JacobsonDSC550Week4

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In the Week 4 Exercise, you will build a linear regression model to predict fuel efficiency (miles per gallon) of automobiles. Download the auto-mpg.csv dataset from: Auto-mpg dataset. Load the data as a Pandas data frame and ensure that it imported correctly.

[30]:
```
import pandas as pd
mpg = pd.read_csv("auto-mpg.csv")
rows,columns=mpg.shape
print("There are {} rows and {} columns.".format(rows,columns))
mpg[mpg['origin']==3].head()
```

```
There are 398 rows and 9 columns.
```

[30]:
```
     mpg  cylinders  displacement horsepower  weight  acceleration  \
14  24.0          4         113.0         95    2372          15.0
18  27.0          4          97.0         88    2130          14.5
29  27.0          4          97.0         88    2130          14.5
31  25.0          4         113.0         95    2228          14.0
53  31.0          4          71.0         65    1773          19.0

    model year  origin              car name
14          70       3  toyota corona mark ii
18          70       3           datsun pl510
29          71       3           datsun pl510
31          71       3          toyota corona
53          71       3    toyota corolla 1200
```

Begin by prepping the data for modeling: * Remove the car name column. * The horsepower column values likely imported as a string data type. Figure out why and replace any strings with the column mean. * Create dummy variables for the origin column. (It appears that 1 Is American, 2 is European, 3 is Japanese)

[31]:
```
mpg = mpg.drop(columns=['car name'])

# Replace string horsepower values with the mean value for the column
horsepower_mean = pd.to_numeric(mpg['horsepower'], errors='coerce').dropna().
  ↪mean()
mask = pd.to_numeric(mpg['horsepower'], errors='coerce').isna()
```

```
print("These are the non-numeric values in the 'horsepower' column, which␣
 ↪caused it to be read as a string:\n",mpg['horsepower'][mask],"\nWe are␣
 ↪replacing them with the mean of: ",horsepower_mean)
modified = mpg['horsepower'].copy()
modified[mask]=horsepower_mean
mpg['horsepower']=modified
mpg['horsepower'] = pd.to_numeric(mpg['horsepower'])

# Add dummy variables (binaries) for origin values
mpg['american']=mpg['origin']==1
mpg['european']=mpg['origin']==2
mpg['japanese']=mpg['origin']==3
```

```
These are the non-numeric values in the 'horsepower' column, which caused it to
be read as a string:
 32     ?
126    ?
330    ?
336    ?
354    ?
374    ?
Name: horsepower, dtype: object
We are replacing them with the mean of:  104.46938775510205
```

Create a correlation coefficient matrix and/or visualization. Are there features highly correlated with mpg?

[32]:
```
mpg.corr()
```

[32]:

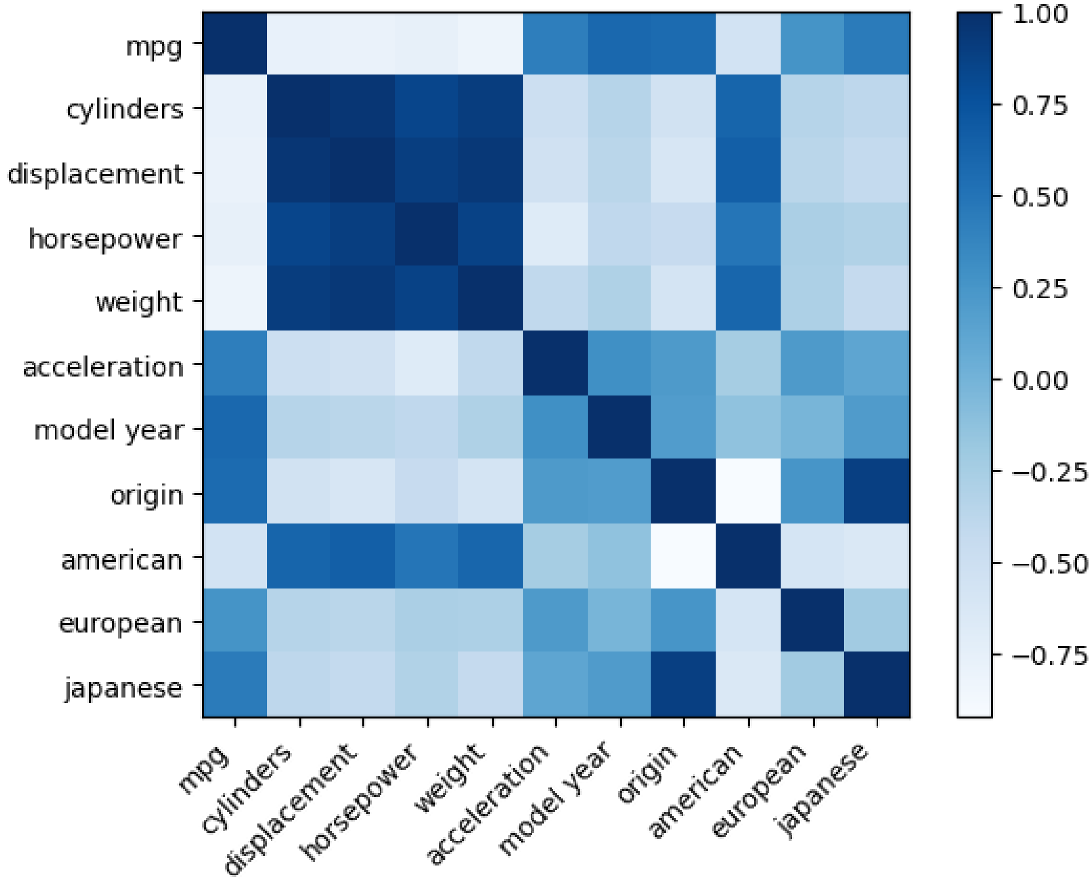
	mpg	cylinders	displacement	horsepower	weight	\
mpg	1.000000	-0.775396	-0.804203	-0.771437	-0.831741	
cylinders	-0.775396	1.000000	0.950721	0.838939	0.896017	
displacement	-0.804203	0.950721	1.000000	0.893646	0.932824	
horsepower	-0.771437	0.838939	0.893646	1.000000	0.860574	
weight	-0.831741	0.896017	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	
american	-0.568192	0.604351	0.651407	0.486083	0.598398	
european	0.259022	-0.352861	-0.373886	-0.281258	-0.298843	
japanese	0.442174	-0.396479	-0.433505	-0.321325	-0.440817	

	acceleration	model year	origin	american	european	japanese
mpg	0.420289	0.579267	0.563450	-0.568192	0.259022	0.442174
cylinders	-0.505419	-0.348746	-0.562543	0.604351	-0.352861	-0.396479
displacement	-0.543684	-0.370164	-0.609409	0.651407	-0.373886	-0.433505
horsepower	-0.684259	-0.411651	-0.453669	0.486083	-0.281258	-0.321325
weight	-0.417457	-0.306564	-0.581024	0.598398	-0.298843	-0.440817

```
acceleration      1.000000    0.288137  0.205873 -0.250806  0.204473  0.109144
model year        0.288137    1.000000  0.180662 -0.139883 -0.024489  0.193101
origin            0.205873    0.180662  1.000000 -0.924486  0.246332  0.886596
american         -0.250806   -0.139883 -0.924486  1.000000 -0.597198 -0.643317
european          0.204473   -0.024489  0.246332 -0.597198  1.000000 -0.229895
japanese          0.109144    0.193101  0.886596 -0.643317 -0.229895  1.000000
```

[34]:

```python
# Adapted from https://www.geeksforgeeks.org/
 ↪create-a-correlation-matrix-using-python/
import matplotlib.pyplot as plt
from sklearn import datasets
import pandas as pd
matrix = mpg.corr()

# plotting correlation matrix
plt.imshow(matrix, cmap='Blues')

# adding colorbar
plt.colorbar()

# extracting variable names
variables = []
for i in matrix.columns:
    variables.append(i)

# Adding labels to the matrix
plt.xticks(range(len(matrix)), variables, rotation=45, ha='right')
plt.yticks(range(len(matrix)), variables)

# Display the plot
plt.show()
```



Looking for correlations values greater than 0.5, the following values are all closely correlated with each other: * cylinders * displacement * horsepower * weight

These same values are inversely correlated with mpg.

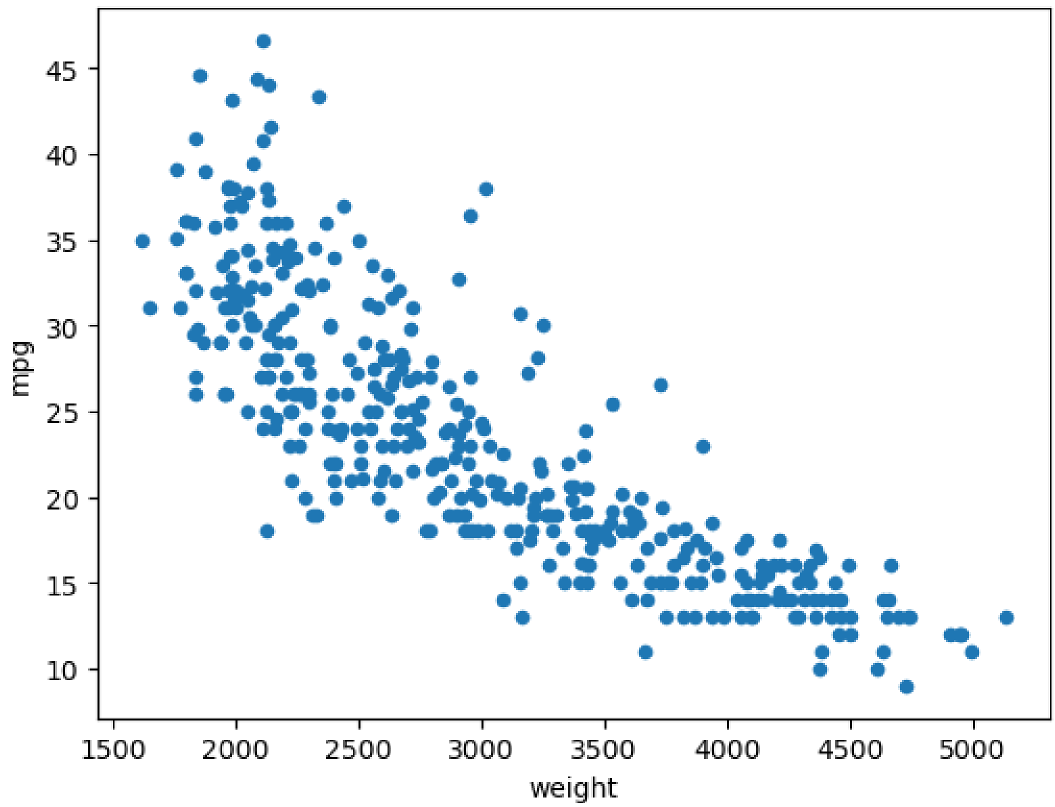
Also, american is correlated with cylinders and displacement, and inversely correlated with mpg.

Additionally, mpg and model year are correlated.

Plot mpg versus weight. Analyze this graph and explain how it relates to the corresponding correlation coefficient.

[36]:
```
mpg.plot.scatter(x='weight', y='mpg')
```

[36]:
```
<Axes: xlabel='weight', ylabel='mpg'>
```



Weight and mpg are inversely correlated fairly strongly with a coefficient of -0.831741. You can see this on the graph in the fact that a trend line would slope downwards towards the right. You can also see that the pattern is a downward slope and might be modeled better logarithmically, but is still modeled very well linearly. Mpg clearly decreases, on average, as weight increases.

Randomly split the data into 80% training data and 20% test data, where your target is mpg.

[38]:
```
from sklearn.model_selection import train_test_split

data = mpg.drop('mpg', axis=1)
target = mpg['mpg']

# Split the data into 80% training and 20% testing
data_train, data_test, target_train, target_test = train_test_split(data,␣
↪target, test_size=0.2, random_state=42)

print(data_train.shape, data_test.shape)
print(target_train.shape, target_test.shape)
```

```
(318, 10) (80, 10)
(318,) (80,)
```

Train an ordinary linear regression on the training data.

[42]:
```
from sklearn.linear_model import LinearRegression
linear_model = LinearRegression()
linear_model.fit(data_train,target_train)
print(linear_model.intercept_)
print(linear_model.coef_)

# Obtain the predictions
target_pred = linear_model.predict(data_test)
```

```
-21.971261257955092
[-0.16373048  0.01958399 -0.01334457 -0.00707275  0.07335016  0.82739747
  0.88430052 -0.97974802  1.07519552 -0.0954475 ]
```

Calculate R2, RMSE, and MAE on both the training and test sets and interpret your results.

[55]:
```
import sklearn.metrics as metrics
import numpy as np

def print_model_metrics(test,pred):
    mae = metrics.mean_absolute_error(test, pred)
    mse = metrics.mean_squared_error(test, pred)
    rmse = np.sqrt(mse) # or mse**(0.5)
    r2 = metrics.r2_score(test, pred)

    print("R-Squared:", r2)
    print("Root Mean Squared Error (RMSE):", rmse)
    print("Mean Absolute Error (MAE): ",mae)

print("Linear Regression Model Metrics:")
print_model_metrics(target_test,target_pred)
```

```
Linear Regression Model Metrics:
R-Squared: 0.8449006123776615
Root Mean Squared Error (RMSE): 2.8877573478836327
Mean Absolue Error (MAE):  2.2875867704421085
```

Pick another regression model and repeat the previous two steps. Note: Do NOT choose logistic regression as it is more like a classification model.

[56]:
```
from sklearn.preprocessing import PolynomialFeatures

# Train polynomial regression model on the whole dataset
poly = PolynomialFeatures(degree = 2, include_bias=False)
train_poly = poly.fit_transform(data_train)
test_poly = poly.fit_transform(data_test)
```

```python
poly_model = LinearRegression()
poly_model.fit(train_poly, target_train)
poly_pred=poly_model.predict(test_poly)

print("Polynomical Regression Model Metrics:")
print_model_metrics(target_test,poly_pred)
```

```
Polynomical Regression Model Metrics:
R-Squared: 0.8945181878762949
Root Mean Squared Error (RMSE): 2.3814663378257643
Mean Absolue Error (MAE):  1.7498402349944164
```

```
[ ]:
```