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-
0isa20g1npvfgm'
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
                          307.0
                                               3504
                                                            12.0
                                       130
70
1 15.0
                8
                          350.0
                                                            11.5
                                       165
                                              3693
```

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()

False mpg cylinders False displacement False False horsepower 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
dtyna: hool	

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):
```

- 0 0.	(10 10.		
#	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
dtype	es: float64(4)	, int64(4), obje	ct(1)
memo	ry 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.

vojab+	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
mpg cylinders displacement horsepower weight acceleration model year origin	accelerat 0.420 -0.505 -0.543 -0.684 -0.417 1.000 0.288 0.205	289 0.57 419 -0.34 684 -0.37 259 -0.41 457 -0.30 000 0.28 137 1.00	year origin 9267 0.563450 8746 -0.562543 0164 -0.609409 1651 -0.453669 6564 -0.581024 8137 0.205873 0000 0.180662 0662 1.000000		

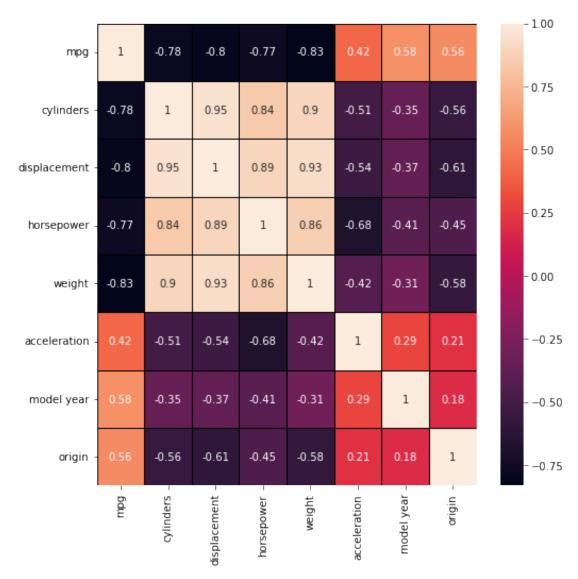
Data Visualizations

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.

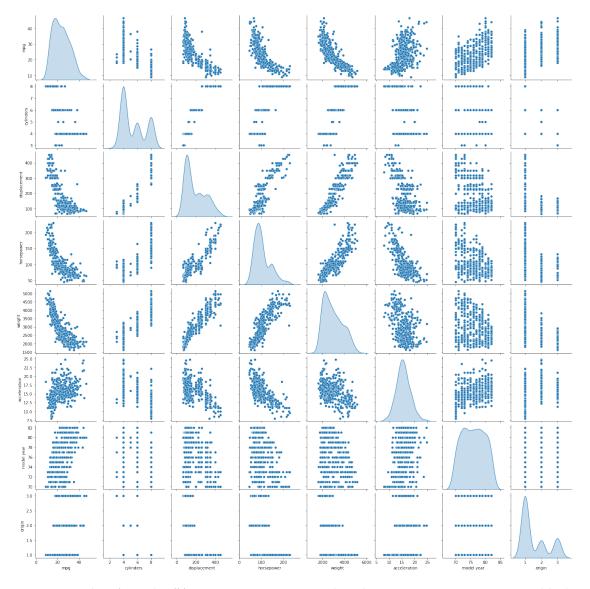
fig=plt.gcf()

fig.set_size_inches(8,8)



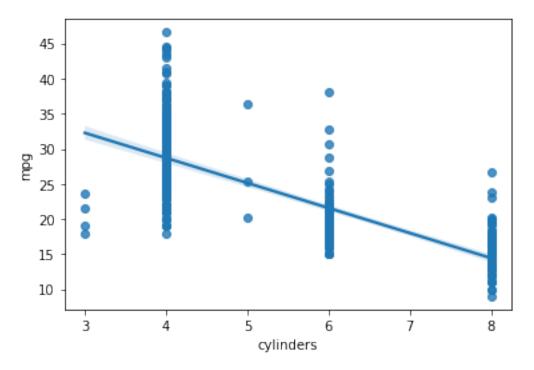
Visualizations of each attributes w.r.t rest of all attributes

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

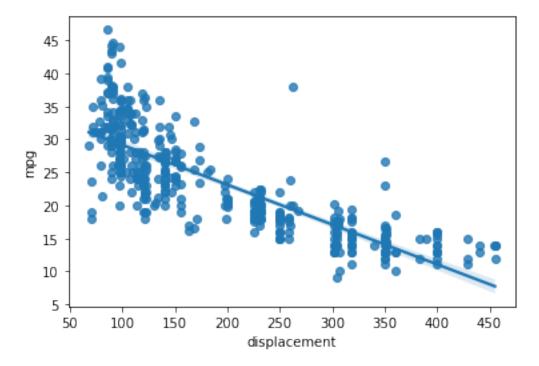


 $Regression\ plots(regplot())\ creates\ a\ regression\ line\ between\ 2\ parameters\ and\ helps\ to\ visualize\ their\ linear\ relationships.$

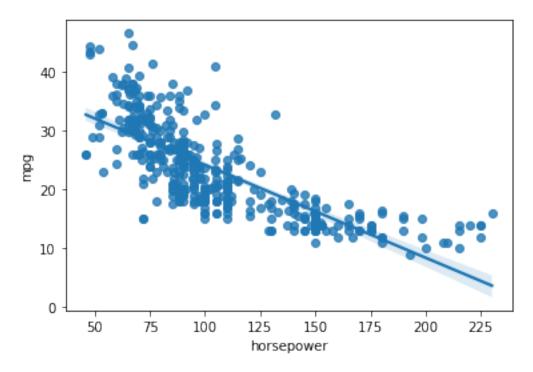
```
sns.regplot(x="cylinders", y="mpg", data=dataset)
<AxesSubplot:xlabel='cylinders', ylabel='mpg'>
```



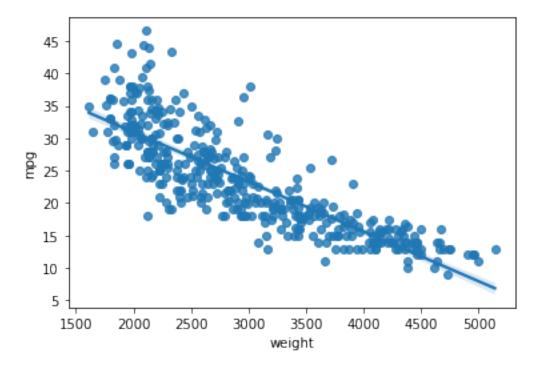
sns.regplot(x="displacement", y="mpg", data=dataset)
<AxesSubplot:xlabel='displacement', ylabel='mpg'>



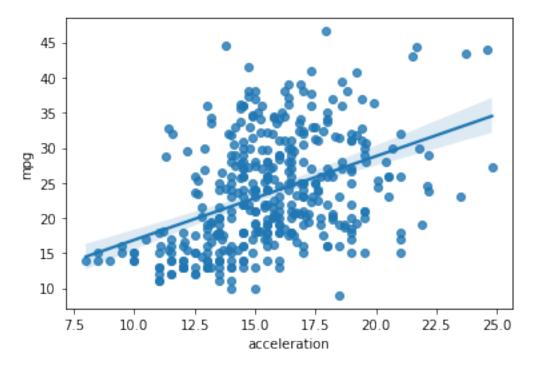
sns.regplot(x="horsepower", y="mpg", data=dataset)
<AxesSubplot:xlabel='horsepower', ylabel='mpg'>



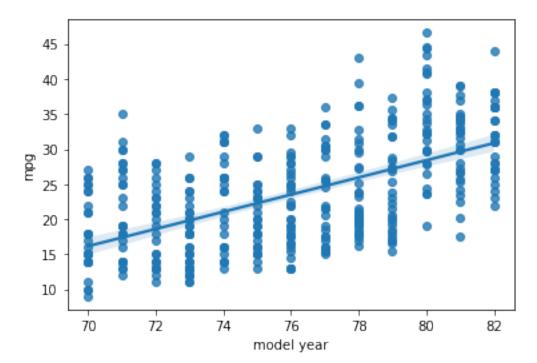
sns.regplot(x="weight", y="mpg", data=dataset)
<AxesSubplot:xlabel='weight', ylabel='mpg'>



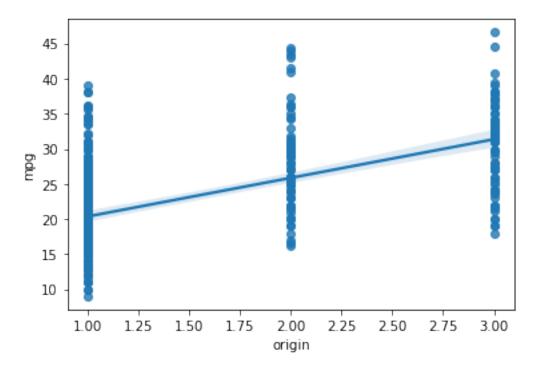
sns.regplot(x="acceleration", y="mpg", data=dataset)
<AxesSubplot:xlabel='acceleration', ylabel='mpg'>



sns.regplot(x="model year", y="mpg", data=dataset)
<AxesSubplot:xlabel='model year', ylabel='mpg'>

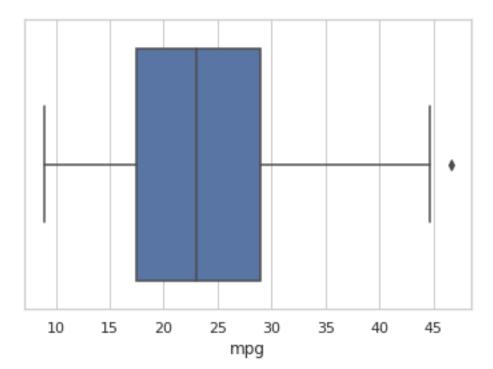


sns.regplot(x="origin", y="mpg", data=dataset)
<AxesSubplot:xlabel='origin', ylabel='mpg'>



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 \dot{c} 0.001: we say there is strong evidence that the correlation is significant. the p-value is \dot{c} 0.05: there is moderate evidence that the correlation is significant. the p-value is \dot{c} 0.1: there is weak evidence that the correlation is significant. the p-value is \dot{c} 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 \dot{c} 0.001, the correlation between cylinders and mpg is statistically significant, and the coefficient of \sim -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 \dot{c} 0.001, the correlation between horsepower and mpg is statistically significant, and the coefficient of \sim -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:
                                          R-squared:
                                    mpg
```

0.717 OLS Adj. R-squared: Model: 0.713 Least Squares F-statistic: Method: 165.5 Wed, 16 Nov 2022 Prob (F-statistic): Date: 4.84e-104 Log-Likelihood: Time: 03:33:54 -1131.1 AIC: No. Observations: 398 2276. Df Residuals: BIC: 391 2304.

Df Model: 6

Covariance Type: nonrobust

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

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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
array([[8.000e+00, 3.070e+02, 1.300e+02, 3.504e+03, 7.000e+01,
1.000e+001,
       [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+001,
       [4.000e+00, 1.200e+02, 7.900e+01, 2.625e+03, 8.200e+01,
1.000e+001.
       [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
array([[18.],
       [15.],
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- [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

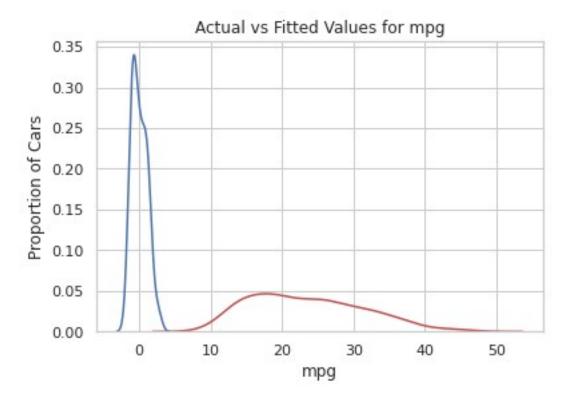
Normalisation

```
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,
                                 -0.718734881,
                             [-0.86550411, -1.21071964, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.31380657, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.44960856, -1.4496085, -1.44960856, -1.44960856, -1.4496085, -1.44960856, -1.44960856, -1.44960856, -1.4
0.80118763,
                                    0.53032865],
                             [0.30154098, 0.53055088, -0.12892518, 0.35799706, -1.3423672]
                                -0.718734881.
                             [-0.86550411, -1.00023639, -0.87990201, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.89319732, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.8931972, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192, -0.893192,
0.26000806,
                                     0.5303286511)
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,
```

```
2.74324153, -0.43685318, 0.33877968, -
        1.43759289,
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

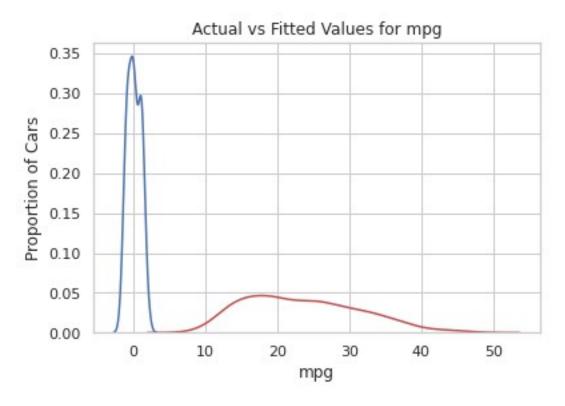
random forest regressor

from sklearn.ensemble import RandomForestRegressor

```
rf=
RandomForestRegressor(n estimators=10, random state=0, criterion='mae')
rf.fit(x train,y_train)
/tmp/wsuser/ipykernel 165/4164760693.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,
                     1.89133811, -0.52734368, 0.26380183, -
        1.36778593,
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,
                     1.0278002 , -0.82596233, 0.97221318, -
       -0.39677881,
0.18735794,
       -0.03610954, -0.59844336, -0.92808732, 1.28375904, -
1.471030321)
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)

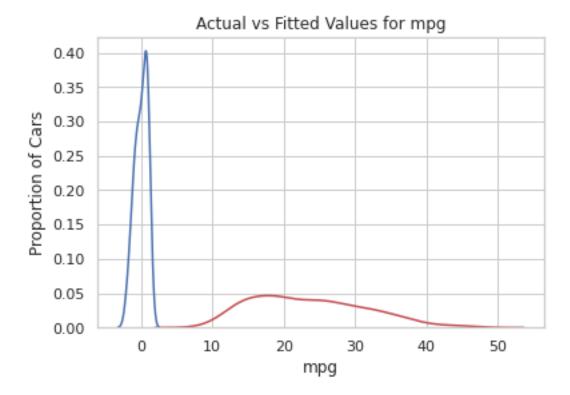
0.08275507905585772

np.sqrt(mean_squared_error(y_test,y_pred2))

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

```
"apikey": "c0AaDte5MvL14V1NwKhlSqGHH34bvKX 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
                               020d69ce-7ac1-5e68-ac1a-31189867356a
kernel-spark3.2-scala2.12
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
spark-mllib 3.0-scala 2.12
                               09f4cff0-90a7-5899-b9ed-1ef348aebdee
base
                               0b848dd4-e681-5599-be41-b5f6fccc6471
pytorch-onnx rt22.1-py3.9
base
ai-function 0.1-py3.6
                               Ocdb0f1e-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
                               10ac12d6-6b30-4ccd-8392-3e922c096a92
pytorch 1.1-py3.6
base
                               111e41b3-de2d-5422-a4d6-bf776828c4b7
tensorflow 1.15-py3.6-ddl
autoai-kb rt22.2-py3.10
                               125b6d9a-5b1f-5e8d-972a-b251688ccf40
runtime-22.1-py3.9
                               12b83a17 - 24d8 - 5082 - 900f - 0ab31fbfd3cb
base
```

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

```
493bcb95-16f1-5bc5-bee8-81b8af80e9c7
pmml-3.0 4.3
base
                              49403dff-92e9-4c87-a3d7-a42d0021c095
spark-mllib_2.4-r_3.6
base
xqboost 0.90-py3.6
                              4ff8d6c2-1343-4c18-85e1-689c965304d3
base
                              50f95b2a-bc16-43bb-bc94-b0bed208c60b
pytorch-onnx 1.1-py3.6
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
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
                              5d3232bf-c86b-5df4-a2cd-7bb870a1cd4e
cuda-py3.8
base
autoai-kb_3.1-py3.7
                              632d4b22-10aa-5180-88f0-f52dfb6444d7
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.
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)
Requirement already satisfied: pyspark==2.1.2 in
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages (2.1.2)
Requirement already satisfied: py4j==0.10.4 in /opt/conda/envs/Python-
3.9/lib/python3.9/site-packages (from pyspark==2.1.2) (0.10.4)
```

```
# 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)
Traceback (most recent call last):
"/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm_watson_mac
hine_learning/libs/repo/mlrepositoryclient/model_collection.py", line
254, in save scikit pipeline model
    model artifact = self. create pipeline model(artifact,
query param)
 File
"/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mac
hine learning/libs/repo/mlrepositoryclient/model collection.py", line
514, in create pipeline model
    model artifact =
self. create pipeline model v4 cloud(model artifact, query param)
 File
"/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mac
hine learning/libs/repo/mlrepositoryclient/model collection.py", line
1005, in create pipeline model v4 cloud
    model output =
self.repository api.ml assets model creation v4 cloud(model input,
query_param, headers)
 File
"/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mac
hine learning/libs/repo/swagger_client/apis/repository_api.py", line
301, in ml assets model creation v4 cloud
    (data) =
self.ml assets model creation v4 cloud with http info(models input,que
ry param, headers, **kwargs)
 File
"/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mac
hine learning/libs/repo/swagger client/apis/repository api.py", line
374, in ml assets model creation v4 cloud with http info
    return self.api client.call api(resource path, 'POST',
"/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mac
hine learning/libs/repo/swagger client/api client.py", line 386, in
call api
```

```
return self. call api(resource path, method,
  File
"/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm_watson_mac
hine learning/libs/repo/swagger client/api client.py", line 206, in
call api
    response data = self.request(method, url,
  File
"/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mac
hine learning/libs/repo/swagger client/api client.py", line 421, in
request
    return self.rest client.POST(url,
"/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mac
hine learning/libs/repo/swagger client/rest.py", line 230, in POST
    return self.request("POST", url,
"/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mac
hine_learning/libs/repo/swagger_client/rest.py", line 202, in request
    raise ApiException(http resp=r)
ibm watson machine learning.libs.repo.swagger client.rest.ApiException
: (400)
Reason: Bad Request
HTTP response headers: HTTPHeaderDict({'Date': 'Wed, 16 Nov 2022
03:34:03 GMT', 'Content-Type': 'application/json', 'Content-Length':
'292', 'Connection': 'keep-alive', 'server-timing':
'intid;desc=e7597afd3f05a666, intid;desc=e7597afd3f05a666', 'Strict-
Transport-Security': 'max-age=31536000; includeSubDomains', 'CF-Cache-Status': 'DYNAMIC', 'Server': 'cloudflare', 'CF-RAY':
'76ad2b2d4c29e470-DFW'})
HTTP response body: {
  "trace": "f9988c9fccf6fb2c9d7662c5c902f67a",
  "errors": [{
    "code": "invalid request entity",
    "message": "Invalid request entity: Unsupported software
specification 'default py3.6'.",
    "more info": "https://cloud.ibm.com/apidocs/machine-learning"
  "status code": "400"
}
Publishing model failed.
Reason: (400)
Reason: Bad Request
HTTP response headers: HTTPHeaderDict({'Date': 'Wed, 16 Nov 2022
03:34:03 GMT', 'Content-Type': 'application/json', 'Content-Length':
'292', 'Connection': 'keep-alive', 'server-timing':
'intid;desc=e7597afd3f05a666, intid;desc=e7597afd3f05a666', 'Strict-
Transport-Security': 'max-age=31536000; includeSubDomains', 'CF-Cache-
```

```
Status': 'DYNAMIC', 'Server': 'cloudflare', 'CF-RAY':
'76ad2b2d4c29e470-DFW'})
HTTP response body: {
  "trace": "f9988c9fccf6fb2c9d7662c5c902f67a",
  "errors": [{
    "code": "invalid request entity",
    "message": "Invalid request entity: Unsupported software
specification 'default py3.6'.",
    "more info": "https://cloud.ibm.com/apidocs/machine-learning"
  }],
  "status_code": "400"
ApiException
                                          Traceback (most recent call
last)
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine_learning/models.py in _publish_from_object_cloud(self, model,
meta props, training data, training target, pipeline, feature names,
label column names, project id)
                        query_param_for_repo client =
   2585
self. client. params()
-> 2586
                        saved model =
self. client.repository. ml repository client.models.save(model artifa
   2587
query param=query param for repo client)
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/mlrepositoryclient/model collection.py in
save(self, artifact, query param)
                if
artifact.meta.prop(MetaNames.TYPE).startswith("scikit-learn"):
--> 213
                    return self. save scikit pipeline model(artifact,
query_param)
    214
                elif
artifact.meta.prop(MetaNames.TYPE).startswith("xgboost"):
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/mlrepositoryclient/model collection.py in
save scikit pipeline model(self, artifact, query param)
    265
                    print(traceback.format exc())
--> 266
                    raise e
    267
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/mlrepositoryclient/model collection.py in
save scikit pipeline model(self, artifact, query param)
```

```
253
                    if artifact.uid is None:
--> 254
                        model artifact =
self._create_pipeline_model(artifact, query_param)
                    else:
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/mlrepositoryclient/model collection.py in
create pipeline model(self, model artifact, query param)
            def create pipeline model(self, model artifact,
query_param=None):
--> 514
                model artifact =
self. create pipeline model v4 cloud(model artifact, query param)
                return model artifact
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/mlrepositoryclient/model collection.py in
create pipeline model v4 cloud(self, model artifact, query param)
   1004
-> 1005
                model_output =
self.repository api.ml assets model creation v4 cloud(model input,
query param, headers)
   1006
                if model output is not None:
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/swagger client/apis/repository api.py in
ml assets model creation v4 cloud(self, models input, query param,
headers, **kwargs)
    300
                else:
--> 301
                    (data) =
self.ml assets model_creation_v4_cloud_with_http_info(models_input,que
ry param, headers, **kwargs)
    302
                    return data
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/swagger client/apis/repository api.py in
ml assets model creation v4 cloud with http info(self, models input,
query param, headers, **kwargs)
    373
                return self.api client.call api(resource path, 'POST',
--> 374
    375
                                                    path params,
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/swagger client/api client.py in call api(self,
resource path, method, path params, query params, header params, body,
post params, files, response type, auth settings, callback,
return http data only)
                if callback is None:
    385
                    return self.__call_api(resource_path, method,
--> 386
    387
                                           path params, query params,
header params,
```

```
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine_learning/libs/repo/swagger_client/api_client.py in
  call_api(self, resource_path, method, path params, query params,
header params, body, post params, files, response type, auth settings,
callback, return http data only)
    205
--> 206
                response data = self.request(method, url,
    207
query params=query params,
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/swagger client/api client.py in request(self,
method, url, query params, headers, post params, body)
                elif method == "POST":
    420
                    return self.rest_client.POST(url,
--> 421
    422
query params=query params,
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/swagger client/rest.py in POST(self, url,
headers, query params, post params, body)
            def POST(self, url, headers=None, query params=None,
    229
post params=None, body=None):
--> 230
                return self.request("POST", url,
    231
                                    headers=headers,
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/libs/repo/swagger client/rest.py in request(self, method,
url, query_params, headers, body, post params)
    201
        if r.status not in range(200, 206):
--> 202
                    raise ApiException(http resp=r)
    203
ApiException: (400)
Reason: Bad Request
HTTP response headers: HTTPHeaderDict({'Date': 'Wed, 16 Nov 2022
03:34:03 GMT', 'Content-Type': 'application/json', 'Content-Length':
'292', 'Connection': 'keep-alive', 'server-timing':
'intid;desc=e7597afd3f05a666, intid;desc=e7597afd3f05a666', 'Strict-
Transport-Security': 'max-age=31536000; includeSubDomains', 'CF-Cache-
Status': 'DYNAMIC', 'Server': 'cloudflare', 'CF-RAY':
'76ad2b2d4c29e470-DFW'})
HTTP response body: {
  "trace": "f9988c9fccf6fb2c9d7662c5c902f67a",
  "errors": [{
    "code": "invalid request entity",
    "message": "Invalid request entity: Unsupported software
specification 'default py3.6'.",
    "more info": "https://cloud.ibm.com/apidocs/machine-learning"
```

```
}],
  'status code": "400"
During handling of the above exception, another exception occurred:
WMLClientError
                                           Traceback (most recent call
last)
/tmp/wsuser/ipykernel 165/2277397662.py in <module>
      5 }
      6
----> 7 published model = client.repository.store model(
      8
            model=rf,
      9
            meta props=metadata,
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/repository.py in store model(self, model, meta props,
training data, training target, pipeline, feature names,
label column names, subtrainingId, round number, experiment metadata)
    410
    411
                return self. client. models.store(model,
--> 412
meta props=meta props, training data=training data,
training target=training target, pipeline=pipeline,
feature names=feature names.
label column names=label column names, subtrainingId=subtrainingId, roun
d number=round number,experiment metadata=experiment metadata)
    413
    414
            @docstring parameter({'str type': STR TYPE NAME})
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine learning/models.py in store(self, model, meta props,
training data, training target, pipeline, version, artifactid,
feature names, label column names, subtrainingId, round number,
experiment metadata)
   1609
                                     meta props=new meta props)
   1610
                            else:
-> 1611
                                 saved model =
self. publish from object cloud(model=model,
   1612
meta_props=meta_props,
   1613
training data=training data,
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/ibm watson mach
ine_learning/models.py in _publish_from_object_cloud(self, model,
meta_props, training_data, training_target, pipeline, feature_names,
label column names, project id)
   2589
```

```
2590
                except Exception as e:
-> 2591
                    raise WMLClientError(u'Publishing model failed.',
e)
   2592
            def upload autoai model content(self, file, url,
   2593
qparams):
WMLClientError: Publishing model failed.
Reason: (400)
Reason: Bad Request
HTTP response headers: HTTPHeaderDict({'Date': 'Wed, 16 Nov 2022
03:34:03 GMT', 'Content-Type': 'application/json', 'Content-Length':
'292', 'Connection': 'keep-alive', 'server-timing':
'intid;desc=e7597afd3f05a666, intid;desc=e7597afd3f05a666', 'Strict-
Transport-Security': 'max-age=31536000; includeSubDomains', 'CF-Cache-
Status': 'DYNAMIC', 'Server': 'cloudflare', 'CF-RAY':
'76ad2b2d4c29e470-DFW'})
HTTP response body: {
  "trace": "f9988c9fccf6fb2c9d7662c5c902f67a",
  "errors": [{
    "code": "invalid request entity",
    "message": "Invalid request entity: Unsupported software
specification 'default py3.6'.",
    "more info": "https://cloud.ibm.com/apidocs/machine-learning"
  }],
  "status code": "400"
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
--2022-11-16 03:36:43--
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'
--2022-11-16 03:36:43--
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'
# 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': '2022-11-16T03:36:38.795Z',
  'id': '155b0257-fd27-455f-ab11-830c50d82d81',
  'modified at': '2022-11-16T03:36:42.209Z',
  'name': 'Gradient',
  'owner': 'IBMid-6620041XAB'.
  'resource key': 'fa8d1e62-bcc4-426e-88b9-e9c92ae3cb56',
  'space id': 'ec50822e-7eed-4693-abad-e892683a6177'},
 'system': {'warnings': []}}
# 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]
array([ 1.46858608, 2.48230464, 2.97856512, 1.62455076, -
1.61295698,
       -0.71873488])
rf.predict([[1.46858608, 2.48230464, 2.97856512, 1.62455076, -
1.61295698,
       -0.71873488]])
array([-1.18663161])
```