

CSE 5526: Introduction to Neural Networks

Unsupervised Learning

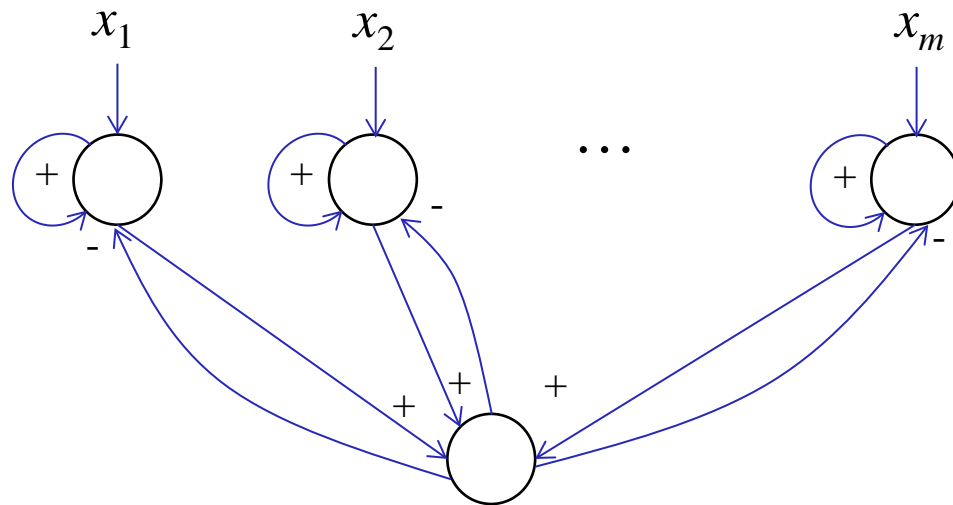
Types of learning

- Supervised learning: Detailed desired output is provided externally
- Reinforcement learning: Evaluative output is provided externally
 - It is sometimes considered a form of supervised learning (reward/penalty)
- Unsupervised learning, comprising competitive learning and self organization

Competitive dynamics

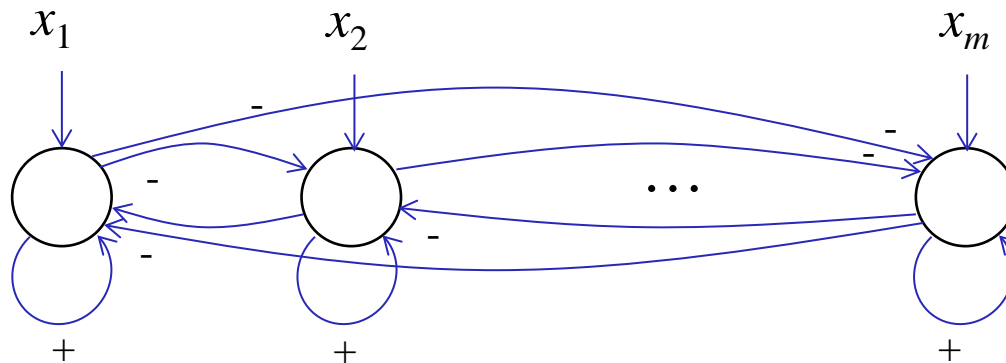
- Winner-take-all (WTA) networks implement competitive dynamics
- Two different architectures of WTA

Global inhibition:



WTA networks

- Two different architectures of WTA
Mutual inhibition



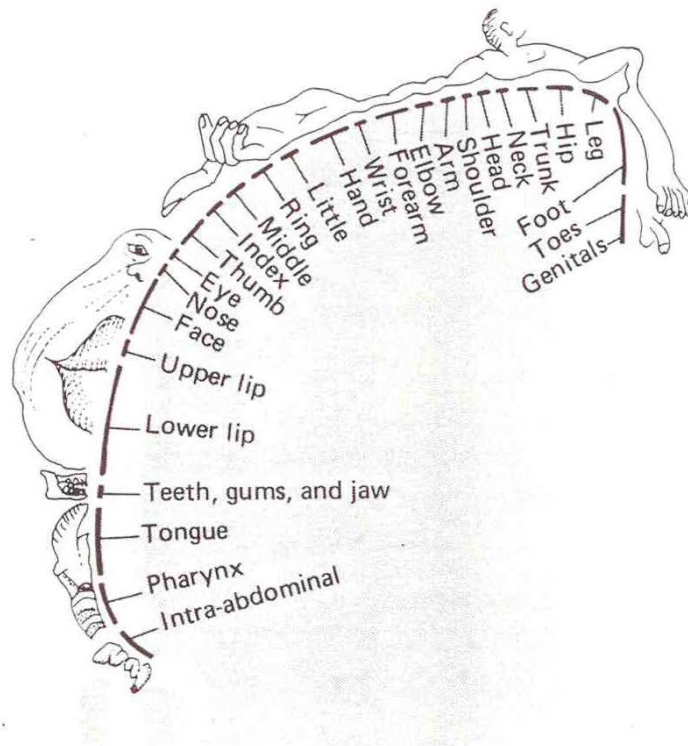
WTA networks (cont.)

- External input sets the initial conditions of neurons. Under certain conditions, only the neuron with the largest input reaches 1 and all the other neurons reach 0
 - Thus WTA is a maximum selector, a parallel implementation of MAX operation

Self-organizing maps (SOM)

- Maps are commonly found in the brain: retinotopic map, tonotopic map, somatosensory (tactile) map, etc.

A Sensory homunculus



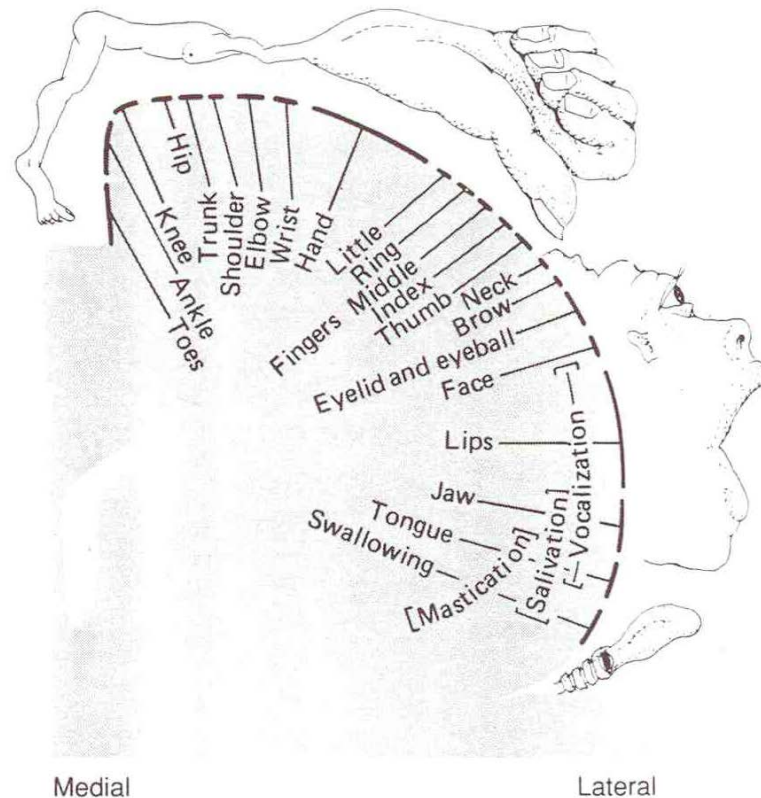
Lateral

Medial

Self-organizing maps (SOM)

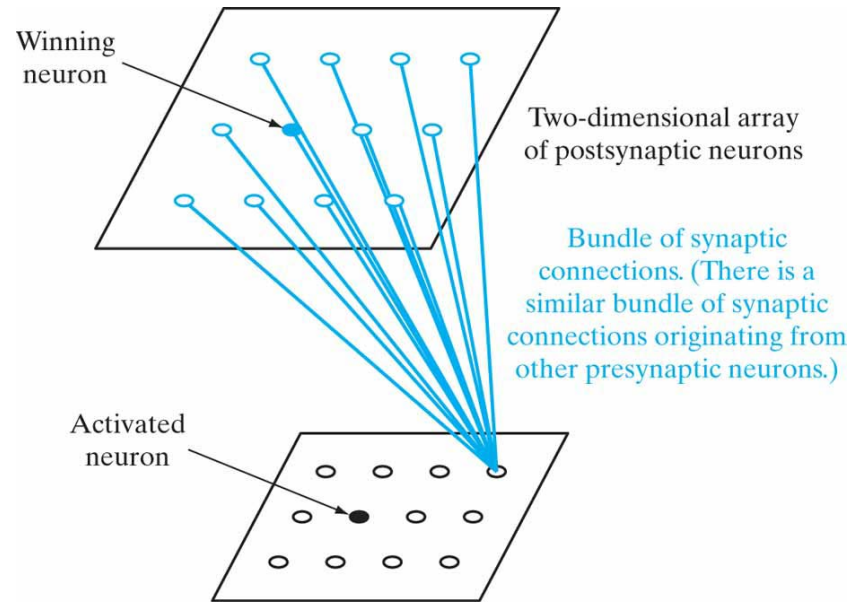
- Maps are commonly found in the brain: retinotopic map, tonotopic map, somatosensory (tactile) map, etc.

B Motor homunculus

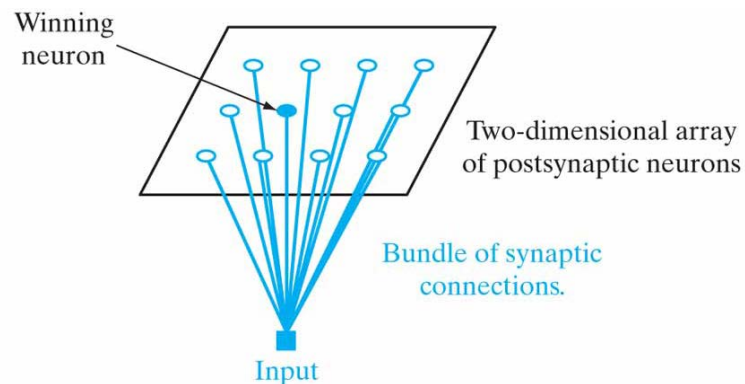


Self-organizing feature maps

- Competition and local cooperation along with synaptic plasticity can produce such maps.



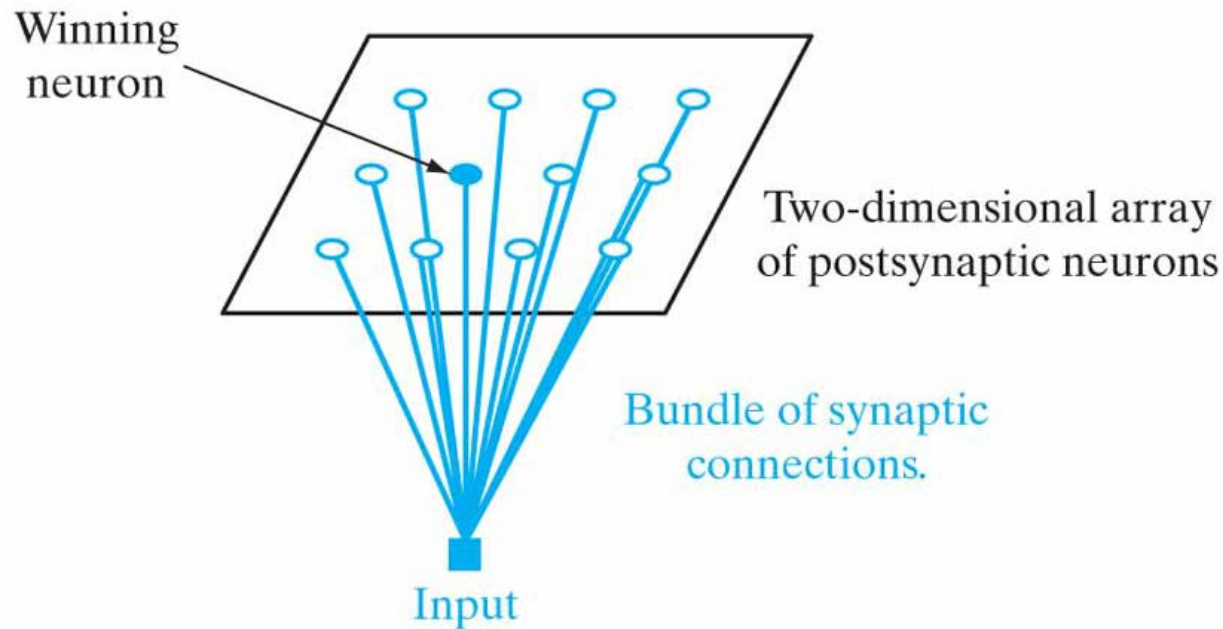
(a) Willshaw-von der Malsburg's model



(b) Kohonen model

SOM architecture

- Architecture: One layer with recurrent connections



(b) Kohonen model

SOM (cont.)

- Question: how to represent the input space by output neurons through training?
- The idea is to adjust the weight vectors of the winning neuron (via WTA competition) and its neighboring neurons, to make them closer to the input vector

Learning rule

- Weight update

$$\mathbf{w}_j(n+1) = \mathbf{w}_j(n) + \eta(n)h_{j,i(\mathbf{x})}(n)[\mathbf{x}(n) - \mathbf{w}_j(n)]$$

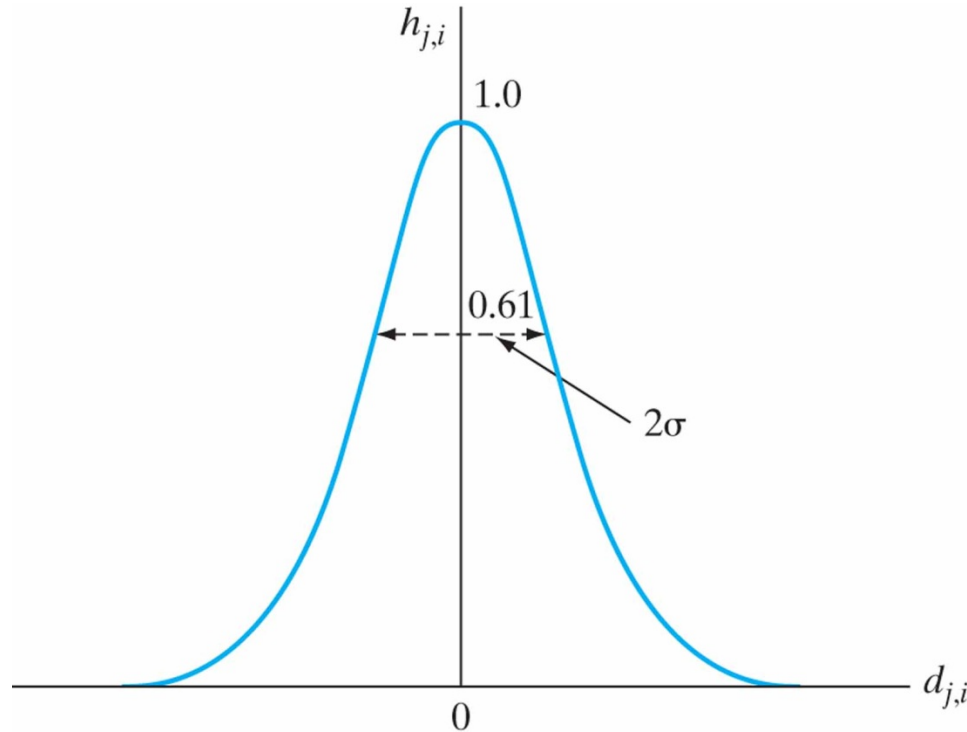
where $i(\mathbf{x})$ indicates the winning neuron, and $h_{j,i}$ denotes a neighborhood function centered at neuron i

- A typical choice for $h_{j,i}$ is a Gaussian function

$$h_{j,i}(n) = \exp\left[-\frac{d_{j,i}^2}{2\sigma^2(n)}\right]$$

where $d_{j,i}$ denotes the Euclidean distance between neuron j and i on the output layer

Neighborhood function



- To ensure convergence, both η and σ need to decrease gradually

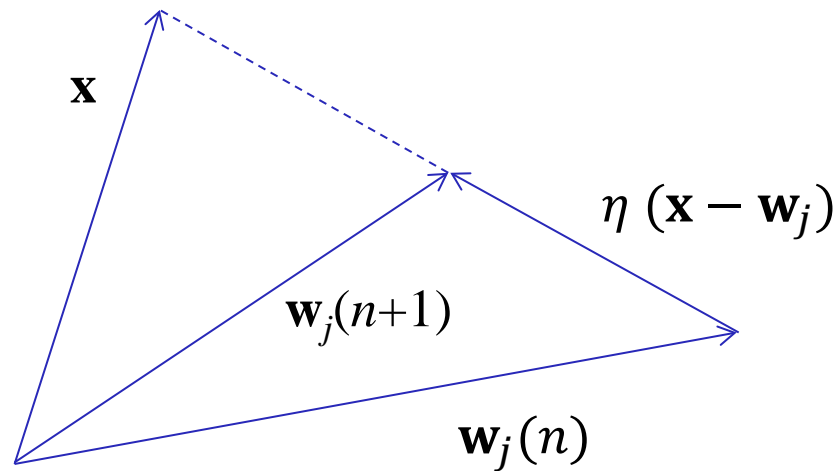
Competitive learning

- For the special case of a neighborhood function that includes just the winning neuron, SOM reduces to competitive learning:

$$\Delta \mathbf{w}_j = \eta y_j (\mathbf{x} - \mathbf{w}_j)$$

Here y_j is the (binary) response of neuron j

Competitive learning illustration



- Competitive learning implements an online version of K-means clustering

Two phases of SOM training

- **Ordering phase:** This phase is to achieve topological ordering of weight vectors by adapting $\sigma(n)$ and $\eta(n)$
- One approach is to set

$$\sigma(n) = \sigma_0 \left(1 - \frac{n}{N_0}\right)$$

where σ_0 is the initial (large) Gaussian width and N_0 is the number of iterations for the phase

$$\eta(n) = \eta_0 \left(1 - \frac{n}{N_0 + K}\right)$$

Here η_0 is the initial learning rate and K is another parameter

Two phases of training (cont.)

- Alternatively, we can set $\sigma(n)$ and $\eta(n)$ as given in textbook

$$\sigma(n) = \sigma_0 \exp\left(-\frac{n}{\tau_1}\right)$$

$$\eta(n) = \eta_0 \exp\left(-\frac{n}{\tau_2}\right)$$

where τ_1 and τ_2 are called time constants

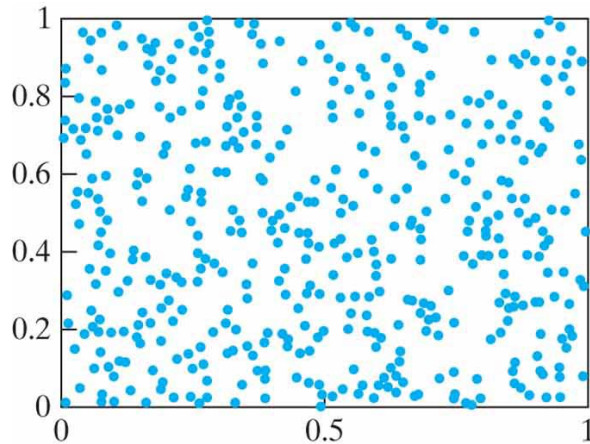
Two phases of training (cont.)

- **Convergence phase.** This phase fine-tunes the output neurons to match the input distribution
- For the convergence phase, $h_{j,i}(n)$ should contain just the nearest neighbors, which may reduce to one neuron. η should be small.

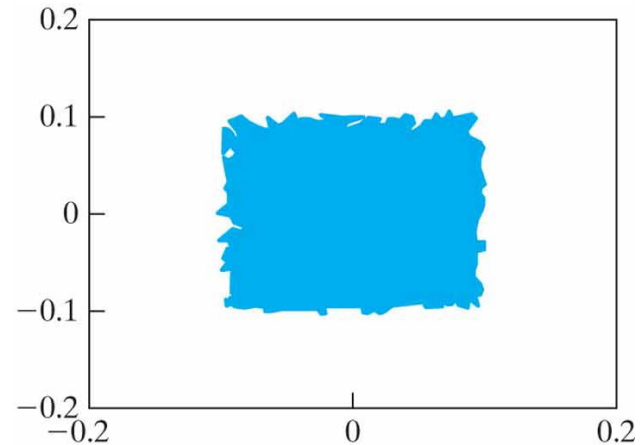
Properties of SOM

- Input space approximation
- Topological ordering
- **Remark:** SOM gives an online version of vector quantization

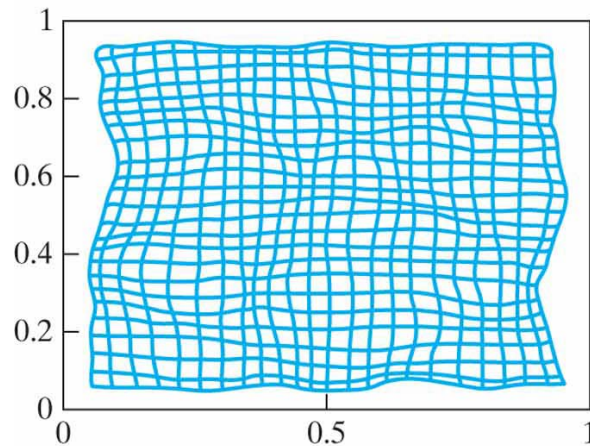
SOM illustrations



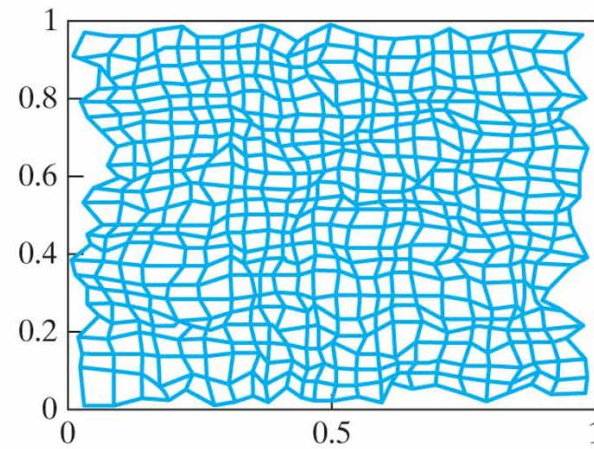
(a) Input distribution



Time = 0
(b) Initial weights

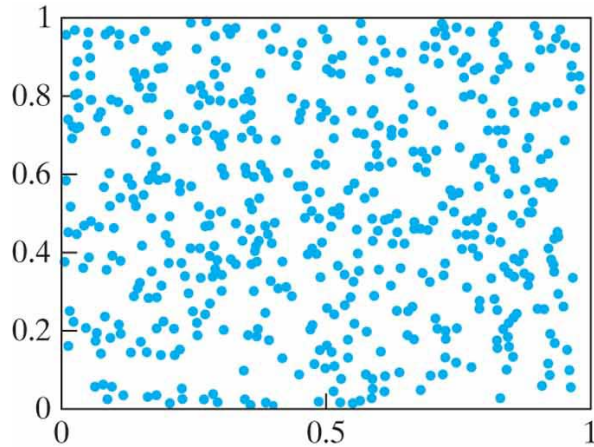


Time = 160 K
(c) Ordering phase

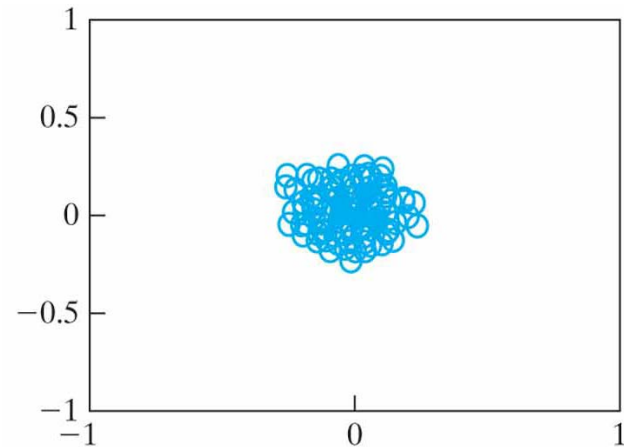


Time = 800 K
(d) Convergence phase

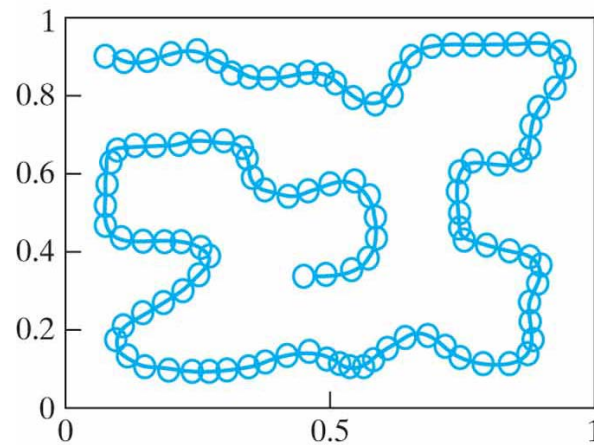
SOM illustrations (cont.)



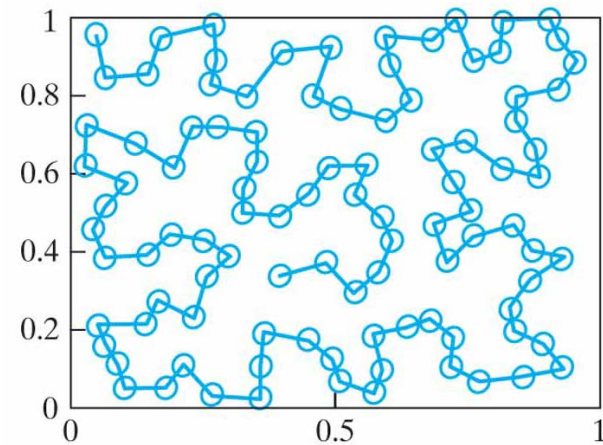
(a) Input distribution



Time = 0
(b) Initial weights

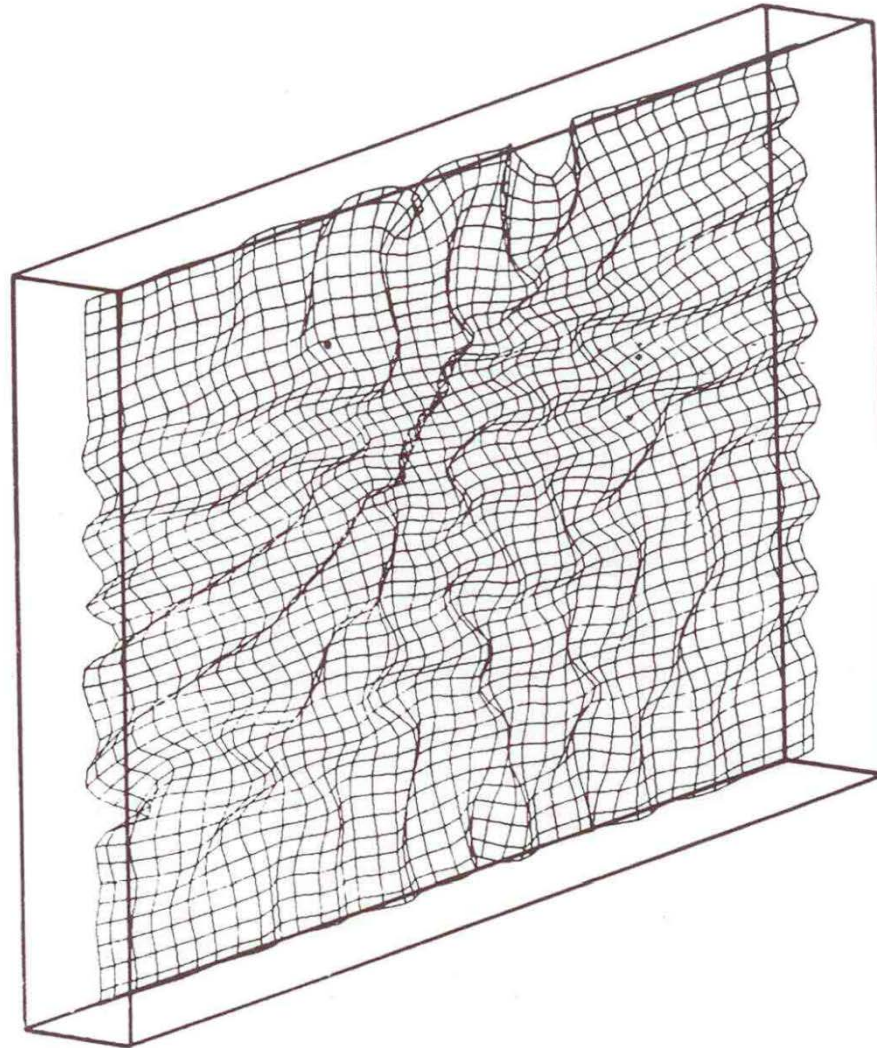


Time = 50 K
(c) Ordering phase



Time = 100 K
(d) Converging phase

SOM illustrations (cont.)



SOM illustrations (cont.)

