A Soar Model of Bottom-Up Learning from Activity

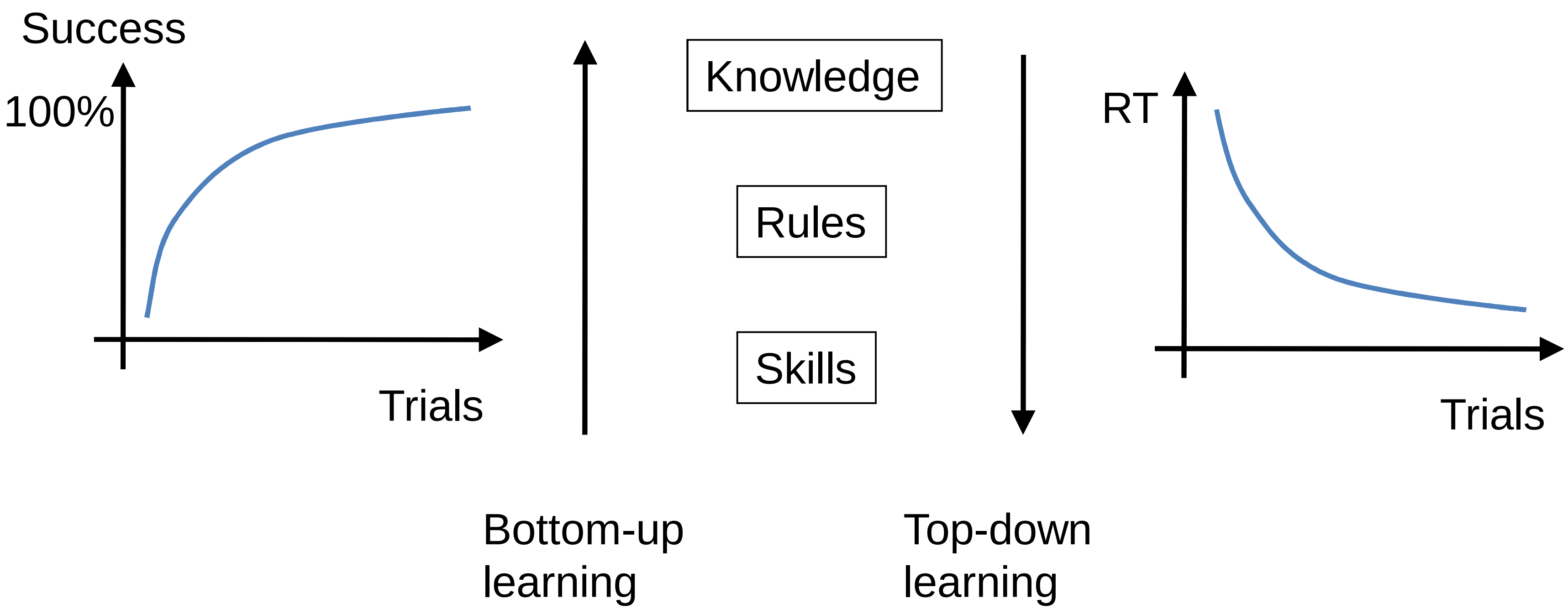
Soar Workshop
June 2009

Olivier L. Georgeon & Frank E. Ritter
olg1@psu.edu
Pennsylvania State University

Outline

- Bottom-up learning
  - Constructivist epistemology
  - Schema mechanism
  - Hierarchical sequence learning
- The model
  - Its principles
  - The task
  - Its activity traces
- Conclusions

Bottom-Up Learning



Construct higher-level goals
To fulfill lower level preferences

Aggregate sub-goals into chunks

Constructivist Epistemology

- Piaget
  - Schemas are the basic building blocks for cognition
  - They are hierarchically constructed
- Implement a bottom-up mechanism of schema construction

Provides agents with a way to organize their behavior so that we can infer they have goals, knowledge and emotions when we observe their activity.

The Schema Mechanism

- Drescher, G. L. (1991). *Made-up minds, a constructivist approach to artificial intelligence*. Cambridge, MA: MIT Press.
  - Schema = (context, action, result)
- Implemented and working but
  - Not scalable
  - No sequence learning

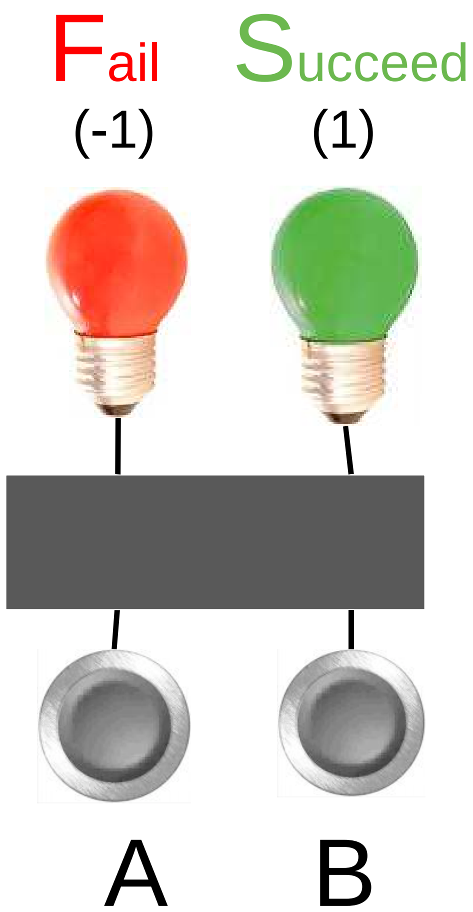
Self Segmentation of Sequences

- Sun, R., & Sessions, C. (2000). Automatic segmentation of sequences through hierarchical reinforcement learning.
  - Sequence learning is the start
- Implemented and working but
  - No schema management

2. The model

- Use schemas as:
  - (context, action, expectation)
- Use reinforcement learning (Soar 9):
- Do hierarchical sequence learning of schemas:
  - context = sub-schema + status
  - intention = sub-schema + status
  - satisfaction = satisfaction(context) + satisfaction(intention)
  - weight = number of enactions

Simple tasks



A F B S B S B S B S

Time

Schema: (nil, AF,-1,1) (AF, BS,0,1) (BS, BS,2,w)

A S B S A S B S A S

Time

Schema: (AF,AS,0,w) (AS,AF,0,w)…
(AS,BS,2,w) (BS,AS, ,2,w)…

More difficult tasks

A F A S B F B S A F A S B F B S

Time

Tertiary — S5 = (S3S,S4S)

Secondary — S3 = (S1S,S2S,0,w) S4 = (S2S,S1S,0,w)

S = (S1S,BF,-1,w)

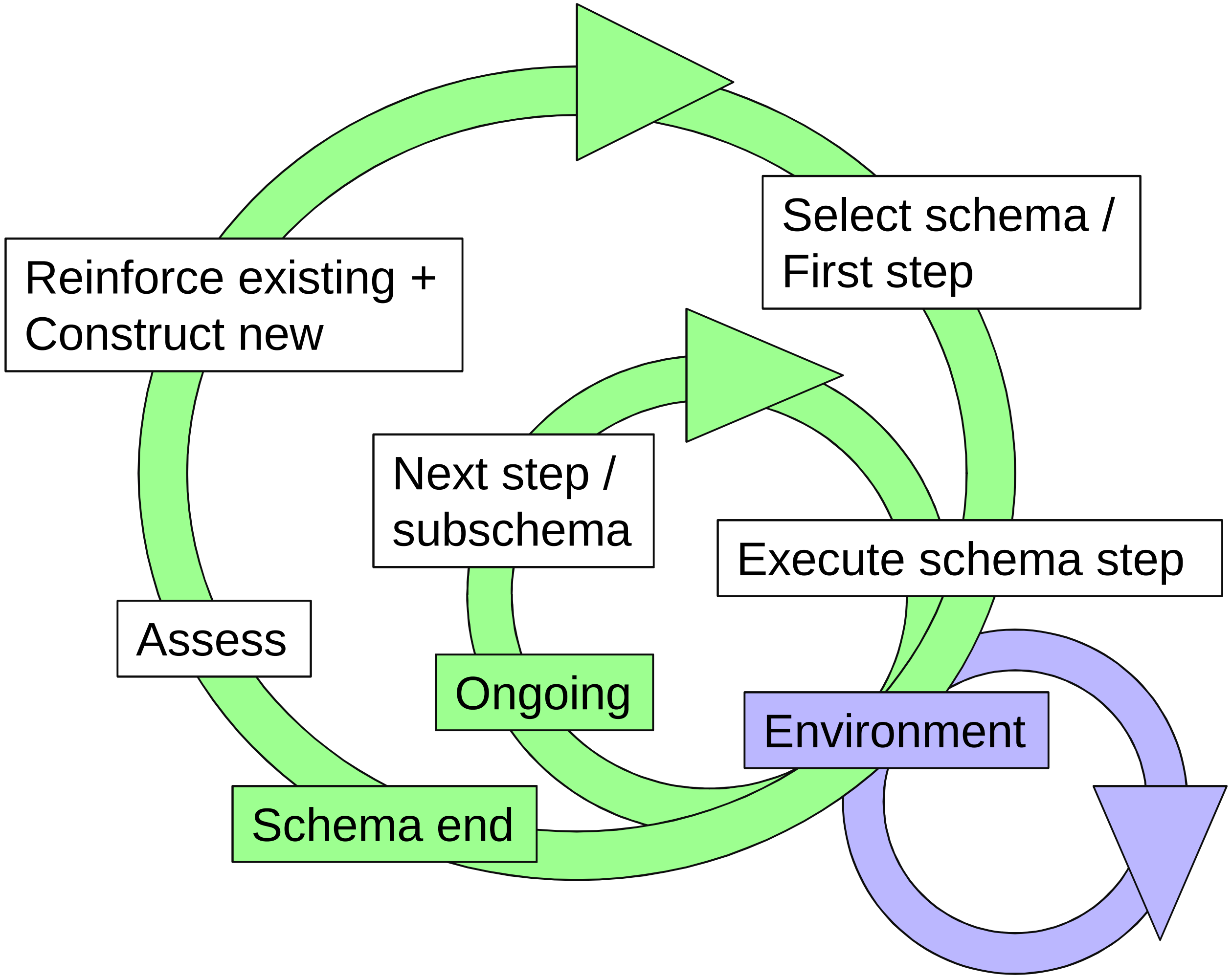
Primary — S1 = (AF,AS,0,w) S2 = (BF,BS,0,w)

S = (AF,AF,-2,w)

Elementary — A = (press A,1) B = (press B,1)

Time

Interaction cycle

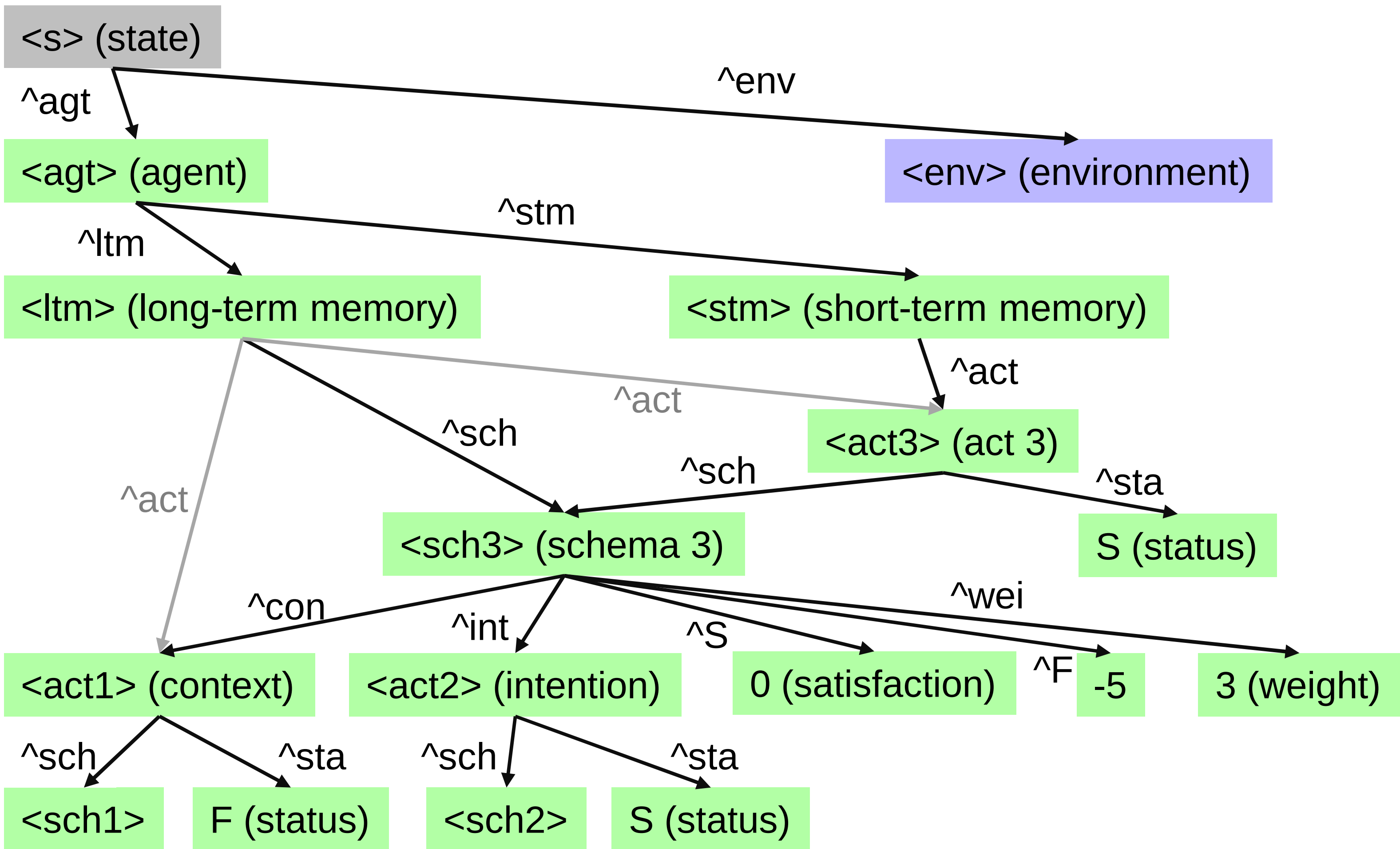


Activity trace

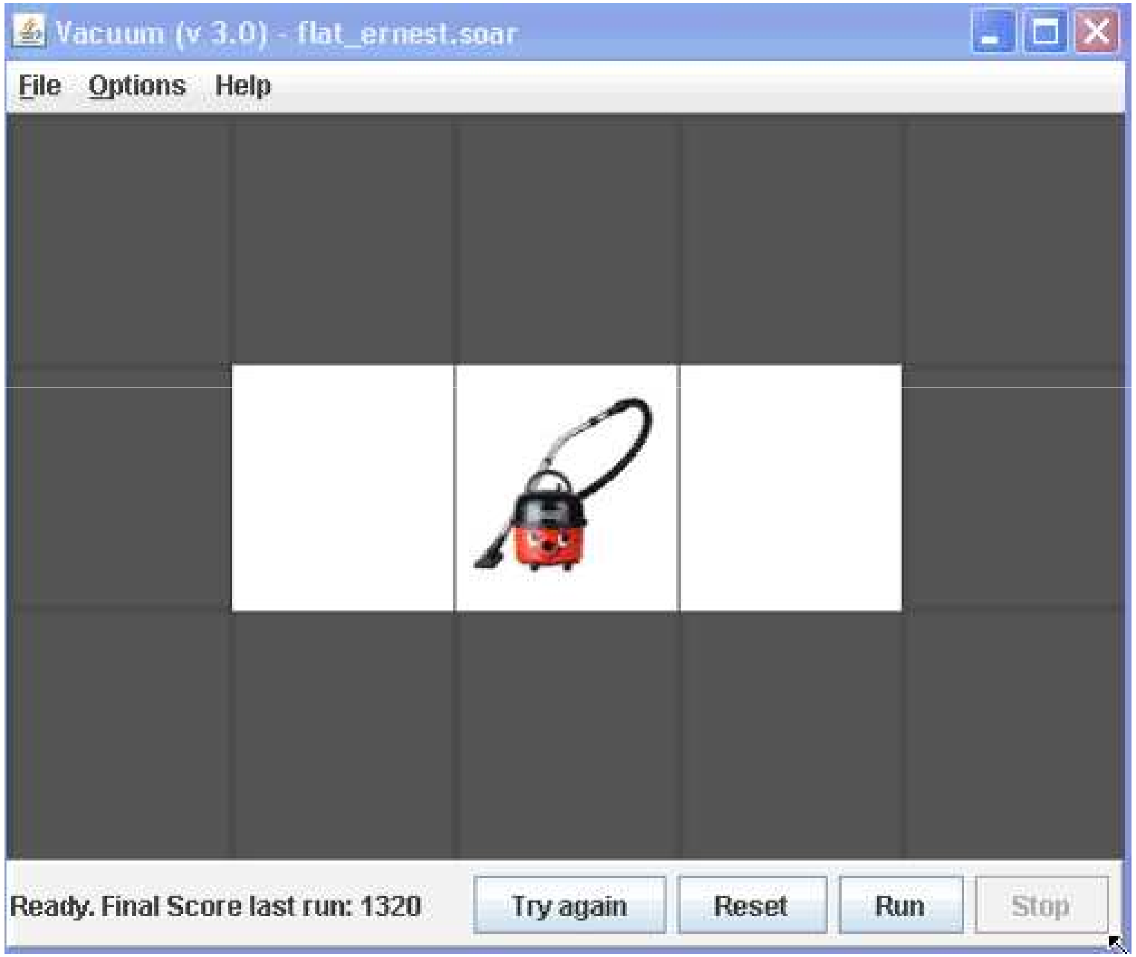
Select B1
Enacted B1F (-1)
Construct S3 = (A1S , B1F , 0 , 1)
Context S3S
Context B1F
Select B1
Enacted B1S (1)
Construct S4 = (S3S , B1S , 1 , 1)
Construct S5 = (B1F , B1S , 0 , 1)
Context S5S
Context B1S
Select A1
Enacted A1F (-1)
Construct S6 = (S5S , A1F , -1 , 1)
Construct S7 = (B1S , A1F , 0 , 1)
Context S7S

Time

Soar memory model



First steps in space



Discussion

- Quite different from classical Soar models:
  - Does not use impasse mechanism nor chunking
  - Does not use the reward mechanism in RLSoar
  - Does not use the stochastic exploration policy
    - Can be stuck in non-optimum solutions: bounded rationality
- But Soar helps a lot:
  - Does use the pattern matching principles
    - Multi value attribute
  - Does use Soar 9's preference mechanism

Conclusions

- Coal
  - It is very low level
  - Long way to go before complex task learning
- Gold
  - It works!
  - It shows that Bottom-up learning can be implemented in Soar.
  - Suggests another type of knowledge representation
  - Includes contest
  - No immediate obstacles in the way

References

- Georgeon O. L., Ritter F. E., Haynes S. R. (2009). Modeling Bottom-Up Learning from Activity in Soar. 18th Annual Conference on Behavior Representation in Modeling and Simulation (BRIMS). Sundance, Utah. March 30 – April 2, 2009.

- Blog:
  - http://olivier-georgeon.blogspot.com/