Quantitative Category Learning in Soar: Progress and Roadblocks

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Soar Technology

Agent-based Modeling & Behavioral Representation Program: Phase III

Phase I/II: Enroute air-traffic control task (R. Chong)

Interaction with real-time display (eye, text, mousing, etc.)

Vary workload and compare to human data

Integrated in DoD's "High Level Architecture" (HLA)

Phase III: Air-traffic control task + Category Learning

Interaction with real-time display (eye, text, mousing, etc.)
+

Additional task: Learn when to allow/disallow "altitude change requests" (synthetic task, other activities pause)
Maps to classic category learning results (3 attr, 2 values ea)

altitude=20,000; size=L; turbulence=1 → accept

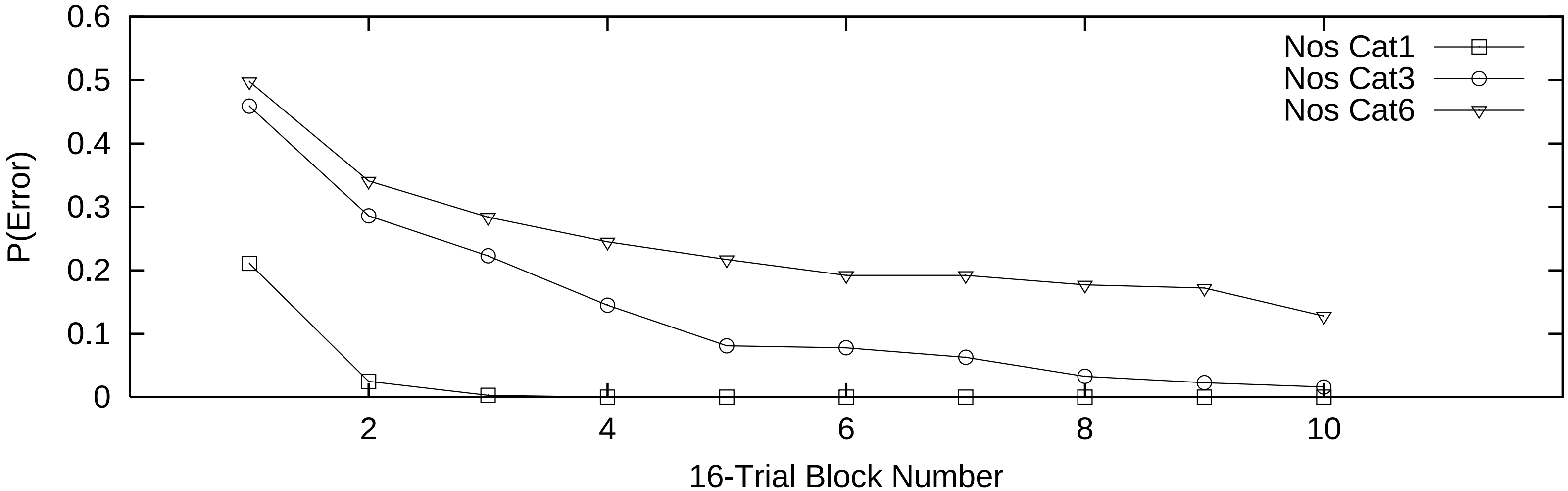
altitude=40,000; size=S; turbulence=3 → reject

Rule-based Categorization

Given identical instances and identical probability distribution of categories, some category definitions are easier to learn than others (Shepard et al., 1961). Shepard et al results were duplicated with statistical confidences by (Nosofsky et al., 1994).

Category 1: One attribute determines classification (alt=20 $\rightarrow$ accept)
Category 3: Like Category 1 but some exceptions (alt=20 $\rightarrow$ accept except ...)
Category 6: No pattern; must memorize instances

Figure 2 from Nosofsky et al (1994) (Reproduced)



Symbolic Concept Acquisition

Soar model of concept acquisition developed by Craig Miller (Miller, 1993)

- General-to-specific search over concept space
- Backtracks, noise-tolerant
- Qualitative fit to Nosofsky data

SCA Algorithm:

```
instance  = input attributes and values
while (no matching prediction rule for instance)
      abstract feature from instance
      store most recently abstracted feature
restore most recently abstracted feature to instance
store new prediction rule for instance
```

Example:

Prediction rules:

alt=20 $\longrightarrow$ accept, (null) $\longrightarrow$ accept, (null) $\longrightarrow$ reject

New instance: size=S,turbulence=3,altitude=20

New Prediction Rule: alt=20, turb=3 $\longrightarrow$ accept

Current Effort: Quantitative Match to Nosofsky

Assumption: Learning curves for AMBR task should match Nosofsky results
(preliminary data from BBN suggests this assumption holds)

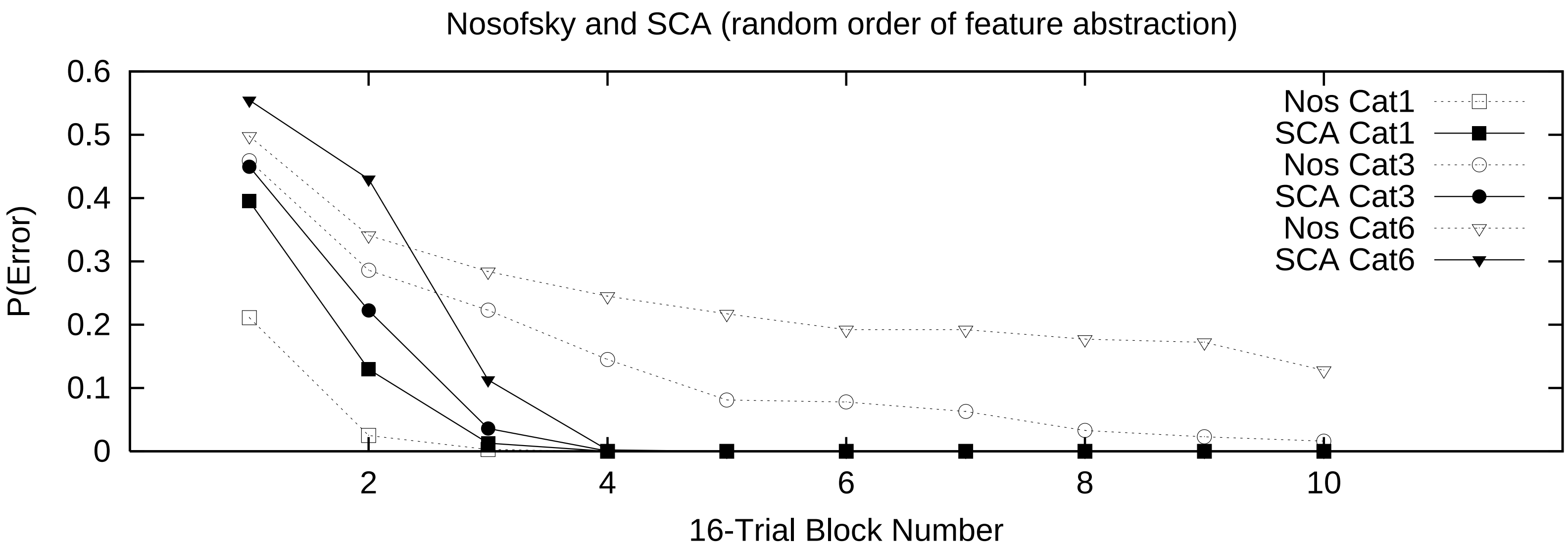
Current Goal: Use SCA + knowledge to achieve reasonable qualitative fits to Nosofsky data

- How close can we get without additional mechanisms? (avoid simulating subsymbolic mechanisms; eg, frequency effects)
- What knowledge is necessary?
  - SCA: modify abstraction order
  - Process models of category learning

Future Work: Look at impact of subsymbolic mechanisms (EPIC-Soar)

Preliminary Results: SCA "out of the box"

SCA with random feature abstraction order (slowest learning)

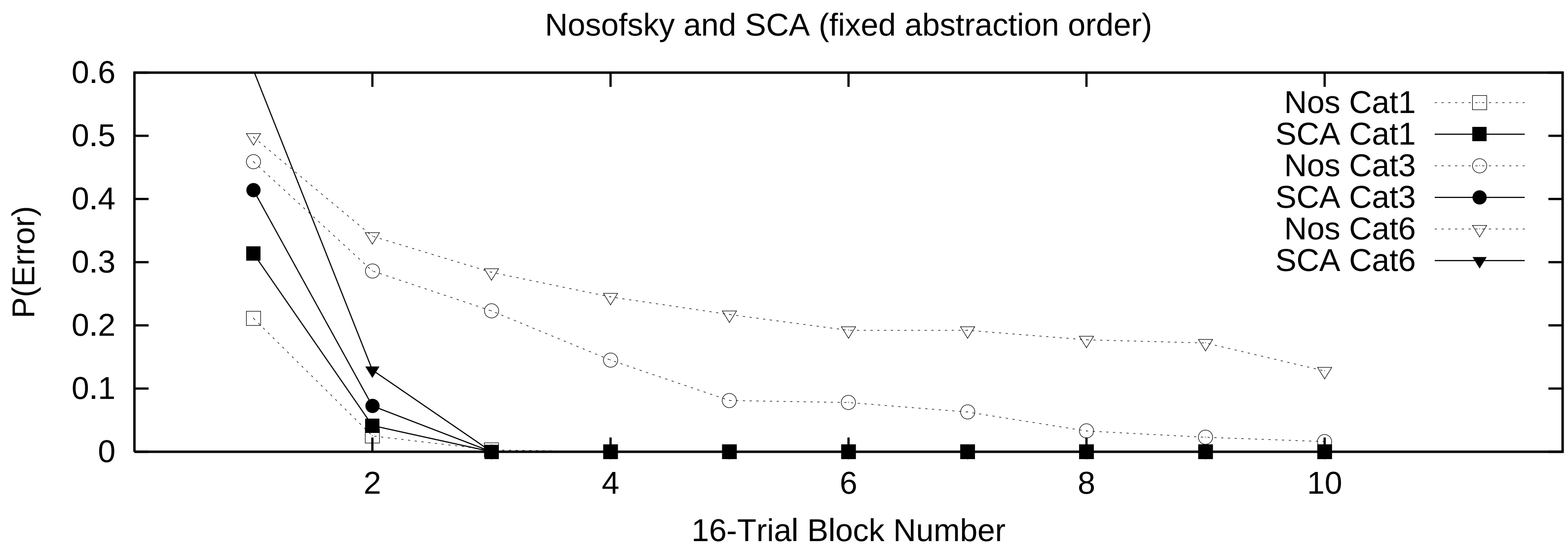


Poor fit for all three categories

SCA in worst case is too powerful: all categories fully learned by 8th presentation of each instance

Preliminary Results: SCA + fixed abstraction order

Idea: These attributes have meaning (esp. altitude for an altitude change request)

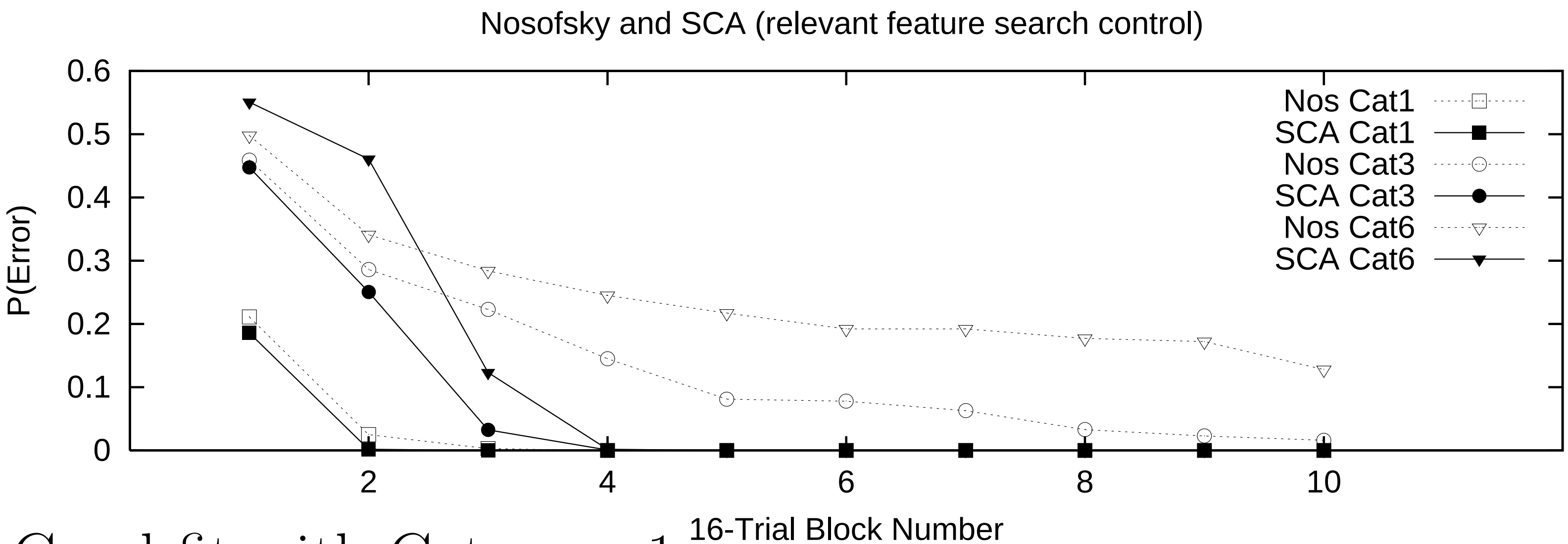


Poor fit for all three categories

SCA even faster here: all categories fully learned by 6th presentation (confirmation of (Miller, 1993): Fixed order will increase learning rate)

Preliminary Results: SCA with simple search control

Simple, common sense knowledge: If an attribute made a difference in a previous prediction, then abstract it last (consider it the most relevant feature)



Good fit with Category 1

Reasonable fit with Category 3 for blocks 1/2

Poor qualitative fit with Category 6

Still much too fast in all but 2 of 20 blocks (Cat 3 & 6)

Improving the Fits

Soar

- Consider additional attributes
  Some subjects reported that they thought other issues could impact category

- Consider other category learning models (existing process models?)

- Is it realistic to learn a new refinement every trial?
  Recall of prior instances is too powerful; perhaps use episodic memory to recall prior instances as in (Altmann and John, 1999)

EPIC-Soar

- Impact of activation/decay memory model

- Impact of chunk forgetting (possibly similar to episodic effects?)

Summary

Soar + SCA + simple knowledge seem unlikely to be able to account for much of the variance in the Nosofsky data

TBD

- Process model of concept learning?
- Impact of episodic memory?
- Explanatory power of subsymbolic mechanisms?
- Generalization of SCA concept (transfer task)?

Soar8 SCA code up on a webpage soon ....

References

Altmann, E. M. and John, B. E. (1999). Episodic indexing: A model of memory for attention events. *Cognitive Science*, 23(2):117–156.

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Nosofsky, R. M., Gluck, M. A., Palmeri, T. J., McKinley, S., and Glauthuier, P. (1994). Comparing models of rule-based classification learning: A replication and extention of Shepard, Hovland, and Jenkins (1961). *Memory & Cognition*, 22(3):352–369.

Shepard, R. N., Hovland, C. I., and Jenkins, H. M. (1961). Learning and memorization of classifications. *Psychological Monographs*, 75(13).