Foundations of Artificial Intelligence

CS472/3 — Fall 1999
Lecture #30 and #31

Bart Selman

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- Neural networks cont.

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Topics

Type of network structure.

Type of representations.

Type of learning algorithms (and applicability).

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Network Structure

Main distinction: **feed-forward** vs. **recurrent**.

Feed-forward: no cycles. Activation flows one direction — from input layer via "hidden" layers to output layer.

Extreme (unlikely) example: input layer — retina cells / output layer — muscle control cells.

Next figure: two (three?) layers. Two input units / two hidden units one output unit

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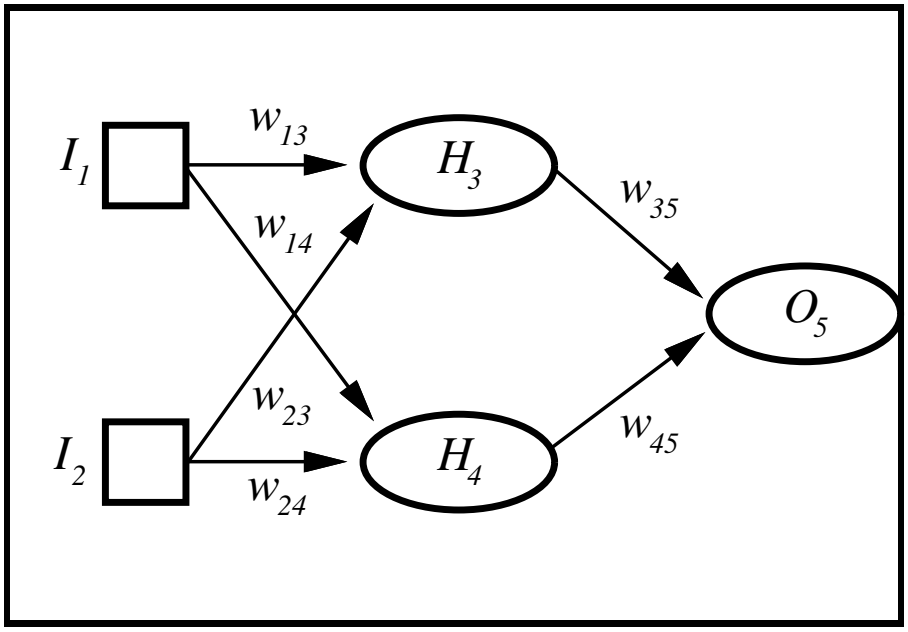

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$$
\begin{aligned}
a_5 &= g(W_{3,5}\ a_3 \ \ + \ \ W_{4,5}\ a_4) \\
&= g(W_{3,5}\ g(W_{1,3}\ a_1 \ \ + \ \ W_{2,3}\ a_2) + W_{4,5}\ g(W_{1,4}\ a_1 + W_{2,4}\ a_2)))
\end{aligned}
$$

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Activation passed from input to output. Does network have internal state? Corresponds to simple reactive agents.

Much used!. *Good learning algorithms for classification / concepts.*

Brain cannot be just a feedforward network!

Need (need short-term memory)

Brain has many feed-back connections.

brain is **recurrent network.**

Cycles!

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Hopfield Networks

Much harder to analyze. Can capture internal state. (activation keeps going around) More complex agents.

Two main types:

Hopfield networks.
Boltzmann machines.

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Hopfield Networks

symmetric connections ($W_{i,j} = W_{j,i}$)

output 0/1 only.

train weights to obtain **associative memory**

eg. store patterns (do figure).

It can be proven that an N unit Hopfiled net can

store up to $0.138N$ patterns reliably.

Note: no explicit storage. All in the weights.

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Boltzmann machines

symmetric connections ($W_{i,j} = W_{j,i}$)

output 0/1 only but network in constant motion:

compute **average output** value of each node.

stochastic

has nice (but slow) learning algorithm. also closely

connected to **probabilistic reasoning**

belief networks.

details beyond the scope of this course.

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Back to Feed-forward

input / output / hidden units.

perceptrons: no hidden units

multilayered

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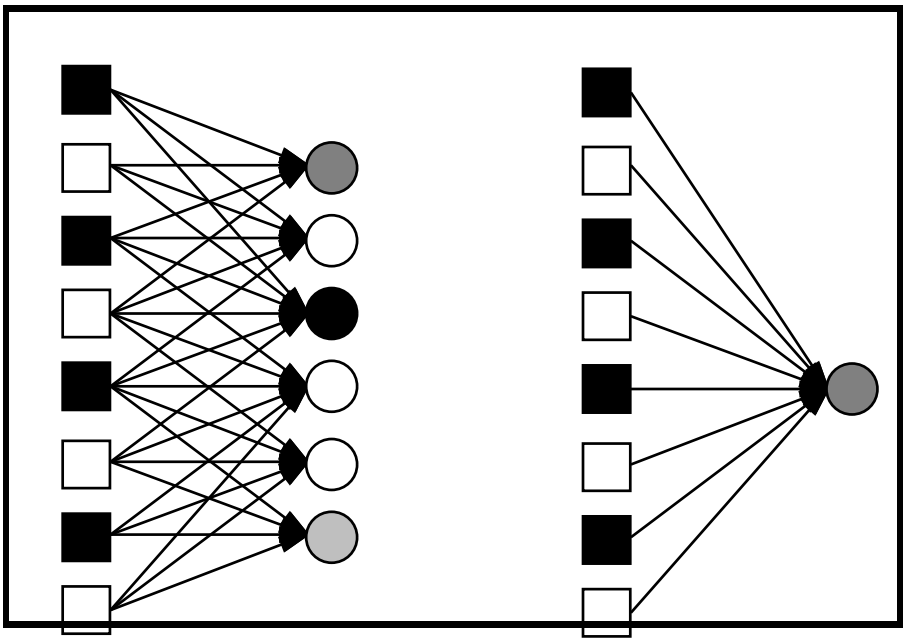

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I_j $W_{j,i}$ O_i I_j W_j O

Input Units | Output Units | Input Units | Output Unit

Perceptron Network | **Single Perceptron**

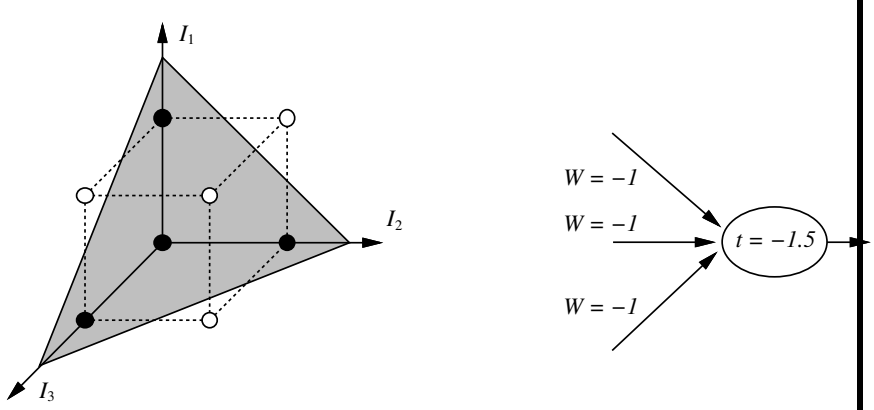
Perceptrons

Remarkable learning algorithm: (Rosenblatt 1960)
if function can be represented by perceptron,
then learning algorithm is guaranteed to quickly converge
to the hidden function!

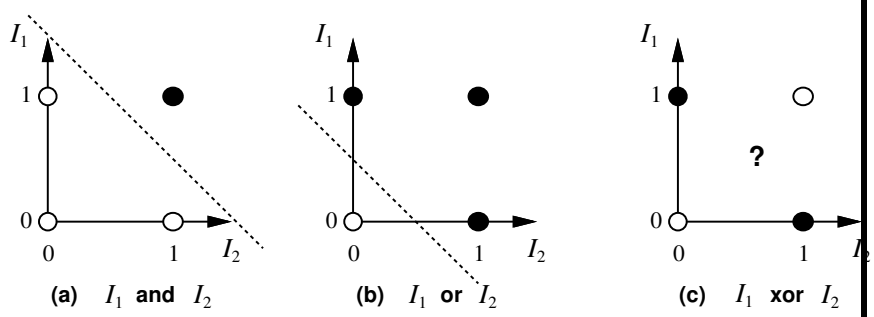
enormous popularity, early / mid 60's

But analysis by Minsky and Papert (1969)
showed certain simple functions cannot be represented
(Boolean XOR)
Killed the field! (and possibly Rosenblatt (rumored)).

Linearly separable functions only



(a) Separating plane **(b) Weights and threshold**



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Mid eighties: comeback — multilayed networks
(Turing machine compatible)
learning procedures: **backpropagation**

Possibly one of the most popular / widely used learning methods today.

John Denker: *"neural nets are the second best thing for learning anything!"*

backprop and perceptron learning

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Representations

How are concepts represented in the brain / neural net?

local representations / grandmother cell
distributed representations

Pros / Cons?

distributed appeared to have won **but**

in May 1997: (UPI news wire): UCLA researchers showed **single** cell can learn a concept! (concept: facial expressions / a cell responding to "angry face"!)