

Practical 1

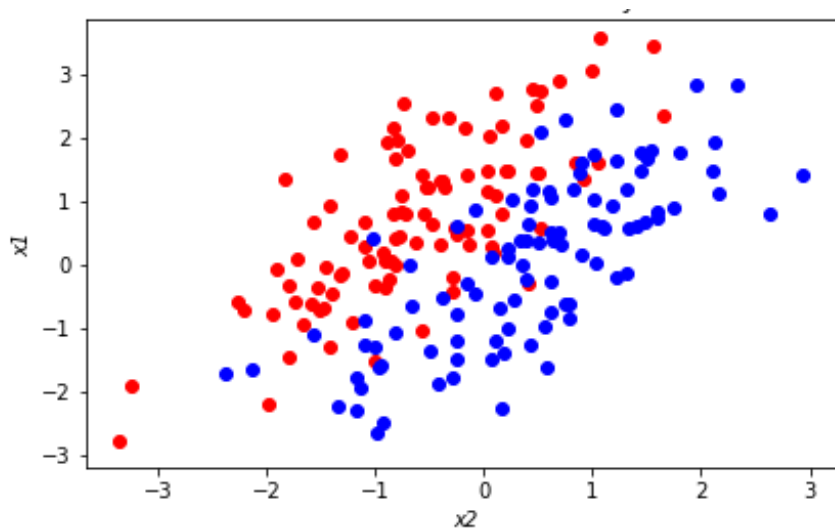
Single layer perceptron SLP Classification

This practical will help you to understand the influence of the basic single-layer perceptron (SLP) parameters on the classification accuracy.

Use Python code *single_layer_perceptron.py*

1. Data

Data – artificially generated two-dimensional Gaussian data sets: class1 (red) and class 2 (blue).



Single-layer perceptron will be trained to discriminate between these two classes.

Each class is described by a mean vector and covariance matrix:

```
mean1 = np.array([-0.5, 1]) # mean vector class 1
mean2 = np.array([0.5, 0]) # mean vector class 2
var1=1 # variance of x1 feature
var2=2 # variance of x2 feature
cor12=0.8 #correlation coefficient between x1 and x2
```

A size of a training set is defined (equal for each class).

```
N_train=100 # number of training samples
N_test=100 # number of testing samples
```

Training set is denoted: data_train1, data_train2.

Test set is denoted: data_test1, data_test2.

Targets:

targets_train1 - zeros, targets_train2 - ones

targets_test1 - zeros, targets_test2 - ones

2. Training and testing of a single layer perceptron

Parameters for training:

```
#parameters for perceptron training
niu = 0.2 # learning Rate
epochs = 200
```

To train and test a perceptron we will use the following functions:

```
# perceptron call
perceptron = Perceptron(data_train, targets_train)

#training
mse=perceptron.train(epochs, niu)

#training errors
error_train, error_train_percent]=perceptron.errors(data_train, targets_train)

#testing errors
[error_test, error_test_percent]=perceptron.errors(data_test, targets_test)
```

The training is implemented in the method

```
def train(self, its, niu):
```

Analyze and understand the code and all methods.

Pay attention to the training gradient descent procedure:

```
def train(self, its, niu):
...

for i in range(N): #over the samples
    cost_prime = 2*(activation[i] - self.targets[i])
    #weight change for a given sample
    for j in range(p+1): #over the features
        delta_weights[j][i] = cost_prime * inputs1[i][j] *
                               self.sigmoid_deriv(z[i])

    #average of the weight change over the learning samples and transpose
    delta_avg = np.array([np.average(delta_weights, axis=1)]).T

    #weight update
    self.weights = self.weights - niu * delta_avg
```

At the end the figures are generated to present the *mse*, classification error during training, data and decision boundary, neuron output for data, *mse* surface as a function of weights. Training and classification errors are printed in the command window.

Task 1. Analyze what effect a number of training iterations has on the *mse*, training and testing errors. Explain the results.

Mean_2 = [0.5,0]

Class observed

[illegible]

Class predicted

[1000100011101010001111101111000010000
0010011000001001010000000110001111000
0011010000100000001000100101101111001
0011111010011111110111100111100111101
1100101011100111010111101010100100101
011101010111100]

Training errors: 73

Training errors: 36.5 %

Class observed

[illegible]

Class predicted

```
[0000100100000010001011101001001000100
0110010001011101001000110011000010101
1111000001001011000100000101101100010
001100010111111110111101100011111001
110000100101110011011110000111111001
10100011110111110]
```

Test errors: 78

Test errors: 39.0 %

Note: the new random data set will be generated in every experiment. You can add additional procedure to work with the same data (optional). It will enable you to compare the results in a correct way as you will work with the same data set.

Task 2. Analyze what effect a learning rate η has on the mse , training and testing errors. Explain the results ($\eta > 0$).

When using Speed rate at = [0.6]

Class observed

[illegible]

Class predicted

$$[00001110000000000010111110000010011111001110011000010000000100100100100000011111011110101000111110001010111011111111111101111000011001101011011111111111011000111111]$$

Training errors: 68

Training errors: 34.0 %

Class observed

[illegible]

Class predicted

[1 1 1 0 0 1 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 1 0 0 0 1 1 0 0 1 1 1 1 0 0
1 1 1 1 1 0 0 1 1 0 0 1 0 0 0 1 0 1 0 1 0 0 0 0 0 1 0 1 0 0 0 1 1 0 1 0 0
0 0 1 1 1 0 0 0 0 0 0 1 0 1 0 0 1 0 1 0 0 0 0 1 1 1 0 1 0 0 0 1 0 1 0 0 1
1 0 0 1 1 1 1 1 1 1 0 1 1 0 0 0 1 1 0 1 1 0 1 1 1 1 1 0 1 1 0 1 1 1 1 0 1
0 1 1 0 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 1 0 1 1 1 0 1 1 0 1 0 1 1 1 1 0
1 1 1 1 0 1 0 1 1 1 1 1 1 1 1 0]

Test errors: 70

Test errors: 35.0 %

Task 3. Analyze what effect a training set size has on the mse , training and testing errors. Explain the results.

When using **Training set size = [50]**

[0.
0.
0. 0. 1.
1.
1. 1. 1. 1.]
Class predicted
[0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 1 1 0 1 1 0 1 1 0 1 1 0 0 0 0 0 1 0 1
0 1 0 0 1 1 1 1 1 1 0 0 0 0 1 1 1 1 1 0 0 0 1 1 0 1 1 0 1 0 1 0 0 0 0 1 1 0 0
0 1 1 1 1 0 0 0 0 1 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1]

Training errors: 39

Training errors: 39.0 % For class 1

Class observed

[illegible]

Test errors: 67

Test errors: 33.5 % class-B

Task 4. Analyze what effect a distance between the classes has on the mse , training and testing errors. Distance between the classes is presented as Mahalanobis distance. The larger the distance, the better class separability is.

Change the mean values and correlation coefficient of the classes:

```
mean1 = np.array([-0.5, 1]) # mean vector class 2
mean2 = np.array([0.5, 0]) # covariance matrix class 2
var1=1 # variance of x1 feature
var2=2 # variance of x2 feature
cor12=0.8 #correlation coefficient between x1 and x2
```

You can also make the class covariance matrices cov1 and cov2 not equal.

Mean = [0.8, 1] and Covariance = [0.5,1]

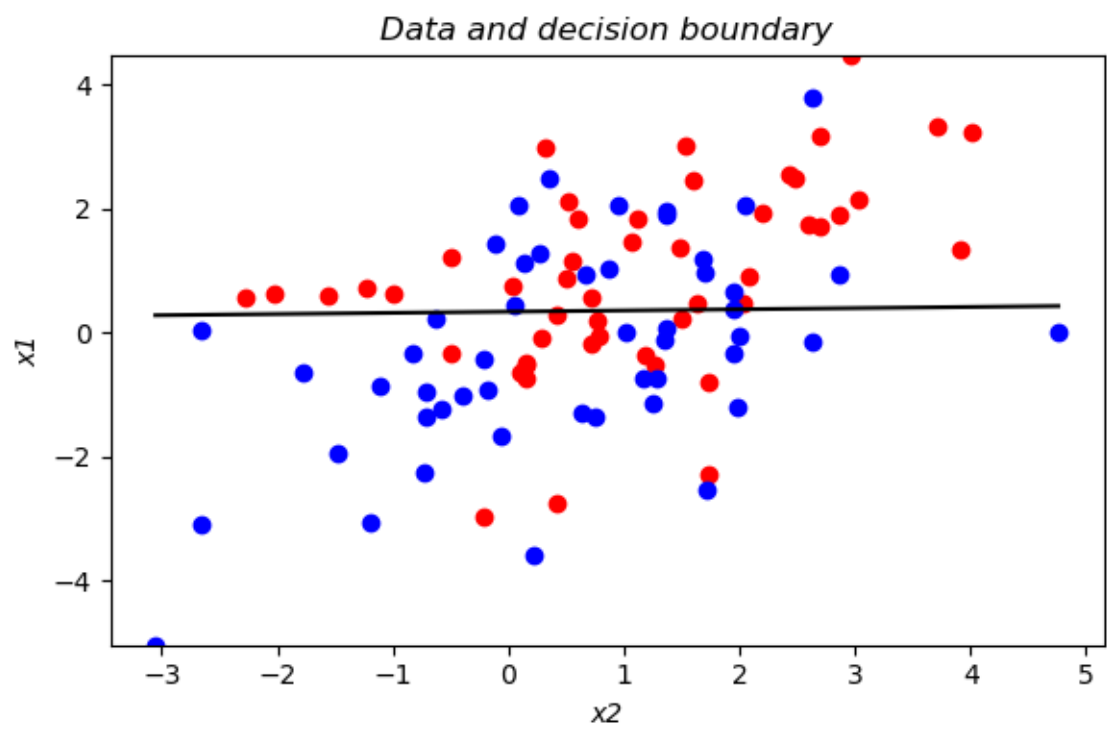
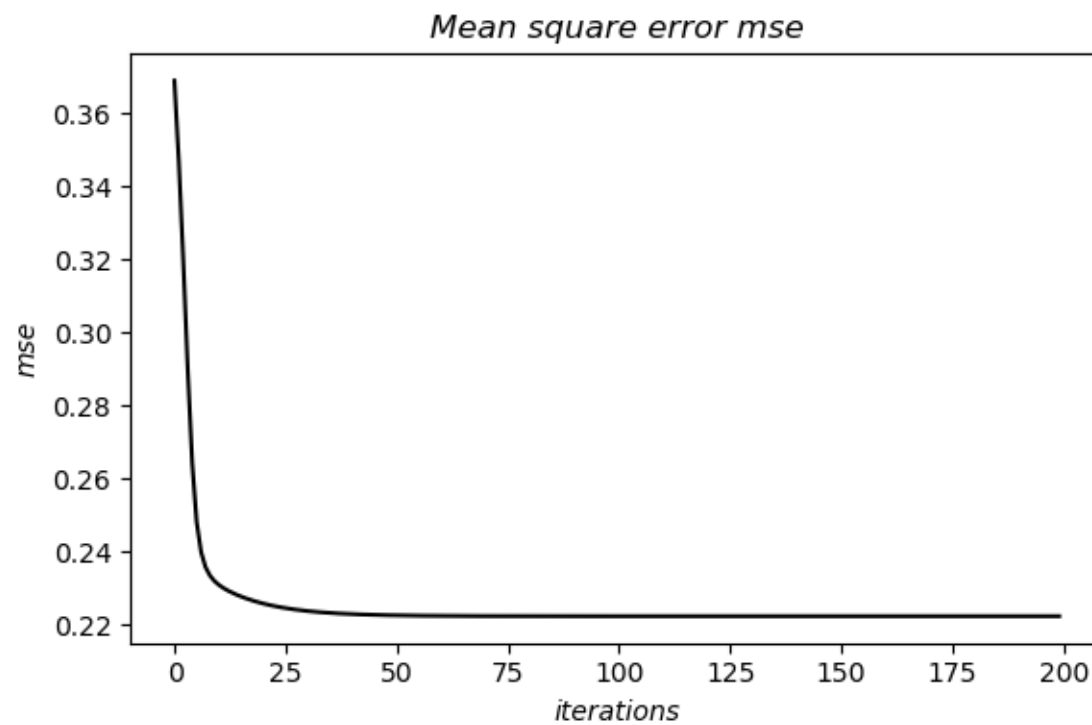
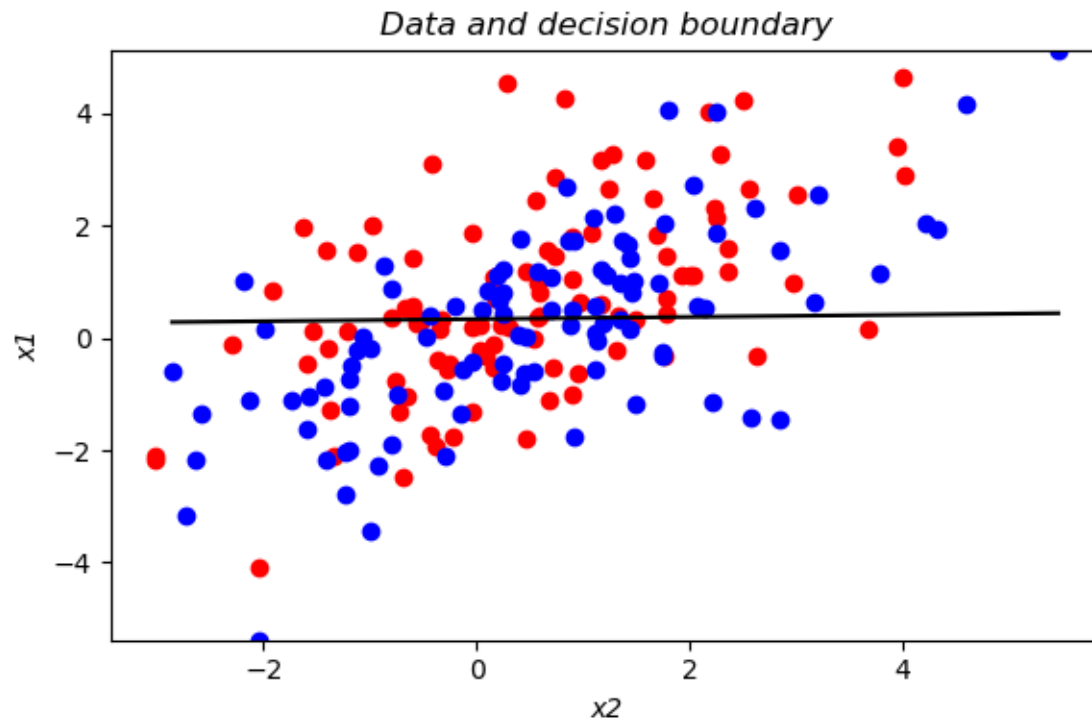


Figure 2 – Class 2



Task 5 (advanced). Calculate the training and test errors for each class.

Task 6 (not obligatory). Classify your own data.

Analyse the results and present in a written report.