```
In [1]: import numpy as np
   import matplotlib.pyplot as plt
   import pandas as pd
```

## Task 1: Implementing MSE Loss Function

## What is a loss/cost function?

**Explanations:** 

- 1. It's a function that determines how well a Machine Learning model performs for a given set of data
- 2. Cost function helps us reach the optimal solution
- 3. A mechanism that returns the error between predicted outcomes and the actual outcomes

In this code block, we will implement one type of loss function:

ullet Mean Squared Error  $rac{1}{m}*\sum_{i=1}^m(y_{pred}^i-y^i)^2$ 

There are many more cost functions that Machine Learning programmers use. You can check out this link.

```
In [7]: #The mean squared error function computes the mean squared error between point guesses a
        def MSE(y pred, y):
          11 11 11
          INPUT:
          y_pred : a numpy array of values that your model predict
          y : a numpy array of ground truth labels/values
          OUTPUT:
          Mean Squared Error Loss
          #########################
          ## YOUR CODE STARTS HERE
          ##########################
          m = len(y)
          sum error squared = np.sum(np.square(y pred - y))
          return sum error squared / m
          ##########################
          ## YOUR CODE ENDS HERE
           ###########################
```

## Task 2: Fitting a line by brute force

- 1. Download and import the line\_fitting.csv data from Bruinlearn
- 2. Graph the points using plt.scatter() note that the first column of the csv is the x coordinates and the second is the y coordinates
- 3. Find values of beta1 and beta0 that create a line that fits your data well
- 4. Use the mean squared error function provided mse() to calculate the error of your line (note: the ypred and y of MSE must be the same size, when you are calculating your y\_guess be sure to calculate the guesses for the points in x\_guess)

How low can you get the error of your line? Can you get the error below 3?

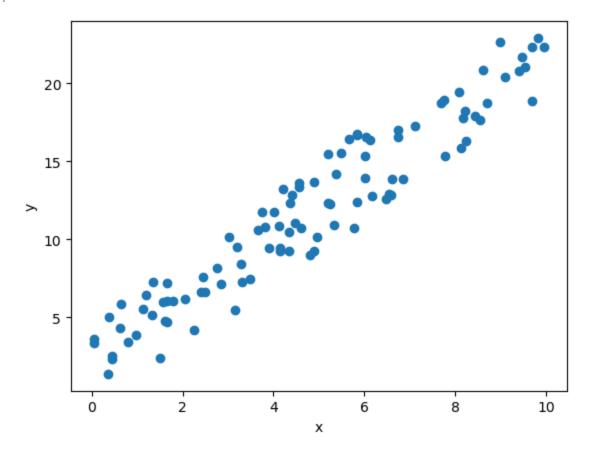
1. Use a brute force approach to find the lowest mean squared error you can get, try 500 values for beta0 and beta1

```
In [8]: line_fitting = pd.read_csv('line_fitting.csv')

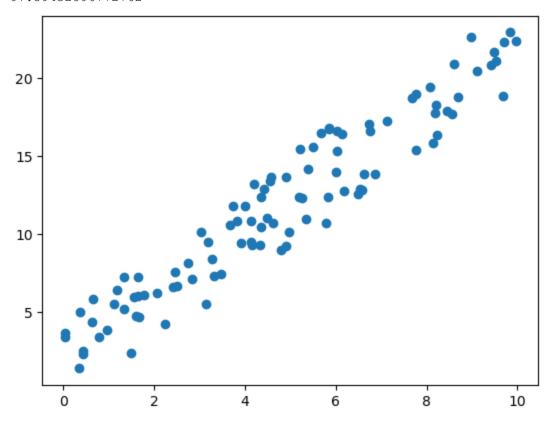
x_points = np.array(line_fitting.x)
y_points = np.array(line_fitting.y)

plt.scatter(x_points, y_points)
plt.xlabel('x')
plt.ylabel('y')
```

Out[8]: Text(0, 0.5, 'y')

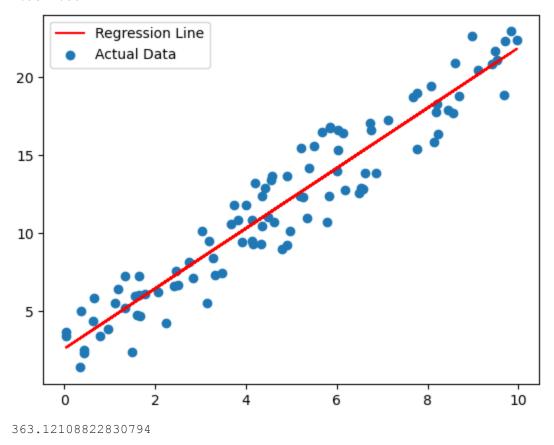


```
In [9]:
        #########################
         ## YOUR CODE STARTS HERE
         #########################
         # guess two values for beta0 and beta1
        beta0 = 0.5 # example guess
        beta1 = 0.5 # example guess
        # calculate your model's guesses for each x in x points, and store it in y guess
        y guess = beta0 + beta1 * x points
         # plot your y guess on the same plot as the scattered points
        plt.scatter(x points, y points)
         # compute and print your mean squared error with your y guess
        error = np.mean(np.square(y guess - y points))
        print(error)
         #########################
         ## YOUR CODE ENDS HERE
         #########################
```



```
In [11]: # update your beta0 and beta1 to be the best value from 250,000 combinations (brute forc
         best error = float('inf')
         best params = (None, None)
         for beta1 guess in np.arange(0, 5, 0.01):
           for beta0 guess in np.arange(0, 5, 0.01):
              #########################
             ## YOUR CODE STARTS HERE
              #########################
              # Calculate model's predictions
             y guess = beta0 guess + beta1 guess * x points
             # Compute the MSE
             error = np.mean(np.square(y guess - y points))
             # Update best parameters if this error is lower
             if error < best error:</pre>
                 best error = error
                 best params = (beta0 guess, beta1 guess)
              ###########################
              ## YOUR CODE ENDS HERE
              #########################
          ##########################
          ## YOUR CODE STARTS HERE
          #########################
          # print your best model parameters
         beta0, beta1 = best params
         print(beta1, beta0)
          # calculate your model's guesses for each x in x points, and store it in y guess
         y guess = beta0 + beta1 * x points
          # plot your y guess on the same plot as the scattered points
         plt.plot(x points, y guess, color="red", label="Regression Line")
         plt.scatter(x points, y points, label="Actual Data")
         plt.legend()
         plt.show()
          # compute and print your mean squared error with your y guess
```

1.93 2.58

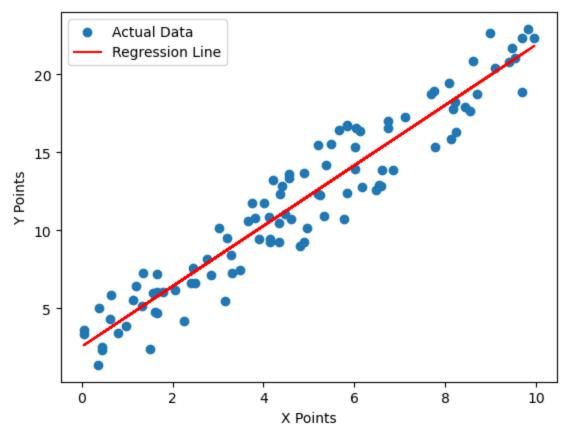


Task 3: Fitting a line using polyfit

- 1. Use the np.polyfit() function to find the solution to the best fit line for the data
- 2. Calculate the mean squared error, how similar is it to the one you found by brute force?

```
In [12]:
         ########################
          ## YOUR CODE STARTS HERE
          #########################
          # find and print values for beta0 and beta1 using np.polyfit
         beta1, beta0 = np.polyfit(x points, y points, 1)
         print(beta1, beta0)
         # calculate your model's guesses for each x in x points, and store it in y guess
         y guess = beta0 + beta1 * x points
          # plot your y guess on the same plot as the scattered points
         plt.scatter(x_points, y_points, label="Actual Data")
         plt.plot(x points, y guess, color="red", label="Regression Line")
         plt.xlabel("X Points")
         plt.ylabel("Y Points")
         plt.legend()
         plt.show()
          # compute and print your mean squared error with your y guess
         error = np.mean(np.square(y guess - y points))
         print(error)
```

1.9349777917522766 2.555030766526259



2.6549986410378392

## Write your report here

Run the next two cells in Google Colab to export your notebook to a pdf for submission

```
In []:
    This is a linear regression project where I
    took data from a set of data and modelled a line
    of best fit by leveraging different methods.

    No difficulties were incurred.
....
```