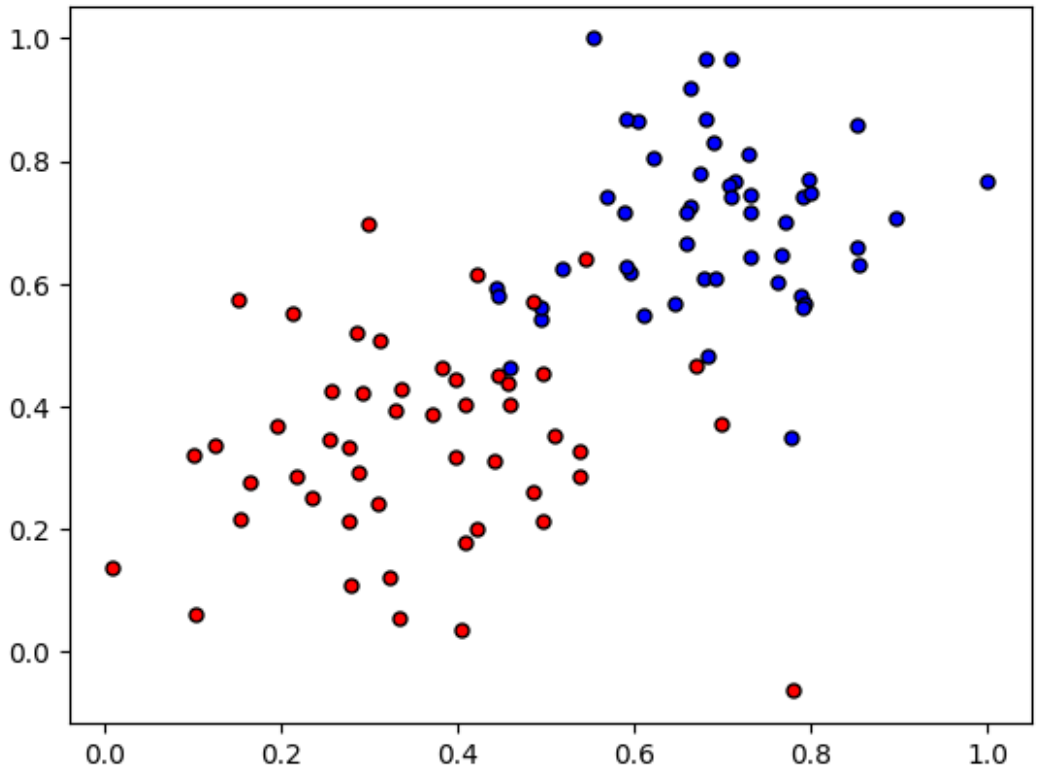
Implementing the Gradient Descent Algorithm

In this lab, we'll implement the basic functions of the Gradient Descent algorithm to find the boundary in a small dataset. First, we'll start with some functions that will help us plot and visualize the data.

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

#Some helper functions for plotting and drawing lines

def plot_points(X, y):
    admitted = X[np.argwhere(y==1)]
    rejected = X[np.argwhere(y==0)]
    plt.scatter([s[0][0] for s in rejected], [s[0][1] for s in
rejected], s = 25, color = 'blue', edgecolor = 'k')
    plt.scatter([s[0][0] for s in admitted], [s[0][1] for s in
admitted], s = 25, color = 'red', edgecolor = 'k')

def display(m, b, color='g--'):
    plt.xlim(-0.05,1.05)
    plt.ylim(-0.05,1.05)
    x = np.arange(-10, 10, 0.1)
    plt.plot(x, m*x+b, color)
```

Reading and plotting the data

```
data = pd.read_csv('data.csv', header=None)
X = np.array(data[[0,1]])
y = np.array(data[2])
plot_points(X,y)
plt.show()
```



TODO: Implementing the basic functions

Here is your turn to shine. Implement the following formulas, as explained in the text.

- Sigmoid activation function

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

- Output (prediction) formula

$$\hat{y} = \sigma(w_1 x_1 + w_2 x_2 + b)$$

- Error function

$$Error(y, \hat{y}) = -y \log(\hat{y}) - (1-y) \log(1-\hat{y})$$

- The function that updates the weights

$$w_i \to w_i + \alpha (y - \hat{y}) x_i$$

$$b \to b + \alpha (y - \hat{y})$$

```
# Implement the following functions

# Activation (sigmoid) function
def sigmoid(x):
```

```
    return 1 / (1 + np.exp(-x))

# Output (prediction) formula
def output_formula(features, weights, bias):
    return sigmoid(np.dot(features, weights) + bias)

# Error (log-loss) formula
def error_formula(y, output):
    return - y*np.log(output) - (1 - y) * np.log(1-output)

# Gradient descent step
def update_weights(x, y, weights, bias, learnrate):
    output = output_formula(x, weights, bias)
    d_error = y - output
    weights += learnrate * d_error * x
    bias += learnrate * d_error
    return weights, bias
```

Training function

This function will help us iterate the gradient descent algorithm through all the data, for a number of epochs. It will also plot the data, and some of the boundary lines obtained as we run the algorithm.

```
np.random.seed(15)

epochs = 100
learnrate = 0.01

def train(features, targets, epochs, learnrate, graph_lines=False):

    errors = []
    n_records, n_features = features.shape
    last_loss = None
    weights = np.random.normal(scale=1 / n_features**.5,
size=n_features)
    bias = 0
    for e in range(epochs):
        del_w = np.zeros(weights.shape)
        for x, y in zip(features, targets):
            weights, bias = update_weights(x, y, weights, bias,
learnrate)

        # Printing out the log-loss error on the training set
        out = output_formula(features, weights, bias)
        loss = np.mean(error_formula(targets, out))
        errors.append(loss)
        if e % (epochs / 10) == 0:
            print("\n========== Epoch", e,"==========")
            if last_loss and last_loss < loss:
```

```
                print("Train loss: ", loss, "  WARNING - Loss
Increasing")
            else:
                print("Train loss: ", loss)
            last_loss = loss

            # Converting the output (float) to boolean as it is a
binary classification
            # e.g. 0.95 --> True (= 1), 0.31 --> False (= 0)
            predictions = out > 0.5

            accuracy = np.mean(predictions == targets)
            print("Accuracy: ", accuracy)
        if graph_lines and e % (epochs / 100) == 0:
            display(-weights[0]/weights[1], -bias/weights[1])


    # Plotting the solution boundary
    plt.title("Solution boundary")
    display(-weights[0]/weights[1], -bias/weights[1], 'black')

    # Plotting the data
    plot_points(features, targets)
    plt.show()

    # Plotting the error
    plt.title("Error Plot")
    plt.xlabel('Number of epochs')
    plt.ylabel('Error')
    plt.plot(errors)
    plt.show()
```

Time to train the algorithm!

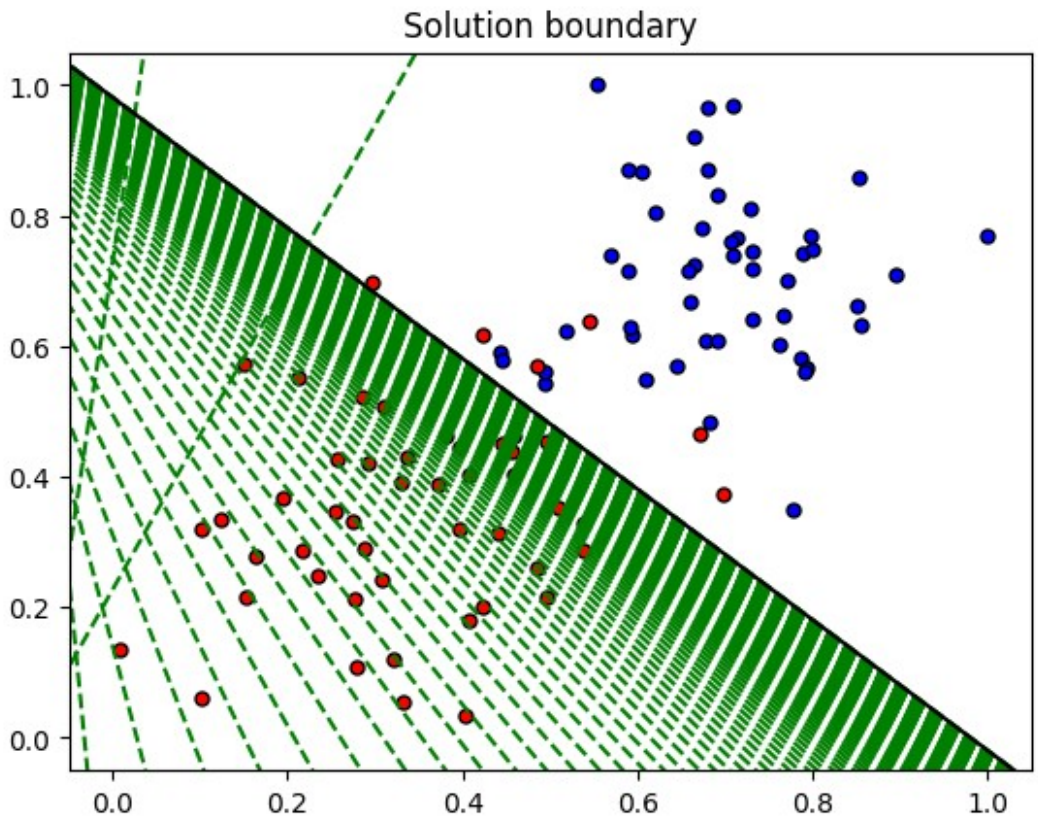
When we run the function, we'll obtain the following:

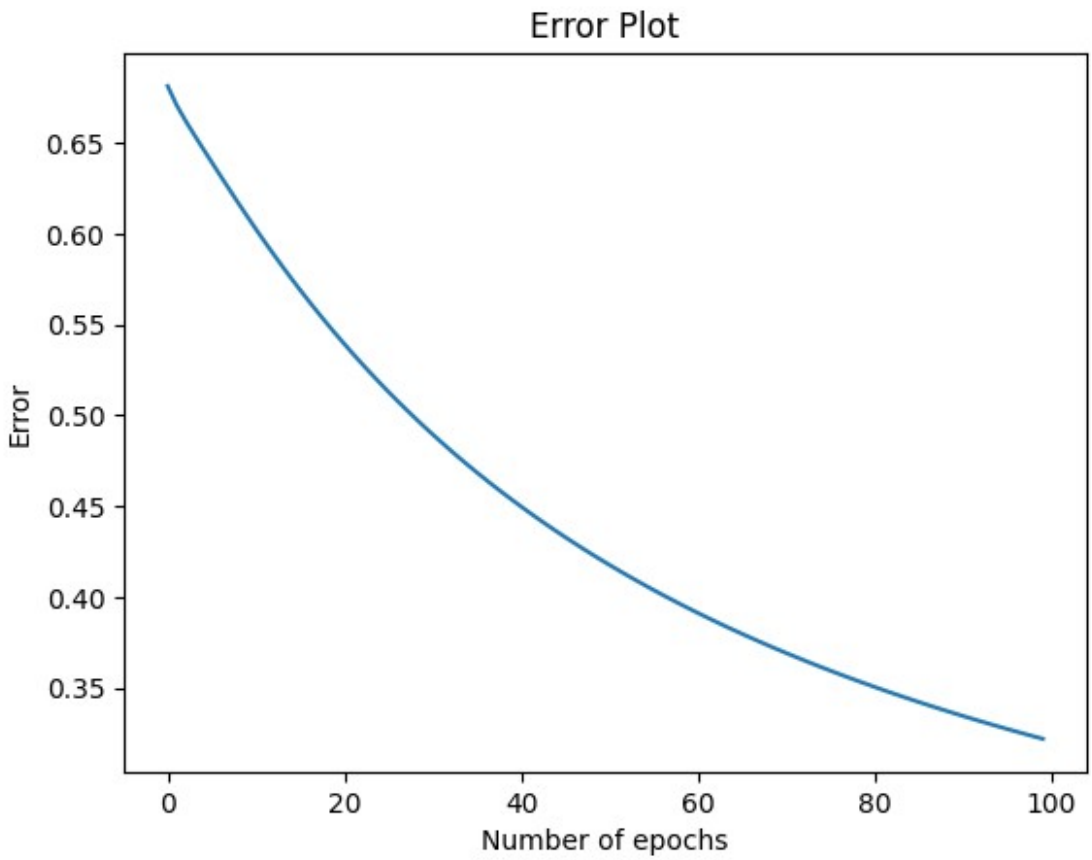
- 10 updates with the current training loss and accuracy
- A plot of the data and some of the boundary lines obtained. The final one is in black. Notice how the lines get closer and closer to the best fit, as we go through more epochs.
- A plot of the error function. Notice how it decreases as we go through more epochs.

```
train(X, y, epochs, learnrate, True)
```

```
========== Epoch 0 ==========
Train loss:  0.6812382304406719
Accuracy:  0.5

========== Epoch 10 ==========
```

```
Train loss:  0.6023467147262574
Accuracy:  0.61

========== Epoch 20 ==========
Train loss:  0.5391445453970423
Accuracy:  0.76

========== Epoch 30 ==========
Train loss:  0.48934922900366085
Accuracy:  0.85

========== Epoch 40 ==========
Train loss:  0.4496702712144526
Accuracy:  0.91

========== Epoch 50 ==========
Train loss:  0.417538421101898
Accuracy:  0.93

========== Epoch 60 ==========
Train loss:  0.39110436158981243
Accuracy:  0.92

========== Epoch 70 ==========
Train loss:  0.36903712917948583
Accuracy:  0.93

========== Epoch 80 ==========
Train loss:  0.3503695525469134
Accuracy:  0.93

========== Epoch 90 ==========
Train loss:  0.3343893579501138
Accuracy:  0.93
```


Solution boundary
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


Error Plot
Error
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0
20
40
60
80
100
Number of epochs