FFR135 HP1

Self organising map

1 Introduction and Method

The goal of this assignment is to create a self organising map, that clusters three different Iris flowers of the Iris-Flower data set [**UCI**].
After loading the data, the first step is to normalise it.

$$data = \frac{data}{max\{data\}}$$

The initial weights are set in a uniform distribution in the range $[0, 1]$. The output is set to a 40×40 array.
The learning rate η is depending on the epoch number, the same with the width σ.

$$\eta = \eta_0 exp(-d_\eta \times epoch) \tag{1}$$

$$\sigma = \sigma_0 exp(-d_\sigma \times epoch) \tag{2}$$

Here the initial values are $\eta_0 = 0.1$, $d_\eta = 0.01$, $\sigma_0 = 0.01$ and $d_\sigma = 0.05$.
Now the network is trained. For every epoch, firstly the updated *learning rate* and *width* are calculated. Then one loops over the input data, and finds the winning neuron, which is the one with the weight vector closest to the input $\mathbf{x}$. With the found winning neuron the weights are updated with

$$\delta \mathbf{w}_i = \eta h(i, i_0)(\mathbf{x} - \mathbf{w}_i) \tag{3}$$

After updating all weights the trained network is evaluated with the input data and the new weights. The result is shown in the next section.

2 Results

When executing the before described code, the following *Self-Organising map* can be found 1. The left side shows the untrained network, the right the trained one. Clustering seems successful, the only visual outlier lies at point $(30, 9)$.

3 Cooperation

I cooperated with Martina Gatti.

4 Python code

The code is attached on the following pages.

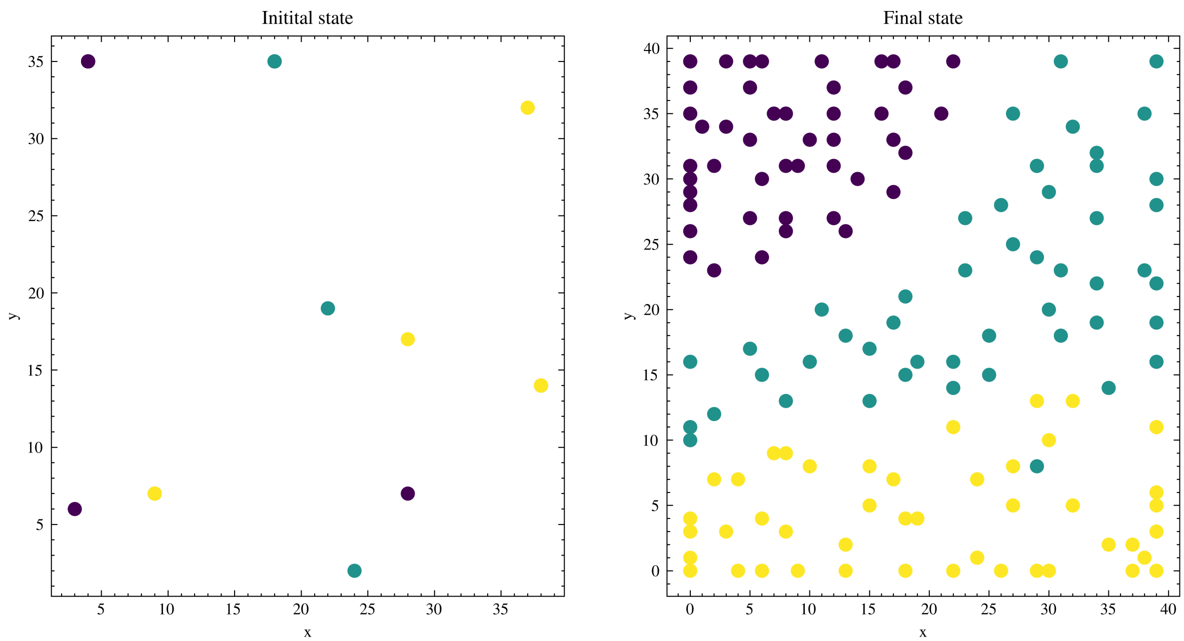

Figure 1: Trained self organising map, for the three Iris-Flowers. Left side of the figure shows the untrained network, where many data points lay above each other. The right side shows the output of the trained network