# Psych229: Language Acquisition

Lecture 15

Productivity & Rules - Modeling

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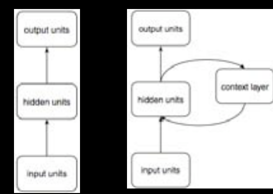
## Marcus (2003): Symbols

Feedforward vs. Simple Recurrent Networks




Simple recurrent networks (SRNs) used for learning linguistic inflection, grammatical knowledge, object permanence, categorization, logical deduction…

SRNs can learn something about the sequence of elements presented over time.

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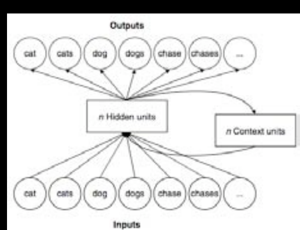
## Marcus (2003): Symbols

Elman (1990, 1993) sentence prediction model

26 input, 26 output nodes




Context layer records copy of activation pattern of hidden layer = gives 1 time step worth of memory

Learning via back propagation

Task: predict next word in sentence
Training: sentences from toy grammar with 23 words and a variety of grammatical dependencies (subject-verb agreement)

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## Marcus (2003): Symbols

Elman (1990, 1993) sentence prediction model

Learned complicated strings like
*cats chase dogs*
*boys who chase dogs see girls*

…without grammatical rules explicitly built in (singular subject has verb with singular ending, match main clause subject with main clause verb).

Taken as strong evidence against the need for grammatical rules in language.

Anderson & Hinton (1981)

"…the symbol-processing metaphor may be an inappropriate way of thinking about computational processes that underlie abilities like learning, perception, and motor skills…alternative models that appear to be more appropriate for machines like the brain."

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## Marcus (2003): Symbols

Rumelhart & McClelland (1986): past tense acquisition model

Two-layer perceptron (no hidden layer)
"provides a distinct alternative…to [rules] in any explicit sense"

But what are the real arguments against symbol manipulation?

One argument: multilayer perceptrons are more compatible with what we know about the way the brain is laid out

Counter-argument: perceptron "neurons" and "synapses" are only loosely based on real brain neurons and synapses - they have properties real ones don't; also, how is back propagation instantiated?

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## Marcus (2003): Symbols

More arguments against symbol-manipulation models

Argument: Connectionist models have been show to degrade gracefully (when part of the network is knocked out, it can still function)

Counter-argument: Symbol-manipulating models can do this, too (error-correction algorithms, partial feature-matching algorithms)

Another argument: they have been show mathematically to be able to represent a large class of functions (universal function approximator, generalization ability)

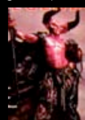
Counter-argument: mathematical proofs don't have real world considerations (like non-infinite data or realistic distributions of data); also, class of representable functions may not be all the ones needed for language (partial recursive functions would be necessary (Hadley (2000))

## Marcus (2003): Symbols

Just what *are* symbols, anyway?

A context-independent category?
Kossyln & Hatfield, 1984: symbols can appear in rules

Marcus: We probably want symbols to stand for particular individuals (Jareth the Goblin King) rather than just categories (villains in 80s fantasy movies)

## Marcus (2003): Symbols

Just what *are* symbols, anyway?

Things we want symbols for:
- categories (villains in 80s fantasy movies)
- variables (if 80s movie has *good villain*, then watch 80s movie)
- computational operations (+, - , concatenate)
- individuals (Jareth the Goblin King)

Not every act of cognition may require all of these
Ex: Tic-Tac-Toe playing program = variables and operations

Ex: connectionist models = context-independent representations (categories)

## Marcus (2003): Symbols

Symbols and relations

Want to represent variables & relations between variables (algebraic rules).
Ex: form progressive in English by adding *-ing*: *sing ~singing*
Applies to novel input: *out-villain ~ out-villaining*
*"He was even out-villaining Jareth"*

Important relation: universally quantified one-to-one mappings
universally-quantified: applies to all instances in domain (ex: verb stems)
one-to-one: each output maps to a single input (ex: progressive form of verb)

Freely generalizable: Can't just memorize these because the domain is unrestricted (any verb stem, can apply to new ones).

Language examples: verb endings (-ing), reduplication (*Are you watching Labyrinth, or watching-watching it*?), combining noun phrases with verb phrases to make sentences

7-month old infants have the ability to freely generalize (March et al. 1999)

## Marcus (2003): Symbols

A sample function

Input and output data.

| Input | Output |
|---|---|
| Training Item | |
| 1010 | 1010 |
| 0100 | 0100 |
| 1110 | 1110 |
| 0000 | 0000 |
| Test Item | |
| 1111 | ? |

What do you think the answer to the test item is?

## Marcus (2003): Symbols

A sample function

Input and output data.

| Input | Output |
|---|---|
| Training Item | |
| 1010 | 1010 |
| 0100 | 0100 |
| 1110 | 1110 |
| 0000 | 0000 |
| Test Item | |
| 1111 | ? |

Humans: 1111

Multilayer perceptrons: 1110

Why? 4th position is always 0 in training set. Local mathematically sound generalization from training data: 4th position is always 0.

But this doesn't seem to be what humans do…

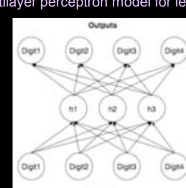
An algebraic system that uses an identity function (f(x) = x) would be able to capture this behavior.

## Marcus (2003): Symbols

Learning freely generalizable functions

Multilayer perceptrons can learn universally quantified one-to-one mapping functions only if they see an example of each input-output combination. This is because each output is independent of the others.

Multilayer perceptron model for learning identity function with 4 digits




Model has no way to tell all digits should be treated uniformly

Point: For situations where humans freely generalize, need a model of cognition that is also capable of free generalization

Language = many places where humans seem to freely generalize from restricted data

## Marcus (2003): Symbols

Another issue: representing binding

Binding: noun phrases with verb phrases, *Jareth* with "subject of sentence", *peach* with "theme of sentence"

Not enough neurons to represent each possible combination in language with a separate neuron (*Jareth* + subject neuron, *Jareth* + agent of giving-peach neuron, …)

If *n* concepts that can each be combined with each other, need $n^2$ neurons. That doesn't include multiple bindings. (*Jareth* + subject + *peach* + object +….)

## Marcus (2003): Symbols

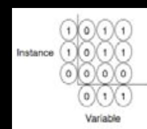
Another issue: representing binding

One idea: distributed representation of concepts

Suppose binary code for each concept.
*n* concepts coded in $\log_2 n$ neurons. (10 neurons can encode > 1000 concepts)

Example combination of concepts: use *tensor* product

Jareth




subject

3 x 3 tensor product:
9 neurons for product + 6 neurons to represent instance and variable (15 total)

Can represent $2^3$ instances with $2^3$ variables = $2^6$ bindings (64).

10 x 10 tensor product:
120 neurons to represent $2^{20}$ = 2048 bindings

## Marcus (2003): Symbols

A problem with distributed representations

Superposition: Can't represent multiple instances simultaneously with same set of units

*Goblins* = [101] *Babies* = [010] *Older sisters* = [011] *Goblin kings* = [100]

Training:
Goblins like peaches.
Older sisters like peaches.

Test: _____ like peaches.

Answer: Goblins & Older sisters

[101] & [011] = activate all 3 units [111]

But this looks no different from [010] (*babies*) & [101] (*goblins*) = [111] or [011] (*older sisters*) & [100] (*goblin kings*)

## Marcus (2003): Symbols

A point about useful questions to ask about human cognition

Good: Does the mind have rules in anything more than the descriptive sense?

Not so good: Can we build a connectionist model that does [insert something humans seem to do, ex: the past tense formation in English]?

Just because the model is implemented in a connectionist style does not mean it doesn't have rules built in.

Better: What design features must a connectionist model that does [insert something humans seem to do] need to include?

Past tense case: The connectionist models that come closest to implementing rules & memory do the best approximation to human performance.

Implication: Rules (operations over variables) are an important part of human cognition.

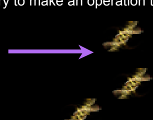
## Marcus (2003): Symbols

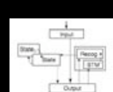
About the biological basis of symbols

Critique from Elman et al. (1996): Nativism (symbols) = DNA as blueprint

DNA as recipe: common in developmental biology
DNA codes for *master control genes* that, when switched on, cause *cascades* in which the actions of many genes are unleashed.

p.165-166: "Genetically driven mechanisms (such as the cascades described above) could, in tandem with activity-dependence, lead to the construction of the machinery of symbol-manipulation - without in any way depending on learning…a set of complicated cell-to-cell interactions that could lead to the construction of a memory register…treelets that permit the representation of structured combinations…machinery to make an operation that performs some computation over a register"





## Marcus (2003): Symbols

About the biological plausibility of multilayer perceptrons

Multilayer perceptrons are entirely prewired - no developmental changes other than connection strengths.

Implication: Entire network is specified in advance (by DNA, presumably)
Elman et al. (1996): allow differences in number of hidden layers, but do not capture notion of cascading genes

Point: Biological plausibility is relative