Neural networks

Chapter 19, Sections 1–5

Outline

◇ Brains

◇ Neural networks

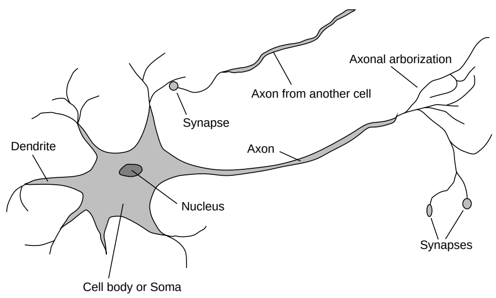
◇ Perceptrons

◇ Multilayer perceptrons

◇ Applications of neural networks

Brains

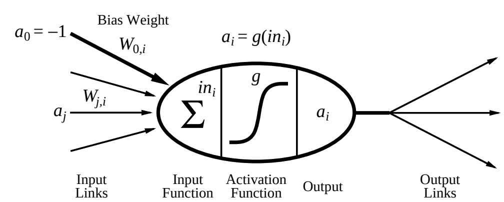
10^{11} neurons of > 20 types, 10^{14} synapses, 1ms–10ms cycle time
Signals are noisy "spike trains" of electrical potential



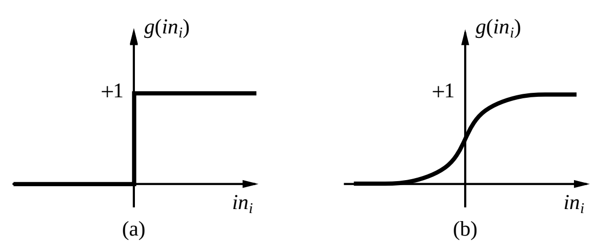
McCulloch–Pitts "unit"

Output is a "squashed" linear function of the inputs:

$a_i \leftarrow g(in_i) = g\left(\Sigma_j W_{j,i} a_j\right)$



Activation functions

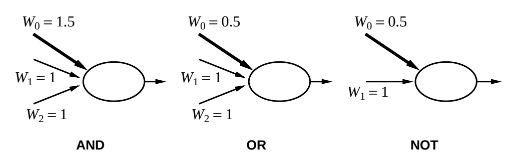


(a) is a step function or threshold function

(b) is a sigmoid function $1/(1 + e^{-x})$

Changing the bias weight $W_{0,i}$ moves the threshold location

Implementing logical functions



McCulloch and Pitts: every Boolean function can be implemented

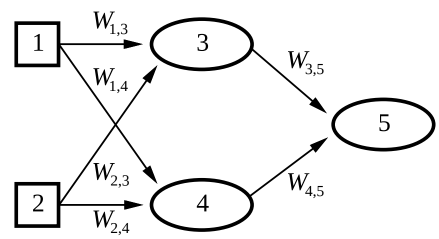
Network structures

Feed-forward networks:
– single-layer perceptrons
– multi-layer perceptrons

Feed-forward networks implement functions, have no internal state

Recurrent networks:
– Hopfield networks have symmetric weights ($W_{i,j} = W_{j,i}$)
$g(x) = \text{sign}(x)$, $a_i = \pm 1$; **holographic associative memory**
– Boltzmann machines use stochastic activation functions,
$\approx$ MCMC in BNs
– recurrent neural nets have directed cycles with delays
$\Rightarrow$ have internal state (like flip-flops), can oscillate etc.

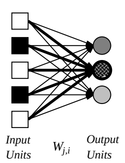
Feed-forward example

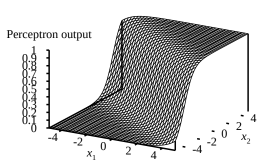


Feed-forward network = a parameterized family of nonlinear functions:

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

Perceptrons





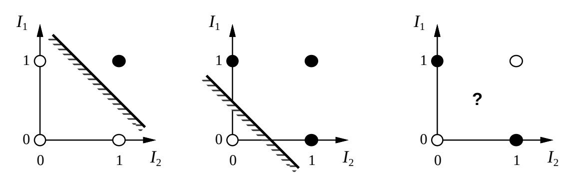
Expressiveness of perceptrons

Consider a perceptron with g = step function (Rosenblatt, 1957, 1960)

Can represent AND, OR, NOT, majority, etc.

Represents a linear separator in input space:

$\Sigma_j W_j x_j > 0$ or $\mathbf{W} \cdot \mathbf{x} > 0$



(a) I_1 **and** I_2 (b) I_1 **or** I_2 (c) I_1 **xor** I_2

Perceptron learning

Learn by adjusting weights to reduce error on training set

The squared error for an example with input $\mathbf{x}$ and true output y is

$$E = \frac{1}{2} Err^2 \equiv \frac{1}{2}(y - h_{\mathbf{W}}(\mathbf{x}))^2 ,$$

Perform optimization search by gradient descent:

$$\begin{aligned} \frac{\partial E}{\partial W_j} &= Err \times \frac{\partial Err}{\partial W_j} = Err \times \frac{\partial}{\partial W_j}\left(y - g(\Sigma_{j=0}^{n} W_j x_j)\right) \\ &= -Err \times g'(in) \times x_j \end{aligned}$$

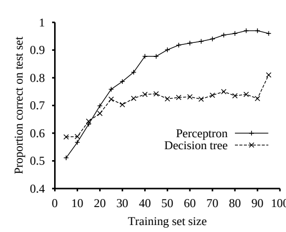
Simple weight update rule:

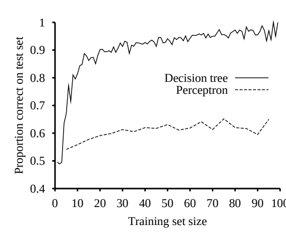
$$W_j \leftarrow W_j + \alpha \times Err \times g'(in) \times x_j$$

E.g., +ve error $\Rightarrow$ increase network output
$\Rightarrow$ increase weights on +ve inputs, decrease on -ve inputs

Perceptron learning contd.

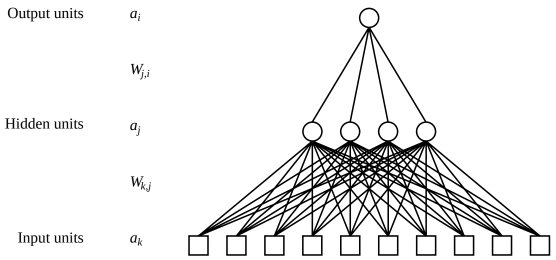
Perceptron learning rule converges to a consistent function
for any linearly separable data set





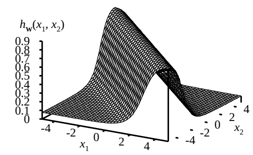
Multilayer perceptrons

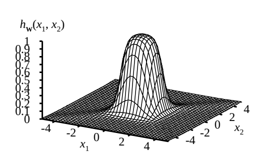
Layers are usually fully connected;
numbers of hidden units typically chosen by hand



Expressiveness of MLPs

All continuous functions w/ 2 layers, all functions w/ 3 layers





Back-propagation learning

Output layer: same as for single-layer perceptron,

$$W_{j,i} \leftarrow W_{j,i} + \alpha \times a_j \times \Delta_i$$

where $\Delta_i = Err_i \times g'(in_i)$

Hidden layer: **back-propagate** the error from the output layer:

$$\Delta_j = g'(in_j) \sum_i W_{j,i} \Delta_i \ .$$

Update rule for weights in hidden layer:

$$W_{k,j} \leftarrow W_{k,j} + \alpha \times a_k \times \Delta_j \ .$$

(Most neuroscientists deny that back-propagation occurs in the brain)

Back-propagation derivation

The squared error on a single example is defined as

$$E = \frac{1}{2} \sum_i (y_i - a_i)^2 \ ,$$

where the sum is over the nodes in the output layer.

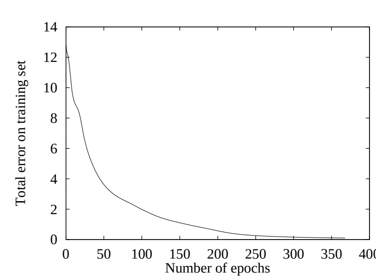
$$\begin{aligned}
\frac{\partial E}{\partial W_{j,i}} &= -(y_i - a_i) \frac{\partial a_i}{\partial W_{j,i}} = -(y_i - a_i) \frac{\partial g(in_i)}{\partial W_{j,i}} \\
&= -(y_i - a_i) g'(in_i) \frac{\partial in_i}{\partial W_{j,i}} = -(y_i - a_i) g'(in_i) \frac{\partial}{\partial W_{j,i}} \left(\sum_j W_{j,i} a_j \right) \\
&= -(y_i - a_i) g'(in_i) a_j = -a_j \Delta_i
\end{aligned}$$

Back-propagation derivation contd.

$$\begin{aligned}
\frac{\partial E}{\partial W_{k,j}} &= -\sum_i (y_i - a_i) \frac{\partial a_i}{\partial W_{k,j}} = -\sum_i (y_i - a_i) \frac{\partial g(in_i)}{\partial W_{k,j}} \\
&= -\sum_i (y_i - a_i) g'(in_i) \frac{\partial in_i}{\partial W_{k,j}} = -\sum_i \Delta_i \frac{\partial}{\partial W_{k,j}} \left(\sum_j W_{j,i} a_j \right) \\
&= -\sum_i \Delta_i W_{j,i} \frac{\partial a_j}{\partial W_{k,j}} = -\sum_i \Delta_i W_{j,i} \frac{\partial g(in_j)}{\partial W_{k,j}} \\
&= -\sum_i \Delta_i W_{j,i} g'(in_j) \frac{\partial in_j}{\partial W_{k,j}} \\
&= -\sum_i \Delta_i W_{j,i} g'(in_j) \frac{\partial}{\partial W_{k,j}} \left(\sum_k W_{k,j} a_k \right) \\
&= -\sum_i \Delta_i W_{j,i} g'(in_j) a_k = -a_k \Delta_j
\end{aligned}$$

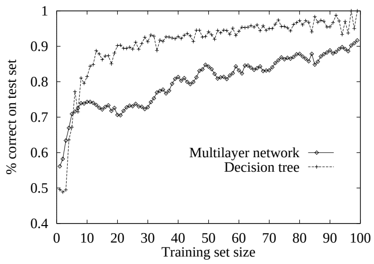
Back-propagation learning contd.

At each epoch, sum gradient updates for all examples and apply

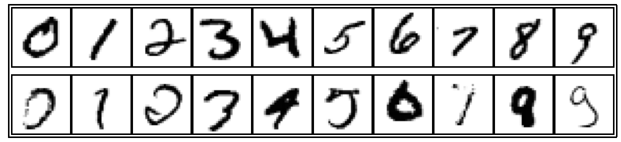


Usual problems with slow convergence, local minima

Back-propagation learning contd.



Handwritten digit recognition



3-nearest-neighbor = 2.4% error
400–300–10 unit MLP = 1.6% error
LeNet: 768–192–30–10 unit MLP = 0.9%

Summary

Most brains have lots of neurons; each neuron ≈ linear–threshold unit (?)

Perceptrons (one-layer networks) insufficiently expressive

Multi-layer networks are sufficiently expressive; can be trained by gradient descent, i.e., error back-propagation

Many applications: speech, driving, handwriting, credit cards, etc.