CSE 572: Lab 7

In this lab, you will practice implementing a logistic regression classifier from scratch and using Scikit-learn.

To execute and make changes to this notebook, click File > Save a copy to save your own version in your Google Drive or Github. Read the step-by-step instructions below carefully. To execute the code, click on each cell below and press the SHIFT-ENTER keys simultaneously or by clicking the Play button.

When you finish executing all code/exercises, save your notebook then download a copy (.ipynb file). Submit the following **three** things:

1. a link to your Colab notebook,
2. the .ipynb file, and
3. a pdf of the executed notebook on Canvas.

To generate a pdf of the notebook, click File > Print > Save as PDF.

Logistic regression from scratch

Create toy dataset

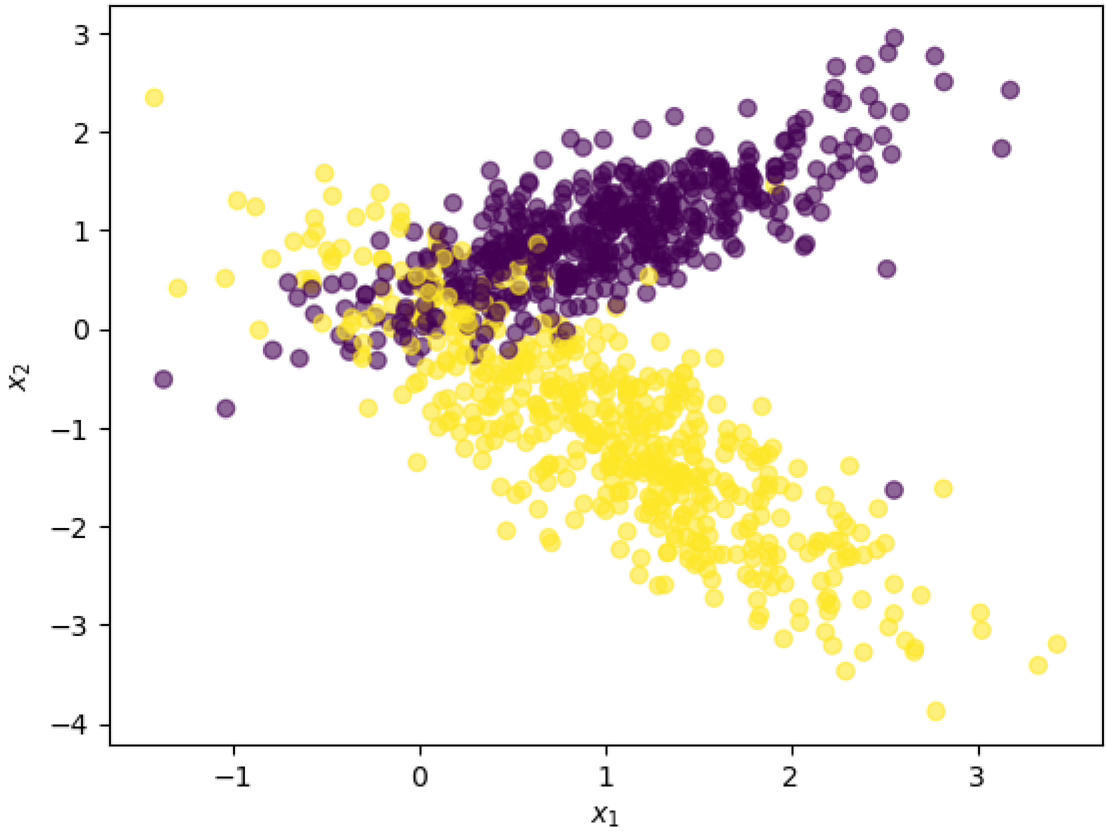
Below we create a toy dataset using the `make_classification()` function from Scikit-learn. You can read more about the arguments used to create the dataset in the documentation.

In [1]:
```
from sklearn.datasets import make_classification

X, y = make_classification(n_samples=1000, n_features=2, n_redundant=0,
                           n_informative=2, random_state=1,
                           n_clusters_per_class=1)
```

In [2]:
```
# Plot the dataset
import matplotlib.pyplot as plt

fig, ax = plt.subplots(1)
ax.scatter(X[:,0], X[:,1], c=y, alpha=0.6)
ax.set_xlabel('$x_1$');
ax.set_ylabel('$x_2$');
```



Standardize the feature values in the dataset

Standardize the input features by subtracting the feature-wise mean and dividing by the feature-wise standard deviation.

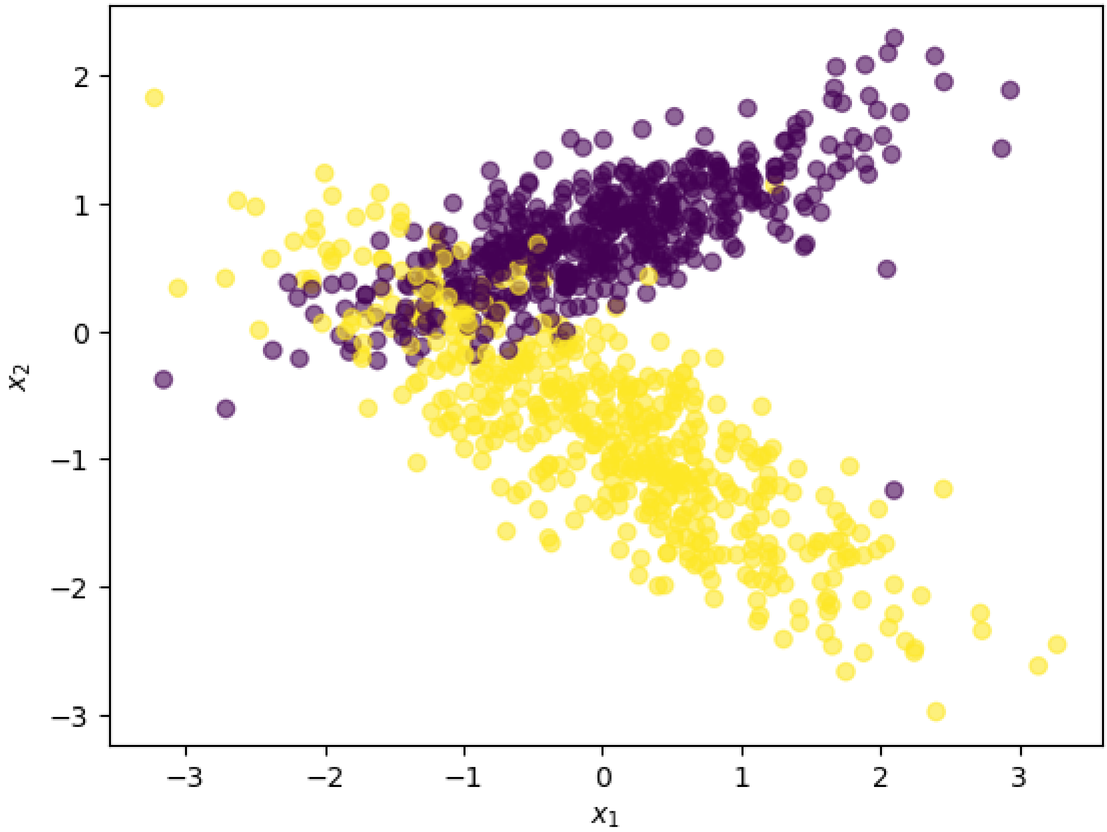
In [3]:
```
# Standardize the inputs
import numpy as np

# YOUR CODE HERE
X = (X - np.mean(X, axis=0))/ np.std(X, axis=0)
X
```

Out[3]:
```
array([[ 0.74079279, -1.06291858],
       [ 0.51647956, -0.47417773],
       [-0.64333915, -0.33634824],
       ...,
       [ 1.1200195 , -2.26806291],
       [ 0.02922649,  0.74269059],
       [ 0.64082105,  0.90406608]])
```

In [4]:
```
# Plot the dataset after standardizing
import matplotlib.pyplot as plt

fig, ax = plt.subplots(1)
ax.scatter(X[:,0], X[:,1], c=y, alpha=0.6)
ax.set_xlabel('$x_1$');
ax.set_ylabel('$x_2$');
```



Define the logistic function

Write a function that returns the output of the logistic function. Write the code for the equation (do not use a library to import the function).

In [5]:
```
def sigmoid(z):
    # YOUR CODE HERE
    return 1.0 / (1 + np.exp(-z))
```

Define the loss function

Recall that the loss function for logistic regression is the log loss or cross-entropy function, which we will average over the samples:

$$L = \frac{1}{n}\sum_{i=1}^{n} L(\hat{y}_i, y_i) = -\frac{1}{n}\sum_{i=1}^{n}[(y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

The below function returns the cross entropy loss given a set of class labels y and the predicted classes $\hat{y}$. Write the equation for cross entropy loss in the function (do not use a library to import the function).

In [6]:
```
def loss(y, y_hat):
    # YOUR CODE HERE
    loss = - np.mean(y*(np.log(y_hat)) + (1-y)*np.log(1-y_hat))
    return loss
```

Calculate the gradients

For gradient descent, we need to calculate the gradient of the loss as a function of the weights/parameters. The below function returns the gradient of the parameters w and b.

In [7]:
```
def gradients(X, y, y_hat):

    # n is number of training examples
```

```python
    n = X.shape[0]

    # gradient of loss w.r.t weights
    dw = (1/n)*np.dot(X.T, (y_hat - y))

    # gradient of loss w.r.t bias
    db = (1/n)*np.sum((y_hat - y))

    return dw, db
```

Train model (learn parameters)

The below function learns the parameters w and b using mini-batch stochastic gradient descent.

In [8]:
```python
def train_sgd(X, y, batchsize, epochs, lr):

    # X: input data
    # y: true class/target value
    # batchsize: number of samples in each batch
    # epochs: number of epochs (complete passes through training data)
    # lr: learning rate

    # n: number of training examples
    # m: number of features
    n, m = X.shape

    # Initialize weights and bias to zeros
    w = np.zeros((m,1))
    b = 1

    # Reshape y to be an n x 1 vector for multiplication
    y = y.reshape(n,1)

    # Empty list to store loss history
    losses = []

    # Training loop
    for i in range(epochs):
        # Loop through each batch in the complete dataset
        for j in range((n-1) // batchsize + 1):

            # Load a batch of data
            start_i = j*batchsize
            end_i = start_i + batchsize
            xbatch = X[start_i:end_i]
            ybatch = y[start_i:end_i]

            # Calculate prediction
            y_hat = sigmoid(np.dot(xbatch, w) + b)

            # Get the gradients of loss w.r.t parameters
            dw, db = gradients(xbatch, ybatch, y_hat)

            # Update the parameters
            w = w - lr*dw
            b = b - lr*db

        # Calculate loss and append it to the list for plotting later
        l = loss(y, sigmoid(np.dot(X, w) + b))
        losses.append(l)

    # return learned weights, bias, and list of losses
    return w, b, losses
```

In [9]:
```python
# Train the model
w, b, loss_history = train_sgd(X, y, batchsize=100, epochs=1000, lr=0.01)
```

Plot the decision boundary

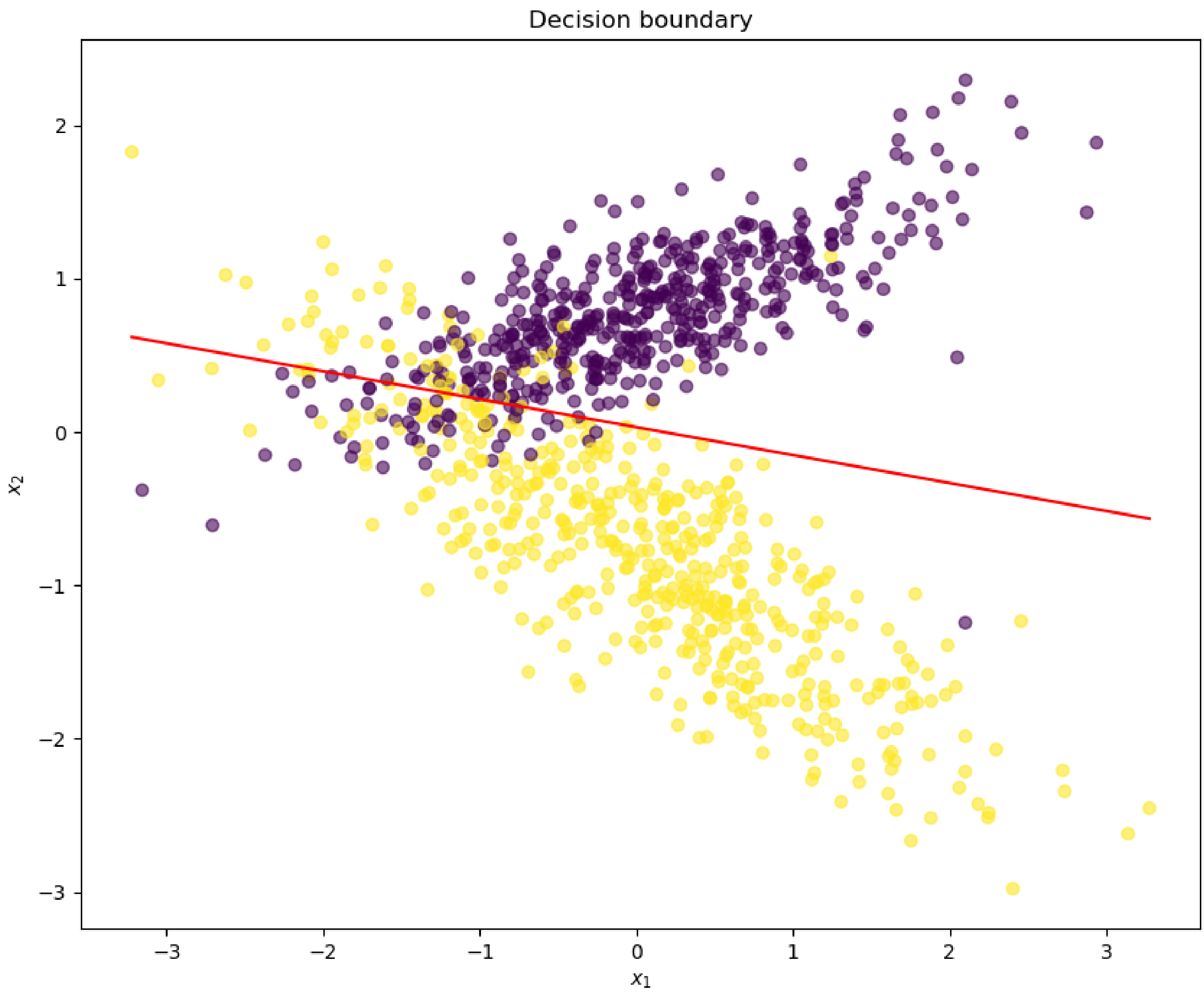
The following function plots the decision boundary learned for classifying our 2-dimensional dataset X.

In [10]:
```python
def plot_decision_boundary(X, w, b):

    # The line we need to plot is y=mx+c
    # We equate mx + c = w.X + b
    # Solve to find m and c
    x1 = [min(X[:,0]), max(X[:,0])]
    m = -w[0]/w[1]
    c = -b/w[1]
    x2 = m*x1 + c

    # Plotting
    fig = plt.figure(figsize=(10,8))
    plt.scatter(X[:,0], X[:,1], c=y, alpha=0.6)
    plt.xlabel("$x_1$")
    plt.ylabel("$x_2$")
    plt.title('Decision boundary')
    plt.plot(x1, x2, 'r-')
```

In [11]:
```python
plot_decision_boundary(X, w, b)
```



Make predictions for training set

The below function makes predictions for a set of data instances and thresholds the model output (which ranges from [0,1]) to a binary output (which has values of 0 or 1). If the model output is >= 0.5, we predict y=1, else we predict y=0.

In [12]:
```
def predict(X, w, b):
    # Calculate predictions using model parameters w, b
    preds = sigmoid(np.dot(X, w) + b)

    # if y_hat >= 0.5 --> round up to 1
    # if y_hat < 0.5 --> round up to 1
    pred_class = [1 if i >= 0.5 else 0 for i in preds]

    return np.array(pred_class)
```

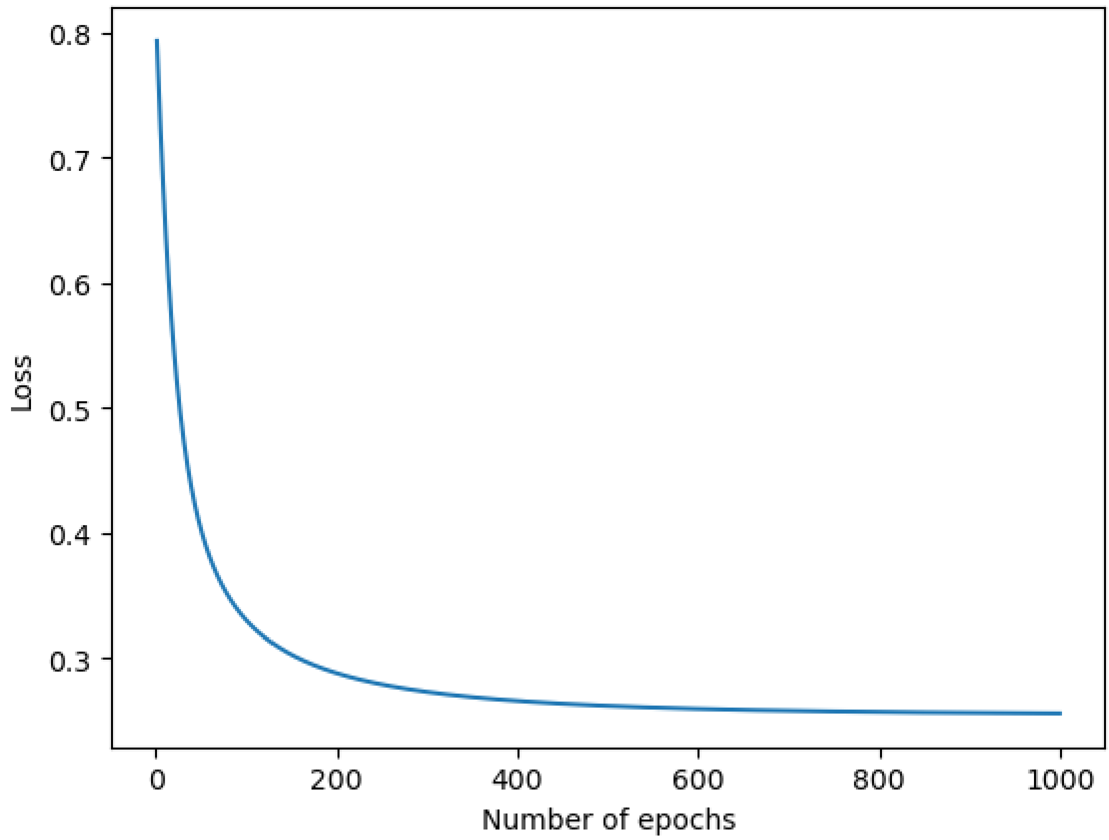
In [13]:
```
y_hat_train = predict(X, w, b)
```

Plot the loss history

The below function takes a list of losses from the training history and plots them as a function of the number of iterations.

In [14]:
```
def plot_loss_history(losses):
    fig, ax = plt.subplots(1)
    ax.plot(range(1, len(losses)+1), losses)
    ax.set_xlabel('Number of epochs')
    ax.set_ylabel('Loss')
```

In [15]:
```
plot_loss_history(loss_history)
```



Question 1: Try changing the learning rate to different values, e.g. 0.1, 0.01, and 0.001. What happens to the plot of the loss history as the learning rate increases?

Answer:

YOUR ANSWER HERE

The loss decreases much more quickly for higher learning rates.

Compute training accuracy

Compute and print the accuracy on the training dataset.

In [16]:
```
from sklearn.metrics import accuracy_score

# YOUR CODE HERE
print('Accuracy on training set: %.2f' % (accuracy_score(y, y_hat_train)))
```

```
Accuracy on training set: 0.90
```

Logistic regression using sklearn

In this section, we'll implement logistic regression for the same classification task using scikit-learn instead of writing the code from scratch.

In [17]:
```
from sklearn.linear_model import LogisticRegression
```

In [18]:
```
# Instantiate a logistic regression classifier and fit it to the training data
clf = LogisticRegression(random_state=0)
clf = clf.fit(X, y)
```

In [19]:
```
y_pred = clf.predict(X)
```

Compute and print the classification accuracy for the training set.

In [20]:
```
# YOUR CODE HERE
print('Accuracy on training set: %.2f' % (accuracy_score(y, y_pred)))
```

```
Accuracy on training set: 0.90
```

Summary

Now you've learned how to implement logistic regression from scratch in python as well as using scikit-learn. Using both methods we got the same classification accuracy on the training set.