```
#1 Read Auto Data
import pandas as pd
import numpy as np
import seaborn as sb
np.random.seed(1234)


df = pd.read_csv('Auto.csv')
print(df.head())
print("Dimensions: ", df.shape)
```

```
    mpg  cylinders  displacement  horsepower  weight  acceleration  year  \
0  18.0          8         307.0         130    3504          12.0  70.0
1  15.0          8         350.0         165    3693          11.5  70.0
2  18.0          8         318.0         150    3436          11.0  70.0
3  16.0          8         304.0         150    3433          12.0  70.0
4  17.0          8         302.0         140    3449           NaN  70.0

   origin                       name
0       1  chevrolet chevelle malibu
1       1          buick skylark 320
2       1         plymouth satellite
3       1              amc rebel sst
4       1                ford torino
Dimensions:  (392, 9)
```

```
#2 Data Exploration
df.describe()
#Range
  #mpg: 37
  #cylinders: 5
  #disp.: 387
  #hrspwr: 284
  #weight: 3527
  #acclr.: 16.8
  #year: 12
  #origin: 2
#Mean
  #mpg:23.45
  #cylinders: 5.47
  #disp.: 194.41
  #hrspwr: 104.47
  #weight: 2977.58
  #acclr.: 15.55
  #year:76
  #origin: 1.58
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origi
count	392.000000	392.000000	392.000000	392.000000	392.000000	391.000000	390.000000	392.00000
mean	23.445918	5.471939	194.411990	104.469388	2977.584184	15.554220	76.010256	1.57653
std	7.805007	1.705783	104.644004	38.491160	849.402560	2.750548	3.668093	0.80551
min	9.000000	3.000000	68.000000	46.000000	1613.000000	8.000000	70.000000	1.00000
25%	17.000000	4.000000	105.000000	75.000000	2225.250000	13.800000	73.000000	1.00000
50%	22.750000	4.000000	151.000000	93.500000	2803.500000	15.500000	76.000000	1.00000
75%	29.000000	8.000000	275.750000	126.000000	3614.750000	17.050000	79.000000	2.00000
max	46.600000	8.000000	455.000000	230.000000	5140.000000	24.800000	82.000000	3.00000

```
#3 Explore Data Types
df.dtypes

df.cylinders = df.cylinders.astype('category').cat.codes
df.origin = df.origin.astype('category')

df.dtypes
```

```
mpg             float64
cylinders          int8
displacement    float64
horsepower        int64
weight            int64
```

```
acceleration     float64
year             float64
origin          category
name              object
dtype: object
```

```
#4 Deal with NAs
acc_mean = np.mean(df.acceleration)
df.acceleration.fillna(acc_mean, inplace = True)

year_mean = np.mean(df.year)
df.year.fillna(year_mean, inplace = True)

df.isnull().sum()
```

```
mpg             0
cylinders       0
displacement    0
horsepower      0
weight          0
acceleration    0
year            0
origin          0
name            0
dtype: int64
```

```
#5 Modify Columns
mpg_mean = np.mean(df.mpg)

df['mpg_high'] = np.where(
    df['mpg'] > mpg_mean, 1, 0
    #np.where (df['mpg'] > mpg_mean, 1)
)

df.mpg_high = df.mpg_high.astype('category')

#df.describe()
df = df.drop(columns=['mpg', 'name']) #always reread data to run this block again
#df.describe()
print(df.head())
```

```
   cylinders  displacement  horsepower  weight  acceleration  year origin  \
0          4         307.0         130    3504      12.00000  70.0      1
1          4         350.0         165    3693      11.50000  70.0      1
2          4         318.0         150    3436      11.00000  70.0      1
3          4         304.0         150    3433      12.00000  70.0      1
4          4         302.0         140    3449      15.55422  70.0      1

  mpg_high
0        0
1        0
2        0
3        0
4        0
```

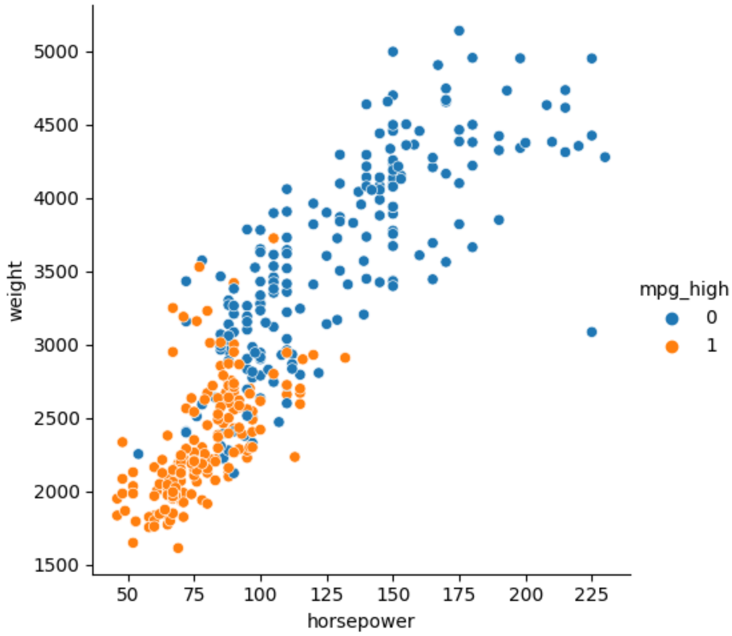
```
#6 Data Exploration w/ Graphs
sb.catplot(x = 'mpg_high', y = 'acceleration', data = df)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f81c69cf1c0>
```

Vehicles with miles per gallon at or below average tend to yield a marginally lower acceleration average

```
sb.relplot(x ='horsepower', y ='weight', data = df, hue = 'mpg_high')
```

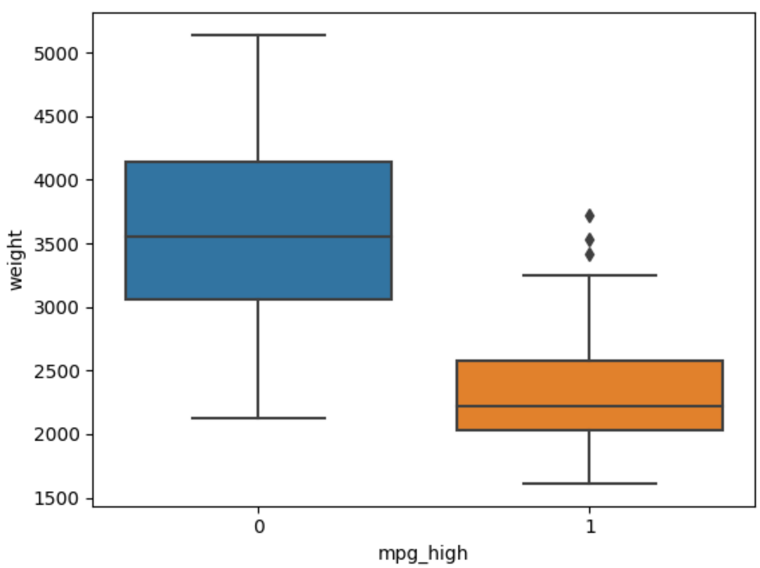
```
<seaborn.axisgrid.FacetGrid at 0x7f81c3f47700>
```



Vehicles over the average miles per gallon tend to weigh less than those at or under the average

```
sb.boxplot(x = 'mpg_high', y = 'weight', data = df)
```

```
<Axes: xlabel='mpg_high', ylabel='weight'>
```



There are a few vehicles exceeding the average weight for vehicles with more efficient mileage, but they are outliers

```
#7 Train/Test Split
#i = np.random.rand(len(df)) < 0.8
```

```
#train = df[i]
#test = df[~i]
#print("Train: ", train.shape)
#print("Test: ", test.shape)

#print(train.dtypes)
#print("\n")
#print(test.dtypes)

from sklearn.model_selection import train_test_split

X = df.loc[:, ['cylinders', 'displacement', 'horsepower']]
y = df.weight

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 1234)

print("Test: ", X_train.shape)
print("Train: ", X_test.shape)
```

```
Test:  (313, 3)
Train:  (79, 3)
```

```
#8 LogReg
from sklearn.linear_model import LogisticRegression

df_lr = LogisticRegression(solver='lbfgs', max_iter=500)
df_lr.fit(X_train, y_train)

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

pred = df_lr.predict(X_test)

print('Accuracy: ', accuracy_score(y_test, pred))
print('Precision: ', precision_score(y_test, pred, average='micro'))
print('Recall: ', recall_score(y_test, pred, average='micro'))
print('F1: ', f1_score(y_test, pred, average='micro'))
```

```
Accuracy:  0.0
Precision:  0.0
Recall:  0.0
F1:  0.0
/usr/local/lib/python3.9/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
#9 Decision Tree
from sklearn.tree import DecisionTreeClassifier

df_dt = DecisionTreeClassifier()
df_dt.fit(X_train, y_train)

pred = df_dt.predict(X_test)

print('Accuracy: ', accuracy_score(y_test, pred))
print('Precision: ', precision_score(y_test, pred, average='micro'))
print('Recall: ', recall_score(y_test, pred, average='micro'))
print('F1: ', f1_score(y_test, pred, average='micro'))
```

```
Accuracy:  0.012658227848101266
Precision:  0.012658227848101266
Recall:  0.012658227848101266
F1:  0.012658227848101266
```

```
#10 NN
from sklearn.neural_network import MLPClassifier
from sklearn.neural_network import MLPRegressor

df_nn1 = MLPClassifier(solver='lbfgs', hidden_layer_sizes=(5, 2), max_iter=500, random_state=1234)
df_nn1.fit(X_train, y_train)

print('Accuracy: ', accuracy_score(y_test, pred))
print('Precision: ', precision_score(y_test, pred, average='micro'))
```

```
print('Recall: ', recall_score(y_test, pred, average='micro'))
print('F1: ', f1_score(y_test, pred, average='micro'))
print("\n")

df_nn2 = MLPRegressor(solver='lbfgs', hidden_layer_sizes=(4, 4), max_iter=700, random_state=1234)
df_nn2.fit(X_train, y_train)

print('Accuracy: ', accuracy_score(y_test, pred))
print('Precision: ', precision_score(y_test, pred, average='micro'))
print('Recall: ', recall_score(y_test, pred, average='micro'))
print('F1: ', f1_score(y_test, pred, average='micro'))
```

```
Accuracy:  0.012658227848101266
Precision:  0.012658227848101266
Recall:  0.012658227848101266
F1:  0.012658227848101266


Accuracy:  0.012658227848101266
Precision:  0.012658227848101266
Recall:  0.012658227848101266
F1:  0.012658227848101266
```

Performance can't be propery measured at this point due to a possible issue with how/what values are being read

A.) So far, the Decision Tree performed better than the other algorithms purely due to logistic reasons. B.) Currently, the only algorithm that outputs classification metrics is the Decision Tree. C.) Decision Trees work best when we are looking for outcomes based on choices, something that can be seen a little with how mileage affected acceleration and other columns. Logistic Regression works best when we want to infer information from data, which is kind of what we sought out to do in this notebook. Neural Networks work best when they have been extensively trained, meaning that the first few iterations will usually yield more innaccurate values. D.) SKLearn felt a little more natural and to the point for me, mainly because I've used this library and editor before. Besides these factors, not having to run into the issues of downloading each individual library was a breath of fresh air.