Complexity Analysis

Enhancing Methodological Rigor for Computational Cognitive Science

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Why do we throw away our tools?

Given computational models, use tools for analyzing computation

Computational Complexity

- Asymptotic computational complexity
 - Resource costs vs. scale n

- O(f(n)): $\exists n', k \text{ such that } n > n' \rightarrow \text{cost} < kf(n)$
- Also: Ω, Θ, expected, amortized...

Establish analytically or empirically

Biological Plausibility



- ~10¹¹ neurons
- ~10¹⁵ synapses
- ~10¹³ "clock cycles"/life

Three way comparison:

- Cost of *n* items
- # items for a mind
- Resource budget

Is it affordable within a few orders of magnitude?

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		noticing a small color patch	millions of visual features	O(log n)

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		working a physics problem	a few models	O(c ⁿ)
Memory to store a set of <i>n</i> items	10 ¹⁴ synapses	relations in a social network	hundreds of friends	O(n⁵)
		word meanings	vocabulary of thousands	O(n³)

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		relations in a social network	hundreds of friends	O(n⁵)
		word meanings	vocabulary of thousands	$O(n^3)$
Time to learn about a set of <i>n</i> items	10° seconds of experience	arithmetic	a few relations	<i>O</i> (<i>c</i> ⁿ)
		word meanings	vocabulary of thousands	$O(n^2)$
		possible body movements	billions of positions	O(n)

What if the model is too expensive?

- Find lower complexity equivalent model
 - e.g. bubble sort vs. heap sort vs. parallel bubble
- Tighten complexity bound
 - e.g. expected fast graph coloring
- Change model requirements
 - e.g. consensus vs. approximate consensus
- Reuse costly components
 - e.g. cognitive substrate approach

Improving Models: Word Learning

Bayesian categorization:

- n examples, |X| in a category
- Assuming O(1) similarity calc
 - O(n) space
 - $O(|X|n^2)$ time per example
 - $O(|X|n^3)$ time to learn words

1 example

3 subordinate examples

3 basic-level examples

3 superordinate examples

10⁶ words/life → ~10⁵ lives to learn?

Incrementalize → ~0.1 lives

Vegetables



(16)









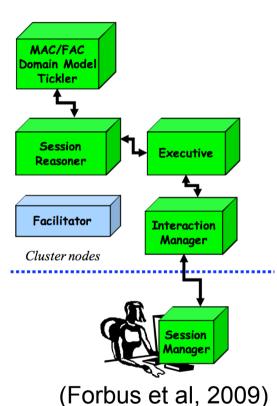


(Xu & Tenenbaum, 2007)

New Predictions: Analogical Reasoning

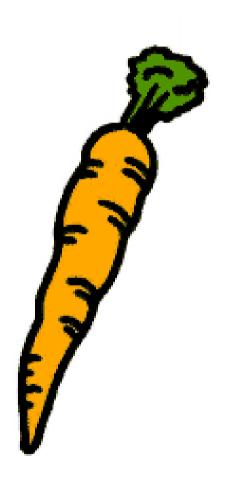
Companions Cognitive Architecture

- k examples, n elements per exa.
 - Retrieval: O(log k) time, O(k) circuit
 - Mapping: $O(n^2)$ time
- $k = \sim 10^9$, $n = \sim 10^3$ (Forbus, 2009)
 - Space OK if noise tolerant
 - Time: 10⁶ is too long, but a greedy algorithm is fast. Do humans fail like the greedy algorithm?



Benefits of Complexity Analysis

- Scaling
 - e.g. 21 objects → language
- Robustness
 - Few confounds scale equivalently
- Composability
 - Experimental grounding is portable
 - e.g. varying defn. of "word sense"
- Longevity
 - Flexible coupling to neuroscience



Must we really?



Complexity analysis : Model =
Significance analysis : Experiment

- Omitting complexity analysis is a scientific problem that...
 - ... misleads non-computational colleagues
 - ... creates erroneous models
 - ... stifles research on open problems

Four Questions for Every Paper

- What resource limitations are pertinent?
- What is the order of growth for each resource?
- What is the scale of the model?
- How does the model compare against current estimates of biological resource limits?

Bounds can always be tightened later

In Summary:

- Computational cognitive models demand analysis of computational complexity
 - Analysis can be theoretical or empirical
 - Adding complexity analysis to papers is easy
- Even loose estimates of biological scale and resources can be strong constraints on models
- Application examples:
 - Exposed challenges to word learning model
 - New behavior predictions for analogical reasoning