Lecture 5:

Self–Organising Maps

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BIS4435

Euclidean Space and Euclidean Distance (Examples)

The Clustering Problem

SOM Architecture and Principles

Training Procedure

Contextual Maps

Applications of SOM

HISTORICAL BACKGROUND

1960s Vector quantisation problems studied by mathematicians (Glienn, 1964; Stratonowitch, 1966).

1973 von der Malsburg did the first computer simulation demonstrating self–organisation.

1976 Willshaw and von der Malsburg suggested the idea of SOM.

1980s Works by Kohonen further developed and studied computational algorithms for SOM.

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or by an m–dimensional vector

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- How can we compute the distance between different points in such a space?

EXAMPLES

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In $\mathbf{R}^3$ (three–dimensional space) points are represented by three coordinates x, y and z (or x_1, x_2 and x_3), such as $\mathbf{a} = (2, -1, 3)$.

EUCLIDEAN DISTANCE

The distance $\rho(\mathbf{a}, \mathbf{b})$ between two points

$$\mathbf{a} = (a_1, \ldots, a_m) \quad \text{and} \quad \mathbf{b} = (b_1, \ldots, b_m)$$

in Euclidean space $\mathbf{R}^m$ is calculated as:

$$\begin{aligned} \|\mathbf{a} - \mathbf{b}\| &= \sqrt{\sum_{i=1}^{m} (a_i - b_i)^2} \\ &= \sqrt{(a_1 - b_1)^2 + \cdots + (a_m - b_m)^2} \end{aligned}$$

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Remark

Note that Euclidean distance is

1. *Positive:* $\rho(\mathbf{a}, \mathbf{b}) \geq 0$, *and* $\rho(\mathbf{a}, \mathbf{b}) = 0$ *iff* $\mathbf{a} = \mathbf{b}$
2. *Symmetric:* $\rho(\mathbf{a}, \mathbf{b}) = \rho(\mathbf{b}, \mathbf{a})$.
3. *Triangle inequality:* $\rho(\mathbf{a}, \mathbf{c}) \leq \rho(\mathbf{a}, \mathbf{b}) + \rho(\mathbf{b}, \mathbf{c})$

Such functions are called metrics, and sets with metrics are called metric spaces.

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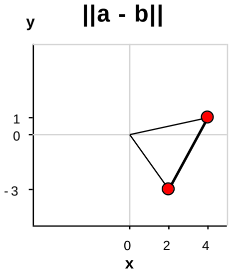
$$\begin{aligned} \|\mathbf{a} - \mathbf{b}\| &= \sqrt{(2-4)^2 + (-3-1)^2} \\ &= \sqrt{20} \approx 4.47 \end{aligned}$$



MULTIDIMENSIONAL DATA IN BUSINESS

- A bank gathered information about its customers:

Case:	Age	Gender	Income ($K p.m.)	Expenses ($K p.m.)	Home owner	Credit score
1	21	0	2	1	0	3
2	18	1	1	2	0	1
3	50	1	6	2	1	5
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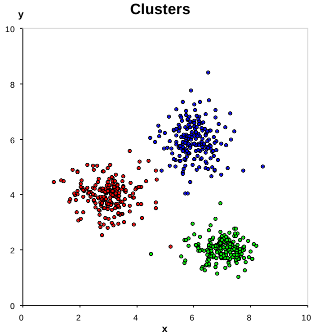
- We may consider each variable (age, gender, income, etc) as a coordinate x_i and each case as a point in an m–dimensional space.
- How far should be similar cases from each other?

CLUSTERS



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- One of the main goals of **multivariate analysis** is to find clusters of points.

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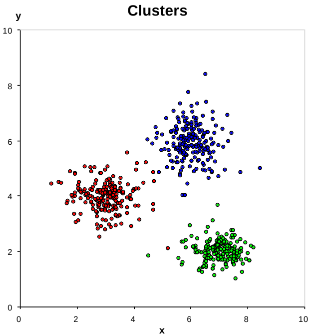
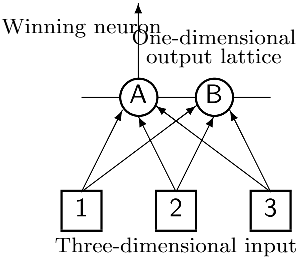
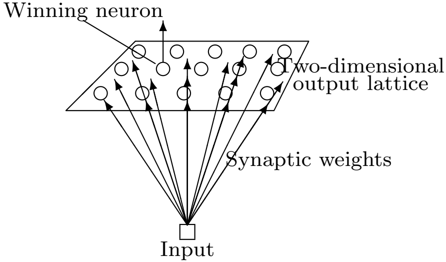


- **Clusters** are groups of points close to each other.
- One of the main goals of **multivariate analysis** is to find clusters of points.
- 'Similar' customers would have small Euclidean distance between them and would belong to the same group (cluster).

SOM ARCHITECTURE

- SOM uses a single layer network of neurons **competing** with each other, so that only one neuron can fire at a time.





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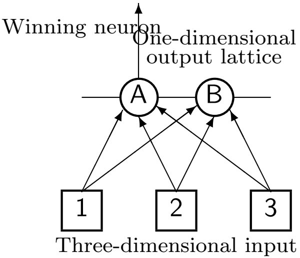
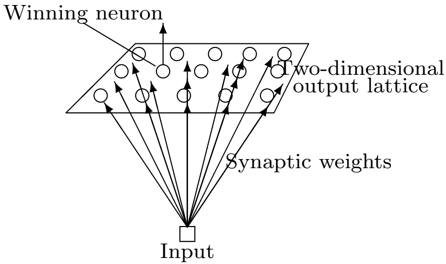
- The algorithm consists of three phases: **competition**, **cooperation** and **adaptation**.





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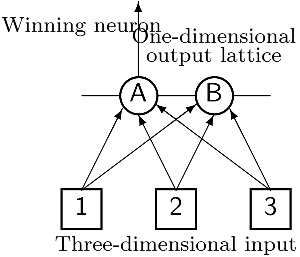

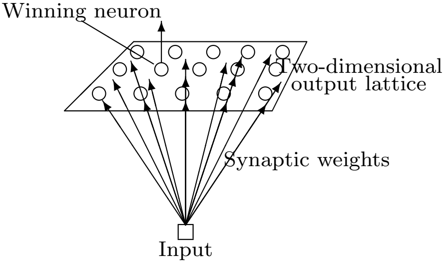

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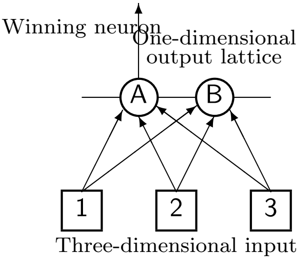

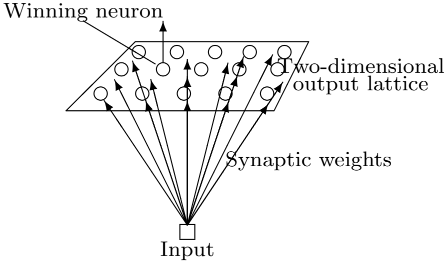

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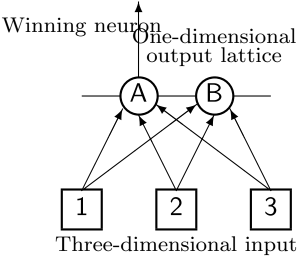
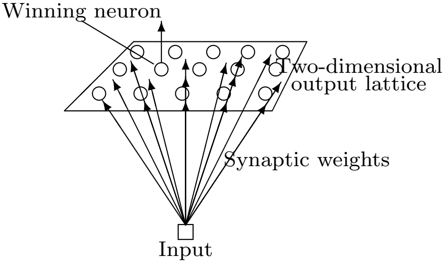
- 'Closeness' (neighbourhood) in the m-dimensional input space $\mathbf{R}^m$ is computed by the Euclidean distance $\rho(\mathbf{x}, \mathbf{w})$.





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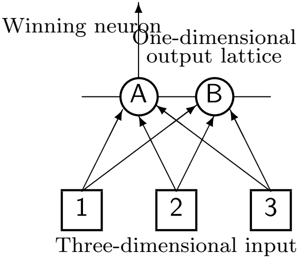

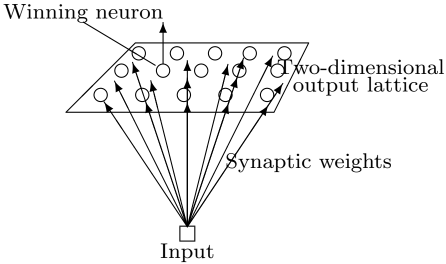

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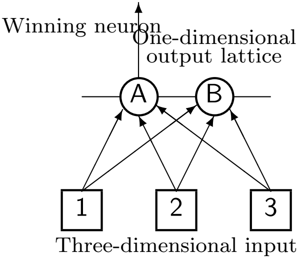

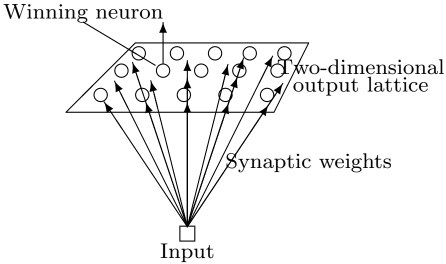

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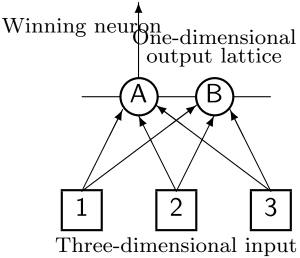

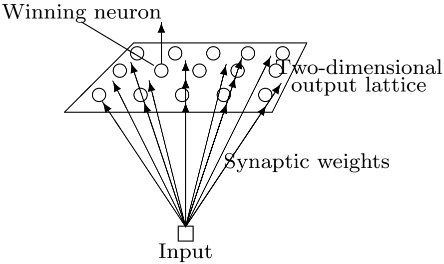

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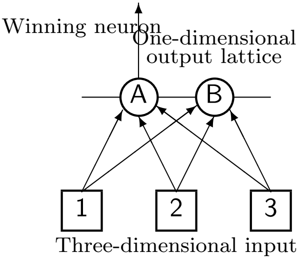

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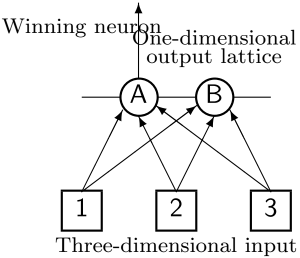

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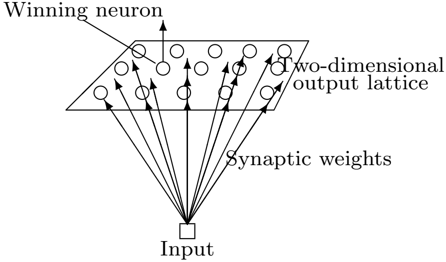

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- The **winner** is the node whose weight $\mathbf{w}_j$ is the closest to the input $\mathbf{x}$ in terms of Euclidean distance:

$$\begin{aligned}
\|\mathbf{x} - \mathbf{w}_1\| &= \sqrt{(x_1 - w_{11})^2 + \cdots + (x_m - w_{m1})^2} \\
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- Thus, nodes 'compete' in the sense which of the nodes $\mathbf{w}_j$ is more 'similar' to a give input pattern $\mathbf{x}$.

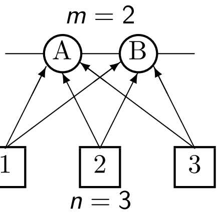
Example

Consider SOM with three inputs and two output nodes (A and B). Let

$$\mathbf{w}_A = (2, -1, 3)\,, \quad \mathbf{w}_B = (-2, 0, 1)$$

Find which node is the winner for the input

$$\mathbf{x} = (1, -2, 2)$$



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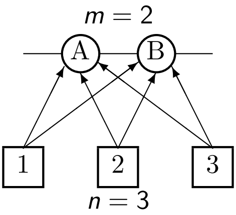

$$\begin{aligned}
\|\mathbf{x} - \mathbf{w}_A\| &= \sqrt{(1-2)^2 + (-2+1)^2 + (2-3)^2} = \sqrt{3} \\
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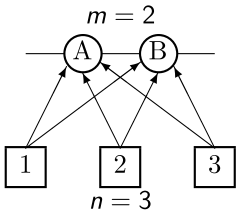

$$\begin{aligned} \|\mathbf{x} - \mathbf{w}_A\| &= \sqrt{(1-2)^2 + (-2+1)^2 + (2-3)^2} = \sqrt{3} \\ \|\mathbf{x} - \mathbf{w}_B\| &= \sqrt{(1+2)^2 + (-2-0)^2 + (2-1)^2} = \sqrt{14} \end{aligned}$$

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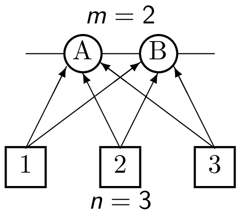

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- Node A is the winner because it is 'closer' ($\sqrt{3} < \sqrt{14}$)
- What if $\mathbf{x} = (-1, -2, 0)$?

ADAPTATION

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- The adaptation formula for node j is:

$$\mathbf{w}_j^{\mathrm{new}} = \mathbf{w}_j^{\mathrm{old}} + \alpha\, h_{ij} \left[\mathbf{x} - \mathbf{w}_j^{\mathrm{old}} \right] \ ,$$

  where

  - $\mathbf{w}_j$ is the weight vector of node j;
  - α is the learning rate coefficient;
  - h_{ij} is the neighbourhood of node j with respect to the winner i.

ADAPTATION (cont.)

To understand better the adaptation formula, let us check how the weights change for different values of α and h_{ij}.

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- Suppose $\alpha = 0$ or $h_{ij} = 0$. Then

  $$\mathbf{w}_j^{\mathrm{new}} = \mathbf{w}_j^{\mathrm{old}} + 0 \cdot 0 \left[\mathbf{x} - \mathbf{w}_j^{\mathrm{old}} \right] = \mathbf{w}_j^{\mathrm{old}}$$

  The weight does not change ($\mathbf{w}_j^{\mathrm{new}} = \mathbf{w}_j^{\mathrm{old}}$).

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- Suppose $h_{ij} = 1$ and $\alpha = 1$. Then

  $$\mathbf{w}_j^{\mathrm{new}} = \mathbf{w}_j^{\mathrm{old}} + \mathbf{x} - \mathbf{w}_j^{\mathrm{old}} = \mathbf{x}$$

  The new weight is equal to the input ($\mathbf{w}_j^{\mathrm{new}} = \mathbf{x}$).

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Although weights of *all* nodes are adapted, they do not adapt equally. Adaptation depends on how close the nodes are from the winner in the output lattice.

- If the winner is node i, then the level of adaptation for node j is defined by the neighbourhood function $h = h_{ij}(d_{ij})$, where $d(i, j)$ is the distance in the lattice.

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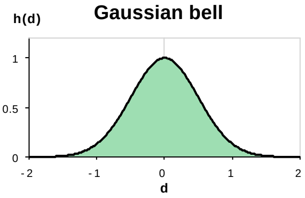

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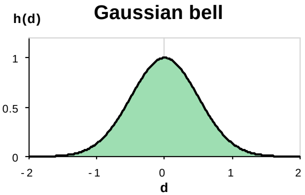

- The winner 'helps' mostly its neighbours to adapt. Note also that the winner is adapted more than any other node (i.e. because $d(i, i) = 0$).

Example

Let $\alpha = 0.5$ and $h = 1$, and let us adapt the winning node A from previous example:

$$\mathbf{w}_A = (2, -1, 3)\,, \quad \mathbf{x} = (1, -2, 2)$$

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$$\begin{aligned}
\mathbf{w}_A &= \begin{pmatrix} 2 \\ -1 \\ 3 \end{pmatrix} + 0.5 \cdot 1 \cdot \left[\begin{pmatrix} 1 \\ -2 \\ 2 \end{pmatrix} - \begin{pmatrix} 2 \\ -1 \\ 3 \end{pmatrix} \right] \\
&= \begin{pmatrix} 2 \\ -1 \\ 3 \end{pmatrix} + 0.5 \cdot \begin{pmatrix} -1 \\ -1 \\ -1 \end{pmatrix} = \begin{pmatrix} 1.5 \\ -1.5 \\ 2.5 \end{pmatrix}
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  3. Adapt the weights of the winner and its neighbours
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- The number of input dimensions (m) is usually very large (e.g. $m = 100$), so we cannot see the clusters directly.
- The output lattice is usually one or two dimensional, so we can visualise and ‘see’ the clusters.

EXAMPLE OF SOM

	dove	hen	duck	goose	owl	hawk	eagle	fox	dog	wolf	cat	tiger	lion	horse	zebra	cow
small	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0
medium	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
big	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
2 legs	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
4 legs	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
hair	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
hooves	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
mane	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0
feathers	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
hunt	0	0	0	0	1	1	1	1	0	1	1	1	1	0	0	0
run	0	0	0	0	0	0	0	0	1	1	0	1	1	1	1	0
fly	1	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0
swim	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0

FEATURE MAP

dog	·	·	fox	·	·	cat	·	·	eagle
·	·	·	·	·	·	·	·	·	·
·	·	·	·	·	·	·	·	·	owl
·	·	·	·	·	·	tiger	·	·	·
wolf	·	·	·	·	·	·	·	·	hawk
·	·	·	lion	·	·	·	·	·	·
·	·	·	·	·	·	·	·	·	dove
horse	·	·	·	·	·	·	hen	·	·
·	·	·	·	cow	·	·	·	·	goose
zebra	·	·	·	·	·	·	duck	·	·

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- Handles missing data
- The learning algorithm is unsupervised.

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- Can be used for pattern recognition (e.g. to identify credit–card fraud, errors in data, etc).