Connectionism: Distributed networks

Phil/Psych 256

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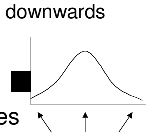
Overview

- Brain-like qualities of localized networks:
  1. They consist of a **network of nodes**.
  2. They operate in **parallel**.
  3. They perform cognitive tasks **holistically**.
- Limitations include:
  - Transparency
  - Learning
- Distributed connectionist networks address these limitations
  - a.k.a. Artificial neural networks (ANNs)

Distributed representation

- Lashley (ca. 1935): cognitive deficits are proportional to brain damage
- Neurons work in groups, e.g., excited by upwards moving objects
  - Mutually excitatory
  - Inhibit excitation of other groups (e.g., downwards moving objects)
- Firing rates within groups are often normally distributed
- Average group behaviour constitutes representation



Perceptrons

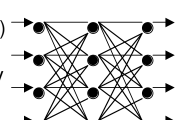
- Rosenblatt (1928–1969) studied perceptrons
  - All nodes in either input or output layers
  - Compute some propositional functions
  - Learn from examples

Perceptrons (cont.)

- Learn to compute AND, OR, NOT
- Learning via *Perceptron learning principle*
- The XOR problem: cannot *learn* XOR function
  - Minsky and Papert (1969): PLP can only teach linearly separable solutions

Multilayered networks

- Minsky and Papert speculated that no network could effectively learn non-linear solutions
- **Backpropagation** procedure (Bryson and Ho 1969) (and later) largely ignored
- Rumelhart, McLelland, Smolensky, et al. Began to experiment with backpropagation (early 1980s)
- Focused on multilayered networks (with hidden nodes)
- A 3-layer network can (approximately) compute any function



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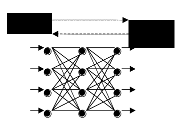
Backpropagation

- Consider the rock/mine problem (Gorman and Sejnowski 1988)
- Learning procedure:
  1. Set weights randomly.
  2. Present an example to the network and allow it to settle.
  3. Determine the error of each node in the output layer.
  4. For each "previous" layer in the network, update the connection weights to minimize the error.
     a) If a receiving node was too active, reduce connection weights to it.
     b) If a receiving node was not active enough, increase connection weights to it.
  5. Repeat (2) until error is no longer reduced or time is up.

Backpropagation (cont.)



- **Feedforward** network: activation arrives at the input layer and flows towards the output layer.
- **Backpropagation:** adjustments to connection weights due to errors begin at the output layer and flow backward towards the input layer.
- Training: the network is presented with each training set several times (*epochs*)
- After training, the network is tested against new examples
  - At the rock/mine problem, 3-node network worked at 98% accuracy
  - Trained humans work at 88–97% accuracy

Gradient descent

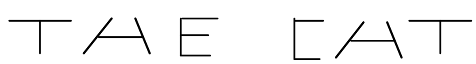
- Weight space: synaptic weights vs. error rate
- **Gradient descent**:
  - Initial state is random, typically high error rate
  - Weight adjustments tend to lower the error rate
- Optimization: weight adjustments to minimize error

NETTalk

- Sejnowski and Rosenberg (1987): turn text into phonemes (speech)
  - “cancer → /kænsr/; “lead” → /led/ or /li:d/
- DecTalk (expert system):
  - 20 years development
  - 78% accuracy
- NETTalk:
  - 50-training epochs
  - 78% accuracy

ALVINN

- Pomerleau (1993): Autonomous land vehicle in a neural network
  - Turns video images into driving directions
- Important features of the problem include:
  - No symbolic theory of driving
  - An inherently noisy problem



- Limitations include:
  - Does not make driving decisions

Representational power

- What sort of knowledge do ANNs acquire?
  - Concepts, i.e., classifications
- How is that knowledge represented?
- Representations are distributed
  - Each hidden node participates in the activation of many outputs
- Connection weights capture the knowledge of the network

Systematicity

- In an ANN, concepts are organized associatively (by similarity)
- Pros:
  - The network can handle novel inputs
  - It generalizes from experience
- Fodor and Pylyshyn (1988): ANNs do not display *systematicity*
- The following sentences are similar:
  - Bill likes Mary
  - Mark likes Bill
- However, the difference in word order is highly significant

Systematicity (cont.)

- It is difficult to train a feedforward network to make the distinction
- Easily distinguished on a rule-based account
  - Knowledge of words
  - Rules for their combination
- Human thinking displays systematicity
  - Neural networks do not, so they are not good cognitive models

Connectionist replies

- Other representation schemes can capture deep relations
  - E.g., HRRs (Plate), RAAMs (Pollack)
- Change network structure
  - E.g., *recurrent networks* (Elman 1991)
- Consider: "The cat the man brought home ate the food"
  1. "The cat … ate the food"
  2. "The man brought [the cat] home"
- In a rule-based system
  - both sentences call for the same approach
  - Grammatical knowledge is all explicit
- In Elman's approach
  - (2) requires a different approach
  - Some grammatical knowledge is implicit or procedural

Neurological plausibility

- Pros:
  - Representation is distributed
  - ANNs display *graceful degradation*
  - Generalize from examples
- Cons
  - ANNs are rarely effective if more than 1000 nodes are used (scaling problem)
  - Much neurological information, e.g., firing patterns, neurotransmitters, are simplified out
  - Backpropagation has no obvious neurological correlate