Train the model on IBM

Team ID	PNT2022TMID50528
Project Name	Machine Learning based Vehicle Performance Analyzer

Importing Libraries

In [1]:

```
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

In [2]:

```
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 c
redentials.
# You might want to remove those credentials before you share the notebook.
cos_client = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='Uede0uog_DlYeHmTn0uQW3GYQhYgYHbY1kvWgQybaYM1',
    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 = 'vehicleperformanceprediction-donotdelete-pr-kj6qz2159y6996'
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()
```

Out[2]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino

Finding missing data

In [3]:

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

Out[3]:

```
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.

In [4]:

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

In [5]:

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

Out[5]:

```
6
```

In [6]:

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

In [7]:

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

In [8]:

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

Out[8]:

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

In [9]:

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

```
<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
```

In [10]:

```
dataset.describe() #Pandas describe() is used to view some basic statistical details of a dat
```

Out[10]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
count	398.000000	398.000000	398.000000	398.000000	398.000000	398.000000	398.000000	398.000000
mean	23.514573	5.454774	193.425879	104.469388	2970.424623	15.568090	76.010050	1.572864
std	7.815984	1.701004	104.269838	38.199187	846.841774	2.757689	3.697627	0.802055
min	9.000000	3.000000	68.000000	46.000000	1613.000000	8.000000	70.000000	1.000000
25%	17.500000	4.000000	104.250000	76.000000	2223.750000	13.825000	73.000000	1.000000
50%	23.000000	4.000000	148.500000	95.000000	2803.500000	15.500000	76.000000	1.000000
75%	29.000000	8.000000	262.000000	125.000000	3608.000000	17.175000	79.000000	2.000000
max	46.600000	8.000000	455.000000	230.000000	5140.000000	24.800000	82.000000	3.000000

There is no use with car name attribute so drop it

In [11]:

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

In [12]:

```
corr_table=dataset.corr()#Pandas dataframe.corr() is used to find the pairwise correlatio n
corr_table
```

Out[12]:

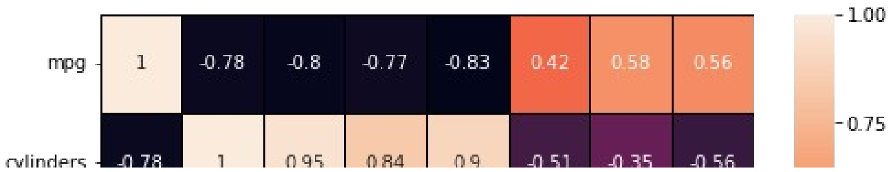
	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
mpg	1.000000	-0.775396	-0.804203	-0.771437	-0.831741	0.420289	0.579267	0.563450
cylinders	-0.775396	1.000000	0.950721	0.838939	0.896017	-0.505419	-0.348746	-0.562543
displacement	-0.804203	0.950721	1.000000	0.893646	0.932824	-0.543684	-0.370164	-0.609409
horsepower	-0.771437	0.838939	0.893646	1.000000	0.860574	-0.684259	-0.411651	-0.453669
weight	-0.831741	0.896017	0.932824	0.860574	1.000000	-0.417457	-0.306564	-0.581024
acceleration	0.420289	-0.505419	-0.543684	-0.684259	-0.417457	1.000000	0.288137	0.205873
model year	0.579267	-0.348746	-0.370164	-0.411651	-0.306564	0.288137	1.000000	0.180662
origin	0.563450	-0.562543	-0.609409	-0.453669	-0.581024	0.205873	0.180662	1.000000

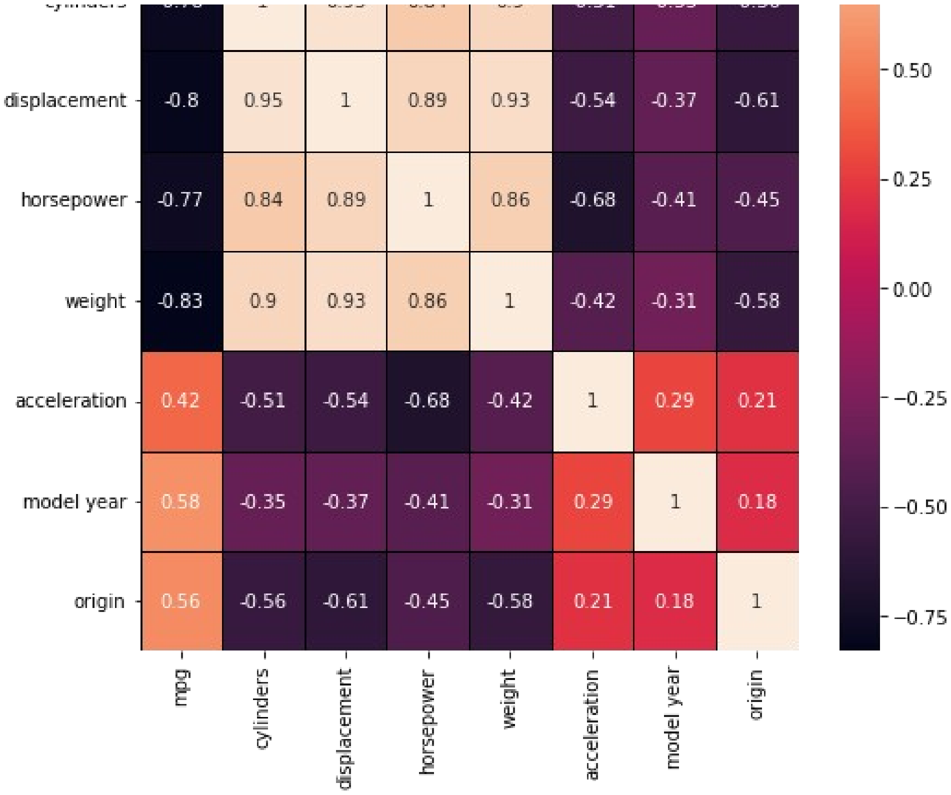
Data Visualizations

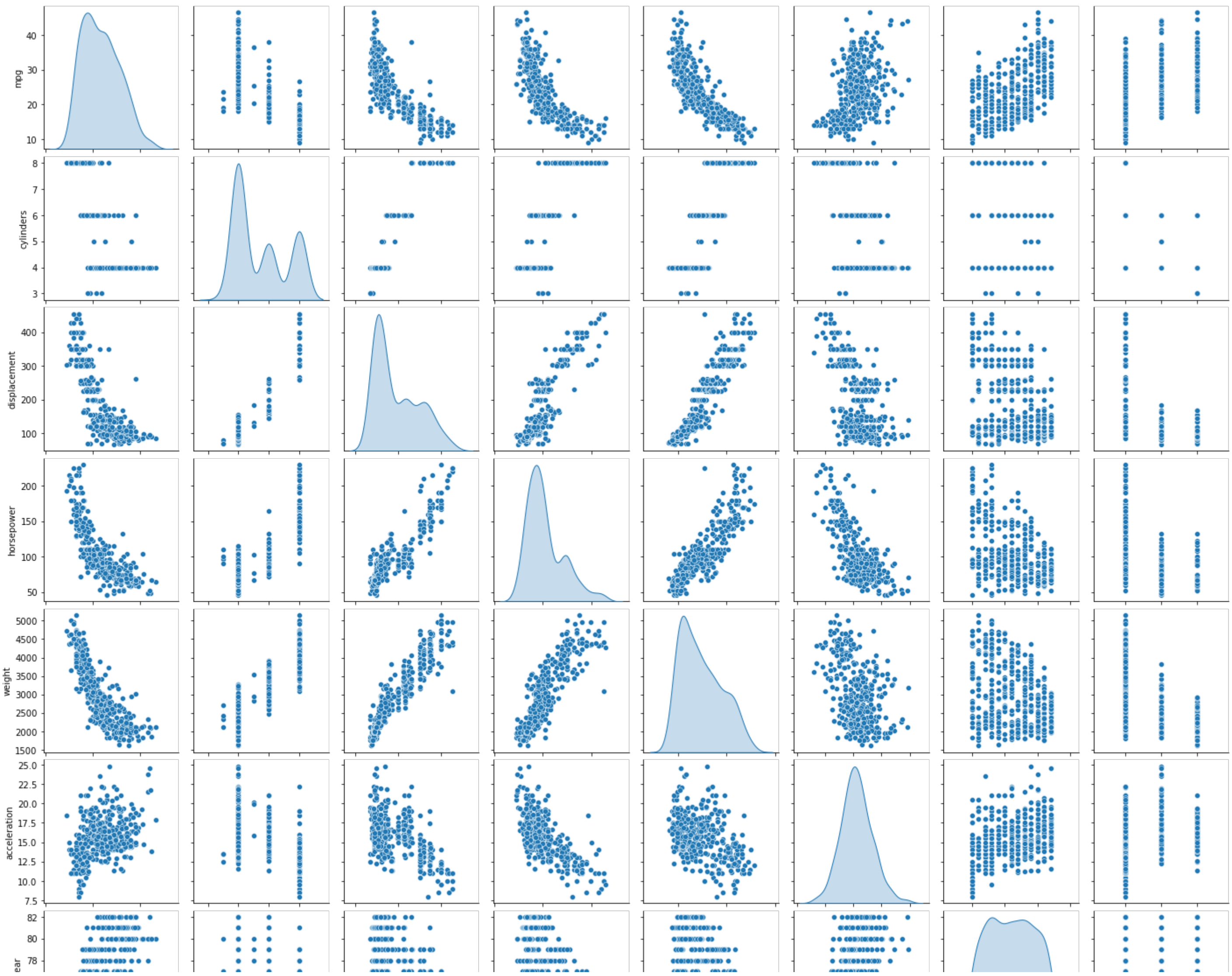
Heatmap : which represents correlation between attributes

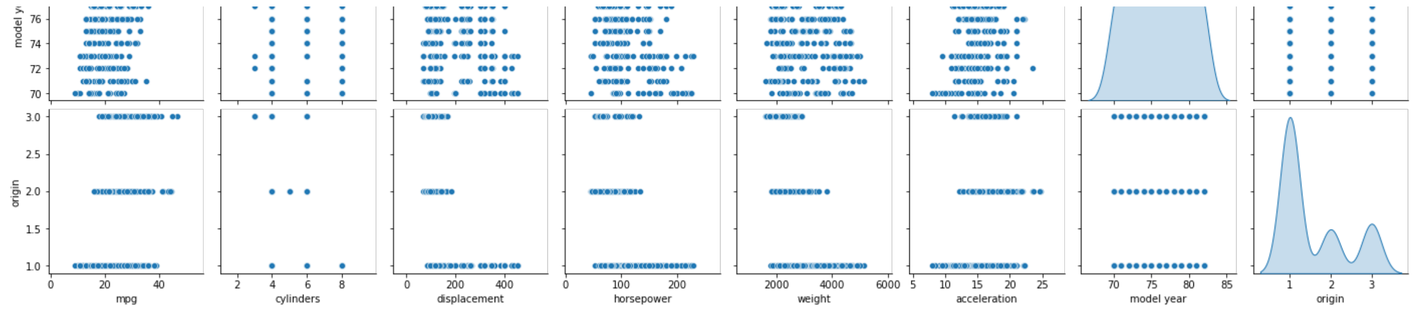
In [13]:

```
sns.heatmap(dataset.corr(),annot=True,linecolor ='black', linewidths = 1)#Heatmap is a wa y to
fig=plt.gcf() fig.set_size_inches(8,8)
```









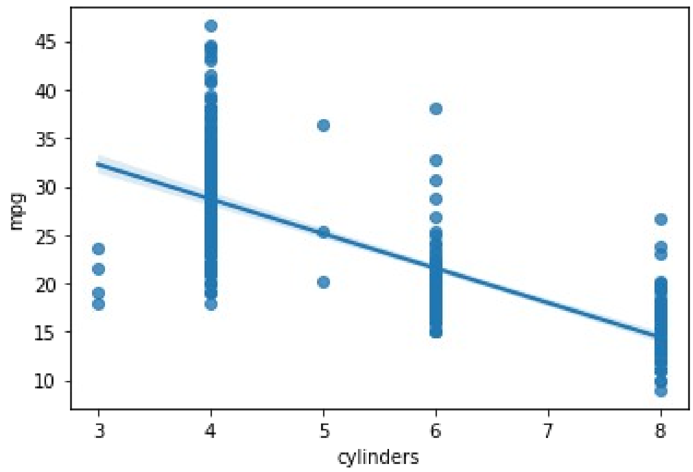
Regression plots(regplot()) creates a regression line between 2 parameters and helps to visualize their linear relationships.

In [15]:

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

Out[15]:

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

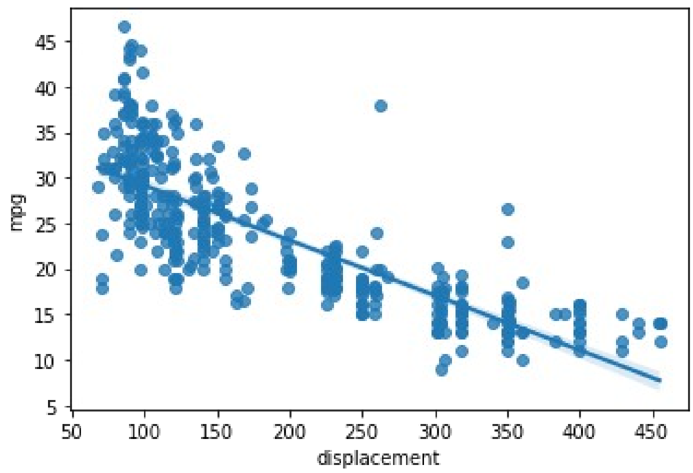


In [16]:

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

Out[16]:

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

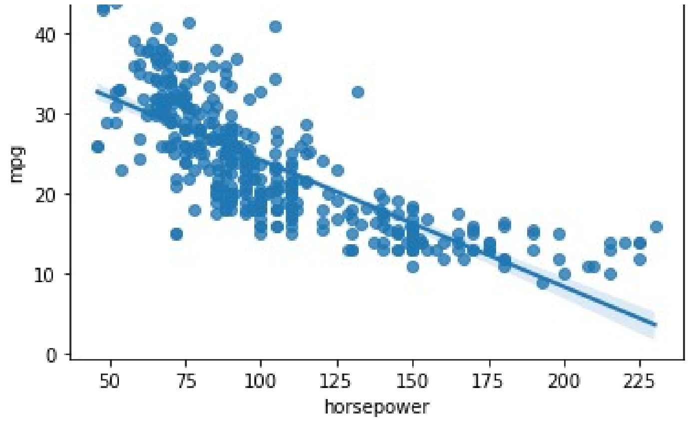


In [17]:

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

Out[17]:

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

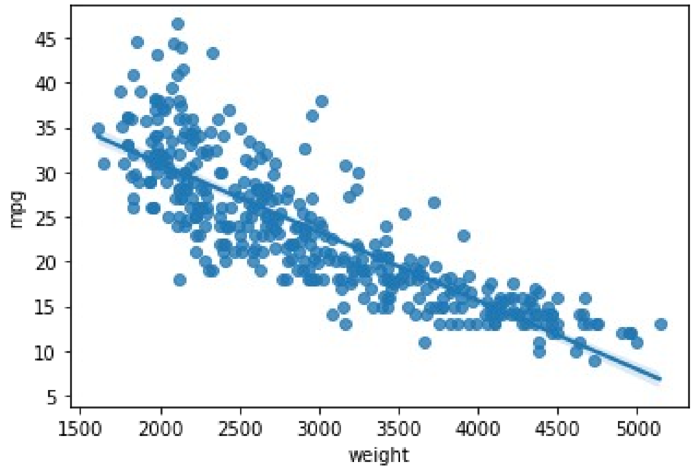


In [18]:

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

Out[18]:

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

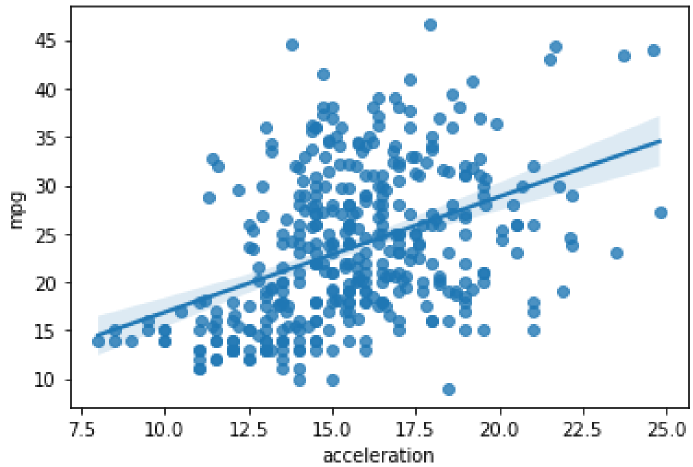


In [19]:

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

Out[19]:

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

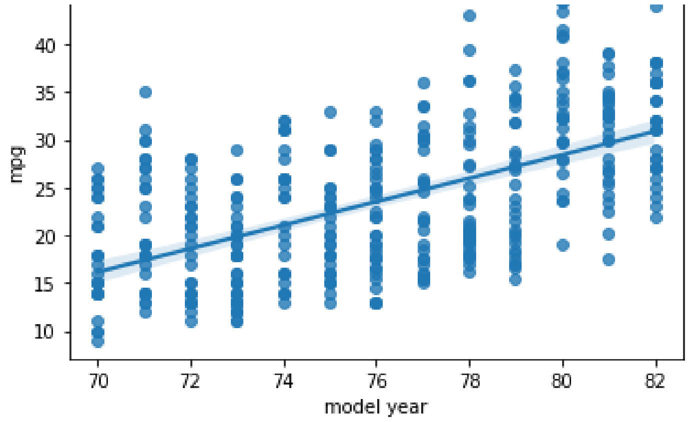


In [20]:

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

Out[20]:

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

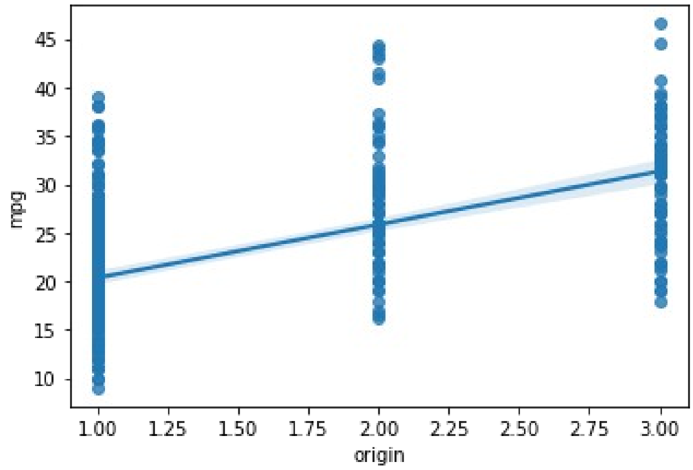


In [21]:

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

Out[21]:

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

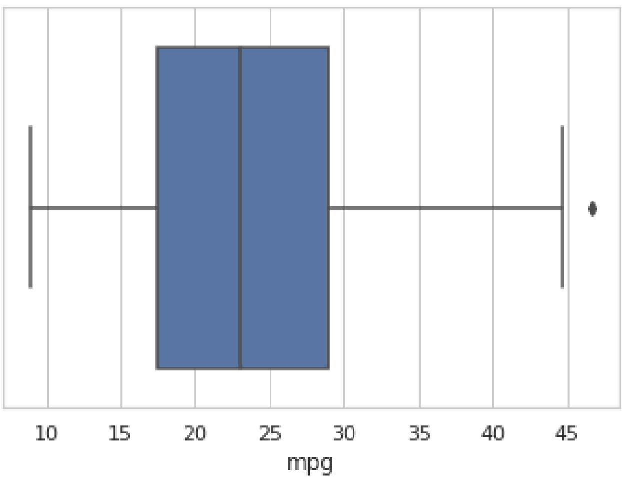


In [22]:

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

Out[22]:

<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.

In [23]:

```
from scipy import stats
```

Cylinders vs mpg

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

In [24]:

```
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 = 4.50399
2246177055e-81
```

Conclusion:

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.

Displacement vs mpg

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

In [25]:

```
pearson_coef, p_value = stats.pearsonr(dataset['displacement'], dataset['mpg']) print("The Pear
_value)
```

```
The Pearson Correlation Coefficient is -0.8042028248058978  with a P-value of P = 1.65588
89101930157e-91
```

Conclusion:

Since the p-value is $<$ 0.1, the correlation between displacement and mpg is statistically significant, and the linear negative relationship is quite strong (~-0.809, close to -1)

Horsepower vs mpg

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

In [26]:

```
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 = 9.25547
7533166725e-80
```

Conclusion:

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.

Weght vs mpg

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

In [27]:

```
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 = 2.972799
5640500577e-103
```

Conclusion:

Since the p-value is $<$ 0.001, the correlation between weight and mpg is statistically significant, and the linear negative relationship is quite strong (~-0.831, close to -1)

Acceleration vs mpg

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

In [28]:

```
pearson_coef, p_value = stats.pearsonr(dataset['acceleration'], dataset['mpg']) print("The Pear
_value)
```

```
The Pearson Correlation Coefficient is 0.4202889121016507  with a P-value of P = 1.823091
535078553e-18
```

Conclusion:

Since the p-value is $>$ 0.1, the correlation between acceleration and mpg is statistically significant, but the linear relationship is weak (~0.420).

Model year vs mpg

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

In [29]:

```
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 = 4.844935
813365483e-37
```

Conclusion:

Since the p-value is $<$ 0.001, the correlation between model year and mpg is statistically significant, but the linear relationship is only moderate (~0.579).

Origin vs mpg

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

In [30]:

```
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 = 1.011482
2102336483e-34
```

Conclusion:

Since the p-value is $<$ 0.001, the correlation between origin and mpg is statistically significant, but the linear relationship is only moderate (~0.563).

Ordinary Least Squares Statistics

In [31]:

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

Out[31]:

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:	Sun, 13 Nov 2022	**Prob (F-statistic):**	4.84e-104
Time:	15:17:17	**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

In [32]:

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

Out[32]:

```
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

In [33]:

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

Out[33]:

```
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. ]])
```

Normalizing

In [34]:

```
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_transfor

x_train
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
/tmp/wsuser/ipykernel_165/1600422500.py in <module>
      1 from sklearn.preprocessing import StandardScaler
      2 sd = StandardScaler()
----> 3 x_train = sd.fit_transform(x_train)
      4 x_test = sd.fit_transform(x_test)
      5 y_train = sd.fit_transform(y_train)

NameError: name 'x_train' is not defined
```

Splitting into train and test data.

In [35]:

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

In [36]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)
```

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

random forest regressor

In [37]:

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

In [38]:

```
rf= RandomForestRegressor(n_estimators=10) rf.fit(x_train,np.ravel(y_train))
```

Out[38]:

```
RandomForestRegressor(n_estimators=10)
```

In [39]:

```
x_train.shape
```

Out[39]:

```
(318, 6)
```

In [40]:

```
! pip install ibm-watson-machine-learning
```

```
Requirement already satisfied: ibm-watson-machine-learning in /opt/conda/envs/Python-
3.9/ lib/python3.9/site-packages (1.0.257)
Requirement already satisfied: certifi in /opt/conda/envs/Python-3.9/lib/python3.9/site-p
ackages (from ibm-watson-machine-learning) (2022.9.24)
Requirement already satisfied: importlib-metadata in
/opt/conda/envs/Python-3.9/lib/pytho n3.9/site-packages (from ibm-watson-machine-
learning) (4.8.2)
Requirement already satisfied: pandas<1.5.0,>=0.24.2 in
/opt/conda/envs/Python-3.9/lib/py thon3.9/site-packages (from ibm-watson-machine-
learning) (1.3.4)
Requirement already satisfied: urllib3 in /opt/conda/envs/Python-3.9/lib/python3.9/site-p
ackages (from ibm-watson-machine-learning) (1.26.7)
Requirement already satisfied: lomond in /opt/conda/envs/Python-3.9/lib/python3.9/site-pa
ckages (from ibm-watson-machine-learning) (0.3.3)
Requirement already satisfied: requests in /opt/conda/envs/Python-3.9/lib/python3.9/site-
packages (from ibm-watson-machine-learning) (2.26.0)
Requirement already satisfied: tabulate in /opt/conda/envs/Python-3.9/lib/python3.9/site-
packages (from ibm-watson-machine-learning) (0.8.9)
Requirement already satisfied: packaging in /opt/conda/envs/Python-3.9/lib/python3.9/site
-packages (from ibm-watson-machine-learning) (21.3)
Requirement already satisfied: ibm-cos-sdk==2.11.* in
/opt/conda/envs/Python-3.9/lib/pyth on3.9/site-packages (from ibm-watson-machine-
learning) (2.11.0)
Requirement already satisfied: jmespath<1.0.0,>=0.7.1 in
/opt/conda/envs/Python-3.9/lib/p ython3.9/site-packages (from ibm-cos-sdk==2.11.*->ibm-
watson-machine-learning) (0.10.0) Requirement already satisfied: ibm-cos-sdk-
s3transfer==2.11.0 in /opt/conda/envs/Python-3
.9/lib/python3.9/site-packages (from ibm-cos-sdk==2.11.*->ibm-watson-machine-learning) (2
.11.0)
Requirement already satisfied: ibm-cos-sdk-core==2.11.0 in /opt/conda/envs/Python-3.9/lib
/python3.9/site-packages (from ibm-cos-sdk==2.11.*->ibm-watson-machine-learning)
(2.11.0) Requirement already satisfied: python-dateutil<3.0.0,>=2.1 in
/opt/conda/envs/Python-3.9/ lib/python3.9/site-packages (from ibm-cos-sdk-core==2.11.0-
>ibm-cos-sdk==2.11.*->ibm-wats on-machine-learning) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in
/opt/conda/envs/Python-3.9/lib/python3.9/s ite-packages (from pandas<1.5.0,>=0.24.2-
>ibm-watson-machine-learning) (2021.3) Requirement already satisfied: numpy>=1.17.3 in
/opt/conda/envs/Python-3.9/lib/python3.9/ site-packages (from pandas<1.5.0,>=0.24.2-
>ibm-watson-machine-learning) (1.20.3) Requirement already satisfied: six>=1.5 in
/opt/conda/envs/Python-3.9/lib/python3.9/site- packages (from python-
dateutil<3.0.0,>=2.1->ibm-cos-sdk-core==2.11.0->ibm-cos-sdk==2.11.*
->ibm-watson-machine-learning) (1.15.0)
Requirement already satisfied: idna<4,>=2.5 in
/opt/conda/envs/Python-3.9/lib/python3.9/s ite-packages (from requests->ibm-watson-
machine-learning) (3.3)
Requirement already satisfied: charset-normalizer~=2.0.0 in
/opt/conda/envs/Python-3.9/li b/python3.9/site-packages (from requests->ibm-watson-
machine-learning) (2.0.4) Requirement already satisfied: zipp>=0.5 in
/opt/conda/envs/Python-3.9/lib/python3.9/site
-packages (from importlib-metadata->ibm-watson-machine-learning) (3.6.0)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /opt/conda/envs/Python-3.9/lib
/python3.9/site-packages (from packaging->ibm-watson-machine-learning) (3.0.4)
```

In [43]:

```
from ibm_watson_machine_learning import APIClient wml_credentials = {
"url":"https://us-south.ml.cloud.ibm.com", "apikey":"k0ToNjB4fREMsVxEr0C3pjHT0bNJzgZvVt1S0SikVpMJ

}
client = APIClient(wml_credentials)
```

In [44]:

```
def guid_from_space_name(client, space_name): space = client.spaces.get_details() print(space)
return(next(item for item in space['resources'] if item['entity']["name"] == space_n ame)['meta
```

In [45]:

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

{'resources': [{'entity': {'compute': [{'crn': 'crn:v1:bluemix:public:pm-20:us-south:a/d1

2096019c744baabc99e2caa9c44ac5:dbc6da1f-aca8-4c0f-937f-da20bd5e08c6::', 'guid': 'dbc6da1f -aca8-4c0f-937f-da20bd5e08c6', 'name': 'Watson Machine Learning-72', 'type': 'machine_lea rning'}], 'description': '', 'name': 'models', 'scope': {'bss_account_id': 'd12096019c744 baabc99e2caa9c44ac5'}, 'stage': {'production': False}, 'status': {'state': 'active'}, 'st orage': {'properties': {'bucket_name': '2e6d79af-2319-41ef-8bb1-13843958cd79', 'bucket_re gion': 'us-south', 'credentials': {'admin': {'access_key_id': 'e2dcdab6300f4292acfd3a9e99 fe8419', 'api_key': 'Ccb36wfmVayFlvEWymudO7rYIVHUT18VXxjXXSf8wNVx', 'secret_access_key': '09d27d5ba8570a63f8ecd4477903c61c66702acd0a8a0cb2', 'service_id': 'ServiceId-113a7385-0ac f-4aca-b0a4-f20ee5949b94'}, 'editor': {'access_key_id': '0b31cfa63a054a40bbe5cbe6a1ddc189 ', 'api_key': 'Nrtr6aPyPH387BlYG2rJrcg3kiA1-ZVXbGR3J7CZQK9e', 'resource_key_crn': 'crn:v1 :bluemix:public:cloud-object-storage:global:a/d12096019c744baabc99e2caa9c44ac5:71972f87-6 ebf-4b35-907f-5b09ff80a63a::', 'secret_access_key': '8db16c6ef99ec8799a31e00fa98d5952b212 f3198510de25', 'service_id': 'ServiceId-48a7874c-09b6-4ba0-8c14-d4b63928000f'}, 'viewer': {'access_key_id': '6a971a0391e947e7a10aa6d0a205eee2', 'api_key': 'p_RHNGsyVx7ybtSaRSn8Osq 2ZkOsOhj8PPAYQEdgGoLK', 'resource_key_crn': 'crn:v1:bluemix:public:cloud-object-storage:g lobal:a/d12096019c744baabc99e2caa9c44ac5:71972f87-6ebf-4b35-907f-5b09ff80a63a::', 'secret _access_key': 'c530568f37883f9c765343301136c7eb763cc3ccf4197718', 'service_id': 'ServiceI d-1a4e051b-6867-4ac8-acab-b942b7b43a75'}}, 'endpoint_url': 'https://s3.us-south.cloud-obj ect-storage.appdomain.cloud', 'guid': '71972f87-6ebf-4b35-907f-5b09ff80a63a', 'resource_c rn': 'crn:v1:bluemix:public:cloud-object-storage:global:a/d12096019c744baabc99e2caa9c44ac 5:71972f87-6ebf-4b35-907f-5b09ff80a63a::'}, 'type': 'bmcos_object_storage'}}, 'metadata': {'created_at': '2022-11-12T15:24:43.319Z', 'creator_id': 'IBMid-6640044ZX7', 'id': 'a7c26 d83-e37a-4e0b-b024-7d3f1f77740b', 'updated_at': '2022-11-12T15:25:03.183Z', 'url': '/v2/s paces/a7c26d83-e37a-4e0b-b024-7d3f1f77740b'}}]}
Space UID-a7c26d83-e37a-4e0b-b024-7d3f1f77740b

In [46]:

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

Out[46]:

'SUCCESS'

In [47]:

```
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
autoai-kb_3.1-py3.7               632d4b22-10aa-5180-88f0-f52dfb6444d7   base
pytorch-onnx_1.7-py3.8            634d3cdc-b562-5bf9-a2d4-ea90a478456b   base
  -----------------------------------------------------------------   ----------
Note: Only first 50 records were displayed. To display more use 'limit' parameter.
```

In [55]:

```
software_spec_uid = client.software_specifications.get_uid_by_name("default_py3.8") software_spe
```

Out[55]:

```
'ab9e1b80-f2ce-592c-a7d2-4f2344f77194'
```

In [60]:

```
! pip install -U pyspark==2.1.2.
```

```
Collecting pyspark==2.1.2.
  Downloading pyspark-2.1.2.tar.gz (181.3 MB)
     |████████████████████████████████| 181.3 MB 36 kB/s s eta 0:00:0100:11████
| 80.9 MB 92.0 MB/s eta 0:00:02��██████                | 92.6 MB 92.0 MB/s eta 0:00:01��██
████████████                      | 100.9 MB 92.0 MB/s eta 0:00:01██████████████████████
| 140.3 MB 92.0 MB/s eta 0:00:01��█████████████     | 154.9 MB 92.0 MB/s eta 0:00:01
Collecting py4j==0.10.4
  Downloading py4j-0.10.4-py2.py3-none-any.whl (186 kB)
     |████████████████████████████████| 186 kB 30.2 MB/s eta 0:00:01
Building wheels for collected packages: pyspark
  Building wheel for pyspark (setup.py) ... done
  Created wheel for pyspark: filename=pyspark-2.1.2-py2.py3-none-any.whl size=181625702 s
ha256=a221cb88d5b137507b757b773f7e777bbb5e48df1aa68852a5bd02e74a0a901e
  Stored in directory: /tmp/wsuser/.cache/pip/wheels/5a/33/84/b0060cb291650c5c52279bc5739
87c98609df6564f3290ccfa
Successfully built pyspark
Installing collected packages: py4j, pyspark
  Attempting uninstall: py4j
    Found existing installation: py4j 0.10.9.5
    Uninstalling py4j-0.10.9.5:
      Successfully uninstalled py4j-0.10.9.5
  Attempting uninstall: pyspark
    Found existing installation: pyspark 3.3.1
    Uninstalling pyspark-3.3.1:
      Successfully uninstalled pyspark-3.3.1
ERROR: pip's dependency resolver does not currently take into account all the packages
th at 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
in compatible.
Successfully installed py4j-0.10.4 pyspark-2.1.2
```

In [58]:

```
! wget https://raw.githubusercontent.com/IBM/monitor-wml-model-with-watson-openscale/mast er/da
```

```
--2022-11-13 15:30:12--  https://raw.githubusercontent.com/IBM/monitor-wml-model-with-wat
son-openscale/master/data/additional_feedback_data.json
```

```
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.109.133, 185.1
99.110.133, 185.199.111.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.109.133|:443.
.. connected.
HTTP request sent, awaiting response... 200 OK
Length: 16506 (16K) [text/plain]
Saving to: ‘additional_feedback_data.json’

additional_feedback 100%[===================>]  16.12K  --.-KB/s    in 0.001s

2022-11-13 15:30:12 (19.6 MB/s) - ‘additional_feedback_data.json’ saved [16506/16506]
```

In [72]:

```
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)
```

In [73]:

```
published_model
```

Out[73]:


```
{'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': '2022-11-13T15:47:35.584Z',
  'id': '34aa257f-40e9-4469-8d59-36d032d38a10',
  'modified_at': '2022-11-13T15:47:39.066Z',
  'name': 'Gradient',
  'owner': 'IBMid-6640044ZX7',
  'resource_key': '31d25942-962e-46a0-8ff9-4407d77716d0',
  'space_id': 'a7c26d83-e37a-4e0b-b024-7d3f1f77740b'},
 'system': {'warnings': []}}
```


In [74]:

```
x_train[0]
```

Out[74]:

```
array([4.000e+00, 1.210e+02, 7.600e+01, 2.511e+03, 7.200e+01, 2.000e+00])
```

In [75]:

```
rf.predict([[4.000e+00, 1.210e+02, 7.600e+01, 2.511e+03, 7.200e+01, 2.000e+00]])
```

Out[75]:

```
array([23.2])
```

In [ ]:

```

```

```python
import requests


# NOTE: you must manually set API_KEY below using information retrieved from your IBM Cloud account.
API_KEY = "k0ToNjB4fREMsVxEr0C3pjHT0bNJzgZvVt1S0SikVpMJ"
token_response = requests.post('https://iam.cloud.ibm.com/identity/token', data={"apikey":
API_KEY, "grant_type": 'urn:ibm:params:oauth:grant-type:apikey'}) mltoken = token_response.json()["access_token"]


header = {'Content-Type': 'application/json', 'Authorization': 'Bearer ' + mltoken}


# NOTE: manually define and pass the array(s) of values to be scored in the next line
payload_scoring = {"input_data": [{"field": [['cylinders', 'displacement', 'horsepower', 'weight','model year', 'origin']], "values": [[8,307,130,3504,70,1]]}]}


response_scoring = requests.post('https://us-south.ml.cloud.ibm.com/ml/v4/deployments/3950d430-efb8-43ea-b408-28233df071d7/predictions?version=2022-11-13', json=payload_scoring, headers={'A
print("Scoring response")
print(response_scoring.json())
```