Train the model on IBM

Team ID	PNT2022TMID41512
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
ataset.
```

```
<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 data frame or a series of numeric values.
```

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 correlation of all columns in the dataframe.
corr_table
```

Out[12]:

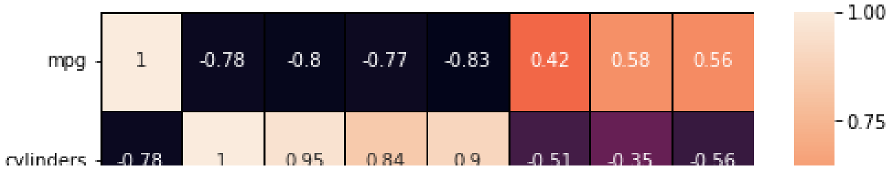
	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
mpg	1.000000	-0.775396	-0.804203	-0.771437	-0.831741	0.420289	0.579267	0.563450
cylinders	-0.775396	1.000000	0.950721	0.838939	0.896017	-0.505419	-0.348746	-0.562543
displacement	-0.804203	0.950721	1.000000	0.893646	0.932824	-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

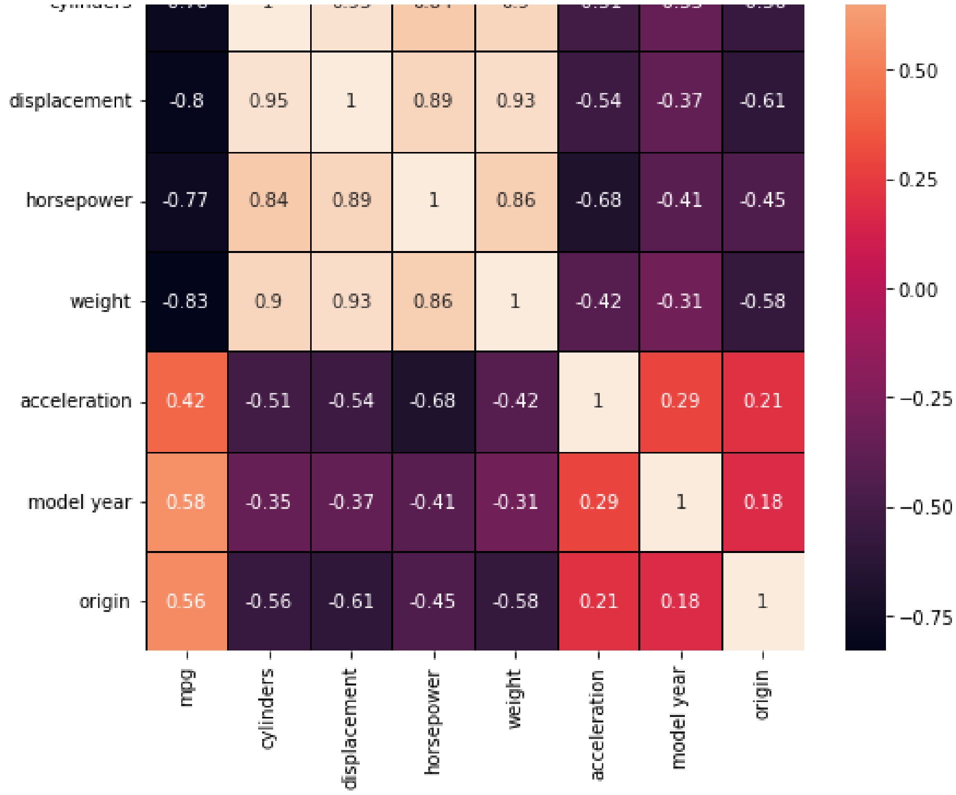
Data Visualizations

Heatmap : which represents correlation between attributes

In [13]:

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

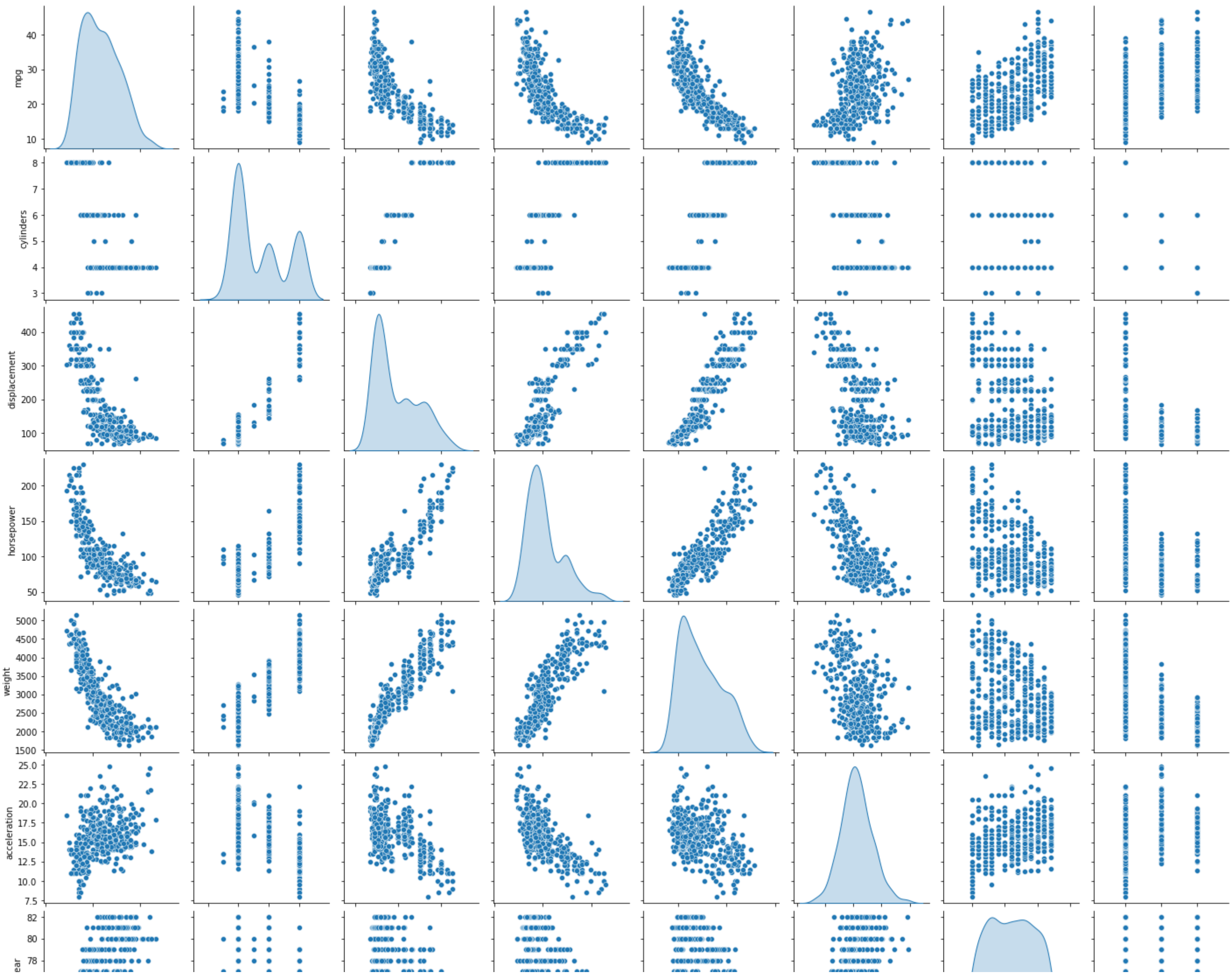


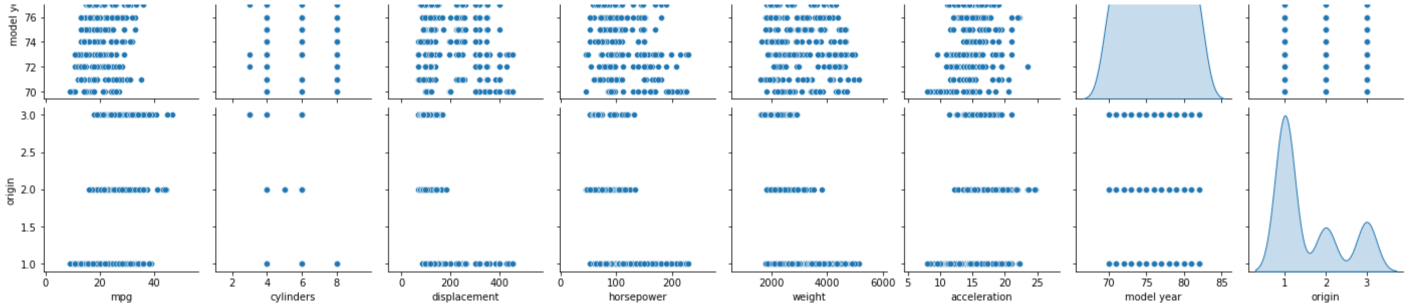


Visualizations of each attributes w.r.t rest of all attributes

In [14]:

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





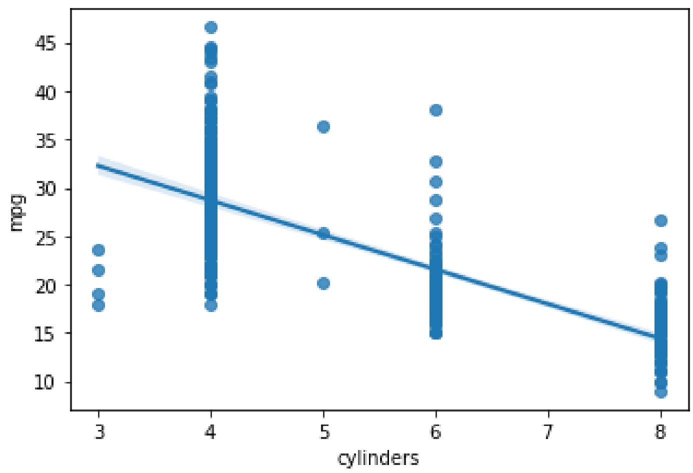
Regression plots(regplot()) creates a regression line between 2 parameters and helps to visualize their linear relationships.

In [15]:

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

Out[15]:

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

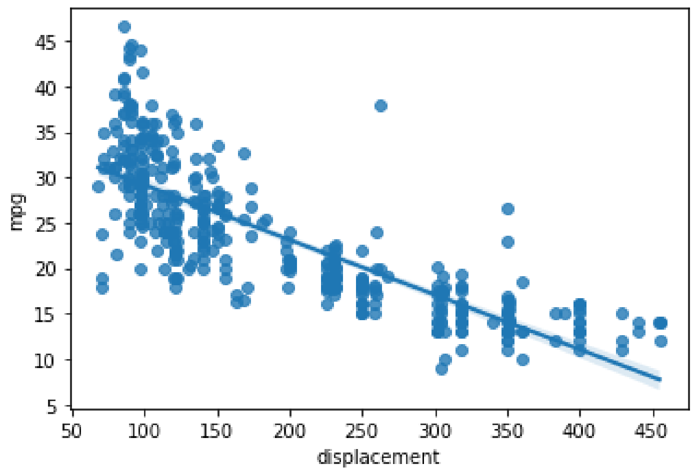


In [16]:

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

Out[16]:

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

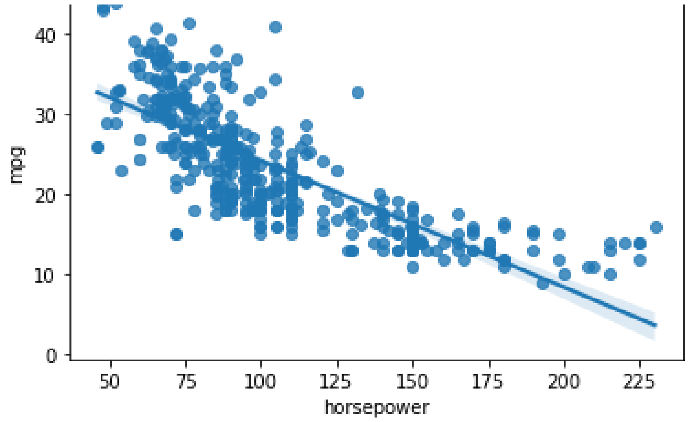


In [17]:

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

Out[17]:

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

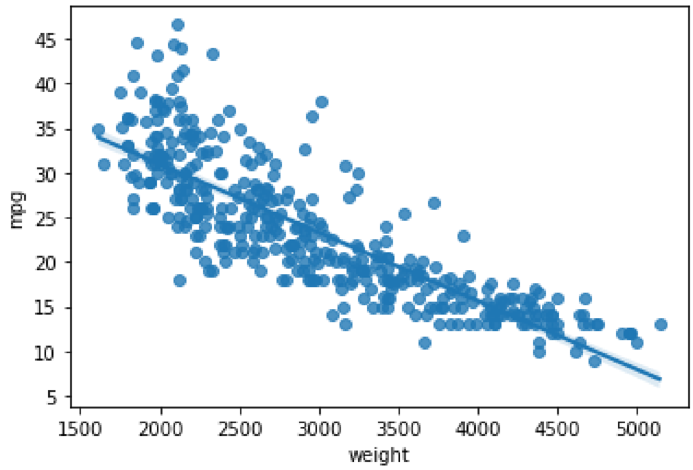


In [18]:

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

Out[18]:

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

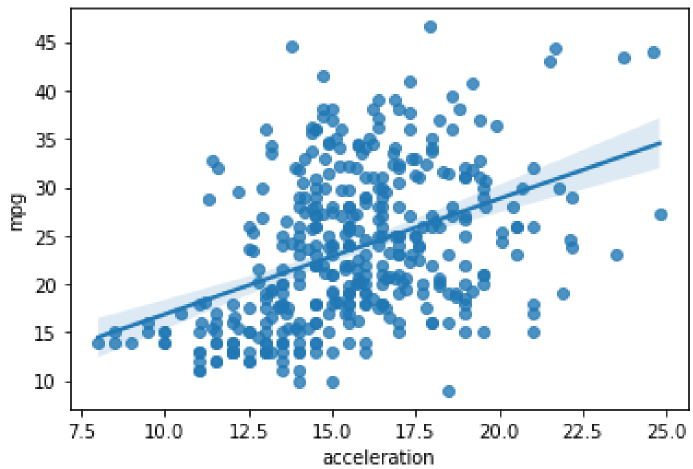


In [19]:

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

Out[19]:

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

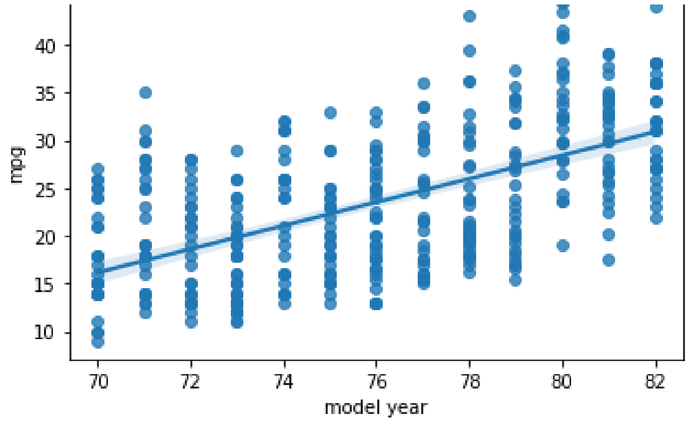


In [20]:

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

Out[20]:

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

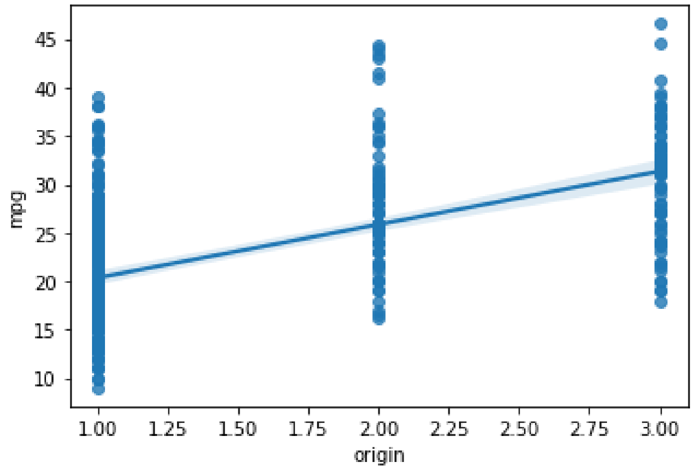


In [21]:

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

Out[21]:

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

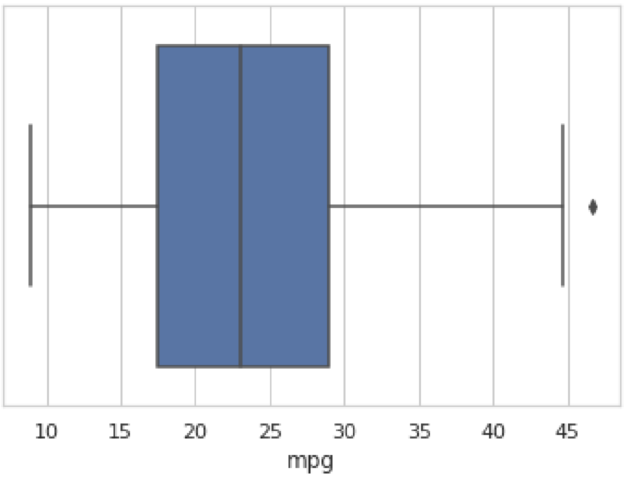


In [22]:

```
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 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 = 1.65588
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 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 = 1.823091
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. ],
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[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_transform(y_train)
y_test = sd.fit_transform(y_test)

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-packages (from ibm-watson-machine-learning) (2022.9.24)
Requirement already satisfied: importlib-metadata in /opt/conda/envs/Python-3.9/lib/python3.9/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/python3.9/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-packages (from ibm-watson-machine-learning) (1.26.7)
Requirement already satisfied: lomond in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (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/python3.9/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/python3.9/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-watson-machine-learning) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/envs/Python-3.9/lib/python3.9/site-packages (from pandas<1.5.0,>=0.24.2->ibm-watson-machine-learning) (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/site-packages (from requests->ibm-watson-machine-learning) (3.3)
Requirement already satisfied: charset-normalizer~=2.0.0 in /opt/conda/envs/Python-3.9/lib/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_name)['metadata']['id'])
```

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_learning'}], 'description': '', 'name': 'models', 'scope': {'bss_account_id': 'd12096019c744baabc99e2caa9c44ac5'}, 'stage': {'production': False}, 'status': {'state': 'active'}, 'storage': {'properties': {'bucket_name': '2e6d79af-2319-41ef-8bb1-13843958cd79', 'bucket_region': 'us-south', 'credentials': {'admin': {'access_key_id': 'e2dcdab6300f4292acfd3a9e99fe8419', 'api_key': 'Ccb36wfmVayFlvEWymudO7rYIVHUT18VXxjXXSf8wNVx', 'secret_access_key': '09d27d5ba8570a63f8ecd4477903c61c66702acd0a8a0cb2', 'service_id': 'ServiceId-113a7385-0acf-4aca-b0a4-f20ee5949b94'}, 'editor': {'access_key_id': '0b31cfa63a054a40bbe5cbe6a1ddc189', 'api_key': 'Nrtr6aPyPH387BlYG2rJrcg3kiA1-ZVXbGR3J7CZQK9e', 'resource_key_crn': 'crn:v1:bluemix:public:cloud-object-storage:global:a/d12096019c744baabc99e2caa9c44ac5:71972f87-6ebf-4b35-907f-5b09ff80a63a::', 'secret_access_key': '8db16c6ef99ec8799a31e00fa98d5952b212f3198510de25', 'service_id': 'ServiceId-48a7874c-09b6-4ba0-8c14-d4b63928000f'}, 'viewer': {'access_key_id': '6a971a0391e947e7a10aa6d0a205eee2', 'api_key': 'p_RHNGsyVx7ybtSaRSn8Osq2ZkOsOhj8PPAYQEdgGoLK', 'resource_key_crn': 'crn:v1:bluemix:public:cloud-object-storage:global:a/d12096019c744baabc99e2caa9c44ac5:71972f87-6ebf-4b35-907f-5b09ff80a63a::', 'secret_access_key': 'c530568f37883f9c765343301136c7eb763cc3ccf4197718', 'service_id': 'ServiceId-1a4e051b-6867-4ac8-acab-b942b7b43a75'}}, 'endpoint_url': 'https://s3.us-south.cloud-object-storage.appdomain.cloud', 'guid': '71972f87-6ebf-4b35-907f-5b09ff80a63a', 'resource_crn': 'crn:v1:bluemix:public:cloud-object-storage:global:a/d12096019c744baabc99e2caa9c44ac5:71972f87-6ebf-4b35-907f-5b09ff80a63a::'}, 'type': 'bmcos_object_storage'}}, 'metadata': {'created_at': '2022-11-12T15:24:43.319Z', 'creator_id': 'IBMid-6640044ZX7', 'id': 'a7c26d83-e37a-4e0b-b024-7d3f1f77740b', 'updated_at': '2022-11-12T15:25:03.183Z', 'url': '/v2/spaces/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]:

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

Out[55]:

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

In [60]:

```python
!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]:

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

```
--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={'Authorization': 'Bearer ' + mltoken})
print("Scoring response")
print(response_scoring.json())
```