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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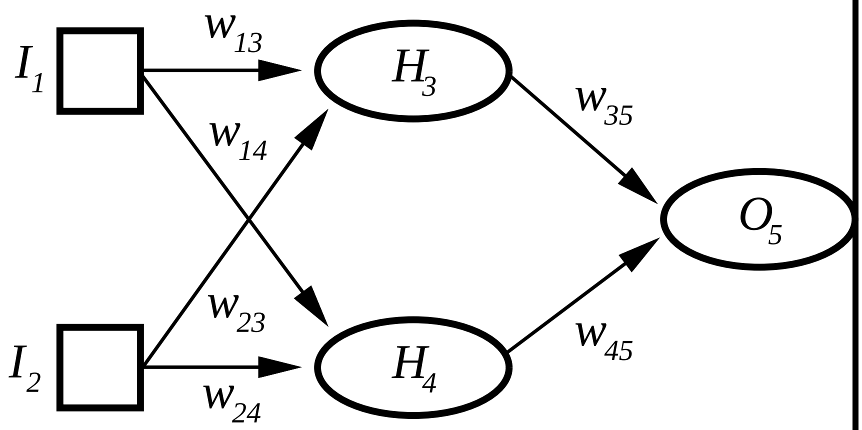

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$$\begin{aligned} a_5 &= g(W_{3,5}\ a_3 \ \ + \ \ W_{4,5}\ a_4) \\ &= g(W_{3,5}\ g(W_{1,3}\ a_1 \ \ + \ \ W_{2,3}\ a_2) + W_{4,5}\ g(W_{1,4}\ a_1 + W_{2,4}\ a_2))) \end{aligned}$$

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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!

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.

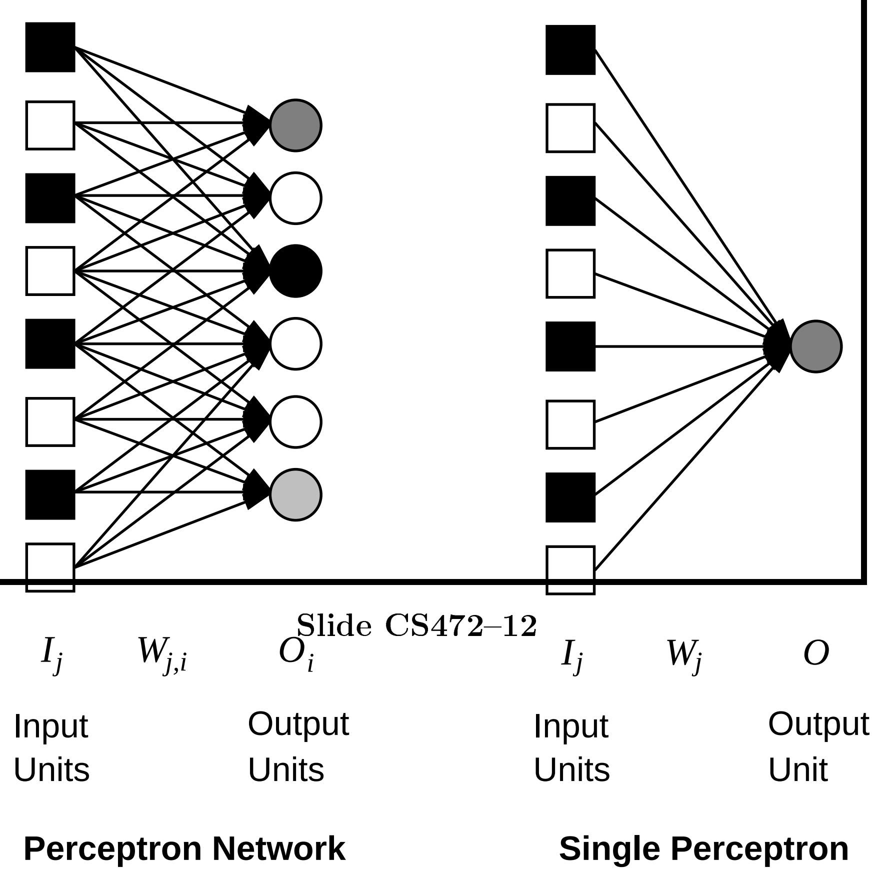
details beyond the scope of this course.

Back to Feed-forward

input / output / hidden units.

perceptrons: no hidden units

multilayered



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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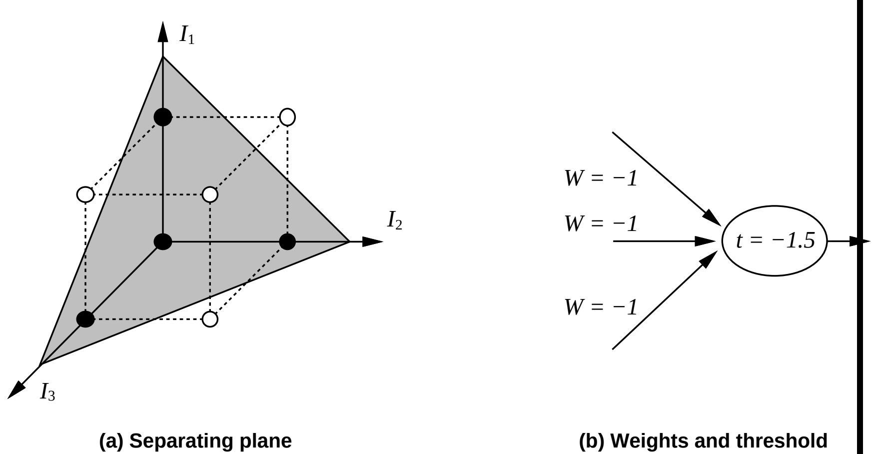
Linearly separable functions only



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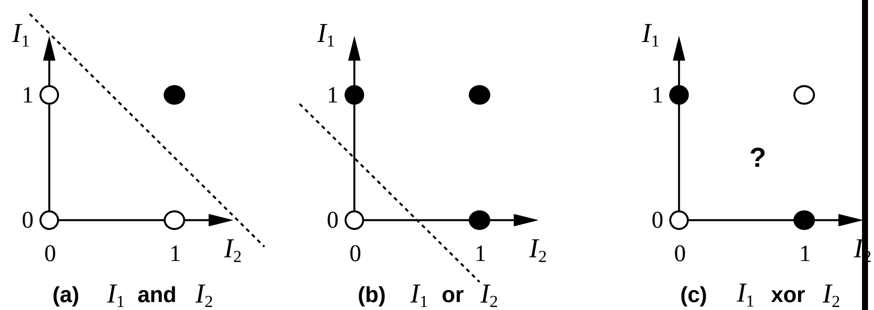

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Mid eighties: comeback — multilayed networks
(Turing machine compatible)
learning procedures: **backpropagation**

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: (UPI news wire): UCLA researchers showed
>> **single** cell can learn a concept! (concept: facial expressions / a cell responding to “angry face”!)