Foundations of Artificial Intelligence

CS472/3
Lecture #36

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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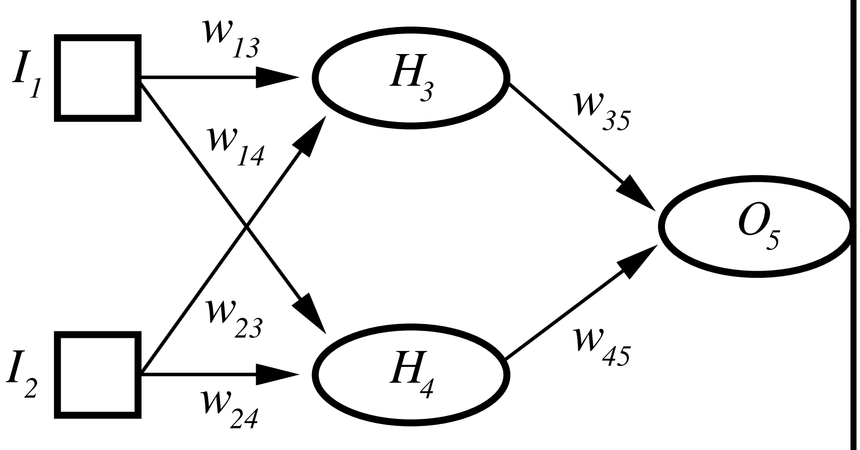

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$$
\begin{aligned}
a_5 &= g(W_{3,5}\ a_3 \quad + \quad W_{4,5}\ a_4) \\
&= g(W_{3,5}\ g(W_{1,3}\ a_1 \quad + \quad W_{2,3}\ a_2) + W_{4,5}\ g(W_{1,4}\ a_1 + W_{2,4}\ a_2)))
\end{aligned}
$$

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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!

Hopfield Networks

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

Two main types:

Hopfield networks.
Boltzmann machines.

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.

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.

Back to Feed-forward

input / output / hidden units.

perceptrons: no hidden units

multilayered

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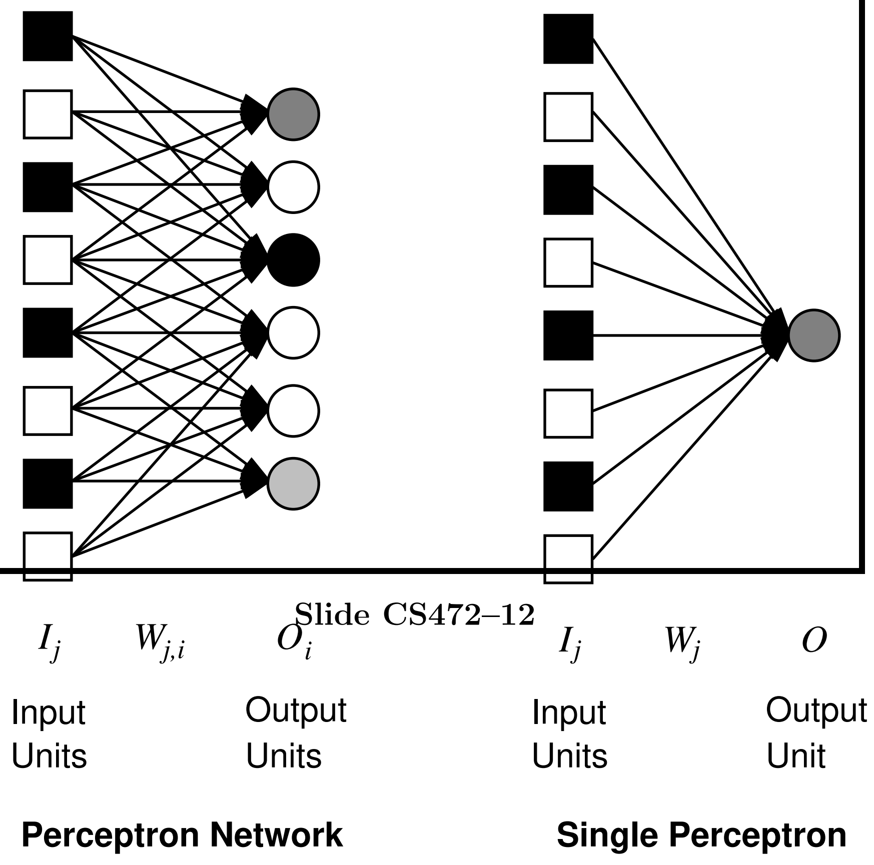

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Perceptrons

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)).

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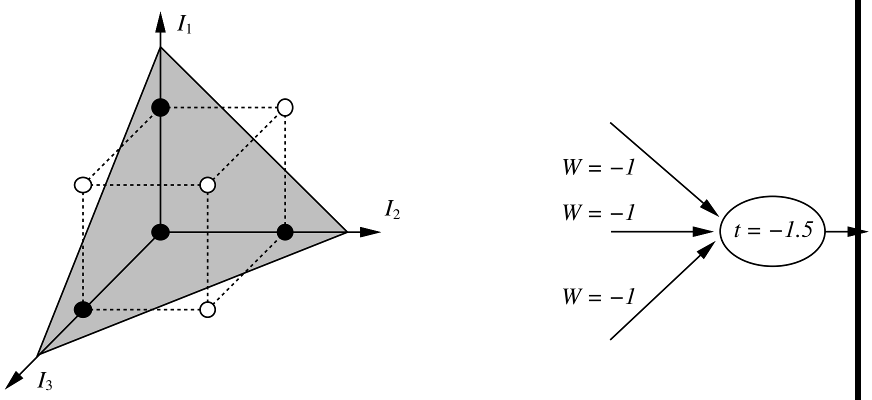
Linearly separable functions only



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

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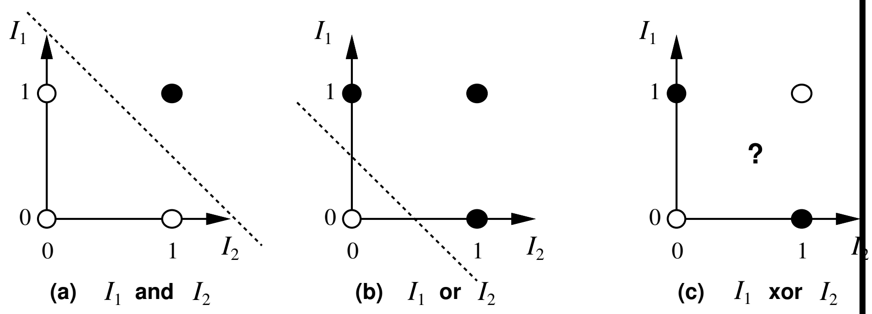

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Mid eighties: comeback — multilayed networks
(Turing machine compatible)
learning procedures: **backpropagation**

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: UCLA researchers showed
single cell can learn a concept! (concept: facial expressions / a cell responding to "angry face"!)