

▼ Data Exploration

▼ Read the Auto Data

Reading the auto.csv with pandas

```
import pandas as pd
df = pd.read_csv('auto.csv')

df.head()
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	name	
0	18.0	8	307.0	130	3504	12.0	70.0	1	chevrolet chevelle malibu	
1	15.0	8	350.0	165	3693	11.5	70.0	1	buick skylark 320	
2	18.0	8	318.0	150	3436	11.0	70.0	1	plymouth satellite	
3	16.0	8	304.0	150	3433	12.0	70.0	1	amc rebel sst	
4	17.0	8	302.0	140	3449	NaN	70.0	1	ford torino	

Dimensions of auto.csv

```
df.shape
```

```
(392, 9)
```

▼ Describing the Data

```
df['mpg'].describe()
```

```
count      392.000000
mean       23.445918
std         7.805007
min         9.000000
25%        17.000000
50%        22.750000
75%        29.000000
max        46.600000
Name: mpg, dtype: float64
```

```
df['weight'].describe()
```

```
count      392.000000
mean     2977.584184
std       849.402560
min     1613.000000
25%     2225.250000
50%     2803.500000
75%     3614.750000
max     5140.000000
Name: weight, dtype: float64
```

```
df['year'].describe()
```

```
count      390.000000
mean        76.010256
std         3.668093
min         70.000000
25%         73.000000
50%         76.000000
75%         79.000000
max         82.000000
Name: year, dtype: float64
```

Averages and Ranges

MPG

- Avg: 23.45
- Range: 37.6

Weight

- Avg: 2977.58
- Range: 3527

Year

- Avg: 76.01
- Range: 12

▼ Checking Data Types

```
df.dtypes
```

```
mpg           float64
cylinders      int64
displacement  float64
horsepower     int64
weight         int64
acceleration   float64
year           float64
origin         int64
name          object
dtype: object
```

Changing cylinders column to categorical

```
df.cylinders = df.cylinders.astype('category')
```

Changing origin column to categorical

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

```
df.dtypes
```

```
mpg           float64
cylinders      category
```

```
displacement    float64
horsepower      int64
weight          int64
acceleration    float64
year            float64
origin          int8
name            object
dtype: object
```

▼ Dealing with NAs

```
df = df.dropna()

# New dimensions
df.shape
```

```
Out[389]: (389, 9)
```

[+ Code](#)[+ Text](#)

▼ Modify Columns

```
mpg_high = df.mpg
mpg_high = list(map(lambda x: 1 if x > df.mpg.mean() else 0, mpg_high))

df = df.drop(columns=['mpg', 'name'])

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

df.head()
```

cylinders	displacement	horsepower	weight	acceleration	year	origin	mpg_high
-----------	--------------	------------	--------	--------------	------	--------	----------



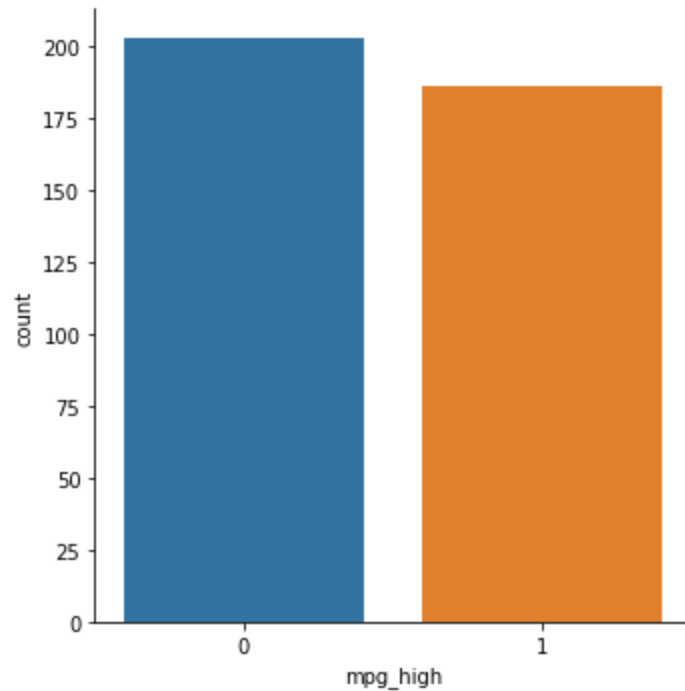
▼ Data Exploration with Graphs

2	8	318.0	150	3436	11.0	70.0	0	0
---	---	-------	-----	------	------	------	---	---

```
import seaborn as sb
```

```
sb.catplot(x="mpg_high", kind='count', data=df)
```

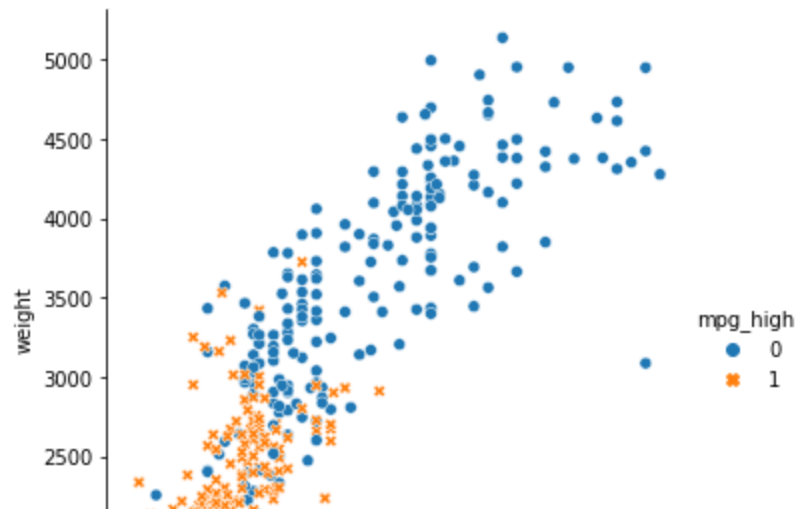
```
<seaborn.axisgrid.FacetGrid at 0x7fc52ced9610>
```



This graph shows that a little less than half the cars have a mpg above average. A little more than half are below average.

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

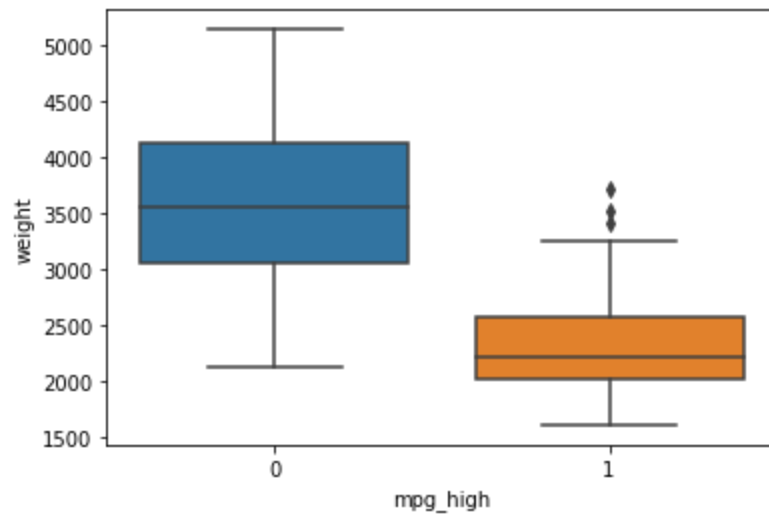
```
<seaborn.axisgrid.FacetGrid at 0x7fc51e279110>
```



It seems that cars with less weight and horsepower tend to have an mpg above average.

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc51ddbc7d0>
```



This graph shows that lighter vehicles tend to have a mpg above average.

▼ Train/test split

```
# train test split
import numpy as np
from sklearn.model_selection import train_test_split
```

```
np.random.seed(1234)
```

```
X = df.loc[:, ['cylinders', 'displacement', 'horsepower', 'weight', 'acceleration', 'year', 'origin']]
y = df.mpg_high
```

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

```
print('train size:', X_train.shape)
print('test size:', X_test.shape)
```

```
train size: (311, 7)
```

```
test size: (78, 7)
```

▼ Logistic Regression

```
from sklearn.linear_model import LogisticRegression
```

```
clf = LogisticRegression(max_iter=300)
clf.fit(X_train, y_train)
clf.score(X_train, y_train)
```

```
0.9067524115755627
```

```
# make predictions
```

```
pred = clf.predict(X_test)
```

```
# evaluate
from sklearn.metrics import accuracy_score
print('accuracy = ', accuracy_score(y_test, pred))
```

```
# classification report
from sklearn.metrics import classification_report
print(classification_report(y_test, pred))

# confusion matrix
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test, pred)
```

accuracy =	0.8717948717948718				
	precision	recall	f1-score	support	
0	0.98	0.82	0.89	50	
1	0.75	0.96	0.84	28	
accuracy			0.87	78	
macro avg	0.86	0.89	0.87	78	
weighted avg	0.89	0.87	0.87	78	

array([[41, 9],	
[1, 27]])	

▼ Decision Tree

```
from sklearn.tree import DecisionTreeClassifier

clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)
```

DecisionTreeClassifier()

```
# make predictions

pred = clf.predict(X_test)
```

```
# Evaluate
print('accuracy = ', accuracy_score(y_test, pred))

# Classification Report
```



```
print(classification_report(y_test, pred))
```

```
# confusion matrix
confusion_matrix(y_test, pred)
```

```
accuracy = 0.9230769230769231
          precision    recall  f1-score   support

     0       0.96      0.92      0.94        50
     1       0.87      0.93      0.90        28

 accuracy          0.92        78
  macro avg       0.91      0.92      0.92        78
 weighted avg     0.93      0.92      0.92        78

array([[46,  4],
       [ 2, 26]])
```

▼ Neural Network

```
# normalize the data
from sklearn import preprocessing
```

```
scaler = preprocessing.StandardScaler().fit(X_train)
```

```
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
# train
from sklearn.neural_network import MLPClassifier
```

```
clf = MLPClassifier(solver='lbfgs', hidden_layer_sizes=(6, 2), max_iter=500, random_state=1234)
clf.fit(X_train_scaled, y_train)
```

```
MLPClassifier(hidden_layer_sizes=(6, 2), max_iter=500, random_state=1234,
              solver='lbfgs')
```

```
# make predictions
```

```
pred = clf.predict(X_test_scaled)
```

```
# output results

print('accuracy = ', accuracy_score(y_test, pred))

# Classification Report
print(classification_report(y_test, pred))

# Confusion Matrix
confusion_matrix(y_test, pred)
```

```

accuracy = 0.8974358974358975
          precision    recall  f1-score   support

     0       0.96      0.88      0.92        50
     1       0.81      0.93      0.87        28

 accuracy          0.90        78
  macro avg       0.88        78
 weighted avg     0.90        78

array([[44,  6],
       [ 2, 26]])
```

```
# try different settings

clf = MLPClassifier(solver='sgd', hidden_layer_sizes=(2,), max_iter=1500, random_state=1234)
clf.fit(X_train_scaled, y_train)

MLPClassifier(hidden_layer_sizes=(2,), max_iter=1500, random_state=1234,
              solver='sgd')
```

```
# make predictions

pred = clf.predict(X_test_scaled)
```

```
# output results

print('accuracy = ', accuracy_score(y_test, pred))

# Classification Report
```

```
print(classification_report(y_test, pred))
```

```
# Confusion Matrix
confusion_matrix(y_test, pred)
```

```

      accuracy =  0.8974358974358975
              precision    recall  f1-score   support

     0           1.00       0.84       0.91         50
     1           0.78       1.00       0.88         28

 accuracy
macro avg       0.89       0.92       0.89         78
weighted avg     0.92       0.90       0.90         78

array([[42,  8],
       [ 0, 28]])
```

Analysis of the 2 Neural Networks

After playing around with the settings on both neural networks, the best I could achieve was an accuracy of .90 for both of them. This is a really high accuracy and I think the performance of the models was similar because they're uncovering the same underlying patterns in the data with the most accuracy possible. If .90 is near the highest accuracy achievable, both models arrived to the same conclusion but on different paths.

Analysis

Suprisingly Decision Tree outperformed all the other algorithms.

Logisitic Regression

- Accuracy: .87
- Recall: .96
- Precision: .75

Generally underperformed a bit compared to the other algorithms

Decision Tree

- Accuracy: .92
- Recall: .93

- Precision: .87

Generally the best algorithm and it had the highest precision and accuracy.

Neural Network lbfgs

- Accuracy: .90
- Recall: .93
- Precision: .81

Did well and was the middle of the pack in all metrics.

Neural Network sgd

- Accuracy: .90
- Recall: 1
- Precision: .78

Did well and interestingly had perfect recall.

Why did DT perform the best?

I believe DT performed the best because the data was very linearly seperable. This was clear when we were exploring the data. I expected the neural networks to outperform it, but they may have overfit in a few small places.

R vs SKLearn

I'm happy that I used R to learn ML. The code itself is shows more of how the algorithm works than SKLearn. That being said, I vastly prefer Python as a language and SKLearn is generally easier to use than R. The ML skills were pretty transferable. Although, I like the way R Notebooks are setup more than Google Colab. Colab is more tedious in my opinion.

Colab paid products - [Cancel contracts here](#)

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