# VII.6 Self-Organizing Maps

## VII.6 Kohonen‘s Self-Organizing Map

(Kohonen, 1997)

### VII.6.1 Introduction

- Self-Organizing Map (SOM) algorithm is an unsupervised learning algorithm
  - visualize high-dimensional data sets on a 2-dimensional regular grid of neurons
  - constructed clusters provide insights into the structure of the given data set
    - → see Data Understanding phase in CRISP DM Methodology
  - distinguish training phase and deployment phase

- SOM is a **heuristic** technique delivering an **exact** assignment of objects to clusters

Example: “Poverty Map“

- describe poverty of countries and/or their citizens with 39 attributes
- data set includes 78 world countries
- similar countries are positioned close to each other

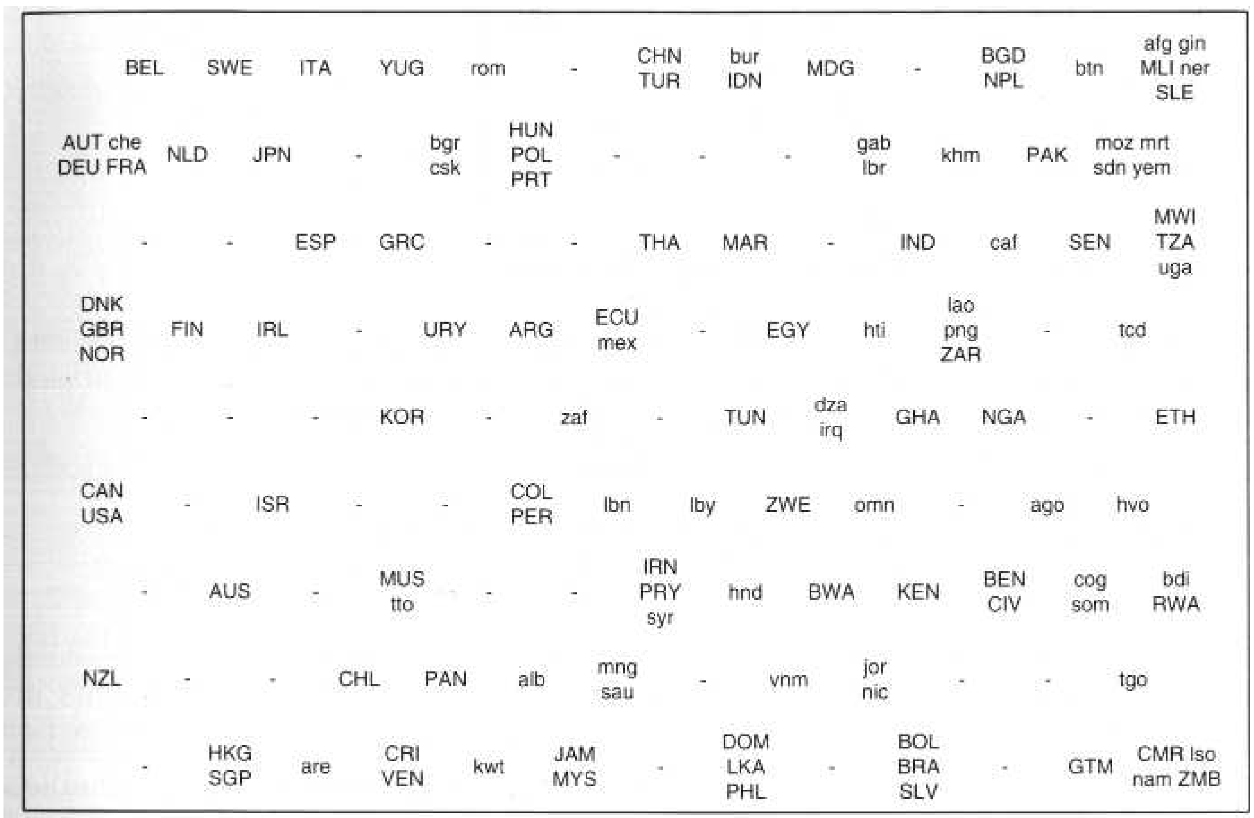



Figure 1: Kohonen, 1997

- <u>grey levels</u> may be used to visualize the cluster structure:

  - light shade is used for indicating high similarity between neighboring elements
  - dark shade indicates low similarity

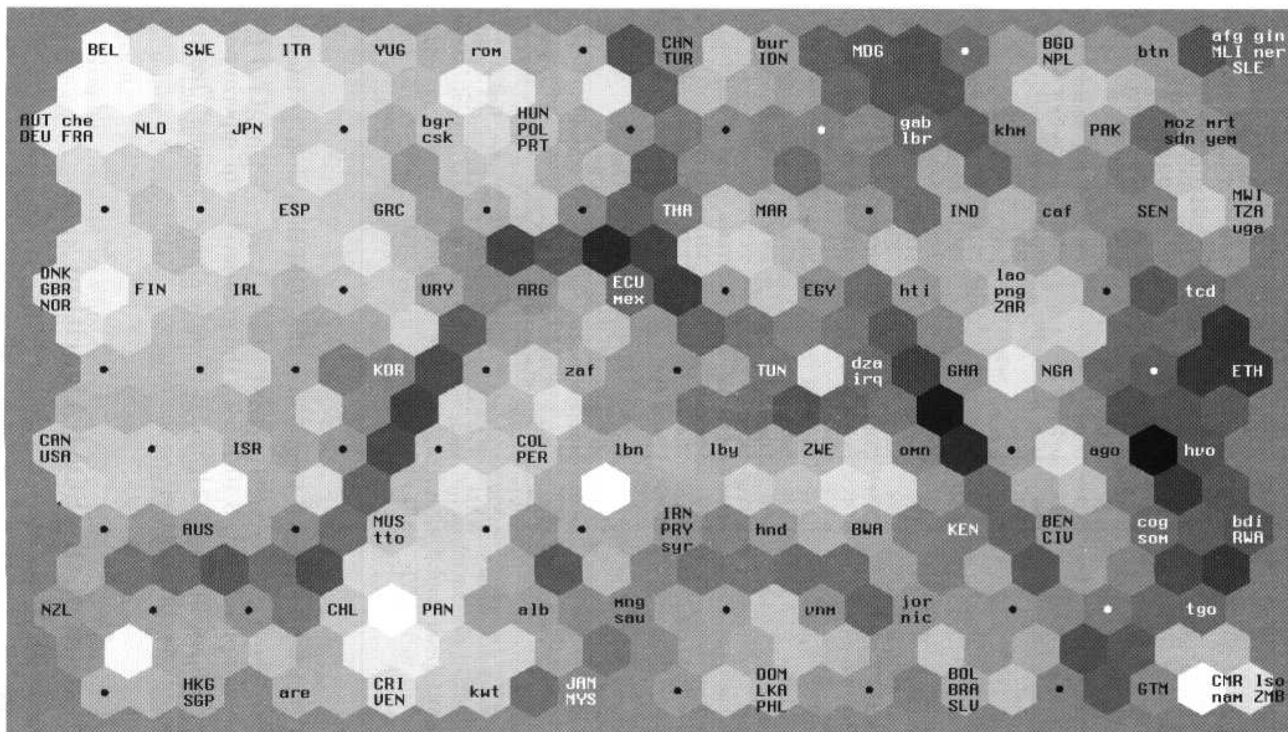



Figure 2: Kohonen, 1997

## VII.6.2 SOM Structure

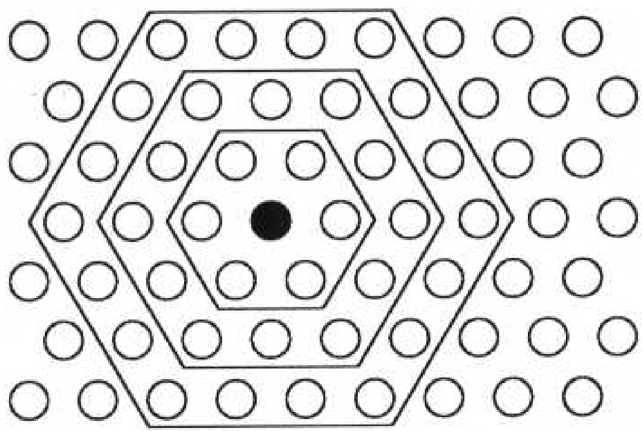
- A SOM is formed of neurons located on a regular, usually 1- or 2-dimensional grid

- each neuron i is represented by a n-dimensional weight vector $m_i = [m_{i_1}, ..., m_{i\,n}]$
  - n is equal to the number of attributes of the training data

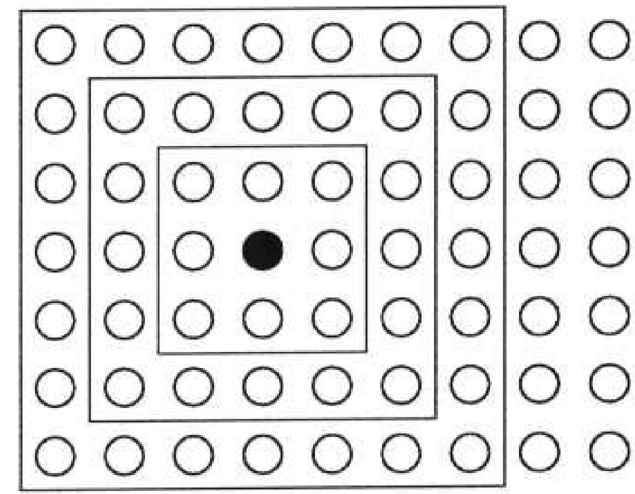
- neurons are connected to adjacent neurons
  - adjacent neurons of a given neuron i belong to the 1-neighbourhood $N_{i,1}$
  - neighborhoods with different sizes may be defined: $N_{i,1}, N_{i,2}, ....$

- 2-dimensional grids may be arranged in a rectangular or a hexagonal structure

# Kapitel VII.6: Kohonen‘s Self-Organizing Map



(a) Hexagonal grid



(b) Rectangular grid

Figure 3: Kohonen,1997

## VII.6.3 Initialization

- number of neurons has to be chosen high enough
  - predefined
  - iterative
- neighborhood size influences smoothness of the learning
- weight vectors have to be initialized
  - e.g. random initialization or sample initialization
    - weight vectors are initialized with random samples drawn from the training set

## VII.6.4 Training

- idea: ‘‘the winner takes all‘‘

  - for a given training instance only a single neuron is activated
    - called Best Matching Unit (BMU)

- BMU is the neuron c whose weight vector has highest similarity with training instance x

  - BMU c is determined by $d(x, m_c) = \min_i d(x, m_i)$

  - choose d e.g. as Euclidean distance

- for every training instance the BMU and additional neurons in the neighborhood of the BMU are adjusted by the Kohonen-Learning-Rule

- Kohonen-Learning-Rule

- weight vector of BMU and its neighborhood are adjusted in such a way that the resulting weight vectors are more similar to the training instance

- $m_i(t+1) = m_i(t) + h_{ci}(t) \cdot [x(t) - m_i(t)]$

  - t: time

  - x(t): training instance processed at time t

  - $h_{ci}(t)$: neighborhood of BMU c at time t; defines region of influence that the training instance has on the SOM; it is a non-increasing function of time and of the distance of unit i from BMU c.

- $h_{ci}(t) = h(d(r_c, r_i), t) \cdot \alpha(t)$

  - h: neighborhood function
  - $r_i$: location of unit i on the map grid
  - $\alpha(t)$: learning rate function

- neighborhood function h:

  - bubble function: constant over the whole neighborhood of BMUc, zero elsewhere
  - Gaussian neighborhood function:

$$\exp\left(-\frac{[d(r_c, r_i)]^2}{2\sigma^2(t)}\right)$$ ($\sigma$ defines neighborhood width)

- learning rate function $\alpha$: ($\alpha(t)$ decreasing function of time)

  - e.g. $\alpha(t) = \frac{A}{t+B}$ ; A,B constants

- neighborhood has to be large enough in the beginnnig
  - global adjustment of the SOM has to be achieved
  - e.g. initial radius of neighborhood may be equal to half the diameter of the SOM
- during learning radius may shrink to 1 unit in order to converge
  - fine adjustment of the direct neighborhood of the BMU

- in order to achieve a good accuracy <u>number</u> of <u>learning steps</u> has to be high enough, e.g. 500 times the number of SOM neurons

- SOM can also handle <u>missing values</u>:

    - leave out the missing attributes from the distance calculation

## VII.6.5 Deployment

- SOM is a good data exploration technique
  - easy and natural visualization
- yet unseen examples activate a single neuron in the SOM: the best matching unit
- SOM algorithm available in various data mining tools
  - e.g.
    - Clementine
    - Sphinx Vision (ASOC)