

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

Biological Plausibility



$\sim 10^{11}$ neurons

$\sim 10^{15}$ synapses

$\sim 10^{13}$ “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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Time to learn about a set of n items	10^9 seconds of experience	arithmetic	a few relations	$O(c^n)$
		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

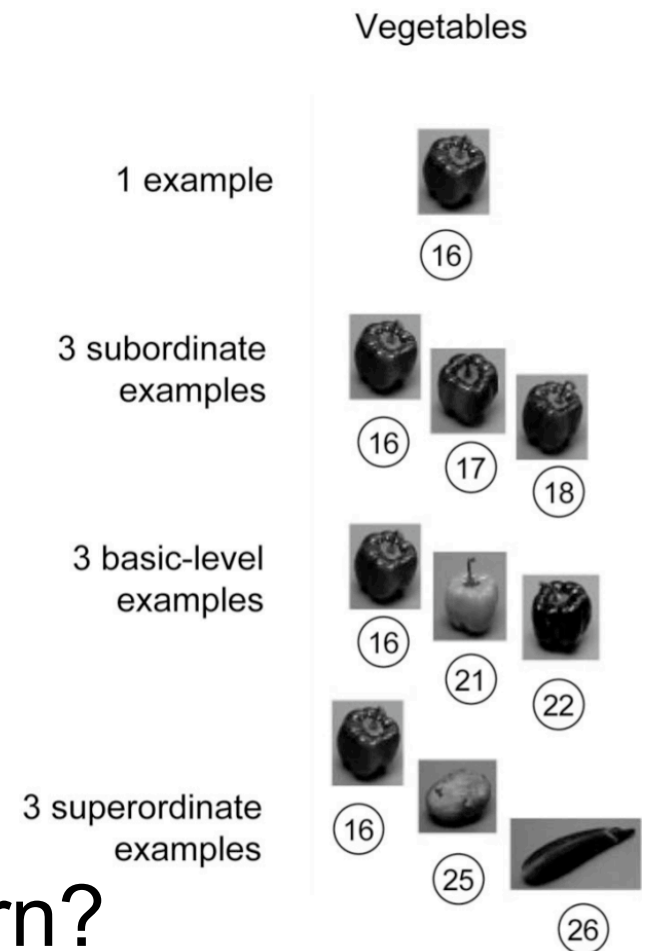
Improving Models: Word Learning

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

10^6 words/life \rightarrow $\sim 10^5$ lives to learn?

Incrementalize \rightarrow ~ 0.1 lives

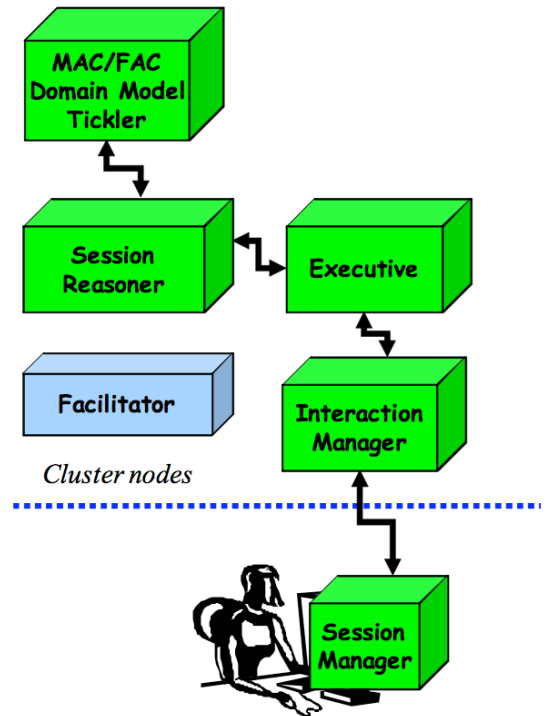


(Xu & Tenenbaum, 2007)

New Predictions: Analogical Reasoning

Companions Cognitive Architecture

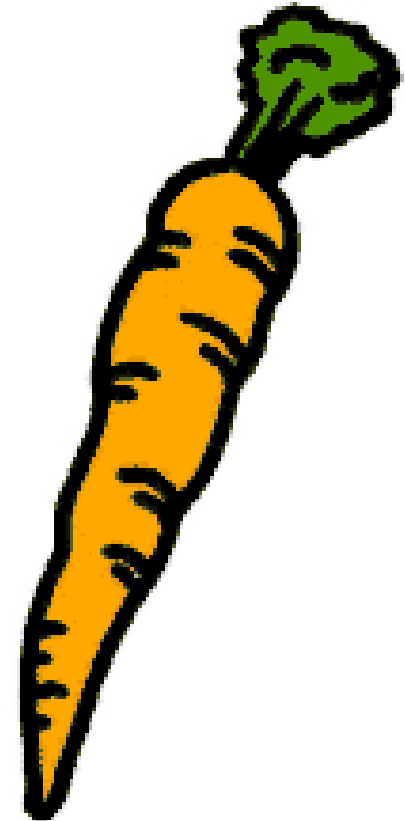
- k examples, n elements per exa.
 - Retrieval: $O(\log k)$ time, $O(k)$ circuit
 - Mapping: $O(n^2)$ time
- $k = \sim 10^9$, $n = \sim 10^3$ (Forbus, 2009)
 - Space OK if noise tolerant
 - Time: 10^6 is too long, but a greedy algorithm is fast. Do humans fail like the greedy algorithm?



(Forbus et al, 2009)

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