

Hebbian learning and Hopfield networks

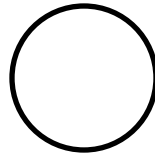
Pietro Berkes, Brandeis University

“Classical” models of learning

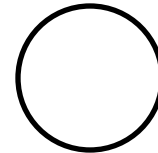
- Characterized by deterministic update and learning rules
- The models have a number of parameters that are adjusted such that the model performs a certain function
- Examples: neural networks, support vector machines, PCA, ...
- Issues: cannot cope with uncertainty

Hebb's rule

- Most of learning in the brain is unsupervised
- Brilliant idea by Hebb (1949):
cells that fire together, wire together



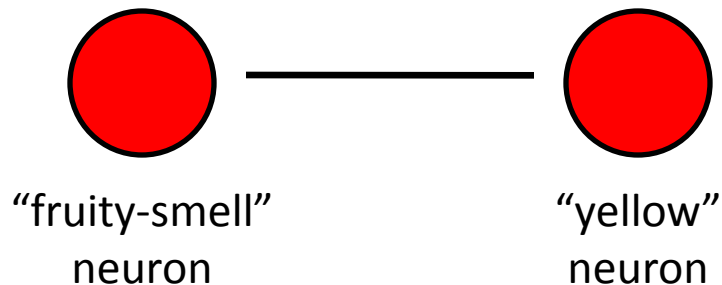
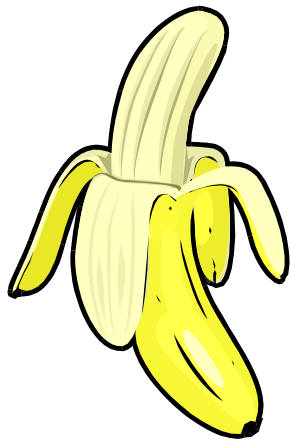
“fruity-smell”
neuron



“yellow”
neuron

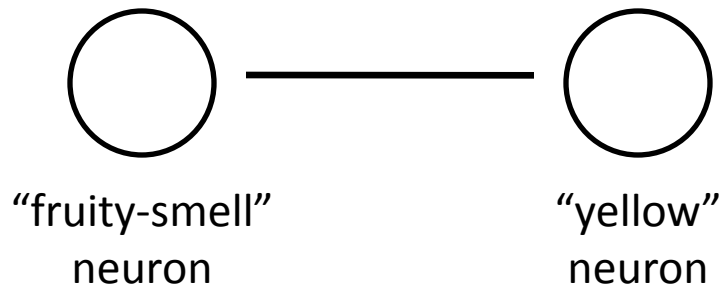
Hebb's rule

- Most of learning in the brain is unsupervised
- Brilliant idea by Hebb (1949):
cells that fire together, wire together



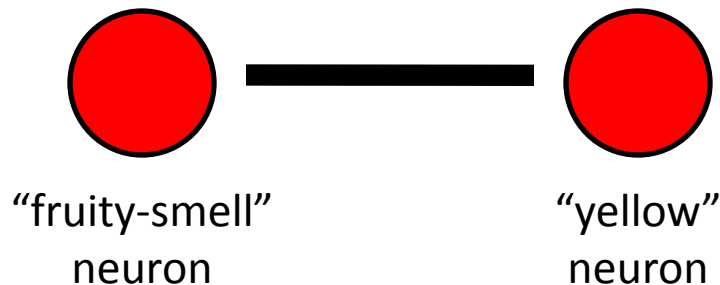
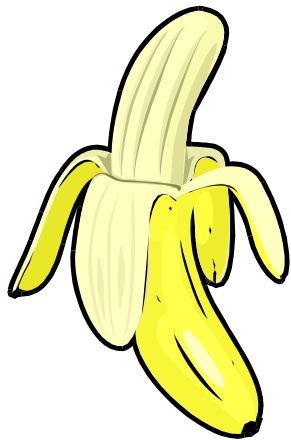
Hebb's rule

- Most of learning in the brain is unsupervised
- Brilliant idea by Hebb (1949):
cells that fire together, wire together



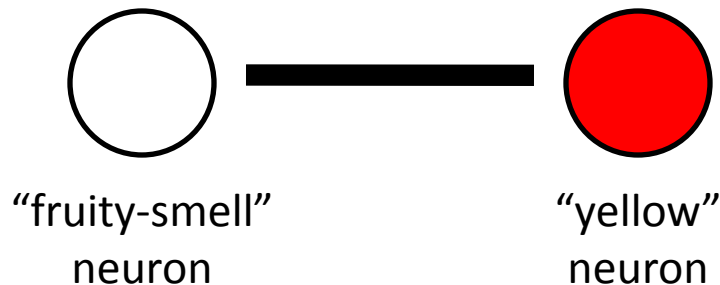
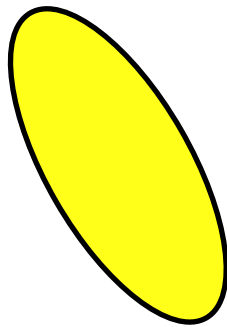
Hebb's rule

- Most of learning in the brain is unsupervised
- Brilliant idea by Hebb (1949):
cells that fire together, wire together



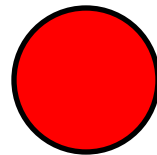
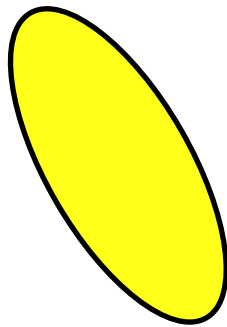
Hebb's rule

- Most of learning in the brain is unsupervised
- Brilliant idea by Hebb (1949):
cells that fire together, wire together

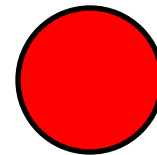


Hebb's rule

- Most of learning in the brain is unsupervised
- Brilliant idea by Hebb (1949):
cells that fire together, wire together



"fruity-smell"
neuron



"yellow"
neuron

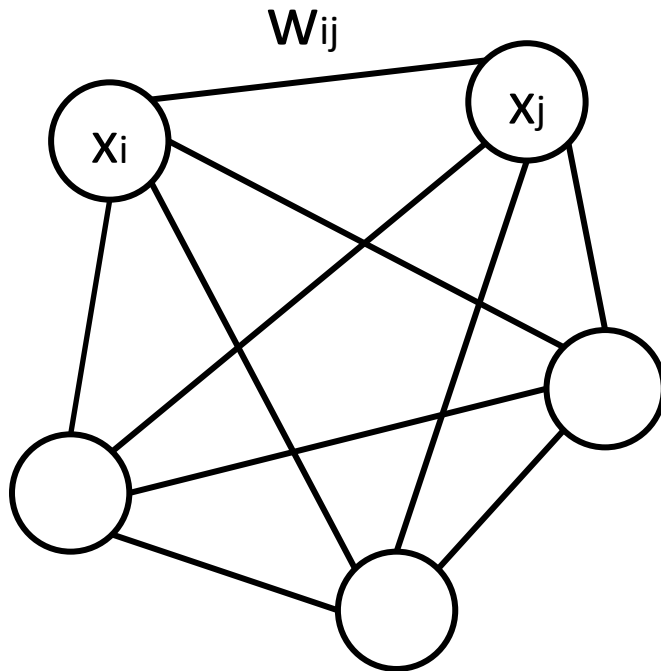
Hopfield network

- Hebb's ideas were formalized much later:
Hopfield network (1982)
- Most direct implementation of Hebb's ideas:

$$\Delta w_{ij} = x_i x_j$$

- Note: local learning rule, no teacher

Architecture



- $x_i = +1$ or -1
(binary neural activity)
- $w_{ii} = 0$ (no self-connections)
- $w_{ij} = w_{ji}$ (symmetric, bidirectional connections)

Learning rule

- Set neurons x_i to desired pattern
- Update weights as $\Delta w_{ij} = x_i x_j$
- i.e., if we have N patterns $x_i^{(n)}$
the final weights will be

$$w_{ij} = \sum_{n=1}^N x_i^{(n)} x_j^{(n)}$$

Activity rule

- For each neuron i :

1) compute activation $a_i = \sum_j w_{ij} x_j$

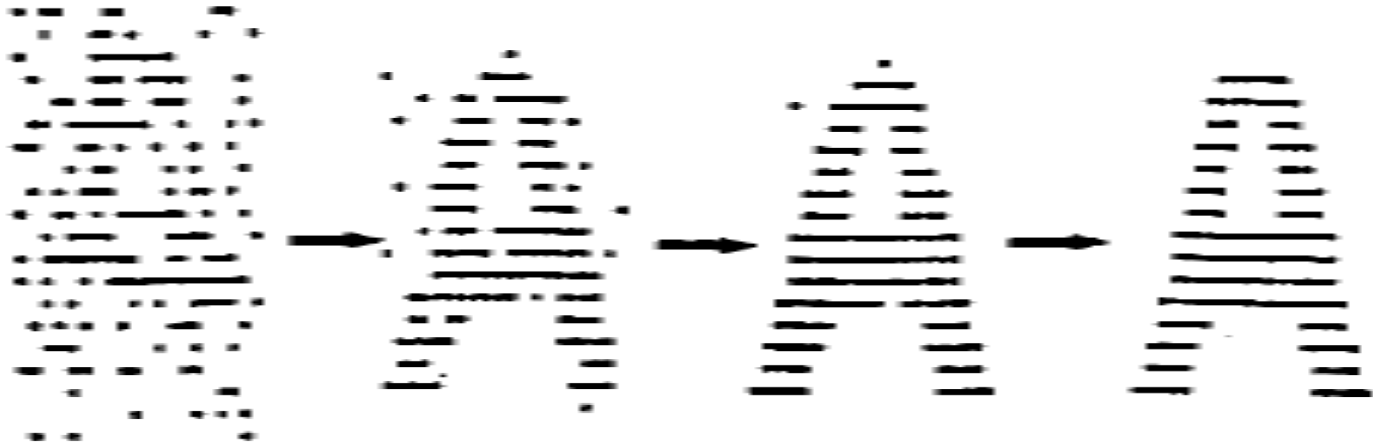
2) update state of neuron as $x_i = \begin{cases} +1 & a \geq 0 \\ -1 & a < 0 \end{cases}$

- Updates can be synchronous or asynchronous

Applications: denoising

noisy pattern

complete pattern

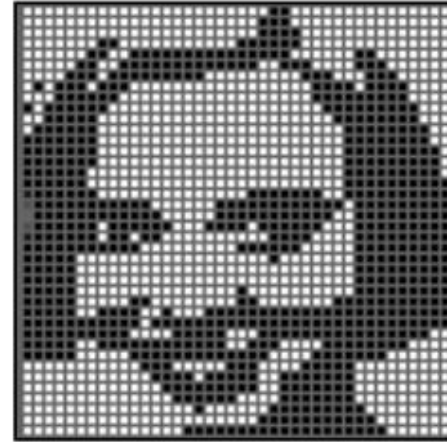


Applications: pattern completion

incomplete pattern

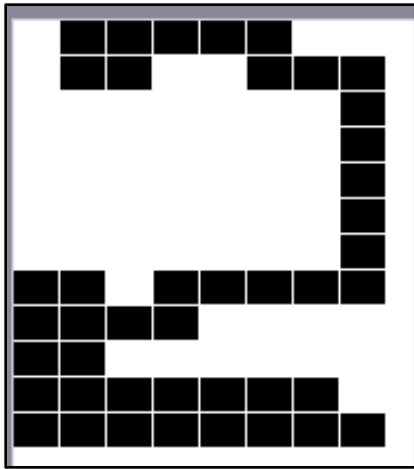


complete pattern

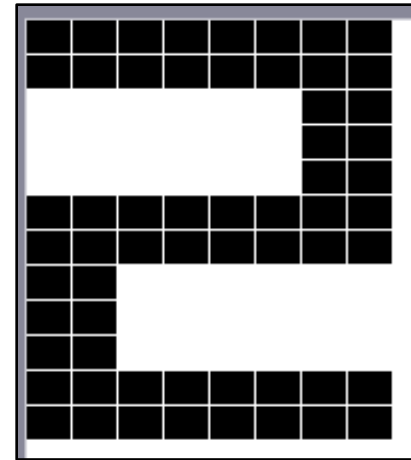


Applications: pattern recognition

novel pattern



stored pattern



Issues

- Capacity of the network: how many memories can be stored?

Not many: $\alpha = M/N = 0.144$

There is a whole literature about memory capacity and information storage in the hippocampus

- Robustness: how much can we modify a stored pattern such that we recover it perfectly/with a small error?

Hands-on part

- Download exercises from

http://people.brandeis.edu/~berkes/data/cognitive_models/exercises2