A Cross Disciplinary Subject

- **Computing Applications -** neural net applications in image processing, robotics etc
- **Artificial Intelligence** - connectionism as a model of artificial intelligence
- **Machine Learning** - neural nets - origin of machine learning
- **Cognitive Psychology** - connectionist models of psychological behaviour

Acknowledgement: Based on O'Reilly and Munakata's slides

- **Philosophy of Mind** - What is the mind? Connectionist metaphors critical
- **(Cognitive) Neuroscience** - neural nets as mathematical models of brain systems: axons, dendrites, synaptic connections etc
- **Statistical Learning** - neural networks can be thought of as performing statistical learning
- **Deep Learning –** the new meaning of Artificial Intelligence.

Acknowledgement: Based on O'Reilly and Munakata's slides

- “The brain is the most interesting (computational) entity in the Universe?” [R. O’Reilly]
- (challenge you to think of anything else more interesting)
- It is also (probably) the most complex

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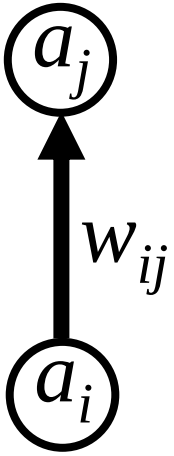
Origins of Connectionist Tradition

- First mathematical abstractions of neural behaviour
  - McCulloch and Pitts (1943)
    - modelling logic using neuron-like computational units
  - Hebb (1949)
    - mathematical definition of neural learning
  - Rosenblatt (1959)
    - the perceptron - supervised error-driven learning



$$\Delta w_{ij} = \varepsilon . a_i . a_j$$

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Historical Perspective

- 1969 - symbolic dominance starts
  - "Perceptrons" (Minsky & Papert) argues neuron-like models computationally limited
- 1980 - connectionist revolution starts
  - Rumelhart, Hinton & Williams rediscover back-propagation - can learn any computable function (modulo local minima)
  - importance of distributed representations (McClelland)
  - Hopfield nets - attractor dynamics
- 2005ish – deep learning and the new AI
  - e.g. deep convolution neural networks

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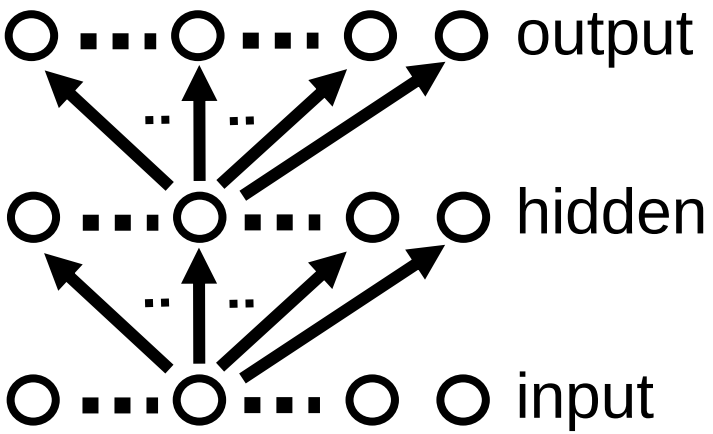
Problem

- Back-propagation not biologically plausible!
  - How are error terms relayed back along processing pathways?
- Hebbian vs back-propagation learning
  - Hebbian
    - anatomically plausible
    - computationally weak



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Computational Cognitive Neuroscience

- "How the brain embodies the mind using biologically based computational models"

  [O'Reilly and Munakata]

- Informed by modern brain sciences -
  - brain imaging, electroencephalogram (EEG) etc
  - brain anatomy
  - traditional experimental psychology
  - pure neural networks research

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Planned Lectures

- **Lecture 1: Cognitive Neural Networks Intro (HB)**
- **Lectures 2, 3, 4, 5 & 6: Computation in Single Neurons (HB)**
  Activation Levels, Spikes, Membrane Potentials
- **Lectures 7, 8, 9, 10 & 11: Networks of Neurons (HB)**
  Feedforward, Recurrent, Inhibitory Mechanisms
- **Lectures 12, 13, 14 & 15: Model Learning (MG)**
  Hebbian Learning
- **Lectures 16, 17, 18, 19 & 20: Task Learning (MG)**
  The Delta Rule and Back Propagation
- **Lecture 21 & 22: Current Perspective (MG)**
  Deep Learning
- **Practical Class (8 Classes, 2 hrs each): From week 4 for rest of first term**
  Running Simulations from O'Reilly and Munakata
- **Two assessments from simulations** for all.
- **MSc students** – extra assessments.

Some maths, not hard.

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