Connectionism (II)

COGS 200

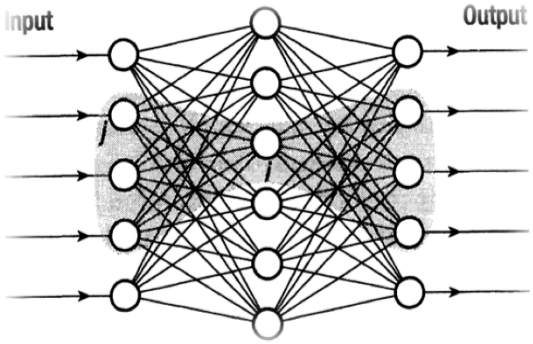
Goals for Today

- Understand why the forms of representation generated by connectionist networks raise a fundamental question for linguistics.
- See the limitations of those representations, as a medium for computation.
- Look at one approach to working with those limitations.

A Neural Network

Typical features:

- Three layer, feed forward architecture.
- Each neuron at each level passes its output to every neuron at the next level.

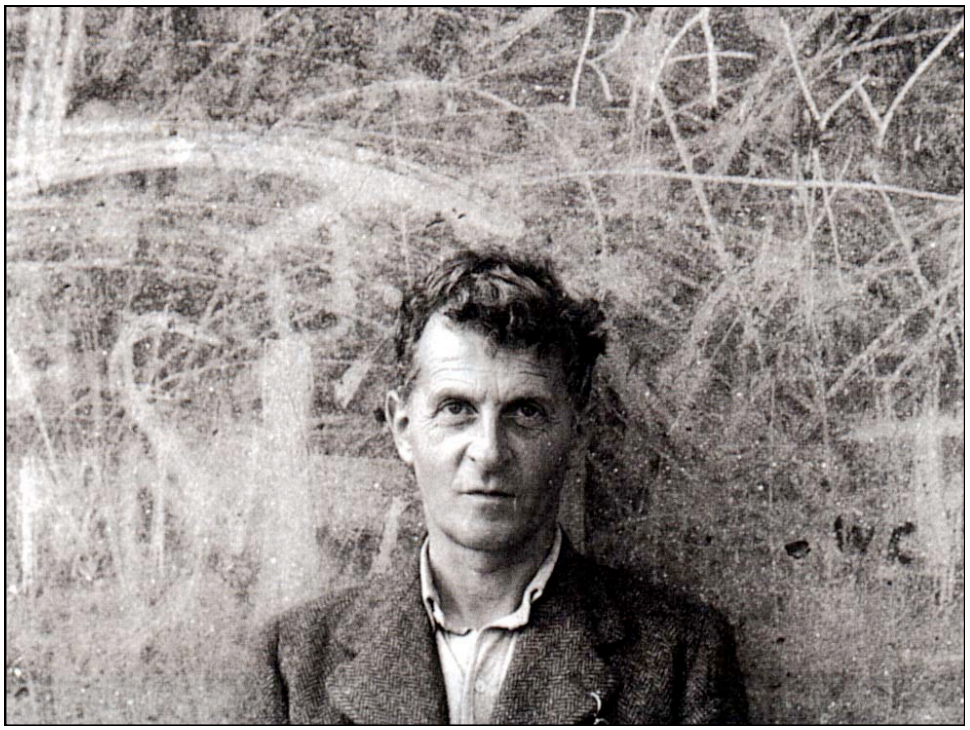


Features of connectionist representation

- Distributed
  - Each of the representations generated is composed from several computationally independent parts of the system.
- Overlapping
  - The different representations generated are composed from overlapping parts
- Holographic
  - Any part of any given representation carries information about every part of the content represented by it

Computationalism

- Any system that is able to cope with human verbal behaviour must have structured transformable representations.
- We are able to cope with human verbal behaviour.
- Therefore: We must have structured transformable representations (presumably, they are somewhere in our heads).

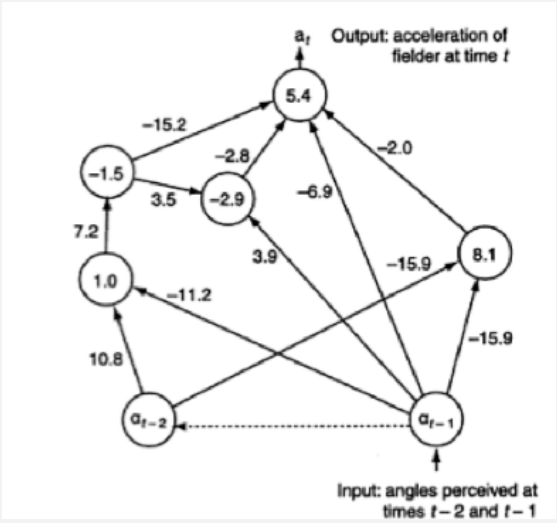


Wittgenstein

"No supposition seems to me more natural than that there is no process in the brain correlated with associating or with thinking; so that it would be impossible to read off thought-processes from brain-processes. I mean this: if I talk or write there is, I assume, a system of impulses going out from my brain and correlated with my spoken or written thoughts. But why should the system continue further in the direction of the centre? Why should this order not proceed, so to speak, out of chaos?" (*Zettel* §. 608)

Ball Catching

- "When a man throws a ball high in the air and catches it again, he behaves as if he had solved a set of differential equations in predicting the trajectory of the ball." (Dawkins, 1989, p. 96)
- Heuristic Solution: Run so that the angle of gaze increases at a decreasing rate.



- The network "behaves as if it had solved a set of differential equations".
- …But nothing in the network looks like a representation of those equations.

- The language user behaves as if she had executed a series of grammatical transformations …
- …does that require a representation of the grammatical rules in the language user's head?

The English Past Tense

- A simple rule (*+ed* to stem).
  - Kiss ⟶ Kissed,
  - Climb⟶ Climbed
  - Part ⟶ Parted
- With about 180 exceptions:
  - Go ⟶ Went
  - Is ⟶ Was
  - Has ⟶ Had
  - Sing ⟶ Sung, Ring ⟶ Rung, Feel ⟶ Felt, Kneel ⟶Knelt.

Two ways of getting to talk about the past

- Make a list.
  - For each verb you know, list its past tense form, together with its stem.
  - When you want to talk about the past, look up the past tense form.
- Learn a rule.
  - Internalize a system that just adds the appropriate form of '_ed' to the stem.
  - When you want to talk about the past, run the verb stem through that system.

Children seem to learn a rule

Berko, 1958

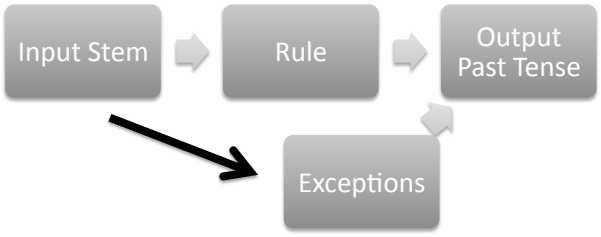
- "This is a man who knows how to spow.
- He is spowing.
- He did the same thing yesterday.
- What did he do yesterday?
- Yesterday he ____."

Children seem to learn a rule

Bybee and Slobin, 1982

- Children over apply the rule.
  - 'goed', 'bringed', 'see-ed'
- They do so more for infrequently heard forms than for regularly heard ones.
- But, in the child's third year, these overregularization errors cease.

Two route model



Problems with this model

- Defective Verbs
  - Why are there some verbs that have no past tense?
  - 'Beware of the dog'
  - ?'You had to beware of the dog.'
  - *'You bewared of the dog'
- Why are some of the child's tense-forming errors irregularizations?
  - 'wipe' → 'wope'
  - In Berko's test: 'spling' →'splang'

Rumelhart and McClelland

"We have, we believe, provided a distinct alternative to the view that children learn the rules of English past-tense formation in any explicit sense. We have shown that a reasonable account of the acquisition of past tense can be provided without recourse to the notion of a 'rule' as anything more than a *description* of the language. […] The child need not figure out what the rules are, or even that there are rules." (1986, p. 267)

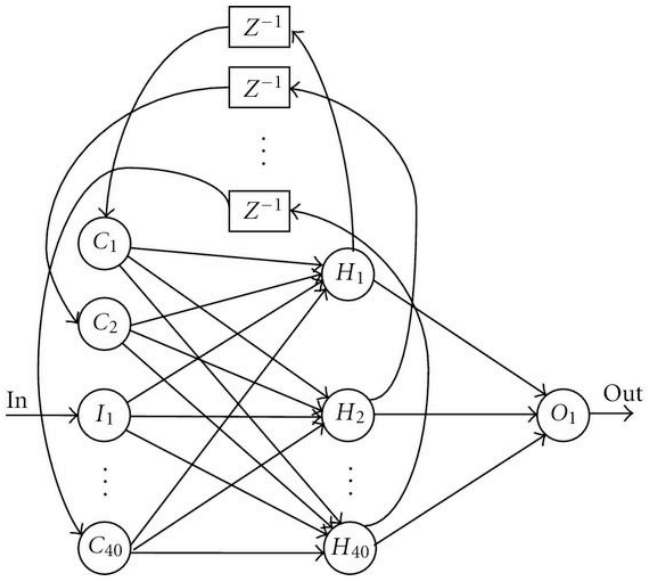
The Connectionist Alternative

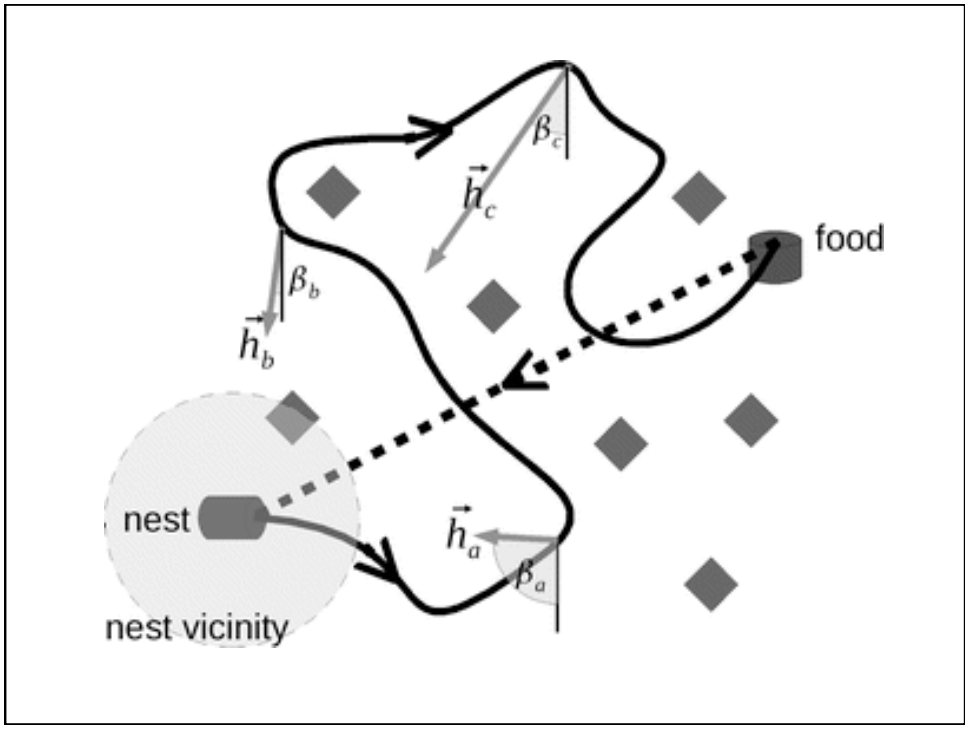
Plunkett and Marchman, 1993.

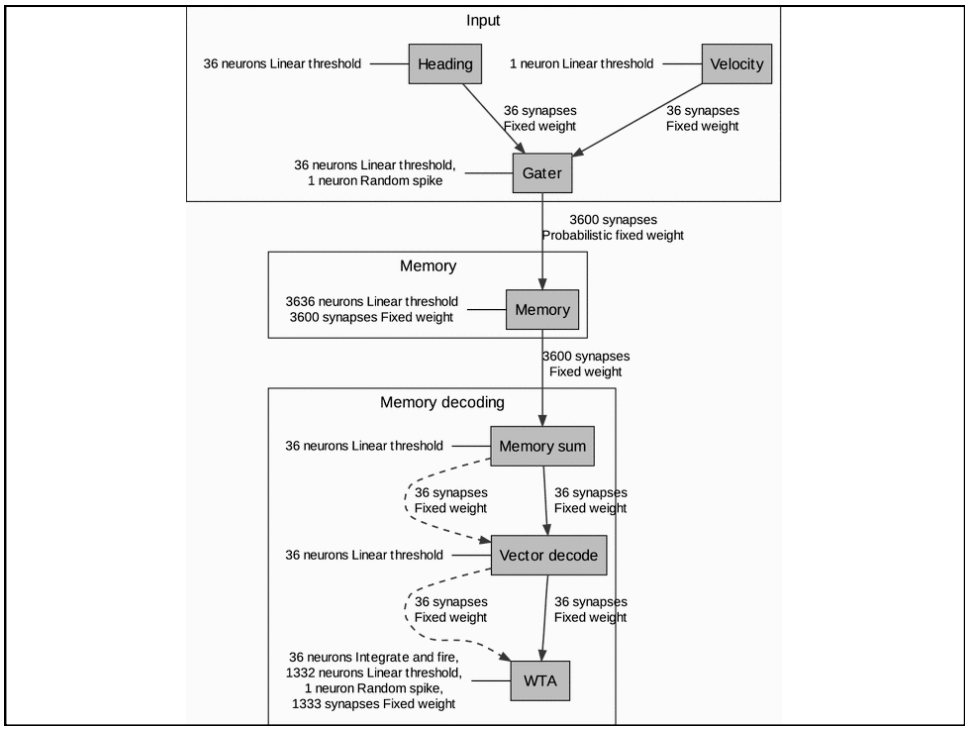
- Built a Connectionist Network with eighteen input units, twenty output units, and thirty hidden units.
- Invented an artificial language with 500 words, and similar structural properties to English.
  - 90% of verbs have a regular inflection.
  - 10% have irregular inflection.
- Trained the network with backpropagation of error.
- The irregular forms in the training set were given much more often. The regular forms were phased in.

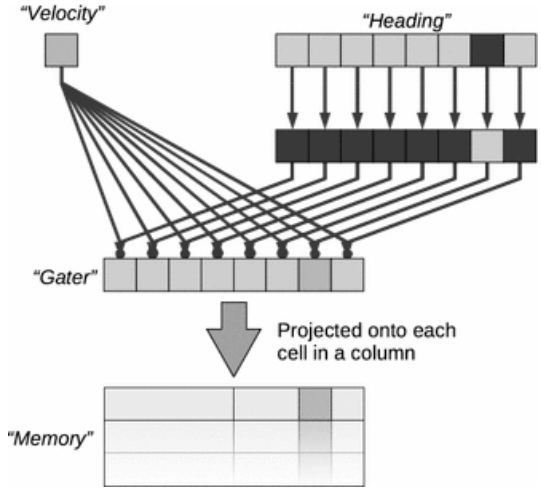
Results

- Early acquisition is error free.
- Some overregularization errors. (Between five and ten percent.)
- Common verbs do not get overregularized.
- A small number of irregularization errors occur (e.g. ‘bat’ for the past tense of ‘bite’.




β_c
$\vec{h}_c$
food
β_b
$\vec{h}_b$
nest
$\vec{h}_a$
β_a
nest vicinity


Input
36 neurons Linear threshold
Heading
1 neuron Linear threshold
Velocity
36 synapses
Fixed weight
36 synapses
Fixed weight
36 neurons Linear threshold,
1 neuron Random spike
Gater
3600 synapses
Probabilistic fixed weight
Memory
3636 neurons Linear threshold
3600 synapses Fixed weight
Memory
3600 synapses
Fixed weight
Memory decoding
36 neurons Linear threshold
Memory sum
36 synapses
Fixed weight
36 synapses
Fixed weight
36 neurons Linear threshold
Vector decode
36 synapses
Fixed weight
36 synapses
Fixed weight
36 neurons Integrate and fire,
1332 neurons Linear threshold,
1 neuron Random spike,
1333 synapses Fixed weight
WTA



"Artificial neural networks are fast but limited systems that in effect, substitute pattern recognition for classical reasoning. As might be expected, this is both a boon and a burden. It is a boon insofar as it provides just the right resources for the tasks humans perform best and most fluently: motor control, face recognition, reading handwritten zip codes, and the like. […] But it is a burden when we confront tasks such as sequential reasoning or long term planning. This is not necessary a bad thing. If our goal is to model human cognition, computational underpinnings that yield a pattern of strengths and weaknesses similar to our own are to be favoured. And we *are* generally better at Frisbee than at logic."
Clark, 1997, p. 60.