Cognitive Science and Long-Term Symbolic Learning

William G. Kennedy
J. Gregory Trafton
Naval Research Laboratory
Washington, DC

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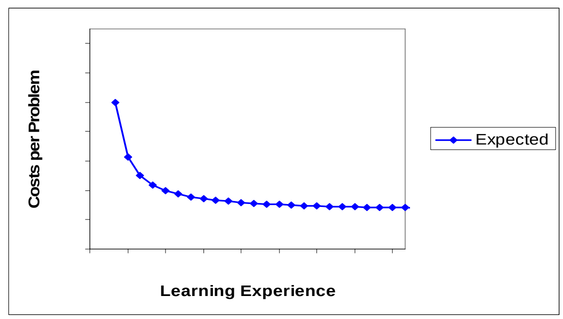
The Issue

- We learn over our entire lifetimes without catastrophic failures.
- Our symbolic learning systems run only hours...
- What do we need to do to get our learning systems to survive infancy?

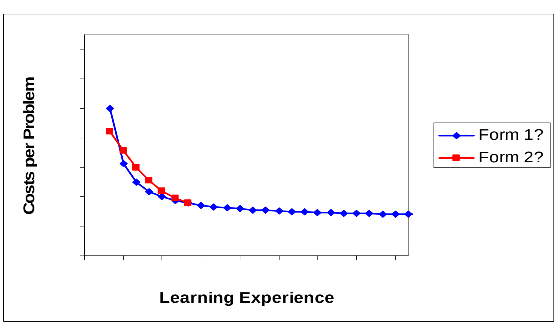
Background & Motivation

- Soar's original claim to fame was its chunking, which matched human data (Newell & Rosenbloom 1981) *(but a footnote reported it failed after 259 problems because of a memory allocation problem...)*
- *Utility Problem*: Performance of AI's symbolic learning systems eventually degrade making continued learning actually detrimental to performance (Minton 1990, Holder 1990) (in Soar: Tambe 1990, Doorenbos 1995, Kennedy 2003)
- Humans don't have a "utility problem"
- Maybe AI & Soar could benefit from the psychological side of cognitive science...

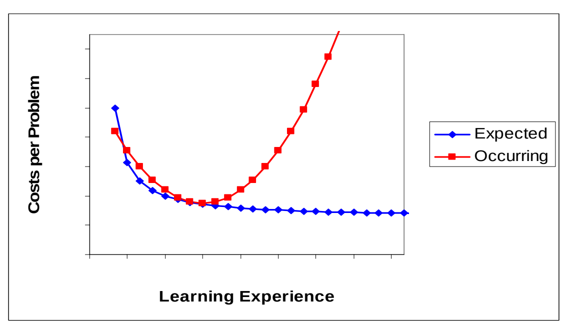
Performance with Learning



Power Law or Exponential Law



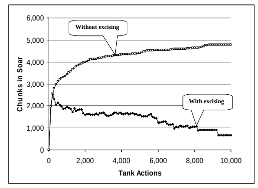
Performance Problem (Occurring)

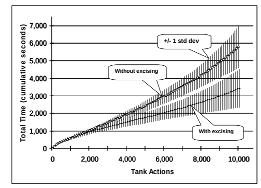


Addressing Performance in Soar

- Restrict expressiveness of chunks (Tambe)
- Improve matching (Doorenbos)
- Forget low-use chunks (Kennedy)

Addressing Performance in Soar





Reduce Chunks in TankSoar **Better performance...**

Cognitive Science Concepts

"Cognitively Inspired"

An intelligent capability exhibited by commonly-accepted intelligent agents BUT, not necessarily performed the same way the intelligent agents do.

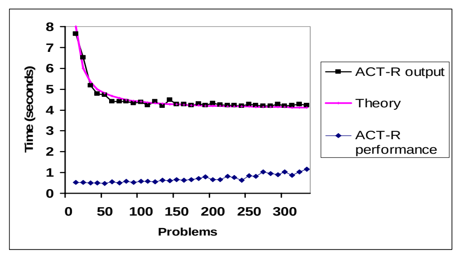
"Cognitively Based/Plausible"

An intelligent capability exhibited by commonly-accepted intelligent agents WITH evidence that it is performed the same way the intelligent agents do.

"Cognitive Science"

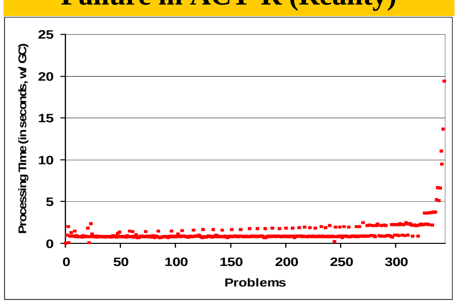
"If you just have formalisms or a model, you are doing 'operations research' or 'AI';
if you just have data and a good study, you are doing 'experimental psychology'; and
if you just have ideas, you are doing 'philosophy'.
-- it takes all three to do cognitive science." (Wayne Gray's e-mail signature)

ACT-R theory, output, & reality



1-step Blocks World problems (on an old, slow, small Mac)

Failure in ACT-R (Reality)



Specifics of one run to failure

Performance Problems of ACT-R

Two causes:

- **Implementation detail: keeping old names around**
- **Calculation of activation for items in memory requires the history of each use of each item**

Activation in ACT-R

Theory's formula for activation (eq. 4.1, Anderson & Lebiere, 1998)

$$B_i = \ln\left(\sum_{j=1}^{n} t_j^{-d}\right) + \beta$$

A more computationally efficient approximation (Petrov, 2006)

$$B_i \approx \ln\left(\sum_{j=1}^{k} t_j^{-d} + \frac{(n-k)}{(1-d)} * \frac{(t_n^{1-d} - t_k^{1-d})}{(t_n - t_k)}\right)$$

Activation in ACT-R

Theory's formula for activation (eq. 4.1, Anderson & Lebiere, 1998)

$$B_i = \ln\left(\sum_{j=1}^{n} t_j^{-d}\right) + \beta$$

0--->unbounded growth!!!

A more computationally efficient approximation (Petrov, 2006)

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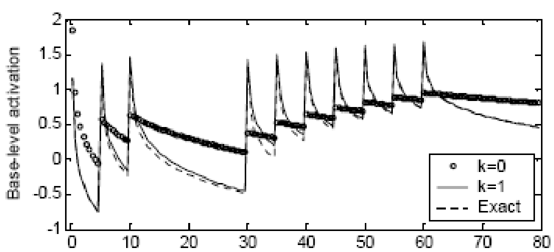
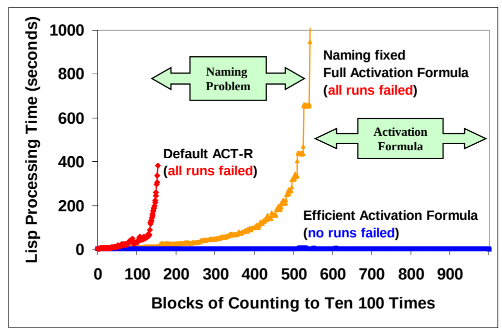
Activation in ACT-R



(from Petrov 2006)

Extending ACT-R's Performance



Gold Nuggets and Coal

- To survive infancy as long-term learning systems, both Soar and ACT-R have challenges:
  - Different approaches to working memory and procedural memory,
  - Different approaches address their performance problems,
  - But it's all centered around memory…
- The problem seems to be in deep in the *vowels* of memory (the I, O, or A support of memories).
- Long-term learning research takes patience…

References:

ACT-R Research Group. *ACT-R* http://act-r.psy.cmu.edu/

Anderson, J. R., and Lebiere, C. 1998. *The Atomic Components of Thought*. Mahwah, NJ: Erlbaum.

Doorenbos, R. B. (1995). *Production Matching for Large Learning Systems.* Carnegie-Mellon University, Pittsburgh.

Holder, L. B. (1990). *The General Utility Problem in Machine Learning.* Paper presented at the Seventh International Conference on Machine Learning, Austin, TX.

Kennedy, W. G., & Trafton, J. G. (2006). Long-Term Learning in Soar and ACT-R. Paper presented at the Seventh International Conference on Cognitive Modeling, Trieste, Italy. (April 5-8, 2006).

Kennedy, W. G., & Trafton, J. G. (in press 2007). Long-Term Symbolic Learning. Cognitive Systems Research.

Minton, S. (1990). Quantitative Results Concerning the Utility of Explanation-Based Learning. *Artificial Intelligence, 42*, 363-391.

Newell, A., & Rosenbloom, P. S. (1981). Mechanisms of Skill Acquisition and the Law of Practice. In J. R. Anderson (Ed.), *Cognitive Skills and Their Acquisition*. Hillsdale, NJ: Erlbaum.

Petrov, A. A. (2006). *Computationally Efficient Approximation of the Base-Level Learning Equation in ACT-R*. Paper presented at the Seventh International Conference on Cognitive Modeling, Trieste, IT.

Tambe, M., Newell, A., & Rosenbloom, P. S. (1990). The Problem of Expensive Chunks and its Solution by Restricting Expressiveness. *Machine Learning, 5*, 299-348.