_learning import APIClient
wml_credentials = {
                   "url": "https://us-south.ml.cloud.ibm.com",
```

```
"apikey":"c0AaDte5MvL14V1NwKhlSgGHH34bvKX_VN8iFiLyAPQ5"

                   }
client = APIClient(wml_credentials)

def guid_from_space_name(client, space_name):
    space = client.spaces.get_details()
    return(next(item for item in space['resources'] if item['entity']
["name"] == space_name)['metadata']['id'])

space_uid = guid_from_space_name(client, 'models')
print("Space UID = " + space_uid)
```

```
Space UID = ec50822e-7eed-4693-abad-e892683a6177
```

```
client.set.default_space(space_uid)
```

```
'SUCCESS'
```

```
client.software_specifications.list()
```

```
-----------------------------  ------------------------------------
----
NAME                           ASSET_ID
TYPE
default_py3.6                  0062b8c9-8b7d-44a0-a9b9-46c416adcbd9
base
kernel-spark3.2-scala2.12      020d69ce-7ac1-5e68-ac1a-31189867356a
base
pytorch-onnx_1.3-py3.7-edt     069ea134-3346-5748-b513-49120e15d288
base
scikit-learn_0.20-py3.6        09c5a1d0-9c1e-4473-a344-eb7b665ff687
base
spark-mllib_3.0-scala_2.12     09f4cff0-90a7-5899-b9ed-1ef348aebdee
base
pytorch-onnx_rt22.1-py3.9      0b848dd4-e681-5599-be41-b5f6fccc6471
base
ai-function_0.1-py3.6          0cdb0f1e-5376-4f4d-92dd-da3b69aa9bda
base
shiny-r3.6                     0e6e79df-875e-4f24-8ae9-62dcc2148306
base
tensorflow_2.4-py3.7-horovod   1092590a-307d-563d-9b62-4eb7d64b3f22
base
pytorch_1.1-py3.6              10ac12d6-6b30-4ccd-8392-3e922c096a92
base
tensorflow_1.15-py3.6-ddl      111e41b3-de2d-5422-a4d6-bf776828c4b7
base
autoai-kb_rt22.2-py3.10        125b6d9a-5b1f-5e8d-972a-b251688ccf40
base
runtime-22.1-py3.9             12b83a17-24d8-5082-900f-0ab31fbfd3cb
base
```

```
scikit-learn_0.22-py3.6         154010fa-5b3b-4ac1-82af-4d5ee5abbc85
base
default_r3.6                    1b70aec3-ab34-4b87-8aa0-a4a3c8296a36
base
pytorch-onnx_1.3-py3.6          1bc6029a-cc97-56da-b8e0-39c3880dbbe7
base
kernel-spark3.3-r3.6            1c9e5454-f216-59dd-a20e-474a5cdf5988
base
pytorch-onnx_rt22.1-py3.9-edt   1d362186-7ad5-5b59-8b6c-9d0880bde37f
base
tensorflow_2.1-py3.6            1eb25b84-d6ed-5dde-b6a5-3fbdf1665666
base
spark-mllib_3.2                 20047f72-0a98-58c7-9ff5-a77b012eb8f5
base
tensorflow_2.4-py3.8-horovod    217c16f6-178f-56bf-824a-b19f20564c49
base
runtime-22.1-py3.9-cuda         26215f05-08c3-5a41-a1b0-da66306ce658
base
do_py3.8                        295addb5-9ef9-547e-9bf4-92ae3563e720
base
autoai-ts_3.8-py3.8             2aa0c932-798f-5ae9-abd6-15e0c2402fb5
base
tensorflow_1.15-py3.6           2b73a275-7cbf-420b-a912-eae7f436e0bc
base
kernel-spark3.3-py3.9           2b7961e2-e3b1-5a8c-a491-482c8368839a
base
pytorch_1.2-py3.6               2c8ef57d-2687-4b7d-acce-01f94976dac1
base
spark-mllib_2.3                 2e51f700-bca0-4b0d-88dc-5c6791338875
base
pytorch-onnx_1.1-py3.6-edt      32983cea-3f32-4400-8965-dde874a8d67e
base
spark-mllib_3.0-py37            36507ebe-8770-55ba-ab2a-eafe787600e9
base
spark-mllib_2.4                 390d21f8-e58b-4fac-9c55-d7ceda621326
base
autoai-ts_rt22.2-py3.10         396b2e83-0953-5b86-9a55-7ce1628a406f
base
xgboost_0.82-py3.6              39e31acd-5f30-41dc-ae44-60233c80306e
base
pytorch-onnx_1.2-py3.6-edt      40589d0e-7019-4e28-8daa-fb03b6f4fe12
base
pytorch-onnx_rt22.2-py3.10      40e73f55-783a-5535-b3fa-0c8b94291431
base
default_r36py38                 41c247d3-45f8-5a71-b065-8580229facf0
base
autoai-ts_rt22.1-py3.9          4269d26e-07ba-5d40-8f66-2d495b0c71f7
base
autoai-obm_3.0                  42b92e18-d9ab-567f-988a-4240ba1ed5f7
base
```

```
pmml-3.0_4.3                    493bcb95-16f1-5bc5-bee8-81b8af80e9c7
base
spark-mllib_2.4-r_3.6           49403dff-92e9-4c87-a3d7-a42d0021c095
base
xgboost_0.90-py3.6              4ff8d6c2-1343-4c18-85e1-689c965304d3
base
pytorch-onnx_1.1-py3.6          50f95b2a-bc16-43bb-bc94-b0bed208c60b
base
autoai-ts_3.9-py3.8             52c57136-80fa-572e-8728-a5e7cbb42cde
base
spark-mllib_2.4-scala_2.11      55a70f99-7320-4be5-9fb9-9edb5a443af5
base
spark-mllib_3.0                 5c1b0ca2-4977-5c2e-9439-ffd44ea8ffe9
base
autoai-obm_2.0                  5c2e37fa-80b8-5e77-840f-d912469614ee
base
spss-modeler_18.1               5c3cad7e-507f-4b2a-a9a3-ab53a21dee8b
base
cuda-py3.8                      5d3232bf-c86b-5df4-a2cd-7bb870a1cd4e
base
runtime-22.2-py3.10-xc          5e8cddff-db4a-5a6a-b8aa-2d4af9864dab
base
autoai-kb_3.1-py3.7             632d4b22-10aa-5180-88f0-f52dfb6444d7
base
-----------------------------  ------------------------------------
----
Note: Only first 50 records were displayed. To display more use
'limit' parameter.
```

```
software_spec_uid =
client.software_specifications.get_uid_by_name("default_py3.6")
software_spec_uid
```

```
'0062b8c9-8b7d-44a0-a9b9-46c416adcbd9'
```

```
!pip install -U pyspark==2.1.2
#  model_details = client.repository.store_model(model=rf,meta_props={
#      client.repository.ModelMetaNames.NAME:"car-performance",
#       client.repository.ModelMetaNames.TYPE:"scikit-learn_1.0",
#
client.repository.ModelMetaNames.SOFTWARE_SPEC_UID:software_spec_uid }
#  )

# model_id = client.repository.get_model_uid(model_details)
```

```
Collecting pyspark==2.1.2
  Downloading pyspark-2.1.2.tar.gz (181.3 MB)
e=pyspark-2.1.2-py2.py3-none-any.whl size=181625702
sha256=3fc28a3896b8706782bfc71c35879f07915f5c02606ec17fbc7de5bdc311c98
1
  Stored in directory:
```

```
/tmp/wsuser/.cache/pip/wheels/5a/33/84/b0060cb291650c5c52279bc573987c9
8609df6564f3290ccfa
Successfully built pyspark
Installing collected packages: py4j, pyspark
  Attempting uninstall: py4j
    Found existing installation: py4j 0.10.9.2
    Uninstalling py4j-0.10.9.2:
      Successfully uninstalled py4j-0.10.9.2
ERROR: pip's dependency resolver does not currently take into account
all the packages that are installed. This behaviour is the source of
the following dependency conflicts.
autoai-ts-libs 1.1.9 requires py4j<0.10.10,>=0.10.9, but you have py4j
0.10.4 which is incompatible.
Successfully installed py4j-0.10.4 pyspark-2.1.2
```

```
# metadata = {
#     client.repository.ModelMetaNames.NAME: 'ML-Model',
#     client.repository.ModelMetaNames.TYPE: 'scikit-learn_0.22',
#     client.repository.ModelMetaNames.SOFTWARE_SPEC_UID:
software_spec_uid
# }

# published_model = client.repository.store_model(
#     model=rf,
#     meta_props=metadata,
#     training_data=x_train,
#     training_target=y_train)


sofware_spec_uid =
client.software_specifications.get_id_by_name("runtime-22.1-py3.9")
metadata = {
client.repository.ModelMetaNames.NAME: 'Gradient',
client.repository.ModelMetaNames.TYPE: 'scikit-learn_1.0',
client.repository.ModelMetaNames.SOFTWARE_SPEC_UID: sofware_spec_uid
}
published_model = client.repository.store_model(
model=rf,
meta_props=metadata)
```

```
!wget https://https://raw.githubusercontent.com/IBM/monitor-wml-model-
with with-watson-openscale/master/data/additional_feedback_data.json
```

```
--2022-11-19 19:14:16--
https://https//raw.githubusercontent.com/IBM/monitor-wml-model-with
Resolving https (https)... failed: Name or service not known.
wget: unable to resolve host address ‘https’
--2022-11-19 19:14:16--
http://with-watson-openscale/master/data/additional_feedback_data.json
Resolving with-watson-openscale (with-watson-openscale)... failed:
```

```
Name or service not known.
wget: unable to resolve host address 'with-watson-openscale'
```

```python
# best_model = 'rf'
# MODEL_NAME="Car-Performance"
# DEPLOYMENT_NAME = "Car-Performance-Deployment"
# BEST_MODEL = best_model

published_model
```


```
{'entity': {'hybrid_pipeline_software_specs': [],
  'software_spec': {'id': '12b83a17-24d8-5082-900f-0ab31fbfd3cb',
   'name': 'runtime-22.1-py3.9'},
  'type': 'scikit-learn_1.0'},
 'metadata': {'created_at': '2022-11-19T19:14:13.167Z',
  'id': 'ba031043-c69e-4719-b9ec-950f75bbb7ad',
  'modified_at': '2022-11-19T19:14:15.659Z',
  'name': 'Gradient',
  'owner': 'IBMid-6620041XAB',
  'resource_key': 'f53c7996-2147-46c8-a43c-6f7fbc7cdb55',
  'space_id': 'ec50822e-7eed-4693-abad-e892683a6177'},
 'system': {'warnings': []}}
```


```python
# model_props={
#     client.repository.ModelMetaNames.NAME:"models".format(rf)
# }

#
published_model_details=client.repository.store_model(model=BEST_MODEL
,meta_props=model_props,training_data=x_train,training_target=y_train)
# stored_model_details =
client.repository.create_version(trained_model_guid,
model_uid="MODELID" ,meta_props=metadata)

# model_id

x_train[0]

rf.predict([[1.46858608,  2.48230464,  2.97856512,  1.62455076, -
1.61295698,
       -0.71873488]])
```