```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Read the Auto data

a. use pandas to read the data

b. output the first few rows

c. output the dimensions of the data

```
# reading data into dataframe
df = pd.read_csv("Auto.csv")
# showing first few rows
df.head()
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	nam
0	18.0	8	307.0	130	3504	12.0	70.0	1	chevrole chevell malib
1	15.0	8	350.0	165	3693	11.5	70.0	1	buic skylar 32
									plymout

```
# show dimensions of the data
df.shape
```

```
(392, 9)
```

2. Data exploration with code

a. use `describe()` on mpg, weight, and year columns

b. write comments indicating the range and average of columns

```
# using describe() on mpg, weight, and year columns
df[['mpg','weight','year']].describe()
```

	mpg	weight	year
count	392.000000	392.000000	390.000000
mean	23.445918	2977.584184	76.010256
std	7.805007	849.402560	3.668093
min	9.000000	1613.000000	70.000000
25%	17.000000	2225.250000	73.000000
50%	22.750000	2803.500000	76.000000
75%	29.000000	3614.750000	79.000000
max	46.600000	5140.000000	82.000000

```
# range for 'mpg': [9, 46.6]; average = 23.445918
# range for 'weight': [1613, 5140.000000]; average = 2977.584184
# range for 'year': [70, 82]; average = 76.010256
```

3. Explore data types

a. check the data types of all columns

b. change the cylinders column to categorical (use `cat.codes`)

c. change the origin column to categorical (don't use `cat.codes`)

d. verify the changes with the dtypes attribute

```
# check the dtypes of columns
df.dtypes
```

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

```
# change the cylinders columns to categorical
df.cylinders = df.cylinders.astype('category').cat.codes
```

```
# change the origin column to categorical
df["origin"] = pd.Categorical(df.origin)
```

```
# verify the changes with dtypes
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

a. delete rows with NAs

b. output the new dimensions

```
# delete rows with NAs
df = df.dropna()
```

```
# output the new dimensions
df.shape
```

```
(389, 9)
```

5. Modify columns

a. make a new column, mpg_high, and make it categorical

b. delete the mpg and name columns (delete mpg so the algorithm doesn't just learn to predict the mpg_high from mpg)

c. output the first few rows of the modified dataframe

```
# make a new columns, mpg_high, and make it categorical
mean_mpg = df["mpg"].mean()
df["mpg_high"] = [1 if v>mean_mpg else 0 for v in df["mpg"]]
```

```
<ipython-input-237-76b87f863abd>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
  df["mpg_high"] = [1 if v>mean_mpg else 0 for v in df["mpg"]]
```

```
# delete the mpg and name columns
df = df.drop(['mpg', 'name'],axis=1)
```

```
# output the first few rows of the new dataframe
df.head()
```

	cylinders	displacement	horsepower	weight	acceleration	year	origin	mpg_hi
0	4	307.0	130	3504	12.0	70.0	1	
1	4	350.0	165	3693	11.5	70.0	1	
2	4	318.0	150	3436	11.0	70.0	1	
3	4	304.0	150	3433	12.0	70.0	1	
6	4	454.0	220	4354	9.0	70.0	1	

6. Data exploration with graphs

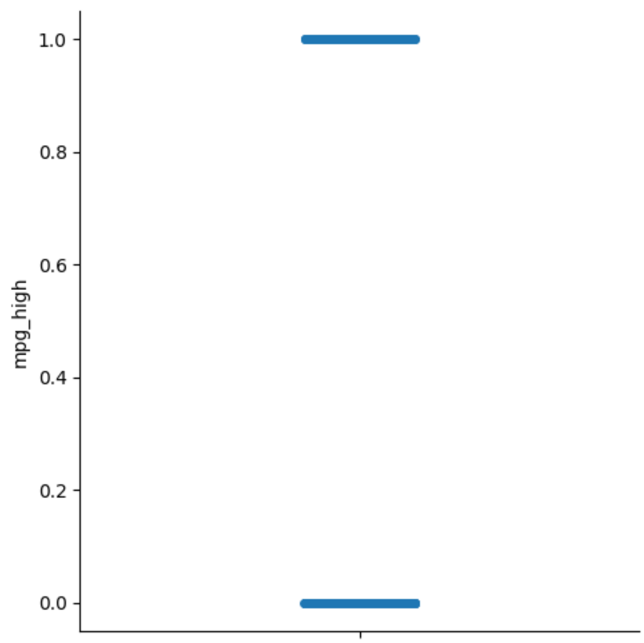
a. seaborn catplot on the mpg_high column

b. seaborn relplot with horsepower on the x axis, weight on the y axis, setting hue or style to mpg_high

c. seaborn boxplot with mpg_high on the x axis and weight on the y axis

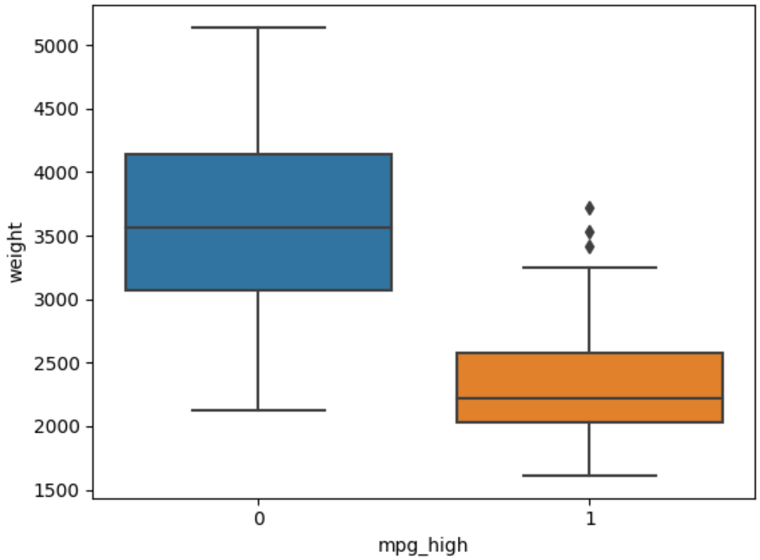
d. for each graph, write a comment indicating one thing you learned about the data from each graph

```
# seaborn catplot on the mpg_high column
g = sns.catplot(df["mpg_high"])
```




```
# seaborn relplot with horsepower on the x axis, weight on the y axis, setting hue or style to mpg_high
# the lower mpg tends towards a lower weight and horsepower
# whereas, the higher mpg tends towards higher weight and horsepower
g = sns.relplot(data=df, x="horsepower", y="weight", hue="mpg_high")
```


```
# there are some outliers on those examples where mpg_high is 1
# the median of those examples where mpg_high is 0 is just over weight 3500
# the median of those examples where mpg_high is 1 is just over weight 2000
g = sns.boxplot(data=df, x="mpg_high", y="weight")
```



7. Train/test split

a. 80/20

b. use seed 1234 so we all get the same results

c. train/test X data frames consists of all remaining columns except mpg_high

d. output the dimensions of the train and test

```
# 80/20,
# use seed 1234 so we all get same results
from sklearn.model_selection import train_test_split

X = df.drop("mpg_high", axis=1)
y = df["mpg_high"]

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

```
# train/test X data frames consists of all remain columns except mpg_high
X_train.head()
```

	cylinders	displacement	horsepower	weight	acceleration	year	origin
184	1	101.0	83	2202	15.3	76.0	2
355	3	145.0	76	3160	19.6	81.0	2
57	1	97.5	80	2126	17.0	72.0	1
170	1	90.0	71	2223	16.5	75.0	2
210	4	350.0	180	4380	12.1	76.0	1

```
# train/test X data frames consists of all remain columns except mpg_high
X_test.head()
```

	cylinders	displacement	horsepower	weight	acceleration	year	origin
43	4	400.0	175	5140	12.0	71.0	1
47	3	250.0	88	3139	14.5	71.0	1
256	3	231.0	105	3380	15.8	78.0	1
62	4	400.0	175	4385	12.0	72.0	1
268	1	134.0	95	2515	14.8	78.0	3

```
# output the dimensions of the train and test
X_train.shape
```

```
(311, 7)
```

```
# output the dimensions of the train and test
X_test.shape
```

```
(78, 7)
```

8. Logistic Regression

a. train a logistic regression model using solver lbfgs

b. test and evalute

c. print metrics using the classification report

```
# train a logistic regression model using solver lbfgs
from sklearn.linear_model import LogisticRegression
model = LogisticRegression(solver='lbfgs', max_iter=1000)
model = model.fit(X_train, y_train)
```

```
# test and evalute
y_pred = model.predict(X_test)
```

```
from sklearn.metrics import classification_report

# print metrics using classification report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      0.80      0.88        50
           1       0.73      0.96      0.83        28

    accuracy                           0.86        78
   macro avg       0.85      0.88      0.85        78
weighted avg       0.89      0.86      0.86        78
```

9. Decision Tree

a. train a decision tree

b. test and evaluate

c. print the classification report metrics

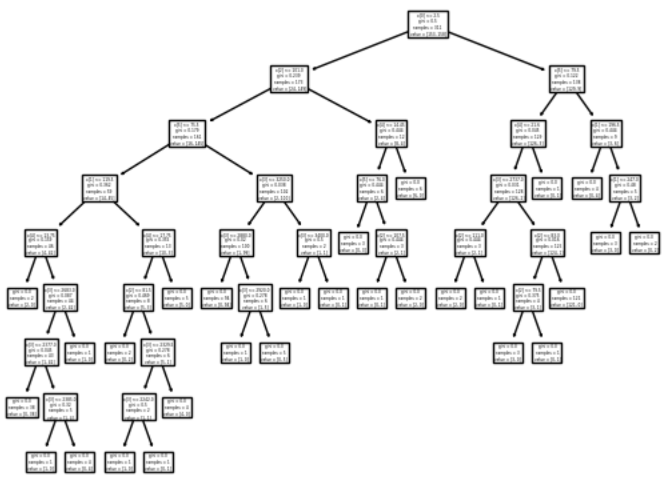
d. plot the tree

```
# train a decision tree
from sklearn import tree

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

```
# test and evaluate
y_pred = clf.predict(X_test)


# print the classification report metrics
print(classification_report(y_test, y_pred))
```

```
              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
```

```
# plot the tree
g = tree.plot_tree(clf)
```



10. Neural Network

a. train a neural network, choosing a network topology of your choice

b. test and evaluate

c. train a second neural network with a different topology and different settings

d. test and evaluate

e. compare the two models and why you think the performance was same/different

```
from sklearn import preprocessing

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

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


# a) training a neural network using topology of choice
from sklearn.neural_network import MLPClassifier

clf = MLPClassifier(solver='lbfgs', hidden_layer_sizes=(10,2), max_iter=500, random_state=1235)
clf.fit(X_train_scaled, y_train)
```

```
MLPClassifier
MLPClassifier(hidden_layer_sizes=(10, 2), max_iter=500, random_state=1235,
              solver='lbfgs')
```

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

```
# b) test and evaluate
print(classification_report(y_test, y_pred))
```

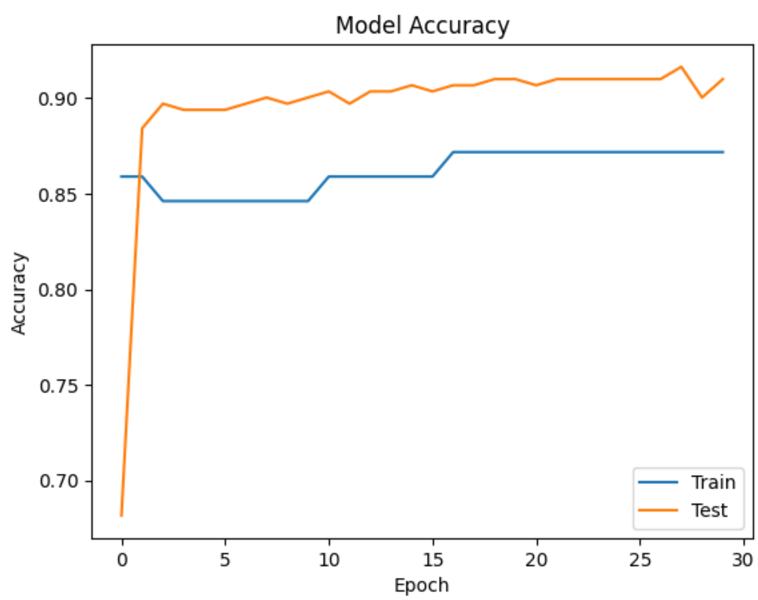
```
              precision    recall  f1-score   support

           0       0.94      0.92      0.93        50
           1       0.86      0.89      0.88        28

    accuracy                           0.91        78
   macro avg       0.90      0.91      0.90        78
weighted avg       0.91      0.91      0.91        78
```

```
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.optimizers import RMSprop

# c. train a second neural network with a different topology and different settings
model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(7,)))
model.add(Dropout(0.2))
model.add(Dense(2, activation='sigmoid'))

y_train = keras.utils.to_categorical(y_train, 2)
y_test = keras.utils.to_categorical(y_test, 2)

model.compile(loss="binary_crossentropy",
              optimizer = RMSprop(),
              metrics=["accuracy"],
)

history = model.fit(X_train_scaled, y_train,
                    batch_size = 128,
                    epochs=30,
                    verbose=1,
                    validation_data=(X_test_scaled, y_test))
```

```
Epoch 1/30
3/3 [==============================] - 1s 91ms/step - loss: 0.6341 - accuracy: 0.6817 - val_loss: 0.4898 - val_accuracy: 0.8590
Epoch 2/30
3/3 [==============================] - 0s 21ms/step - loss: 0.4955 - accuracy: 0.8842 - val_loss: 0.4222 - val_accuracy: 0.8590
Epoch 3/30
3/3 [==============================] - 0s 23ms/step - loss: 0.4277 - accuracy: 0.8971 - val_loss: 0.3821 - val_accuracy: 0.8462
Epoch 4/30
3/3 [==============================] - 0s 24ms/step - loss: 0.3837 - accuracy: 0.8939 - val_loss: 0.3558 - val_accuracy: 0.8462
Epoch 5/30
3/3 [==============================] - 0s 35ms/step - loss: 0.3534 - accuracy: 0.8939 - val_loss: 0.3344 - val_accuracy: 0.8462
Epoch 6/30
3/3 [==============================] - 0s 23ms/step - loss: 0.3253 - accuracy: 0.8939 - val_loss: 0.3202 - val_accuracy: 0.8462
Epoch 7/30
3/3 [==============================] - 0s 25ms/step - loss: 0.3062 - accuracy: 0.8971 - val_loss: 0.3087 - val_accuracy: 0.8462
Epoch 8/30
3/3 [==============================] - 0s 35ms/step - loss: 0.2888 - accuracy: 0.9003 - val_loss: 0.2997 - val_accuracy: 0.8462
Epoch 9/30
3/3 [==============================] - 0s 31ms/step - loss: 0.2773 - accuracy: 0.8971 - val_loss: 0.2915 - val_accuracy: 0.8462
Epoch 10/30
3/3 [==============================] - 0s 26ms/step - loss: 0.2641 - accuracy: 0.9003 - val_loss: 0.2854 - val_accuracy: 0.8462
Epoch 11/30
3/3 [==============================] - 0s 29ms/step - loss: 0.2583 - accuracy: 0.9035 - val_loss: 0.2790 - val_accuracy: 0.8590
Epoch 12/30
3/3 [==============================] - 0s 21ms/step - loss: 0.2505 - accuracy: 0.8971 - val_loss: 0.2704 - val_accuracy: 0.8590
Epoch 13/30
3/3 [==============================] - 0s 20ms/step - loss: 0.2412 - accuracy: 0.9035 - val_loss: 0.2677 - val_accuracy: 0.8590
Epoch 14/30
3/3 [==============================] - 0s 21ms/step - loss: 0.2382 - accuracy: 0.9035 - val_loss: 0.2624 - val_accuracy: 0.8590
Epoch 15/30
3/3 [==============================] - 0s 25ms/step - loss: 0.2308 - accuracy: 0.9068 - val_loss: 0.2607 - val_accuracy: 0.8590
Epoch 16/30
3/3 [==============================] - 0s 28ms/step - loss: 0.2300 - accuracy: 0.9035 - val_loss: 0.2522 - val_accuracy: 0.8590
Epoch 17/30
3/3 [==============================] - 0s 21ms/step - loss: 0.2254 - accuracy: 0.9068 - val_loss: 0.2497 - val_accuracy: 0.8718
Epoch 18/30
3/3 [==============================] - 0s 22ms/step - loss: 0.2204 - accuracy: 0.9068 - val_loss: 0.2454 - val_accuracy: 0.8718
Epoch 19/30
3/3 [==============================] - 0s 20ms/step - loss: 0.2151 - accuracy: 0.9100 - val_loss: 0.2359 - val_accuracy: 0.8718
Epoch 20/30
3/3 [==============================] - 0s 23ms/step - loss: 0.2145 - accuracy: 0.9100 - val_loss: 0.2430 - val_accuracy: 0.8718
Epoch 21/30
3/3 [==============================] - 0s 33ms/step - loss: 0.2106 - accuracy: 0.9068 - val_loss: 0.2331 - val_accuracy: 0.8718
Epoch 22/30
```

```
3/3 [==============================] - 0s 31ms/step - loss: 0.2048 - accuracy: 0.9100 - val_loss: 0.2386 - val_accuracy: 0.8718
Epoch 23/30
3/3 [==============================] - 0s 22ms/step - loss: 0.2043 - accuracy: 0.9100 - val_loss: 0.2358 - val_accuracy: 0.8718
Epoch 24/30
3/3 [==============================] - 0s 24ms/step - loss: 0.2040 - accuracy: 0.9100 - val_loss: 0.2317 - val_accuracy: 0.8718
Epoch 25/30
3/3 [==============================] - 0s 21ms/step - loss: 0.1991 - accuracy: 0.9100 - val_loss: 0.2311 - val_accuracy: 0.8718
Epoch 26/30
3/3 [==============================] - 0s 21ms/step - loss: 0.1989 - accuracy: 0.9100 - val_loss: 0.2299 - val_accuracy: 0.8718
Epoch 27/30
3/3 [==============================] - 0s 24ms/step - loss: 0.1959 - accuracy: 0.9100 - val_loss: 0.2315 - val_accuracy: 0.8718
Epoch 28/30
3/3 [==============================] - 0s 20ms/step - loss: 0.1913 - accuracy: 0.9164 - val_loss: 0.2277 - val_accuracy: 0.8718
Epoch 29/30
3/3 [==============================] - 0s 21ms/step - loss: 0.1916 - accuracy: 0.9003 - val_loss: 0.2264 - val_accuracy: 0.8718
```

```
# d) test and evaluate

import matplotlib.pyplot as plt

plt.plot(history.history['val_accuracy'])
plt.plot(history.history['accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()

score = model.evaluate(X_test_scaled, y_test, verbose=0)
print(f"Test Loss: {score[0]:.5%}")
print(f"Test Accuracy: {score[1]:.5%}")
```




```
Test Loss: 22.90113%
Test Accuracy: 87.17949%
```

Both of these models shared the same data transformations. Initially, the independent variables (X_train, X_test) were scaled while the dependent variables were left to their categorical representation.

The first was a multi-layer perceptron (MLP) classifier. For this model, there was only 2 hidden layers in the neural network, one with 5 nodes and one with 2 nodes. I chose to use an lbfgs solver since the dataset was relatively small, this could help with faster convergence. The accuracy of this model was quite high at about 91%. The precision and recall showed that the model was better at predicting an automobile with low mpg (mpg_high is 0), than the contrary.

The second was a sequential model of layers. It had several layers, the first initial layer had 7 inputs and output dimensionality of 512, followed by dropout layer of 20%. The final layer was a Dense layer with an output of 2, using the 'sigmoid' activation function since this was a binary classification problem. The optimizer used was root mean squared propagation to help with faster convergence. The accuracy on this model was a bit lower than that of the MLPClassifier at about 87.18%.