Connectionist and Statistical Language Processing

Lecture 1: Introduction

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Overview

- The problem of language acquisition and language processing
  - What constitutes a theory of language?
  - How does acquisition take place
- Two (and a half) solutions:
  - Rationalist: symbolic/rule-based, theory-driven
  - Empiricist: *tabula rasa*, data-driven
  - Connectionist: Distributed information processing and learning mechanism
- The connectionist perspective
  - Connectionism and the brain
  - The appeal of connectionist modelling
- Basics of connectionist information processing

- Reference for lecture:
  - McLeod et al. (1998). Chapter 1: Introduction of connectionist modelling of cognitive processes. OUP, UK.

The Problem: Natural Language is ...

- Complex
  - Consider the formal systems of rules and representations required:
    - Phonology, Morphology,Syntax, Semantics, Discourse and Pragmatics
  - Interaction with reasoning, perception, context, task, ...
- Ambiguous
  - Speech:
    - “Recognise speech” *versus* “wreck a nice beach”
  - Language:
    - Lexical: “Time flies like an arrow”
    - Structural: “Sabine broke the window with her brother”
    - Semantic: “Every woman loves a man”
- Noisy
  - Speech: signal never the same, difference speakers, overlap, slips, restarts
  - Language: ungrammaticalities, unknown words

Theories of Language

- Theories of the human language faculty:
  - Knowledge: What is the nature of our knowledge of language?
    - Rules and Representations
    - Symbolic versus Distributed
    - Explicit versus Implicit
  - Acquisition: Where does knowledge come from?
    - Is some knowledge innate?
    - What linguistic knowledge learned, and how?
  - Use: How do people use knowledge to process new input?
    - What mechanisms do people use in applying existing linguistic knowledge to the interpretation of novel input?
- Connectionist models of human language:
  - Addresses these issues simultaneously

The “Traditional” Perspective

- Modern cognitive modelling has been heavily influenced by available theories of computation.
  - This has put an emphasis on digital, symbolic, logic-based accounts.

- Symbolic processing:
  - Emphasis on explicit rules and representations
  - Computation: digital computers, logic based
  - Language: Chomskian theory
    - Criticism of statistical approaches
  - General problem solving: Newell and Simon

Connectionist Information Processing

- Connectionist models of information processing can become complex, but the idea is based on simple neuronal processing in the brain:

  - Basic computational operation involves one neuron passing information related to the sum of the signals reaching it to other neurons
  - Learning involves changing the strength of the connections between neurons, and thus the influence they have upon each other
  - Cognitive processes involve the use large numbers of neurons to perform many of these basic computations in parallel
  - Information about an input signal or memory of past events, is distributed across many neurons and connections

- Terms: connectionism, parallel distributed processing, neural networks, neurocomputing

The “Connectionist” Perspective

- Rumelhart and McClelland (1987, p. 196):
  - *“... implicit knowledge of language may be stored among simple processing units organized into networks. While the behaviour of such networks may be describable (at least approximately) as conforming to some system of rules, we suggest that an account of the fine structure of the phenomena of language and language acquisition can be best formulated in models that make reference to the characteristics of the underlying networks”*

- Key ideas:
  - Neurologically based (but not true models of the brain)
  - Distributed, implicit representations
  - Dense connectivity
  - Communication of “real values” not “symbols”
  - Representations and processing are the same
  - Learning: supervised and unsupervised

Central issues

- All accept the fact that human language, like other cognitive and perceptual faculties, are realised (or implemented) in the neural-tissues of the brain.

- Big Questions:
  - What is the right computational level at which to develop our theories?
  - Can connectionism fully replace symbolic accounts or should it be viewed as complementary?
  - Is there a clear boundary between connectionist and symbolic computation in the brain, or does symbol/rule-like behaviour emerge gradually?
  - What kinds of cognitive function require connectionist explanation, and what are best suited to symbolic accounts?
  - Can statistical models be used to augment symbolic approaches with some of the relevant characteristics of the distributed/neural architecture?

Theory development

- **Neuroscience:** developing more faithful and accurate models of information processing in the brain.
- **Cognitive science:** modelling human behaviour as observed in
  - Linguistics: explaining linguistic knowledge
  - Psycholinguistics: modelling how knowledge is used
  - Cognitive psychology: psychological studies of human behaviour

- **Symbolic perspective:** develop a symbolic account, and then provide a connectionist implementation
- **Intermediate:** the possibility of connectionist implementation, and (relevant) properties of connectionist networks should inform theory development
- **Radical connectionist:** connectionism is so fundamentally different, it challenges the very foundations of symbolic theories.

Properties of Connectionist Networks

- Learning
  - There is usually no predetermined (innate) knowledge of language, but ...
    - Input/output representation are often specified
    - The architecture of the network may be "suited" to a particular task
    - The learning mechanism and parameters provide degrees of freedom
  - Learning is takes place in direct response to experience

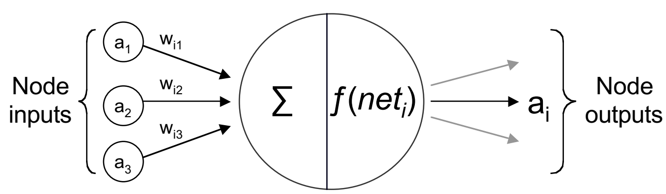
- Generalisation
  - Networks are able to learn generalisations not just by rote
  - More efficient representation of information
  - Novel inputs can be processed

- Representation
  - Learned automatically, and typically distributed

Properties continued

- Rules versus exceptions
  - Single mechanism to explain both general rules and also exceptions
- Graded:
  - Can often give a useful output to new, partial, noisy input
  - Damage is distributed, and some performance is still possible:
    - Modelling of brain damage and neurological disorders in possible
- Frequency effects
  - Model response time behaviours where high frequency inputs are recognised faster than low frequency ones

Basic Structure of Nodes



- A node can be characterised as follows:
  - Input connections representing the flow of activation from other nodes or some external source
  - Each input connection has its own *weight*, which determines how much influence that input has on the node
  - A node *i* has an output activation $a_i = f(net_i)$ which is a function of the weighted sum of its input activations, *net*.
- The net input is determined as follows: $net_i = \sum_j w_{ij} a_j$

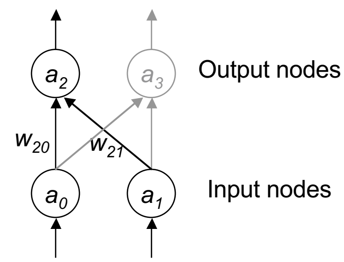
An example

- A two-layer feed-forward network:

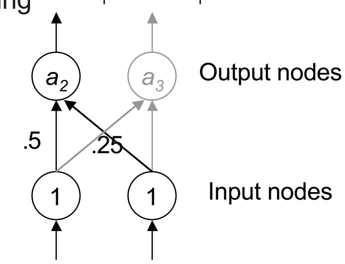
$$net_i = \sum_j w_{ij} a_j$$

- So the net input for a_2 is:

$$\text{net input } a_2 = w_{20} \cdot a_0 + w_{21} \cdot a_1$$



- Consider the network with the following inputs and weights:



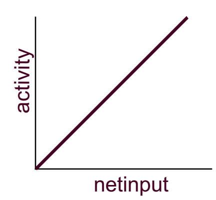
- The net input for node a_2 is:
  - 1 x .5 + 1 x .25 = 0.75

Activation functions

- The activation function determines the activation a_i for node i from the net input (net_i) to the node: $f(net_i)$

- Linear activation function
  - (McCulloch-Pitts neurode, perceptron)
  - Identity: the $a_i = net_i$

$$\boxed{\begin{aligned} f(net_i) &= net_i \\ f(0.75) &= 0.75 \end{aligned}}$$



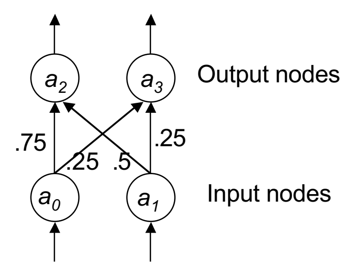
- Other activation functions:
  - Threshold
  - Binary threshold
  - Sigmoid function

About weights

- Node *j* influences a unit *i* by passing information about its activity level.
- The degree of influence it has is determined by the weight connecting node *j* to node *i*.
  - A smaller weights correspond to reduced influence of one particular node on another
- Weights can be either positive or negative
  - Positive weights contribute activation to the net input
  - Negative weights lead to a reduction of the net input activation
  - Brain: *excitatory* versus *inhibitory* connections

Übung

- Consider the following network:
  - Assume a linear activation function
- Determine the network outputs for the following inputs:
  - 0 0
  - 1 0
  - 0 1
  - 1 1

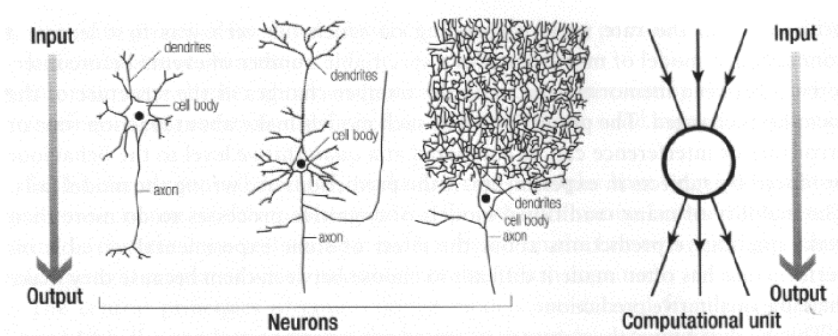


Assumptions about the brain ...

- ... On which connectionist models are based.

- Neurons integrate information:
  - *All neurons types sum inputs and compute an output*
- Neurons pass information about the level of their input:
  - *Output encodes information about the degree of input: firing rate*
- Brain structure is layered:
  - *Information passes through sequences of independent structures*
- Influence of one neuron upon another depends on connection strength:
  - *A given neuron is connected to thousands of other neurons, but it's influence on a particular node is determined by synaptic strength*
- Learning is accomplished through changing connection strengths:
  - *There is evidence that this is so*
  - *BUT most connectionist learning rules are not biologically plausible.*

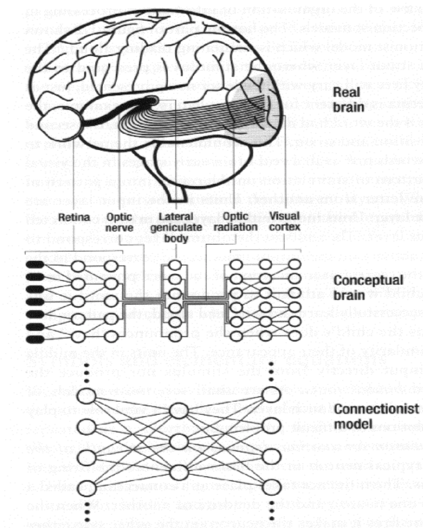
Neurons versus Nodes



• Neurons receive signals (excitatory or inhibitory) from other neurons via synaptic connections to its dendrites.
• If the sum of these signals exceeds a threshold, then the neuron fires, sending a signal on it axon.

Brain versus Network

- The human brain contains approximately 10^{10} - 10^{11} neurons
- Those neurons are densely interconnected:
  - 10^5 connections per neuron
- Connections can be both excitatory and inhibitory
- Learning involves modifying of synapses (connections)
- Connections can be both added and eliminated



Computational Properties of Networks

- Neurally inspired:
  - Slow and parallel
  - Highly interconnected
  - Learning by changing connection strength
  - Processing is distributed/"decentralized"
- Neuron is the basic processing unit
- Network configuration = "program"
- Local computation yields global behaviour
- Long-term memory is in the strength of connections (weights)
- Short-term memory is in the pattern of activity