Welcome to the introduction to computational cognitive modelling workshop!

Part 2: Introduction to artificial neural networks

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What is a neural network?

A mathematical model

- Inspired by the nervous system
- A set of units, connected by weights
- ► The network *runs* by passing *activations* from the *input* (to the *hidden*) to the *output* units

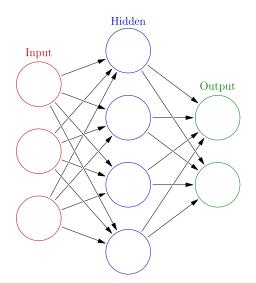


Figure: Glosser.ca / CC-BY-SA-3.0

Why use artificial neural networks for modelling?

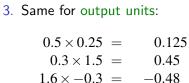
Some aspects of their behaviour are like their namesake!

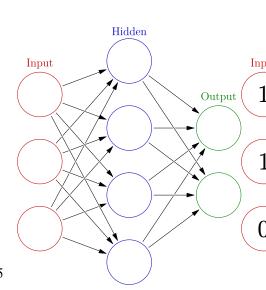
- Learn pretty much any input-output data
- Uncover rules on their own about data
- Generalise from what they have learnt
- Cope with noise and damage

By using maths, predictably!

- 1. Input units are set to a pattern
- 2. Calculate hidden units' states:

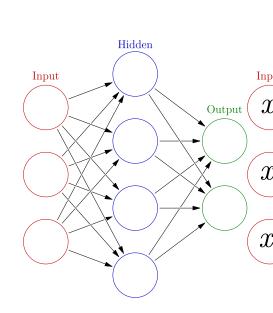
$$\begin{array}{rcl}
1 \times 0.5 & = & 0.5 \\
1 \times 0.0 & = & 0.0 \\
0 \times 0.8 & = & 0.0 \\
\hline
0.5
\end{array}$$





By using maths, predictably!

- But programmers are lazy! General names save time
- ightharpoonup input units: x_i
- ► hidden units: a_i
- ▶ output units: *y_k*
- ightharpoonup connection weights: w_{ij}
- ► subscripts general: *ijklm*... specific: 12345...



By using maths, predictably!

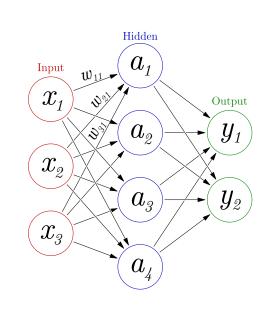
We use general names to write a general equation:

$$a_i =$$

$$a_i = x_j \times w_{ji}$$

$$a_i = \sum_{j=1}^{N} x_j \times w_{ji}$$

$$a_i = f\left(\sum_{j=1}^{N} x_j \times w_{ji}\right)$$



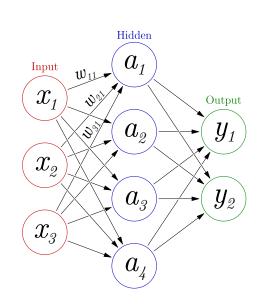
By using maths, predictably!

We use this equation by replacing *iterators i* and *j*:

$$a_i = f\left(\sum_{j=1}^N x_j \times w_{ji}\right)$$

$$a_1 = f\left(\sum_{j=1}^N x_j \times w_{j1}\right)$$

$$a_1 = f\left(\sum_{j=1}^3 x_j \times w_{j1}\right)$$



How do networks learn? Cunning!

- Many options: Hebbian learning, back-propagation of error, Boltzmann machine learning, self-organising map algorithm, etc.
- All learning algorithms work by changing the connection weights
- Learning can be divided into supervised, unsupervised, and reinforcement

Hebbian learning

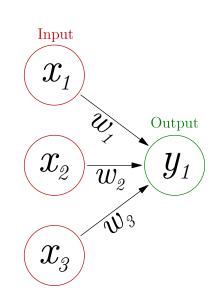
A very simple learning rule

"Cells that fire together, wire together"

— Carla Shatz

$$\Delta w_i = \eta \times \underline{x_i} \times y_j$$

which means each weight is changed by a small in/decrement for every pattern



Hebbian learning

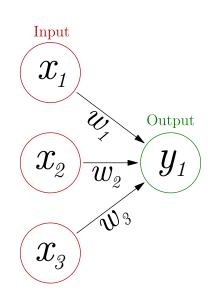
"Cells that fire together, wire together" — Carla Shatz

Hebb's rule is simple, but *very unstable*!

$$\Delta w_i = \eta \times x_i \times y_j$$

$$\Delta w_1 = 0.15 \eta 0.5 \times x_i x_1 1.0 \times y_j y_1 0.3$$

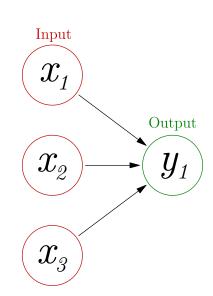
$$\begin{array}{l} \textbf{new} \ w_1 = \textbf{old} \ w_1 + \Delta w_1 \\ \textbf{new} \ w_1 = 0.0 + \Delta w_1 \\ \textbf{new} \ w_1 = 0.0 + 0.15 \\ \textbf{new} \ w_1 = 0.15 \quad w_1 = 0.15 \\ w_1 = 0.15 + \text{something} \\ \textbf{positive} \quad w_1 = 0.15 + \\ \textbf{something} \ \textbf{positive} + \end{array}$$



The perceptron

A simple classifier

- Created in 1957 at the Cornell Aeronautical Laboratory by Frank Rosenblatt
- ▶ Linear classifier
- Simplest form of feedforward network



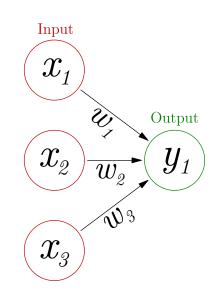
How does the perceptron learn?

Maths again!

- 1. Initialise weights
- 2. Run network using:

$$y_j = f\left(\sum_{1}^{N} w_i \times x_i\right)$$

same as always!



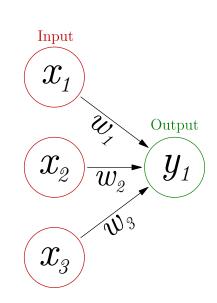
How does the perceptron learn?

Maths again!

- 1. Initialise weights
- 2. Run network
- 3. Update weights using:

$$\Delta w_i = \eta \ (d_j - y_j) \ y_j \times x_i$$

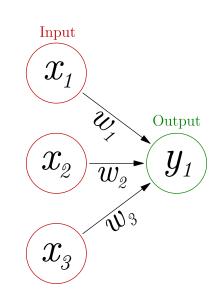
where d is what we want y to be given x, and η is the learning rate.



How does the perceptron learn?

Maths again!

- 1. Initialise weights
- 2. Run network
- 3. Update weights
- 4. Repeat 2 and 3
- 5. When do we stop?



The end

Time to program a perceptron!

Oh, and join our mailing list so we can send you stuff: https://groups.google.com/d/forum/introcompcog