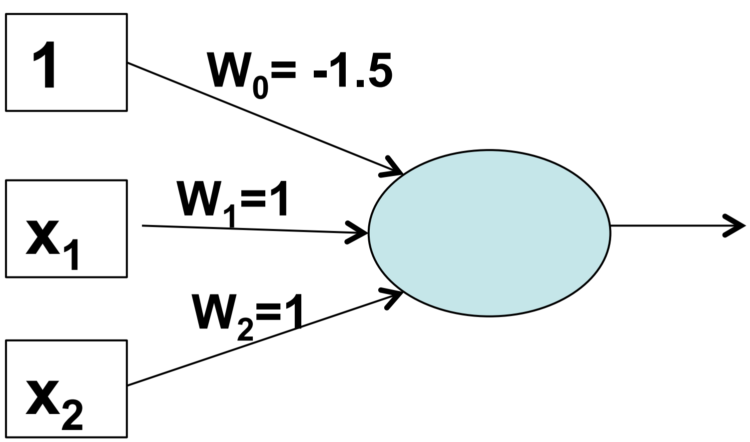
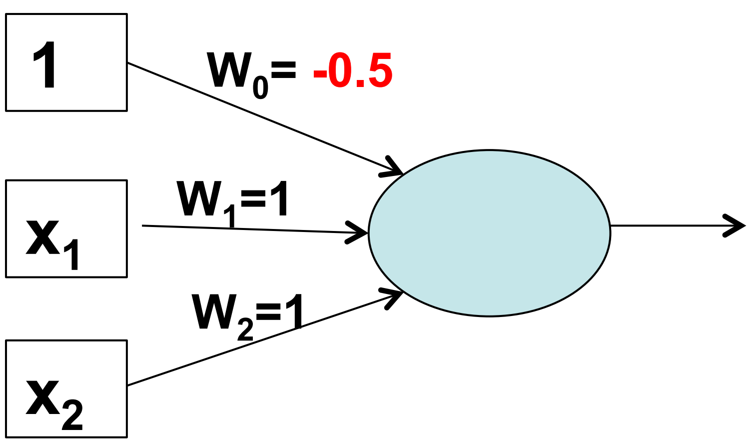
What does this do?



unit turns on when

$$\Sigma_j w_j x_j > 0$$

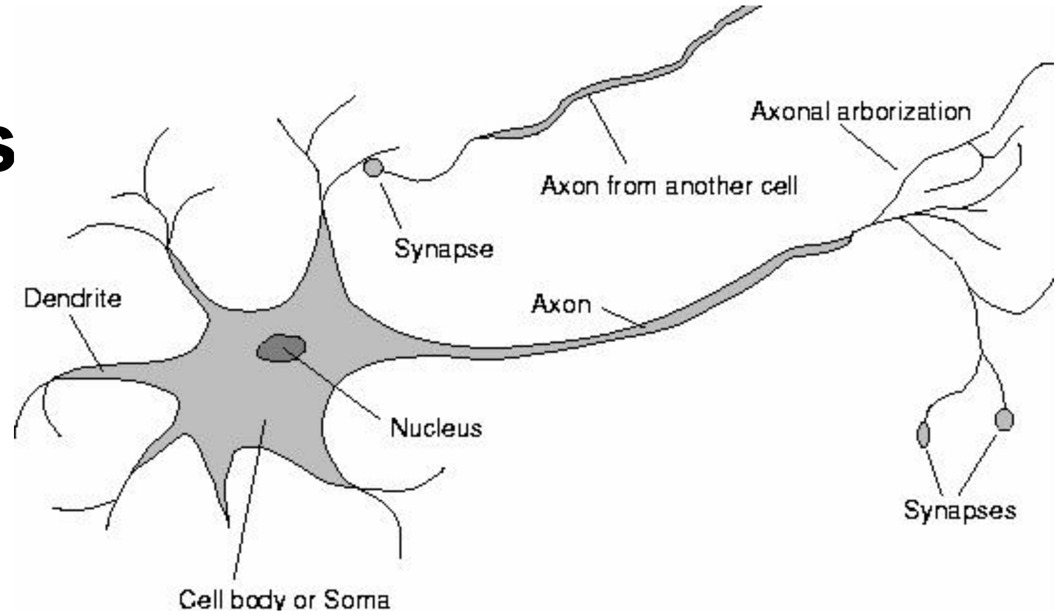
What about this one?

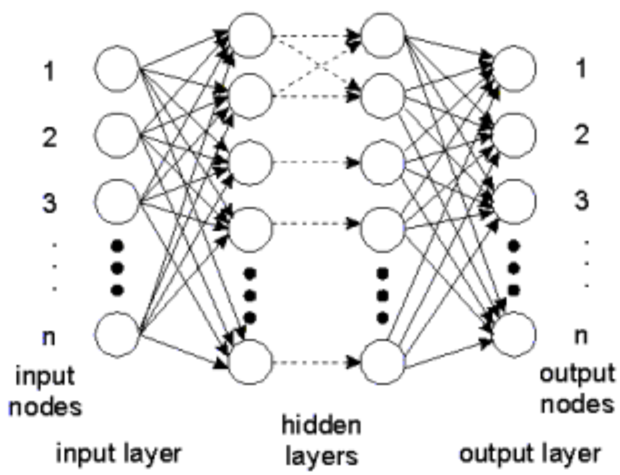


unit turns on when

$\Sigma_j w_j x_j > 0$

Neural Networks



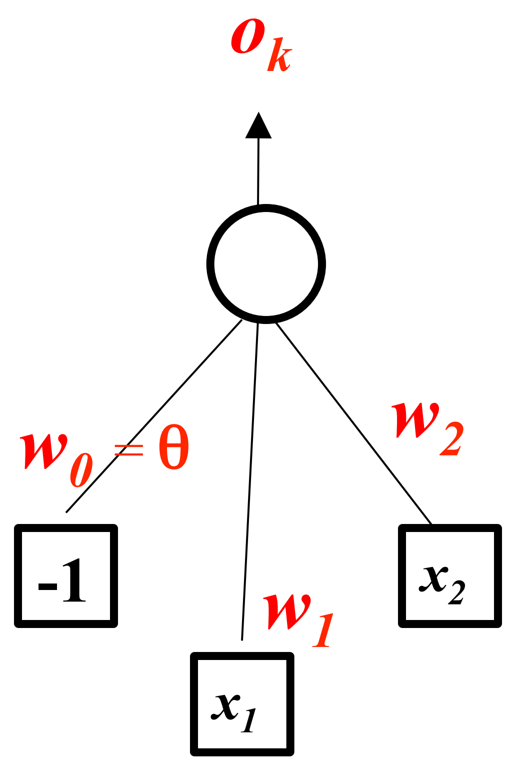


Notation: a perceptron *j* has

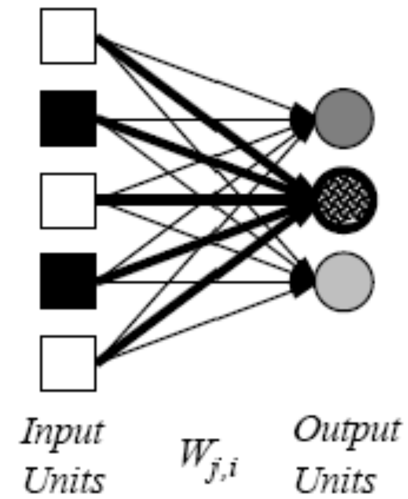
- a current output or *activation* level, o_j
- a target or desired output level, t_j
- links from input values of weight w_{ij}
- a threshold or bias θ at which it activates
  - treat as constant input of -1 connected by weight θ

Input and Output

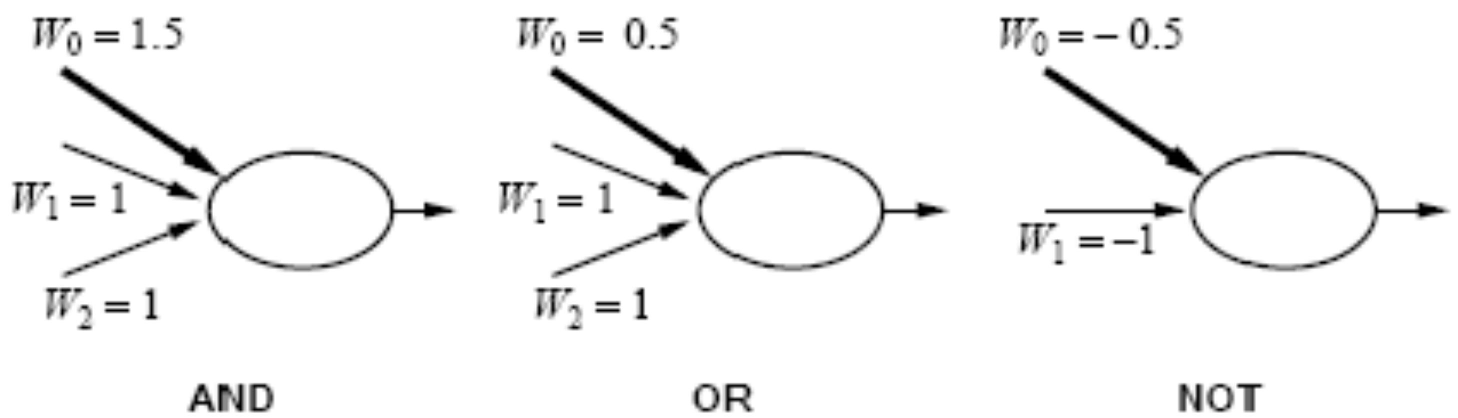
- each cell's output o_k is determined by:
  - $o_k = step(net_k)$
- where the net input net_k to cell k is summed:
  - $net_k = \Sigma_j w_j o_j$



Perceptrons:
Single layer feed-forward networks



- response given by: $o = step(\Sigma_j w_j x_j)$



Perceptron (or "Delta Rule") Learning

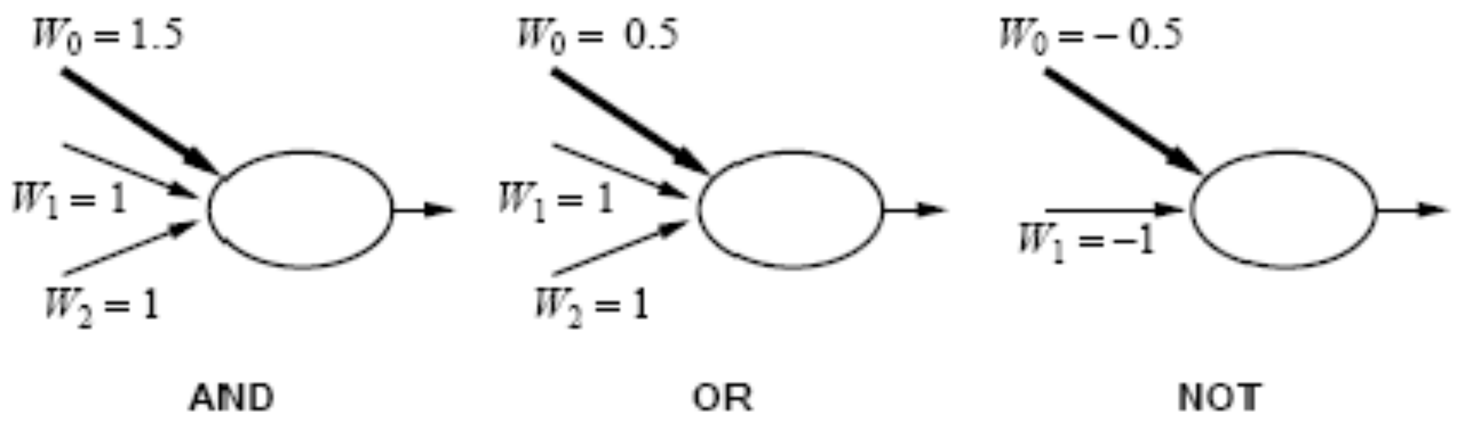
[Widrow and Hoff; Rosenblatt 1960]

- recall
  $o = \Sigma_j w_j x_j$
- LMS expresses error as sum of squared errors:
  $E = \frac{1}{2} Err^2 = \Sigma \frac{1}{2}(t - o)^2$
- calculate partial of Error with respect to each weight:
  $\partial E / \partial w_j = (\partial E / \partial o)(\partial o / \partial w_j) = -(t - o) x_j$
- now modify weights along negative of error gradient, for some learning rate, α:
  $\Delta w_j = \alpha (t - o) x_j$

t	o	
0	0	good

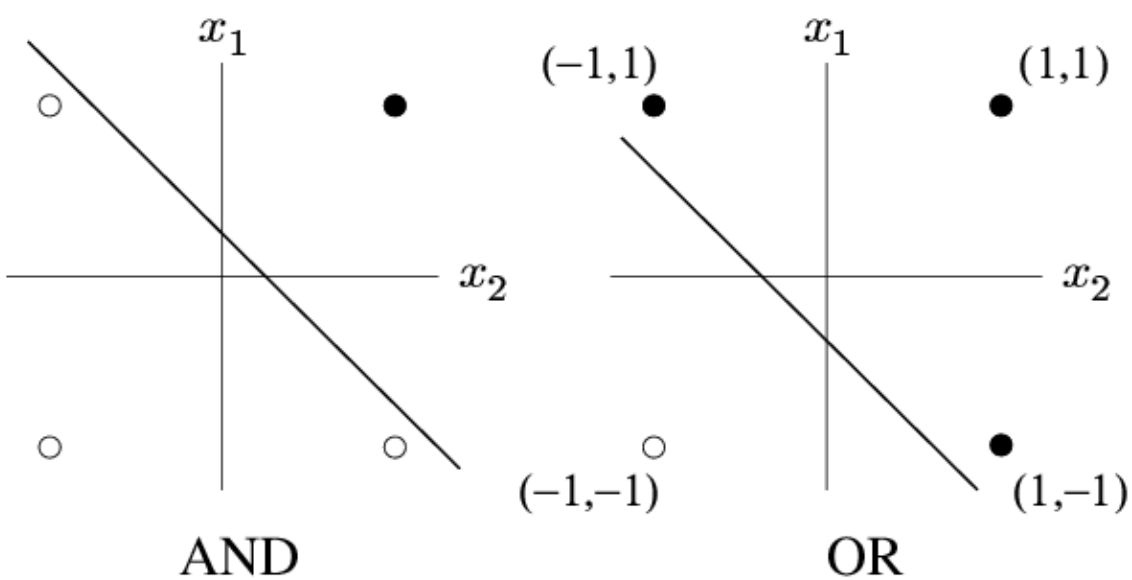
How do you build XOR?

- response given by: $o = \Sigma_j w_j x_j$



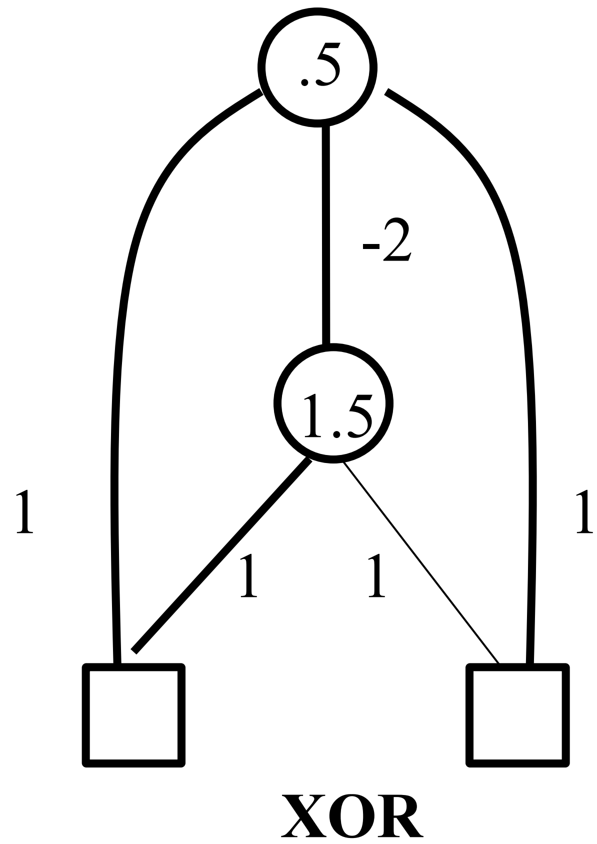
Linear non-separability problem

Minsky and Papert [1969]



Two-layer feedforward nets

- multilayer perceptron can solve XOR



Minsky and Papert's Criticism

- no solution for how to *learn* weights for hidden units:
  - how to give credit (or blame) to the hidden layer units for their contribution to the error?

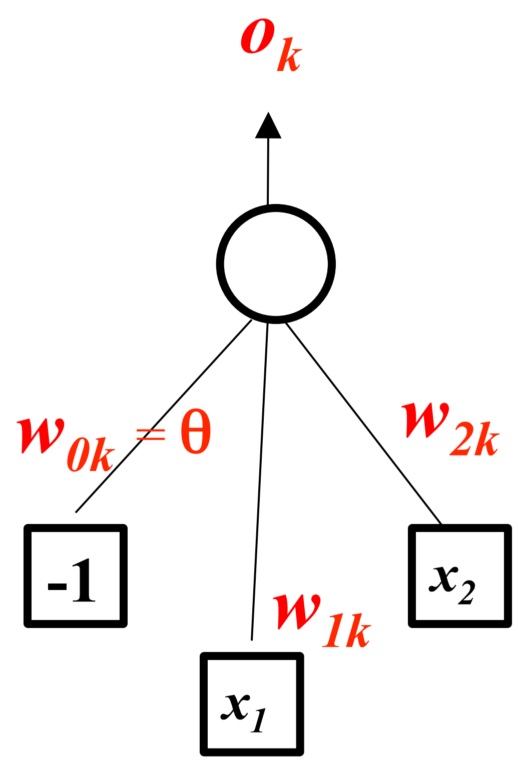
Backpropagation

[Werbos 1974; Rumelhart, Hinton & Williams 1986, etc.]

- recursive method for weight adjustment in multilayer feed-forward networks
- based on generalization of the delta rule for non-linear activation functions
- assigns error value to output in hidden layers

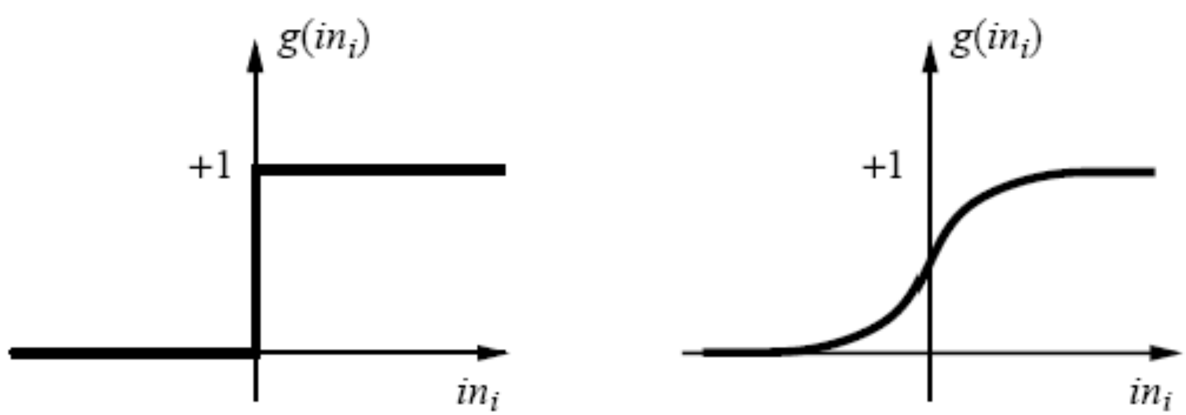
Input and Output

- each cell's output o_k is determined by:
  - $o_k = g(net_k)$
- where the net input net_k to cell k is summed:
  - $net_k = \Sigma_j \, w_{jk} \, o_j$



Activation Functions

- typically non-linear, monotonic (or discontinuous at one point)
- common options:
  - tanh()
  - sigmoid(x) = $1 / (1 + e^{-x})$



(a) (b)

How does weight w_{jk} to output k affect error?

$$E = \frac{1}{2}(t_k - o_k)^2$$

$$\begin{aligned}
\frac{\partial E}{\partial w_{jk}} &= \frac{\partial E}{\partial o_k}\frac{\partial o_k}{\partial w_{jk}} \\
&= -(t_k - o_k)\frac{\partial g(net_k)}{\partial w_{jk}} \\
&= -(t_k - o_k)g'(net_k)\frac{\partial net_k}{\partial w_{jk}} \\
&= -(t_k - o_k)g'(net_k)\frac{\partial}{\partial w_{jk}}\Sigma_j(w_{jk}o_j) \\
&= -(t_k - o_k)g'(net_k)o_j
\end{aligned}$$

define modified error measure:

$$\delta_k = (t_k - o_k)g'(net_k)$$

$$\frac{\partial E}{\partial w_{jk}} = -o_j\delta_k$$

Continuing…

recall: $\delta_k = (t_k - o_k) g'(net_k)$

now let's consider g() as the sigmoid: $g(x) = 1/(1+e^{-x})$

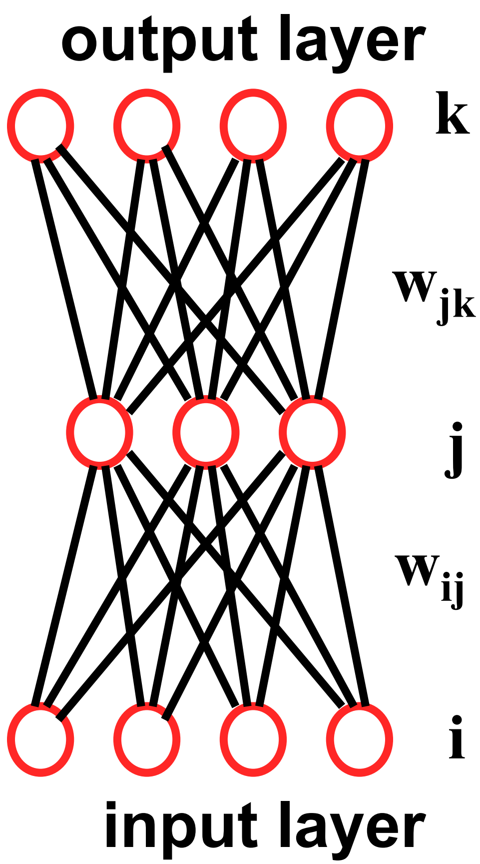
and so:

$$\begin{aligned} g'(x) &= e^{-x}/(1+e^{-x})^2 \\ &= \frac{1}{1+e^{-x}} \frac{e^{-x}}{1+e^{-x}} \\ &= g(x)(1-g(x)) \end{aligned}$$

which gives:

$$\begin{aligned} \delta_k &= (t_k - o_k) g(net_k)(1 - g(net_k)) \\ &= (t_k - o_k) o_k (1 - o_k) \end{aligned}$$

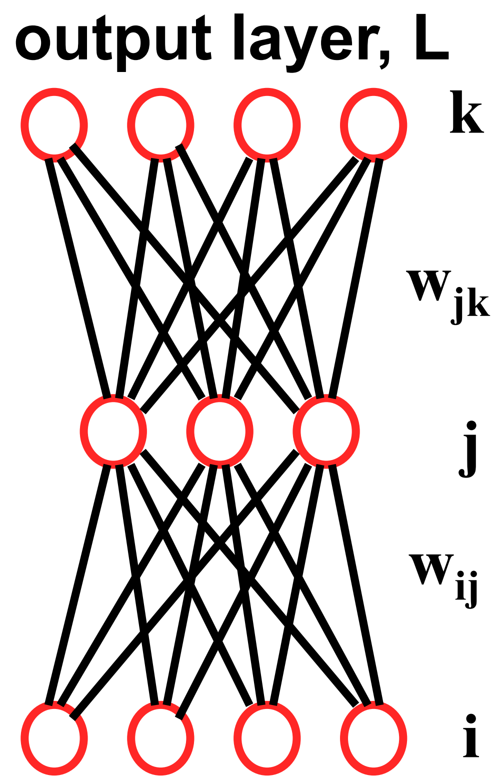
Network Architecture



How does weight w_{ij} (to hidden unit j) affect error?

- consider impact of unit *j* on error over all output-layer (L) units *k* to which it is connected

$$\text{Error} = \sum_{k \in L} E_k$$



How does weight w_{ij} (to hidden unit j) affect error?

- compute recursively via Chain Rule

$$\frac{\partial E}{\partial w_{ij}} = \sum_k \frac{\partial E}{\partial o_k} \frac{\partial o_k}{\partial net_k} \frac{\partial net_k}{\partial o_j} \frac{\partial o_j}{\partial net_j} \frac{\partial net_j}{\partial w_{ij}}$$

$$= \sum_k -(t_k - o_k) o_k (1 - o_k) w_{jk} o_j (1 - o_j) o_i$$

$$= \sum_k -\delta_k w_{jk} o_j (1 - o_j) o_i$$

$$= -o_i o_j (1 - o_j) \sum_k \delta_k w_{jk}$$

Knowing the Limits

- sigmoid is asymptotic at 0 and 1
  - g(∞) = 1, g(-∞) = 0 and recall:

$$net_k = \sum_j w_{jk} o_j$$

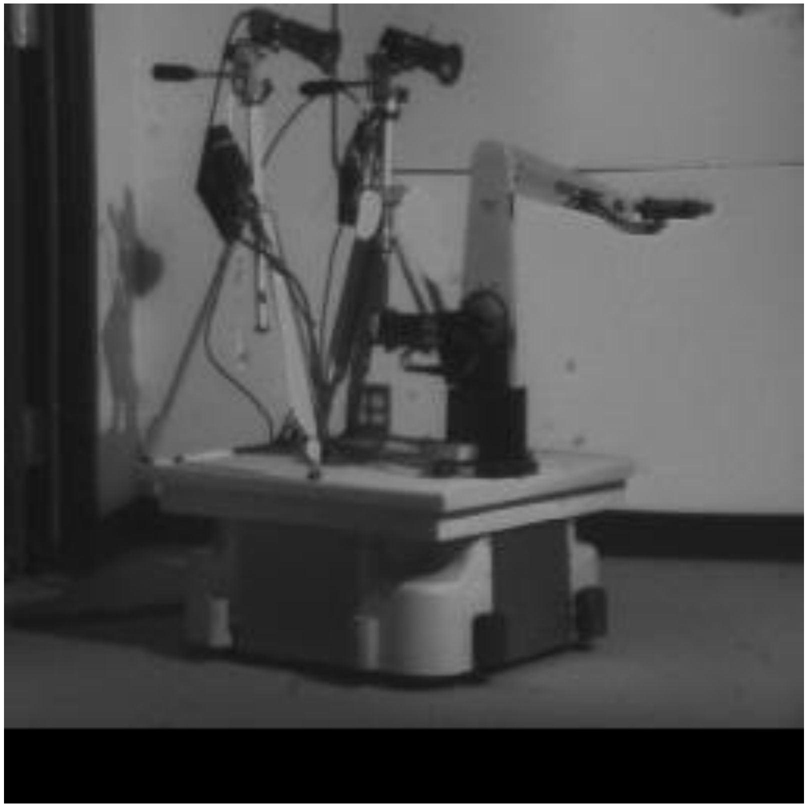
  - since o_j is determined by output of other units, we can only vary w_{jk}
  - adjusting w_{jk} risks leading to infinite weights

When should we use NN's?

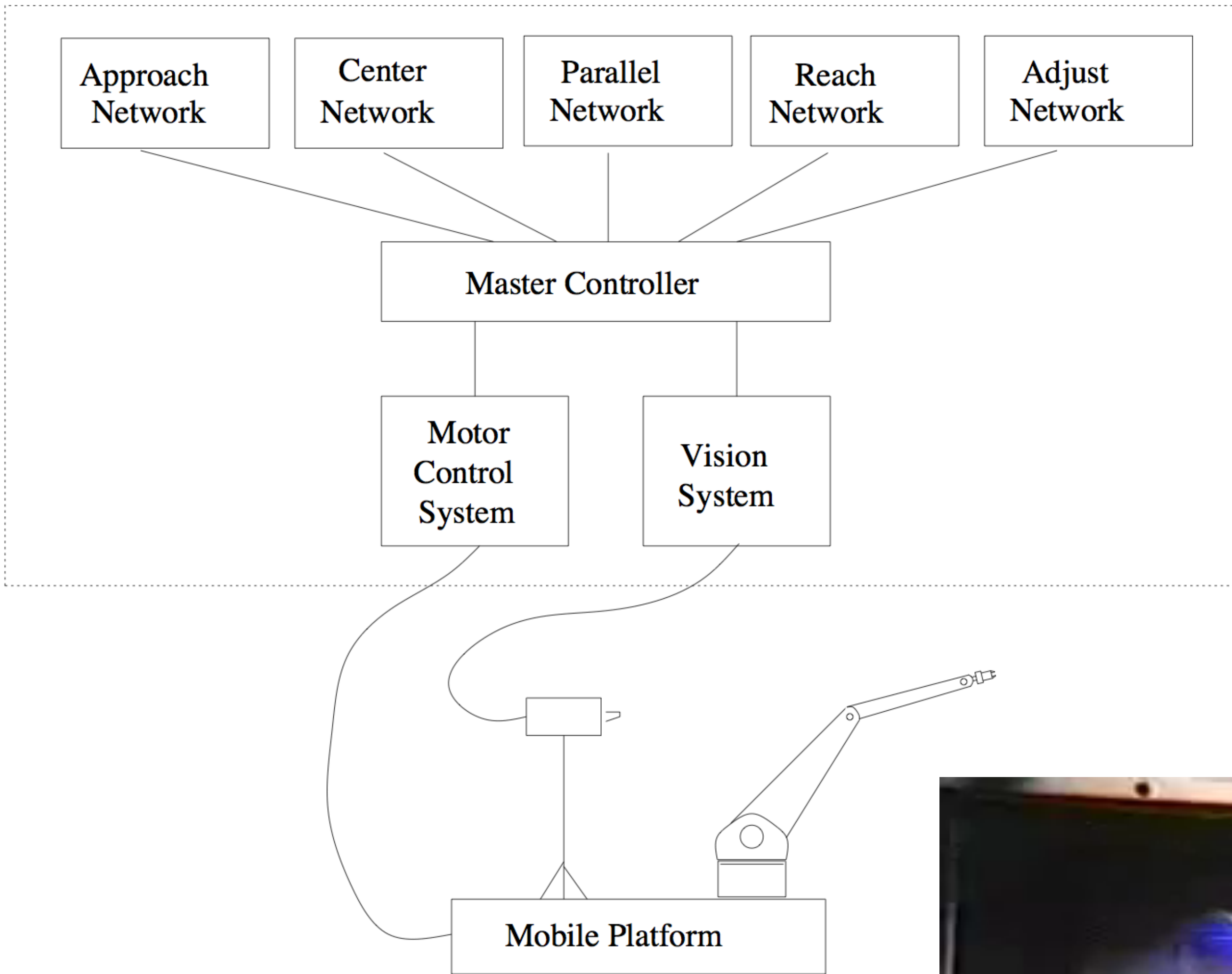
- where complex mapping needs to be found for which a closed-form analytic solution is not readily available or computationally efficient

Backprop Applications

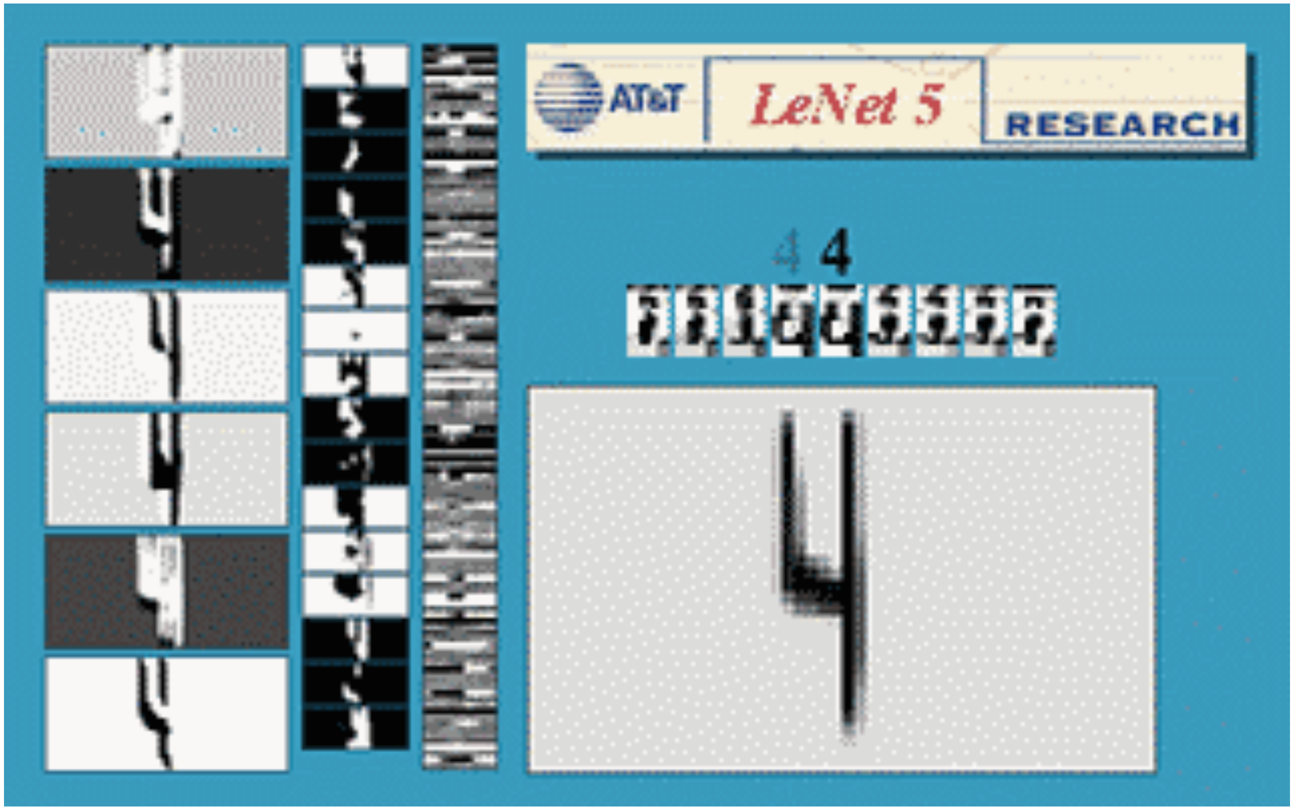
NOVICE



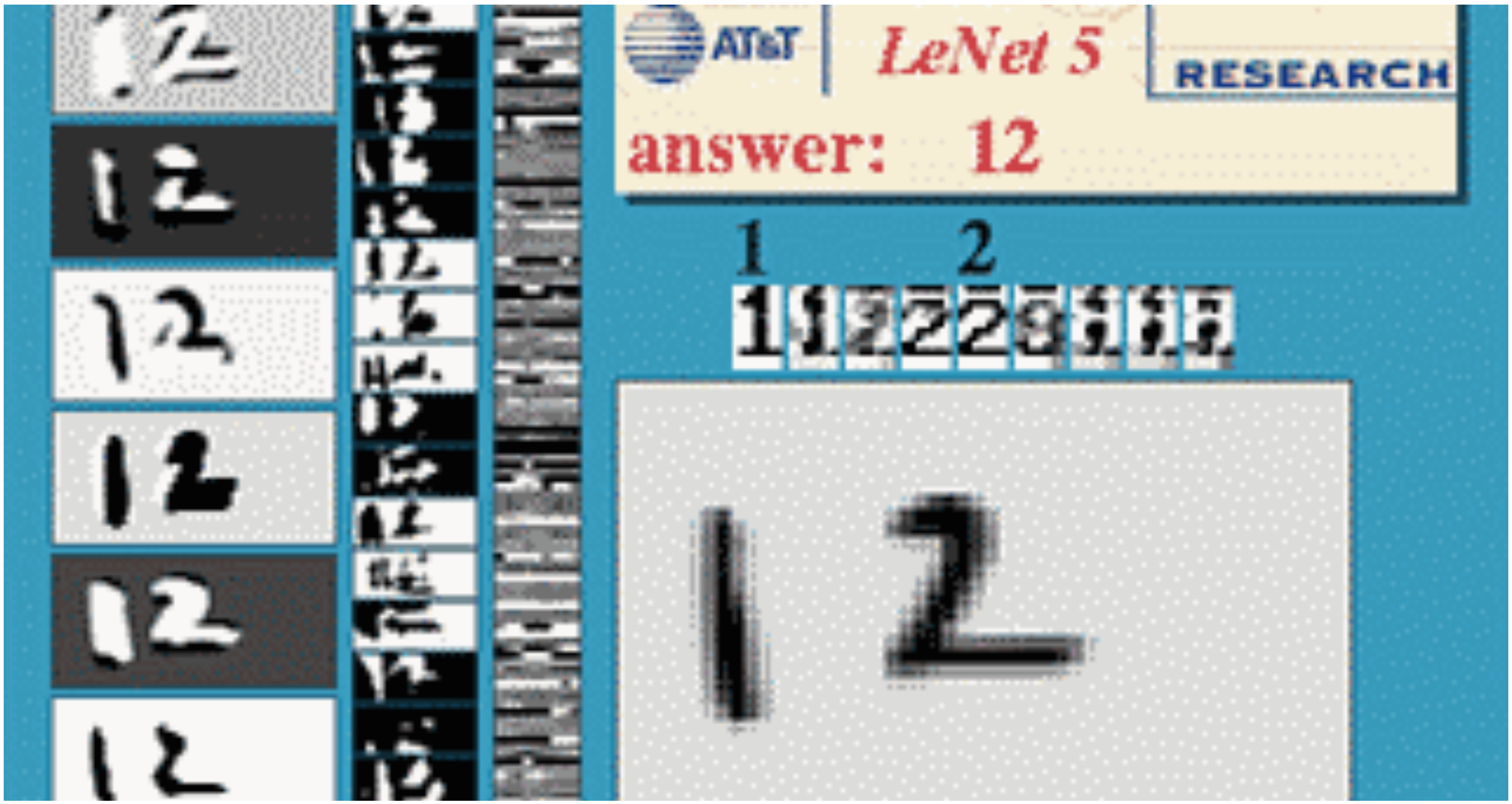
- multiple networks used for different activities (e.g. base steering, approaching, reaching)
- solves inverse perspective projection and inverse kinematic mappings
- adapts on-line to changes in configuration


Approach Network
Center Network
Parallel Network
Reach Network
Adjust Network
Master Controller
Motor Control System
Vision System
Mobile Platform

LeNet: Numeric character recognition



LeNet: overlapping digits

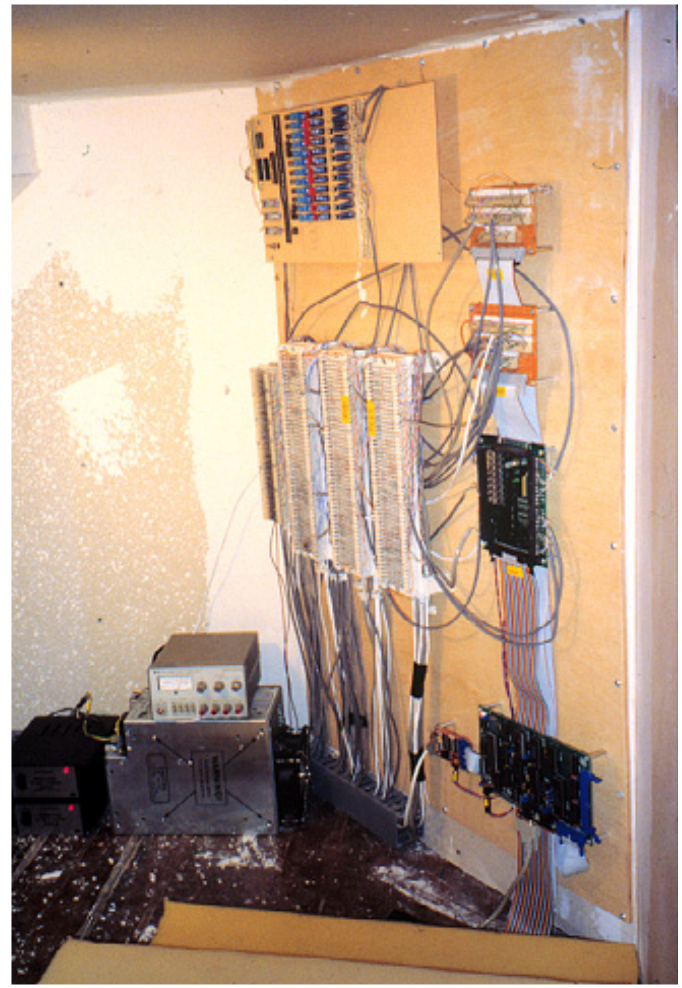


Character Recognition

- OCHRE
  - Java demo

Mozer's Adaptive House

… a home that essentially PROGRAMS ITSELF by observing the actions of the inhabitants



Training

Testing the “anticipator” neural net

Multi-zone lighting selections

ALVINN - Driving a Car

- Gaussian output array PDF
  - overcomes problem of severe non-linearities
- training "on the fly"
  - management of training data to avoid overlearning
  - artificial synthesis of unseen training data

Speech Synthesis

1. create *if-then* rules to encode all regularities
2. maintain database of exceptions to rules
3. build a production system to resolve conflicts: very difficult

- e.g. ‘c’ can either be pronounced ‘s’ as in center, icy, and city or a ‘k’ as in cat and crumb
  - if a ‘c’ appears before an i, e, or y
  - then pronounce it like an ‘s’
  - else pronounce it like a ‘k’
  - exception: celtic

NETTalk approach

- Rationale: non-intuitive pronounciations can be “discovered” by network whereas they might not be recognizable by human programmer
  - Trained on random pick of 16,000 of 20,000 words from Webster's
  - Testing yielded correct response to 90% of 4,000 remaining words

GloveTalk

- translates hand gestures to speech through an adaptive interface
- gestures are mapped continuously to ten control parameters of a parallel formant speech synthesizer
- allows the hand to act as an artificial vocal tract that produces speech in real time
- one subject trained to speak intelligibly with Glove-TalkII

Glove-TalkII

S. Fels & G. Hinton

Sam I Am