Interactive Task Learning

(FA9550-15-1-0157)

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Ph.D. Students: James Kirk, Peter Lindes

AFOSR Program Review:

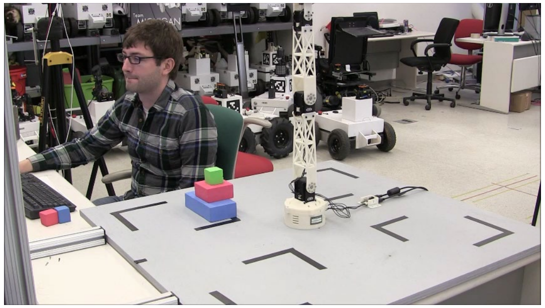
Computational Cognition and Machine Intelligence Program

(October 8, 2020; Cyberspace)

Interactive Task Learning

- Interactively teach AI agents in real-time using natural language.
  – Learn all aspects of task from scratch
  – Emphasize natural language and shared context
  – Real-time, online, one-shot learning
  – Reuses knowledge learned from previous instruction

- Rosie (implemented in Soar):
  – Uses Soar’s innate Level 1 learning mechanisms
  – Pre-encoded procedural and semantic knowledge implement L2 task learning strategies
    – Natural language understanding
    – Task interpretation and operationalization
    – Retrospective analysis, …
  – Learns office tasks and >60 games/puzzles; 4 robot platforms; 4 simulators
    – Learns diverse types of tasks, actions, and control structures.



Mininger, A. & Laird J. E. (2018). Interactively Learning a Blend of Goal-Based and Procedural Tasks, AAAI-2018.
Kirk, J. R. & Laird, J. E. (2019). Learning Hierarchical Symbolic Representations to Support Interactive Task Learning and Knowledge Transfer. IJCAI-2019.

Task Learning Process: L2 using L1

1. Perceive Environment
2. Ask & Receive Instruction
3. Comprehend & Ground Language
   - Ask for Definitions of new Words
   - New Definitions Added to Semantic Memory
4. Construct Declarative Task Representation
   - Operationalize concepts
   - Task Network Added to Semantic Memory
5. Act or Internally Search for Solution
   - Interpret Task Representation (SMem)
   - Compiles into Procedural Knowledge [80x]
   - Ask for Advice if can't find Solution
   - History of Action Added to Episodic Memory
6. Retrospective Analysis of Solution (EpMem)
   - Learned Policy Added to Procedural Memory

L1 learning mechanisms:

- Perceptual Learning
- Episodic Learning
- Semantic Learning
- Chunking
- Reinforcement Learning

Overall ITL Progress

1. Learn complex task concepts from language.
   – Games and puzzles

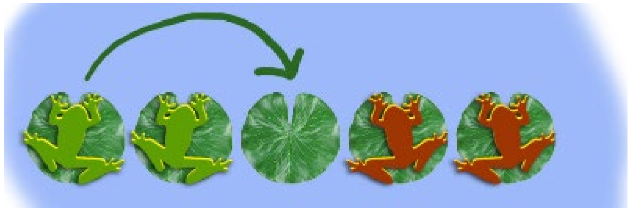
2. Learn complex task procedures from language.
   – Mobile robot tasks

3. Model human procedure learning.
   – Psychological lab tasks

Learned Concept Diversity and Complexity

60 Games and Puzzles: James Kirk

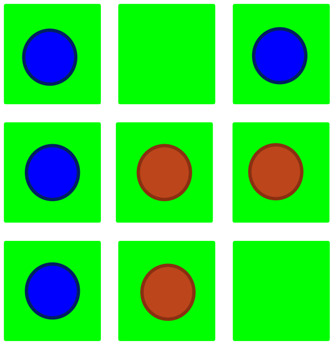
- **Diverse language:**
  - nouns [26], verbs [19], adjectives [68], prepositions [9].
- **Recursive learning of hierarchical concepts:**
  - "The goal is that three of the captured locations are in a line."
  - "If a location is below a red block then the location is captured."
  - "If a block is on a location then the location is below the block."
- **Ambiguous definitions:**
  - "If there is no mark on a location then it is clear." [Marking Tic-tac-toe.]
  - "If there is nothing above a location then it is clear." [Piece Tic-tac-toe.]
  - "If a toad is to the right of a clear location then you can move the toad onto the location."
  - *"How many actions are present: 1 or 2?"*



Transfer Between Tasks

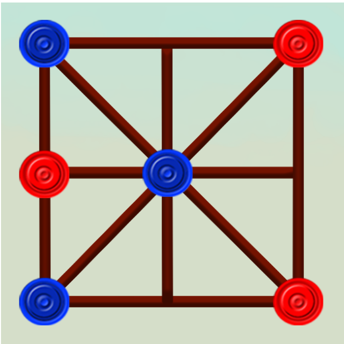
<u>Tic-Tac-Toe</u>

The name of the game is tic-tac-toe.
The name of an action is place-piece.
You can move a clear available red piece onto a clear location.
If a piece is not on a location then it is available.
If a location is not below an object then it is clear.
The name of the goal is three-in-row.
The goal is that three of the captured locations are in a line.
If a location is below a red piece then it is captured.
If the locations are linear then they are in a line.



<u>Three-Mens-Morris</u>

The name of the game is three-mens-morris.
The name of an action is place-piece.
You can move a clear available red piece onto a clear location.
If a piece is not on a location then it is available.
If a location is not below an object then it is clear.
If all the red pieces are on their locations and a red piece is next to a clear location then you can move the piece onto the clear location.
The name of the goal is three-in-row.
The goal is that three of the captured locations are in a line.
If a location is below a red piece then it is captured.
If the locations are linear then they are in a line.



Task Diversity and Complexity:
Mobile robot tasks: Aaron Mininger

- **Diverse task formulations:**
  - Goals, procedures, hierarchical, composite, …
- **Diverse actions:**
  - Physical, perceptual, communication, mental
- **Complex control:**
  - Conditional execution, loops, interruption, hierarchical, …
- **Generalization:**
  - Instructed knowledge transfers to similar tasks
- **Specialization:**
  - Tasks extended with context-dependent behavior
- **Minimize instruction:**
  - Agent does problem solving when possible

UNITED STATES MARINE CORPS
THE BASIC SCHOOL
MARINE CORPS TRAINING COMMAND
CAMP BARRETT, VIRGINIA 22134-5019

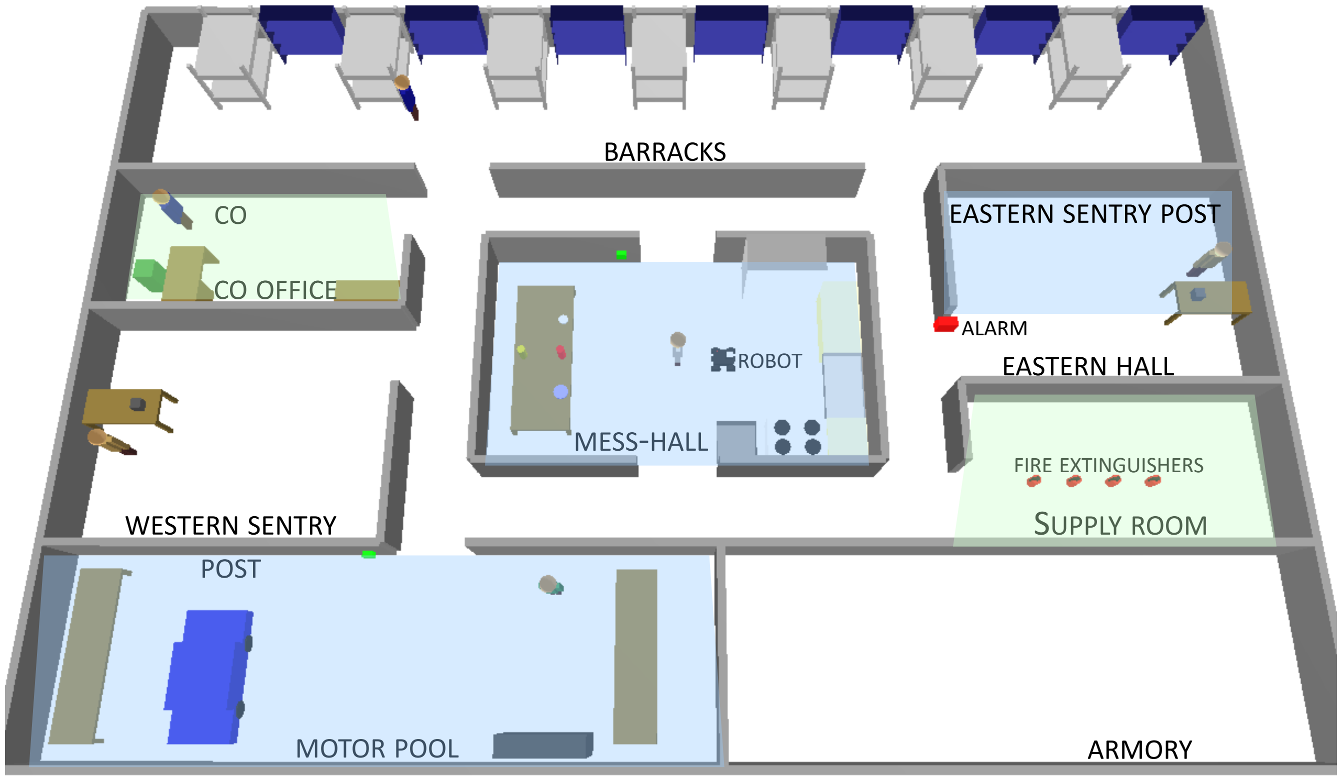
RESPONSIBILITIES OF THE INTERIOR GUARD
B141136
STUDENT HANDOUT

Basic Officer Course

Types of Task Knowledge

1. Innate preprogrammed knowledge
    - Building layout.
    - Primitive actions; navigation and maneuvering; pickup/putdown; turn on and off lights; say; remember; …
2. Knowledge learned from earlier instruction.
    - **Fetch** an object from another location.
    - **Ensure** someone is at their post.
3. **<u>Instructions taught for interior guard and subtasks</u>**
    - New words, new task structures, new goals, new policies

Interior Guard Simulation Environment



Interior Guard

Interior Guard: Overall
- Ask "Who is my relieving officer?"
- Remember the answer as the relieving officer.
- Repeat the following actions until the relieving officer is present.
  - Inspect mess-hall
  - Inspect eastern sentry-post
  - Inspect motor-pool

Inspect Room: General
- Go to the room.
- If the light-switch is off, then turn it on.
- If the current location is empty, then turn off the light-switch.

Inspect Room: Sentry-post
- If you are in a sentry-post and an extinguisher is not-present, then fetch an extinguisher from the supply room.

Inspect Room: Motor-Pool
- Ensure a sentry is present.
- Ensure a dispatcher is present.
- If a vehicle is unlocked, then lock it.

Inspect Room: Mess-hall
- If you are in the mess-hall and a plate is on the table, then move the plate into the sink.
- If you are in the mess-hall and a condiment is on the table, then store the condiment.

Move Plate into Sink
- The only goal is that the plate is in the sink.

Store the Condiment
- If the object is a condiment, then the only goal is that the condiment is in the fridge and the fridge is closed.

GUARD


Sentry
Rosie: I am ready for a new task.


GUARD > INSPECT ESP > GO TO EAST S.P.
[8X]
(A fire is placed in the eastern sentry post)

Rosie Interior Guard Demo

(Fully Trained)

Aaron Mininger, John E. Laird

University of Michigan

July 2020

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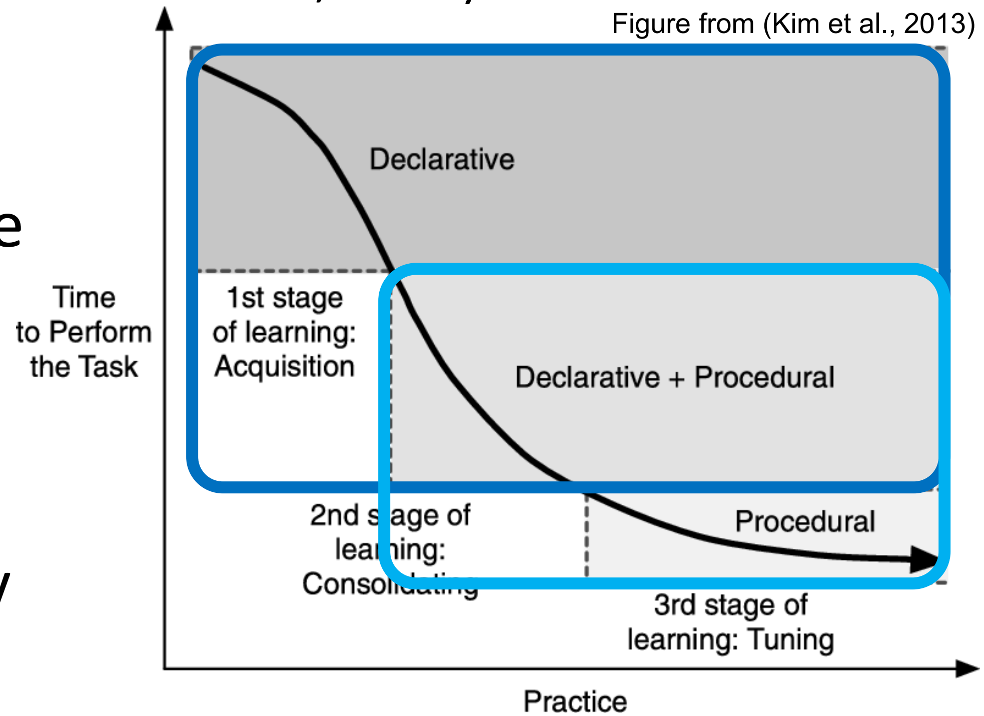
Phases of Skill Learning

Three-phase theory: (Fitts and Posner, 1967)

1. *Cognitive*
   – Learn what to practice
2. *Associative*
   – Learn expertise
3. *Autonomous*
   – Execute automatically

Figure from (Kim et al., 2013)

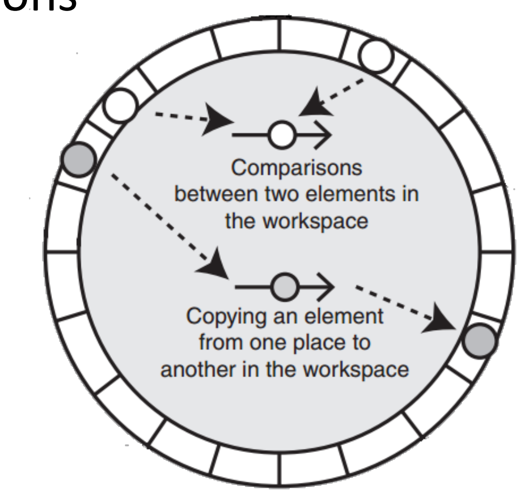


Fitts, P., & Posner, M. (1967). Human performance. Belmont, CA: Brooks/Cole Pub. Co.

Kim, J. W., Ritter, F., & Koubek, R. (2013). An integrated theory for improved skill acquisition and retention in the three stages of learning. *Theoretical Issues in Ergonomics Science*, 14 (1), 22:37.

Modeling Near and Far Transfer in Human Task Learning: PRIMS (Taatgen 2013)

- Implemented in ACTransfer, based on ACT-R
- Fetches instructions from LTM and then interprets them
- Two L1 architectural learning mechanisms:
  - Production composition speeds up repeated internal actions
  - Speed up LTM retrievals (base-level activation)
- Introduced new level of processing
  - Primitive memory operations below traditional rules:
  - Compare memory locations, copy value, …
- Learns rules from composing these operations.
- Achieves *distant transfer* by learning hierarchies of intermediate memory operations across very different tasks.



PROP models (Stearns and Laird)

- Replicate PRIMS in Soar
- Similar L1 learning mechanisms
- Different representation of knowledge (graph vs. fixed slots)
  - Requires extra level of processing to traverse graph
  - Slower processing, but potentially more transfer
- Expands theory to all phases of learning: learning ordering
- *<u>Achieves better fits to human data across multiple tasks</u>*

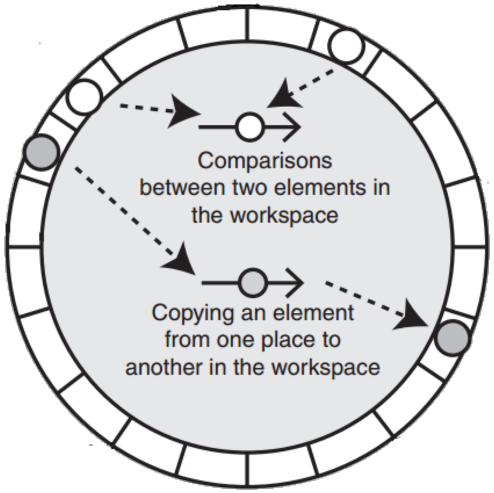
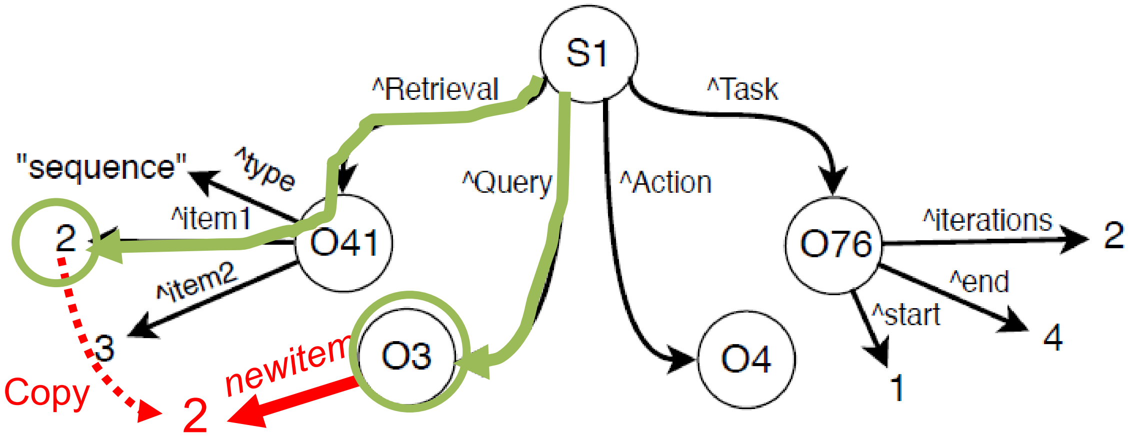


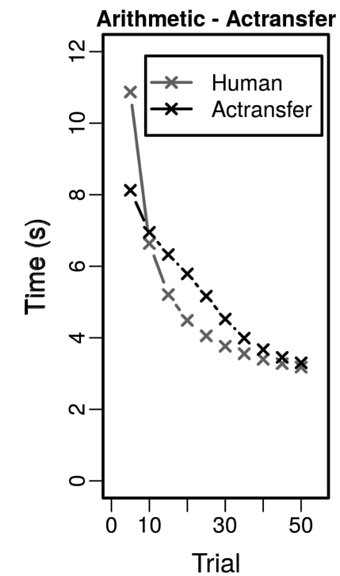
Figure from (Taatgen, 2013)

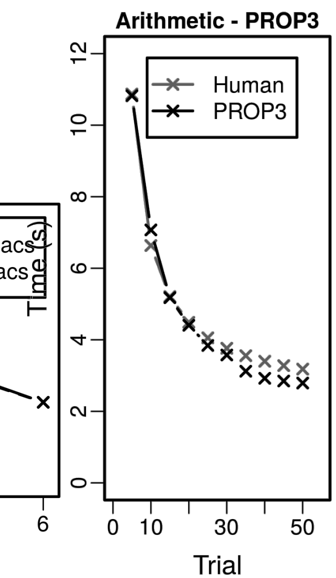


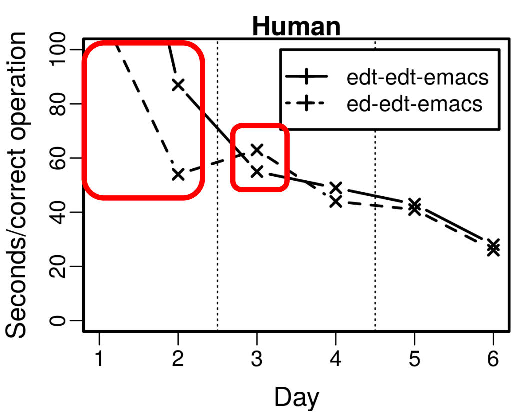
PROPs: More Complete Task Analysis

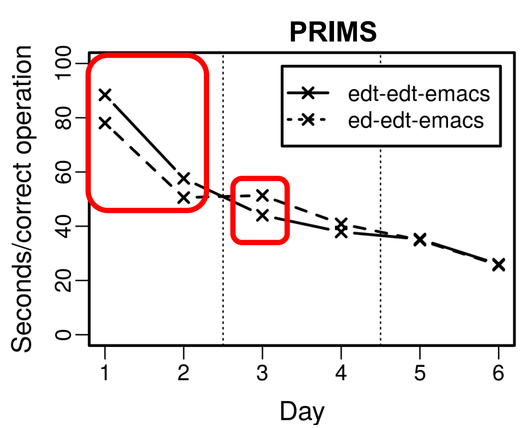
1. Memory traversals slows early performance
   - Learns methods that transfer to similar memory structures.

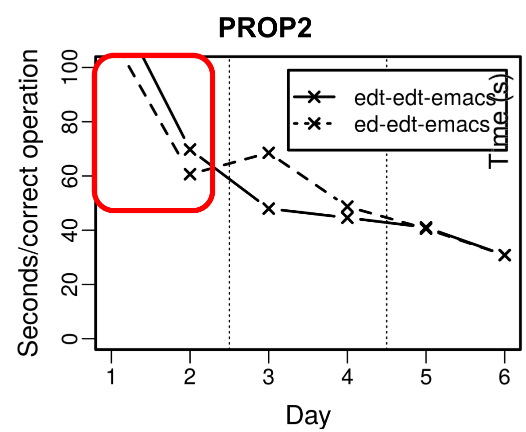
2. Learns ordering information for task actions.
   - PRIMS assumed ordering information given (not learned).
   - PROP must *learn ordering.*
   - Slows initial performance but is quickly learned.
   - [Arithmetic problems had pre-training]







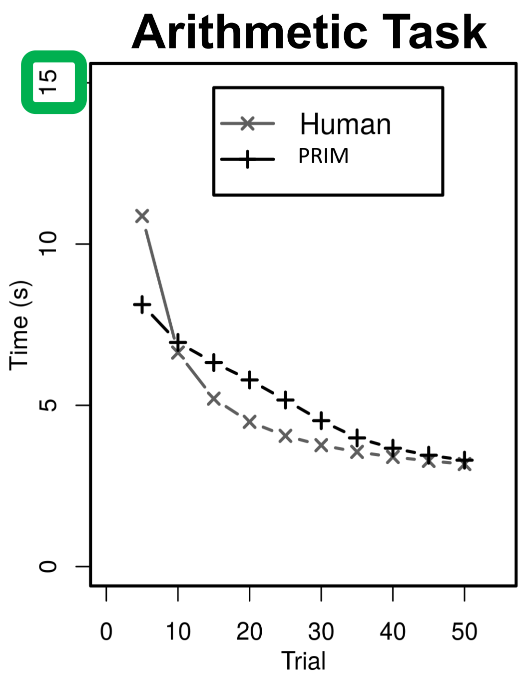




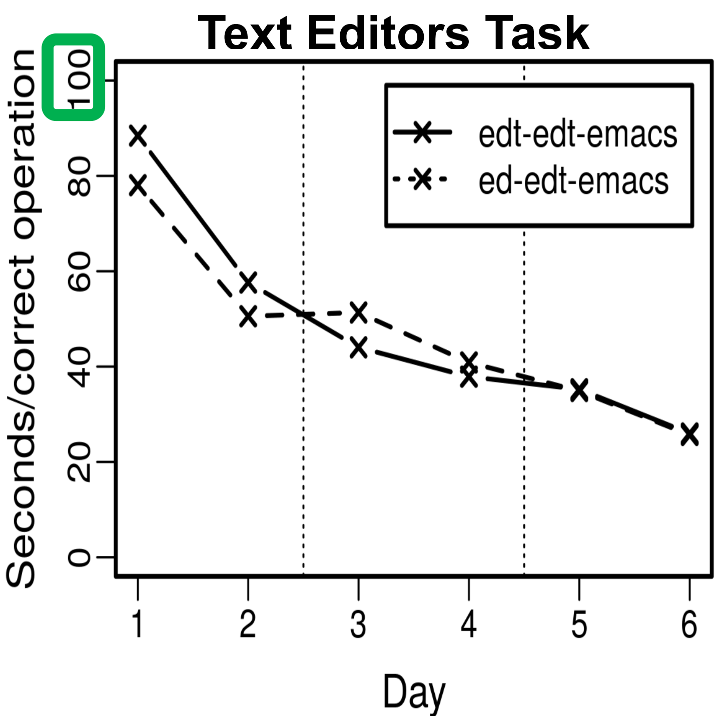
“Flexibility” in Latency-Factor Coefficient

- Retrieval time calculation: $T_{retrieve} = F_r \times e^{-A}$
  - $T_{retrieve}$: Declarative memory retrieval time
  - A : Activation value
  - F_r : Latency-factor coefficient

F_r = 0.15

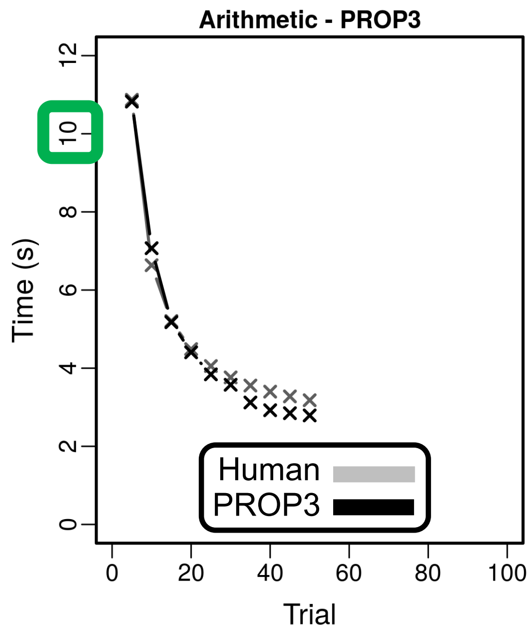


F_r = 1.5

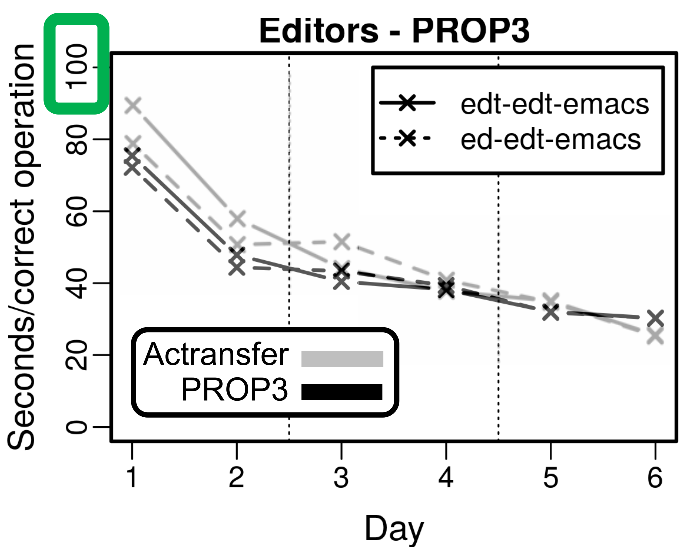


F_r should be a constant across all tasks.

PROP3 Results: Same F_r



- PROP3 includes cost for task decomposition – consistent with Task Set Theory.



Summary – More complete model:

1. Finer grain primitive actions that include memory traversal.
2. Must learn ordering of instructions.
3. Time require for task decomposition.

Overall ITL Progress

1. Learn complex task concepts from language.
   – Games and puzzles

2. Learn complex task procedures from language.
   – Mobile robot tasks

3. Model human procedure learning.
   – Psychological lab tasks

4. Expand language processing & explanation.

List of Publications, Awards, Honors, etc. Attributed to the Grant

- Kirk, J. R. and Laird, J. E. (2019) Learning Hierarchical Symbolic Representations to Support Interactive Task Learning and Knowledge Transfer. *Proceedings of the 28th International Joint Conference on Artificial Intelligence*. (pp. 6095-6102). AAAI Press.
- Kirk, James. "Learning Hierarchical Compositional Task Definitions through Online Situated Interactive Language Instruction." PhD diss., 2019.
- John E. Laird was co-winner (with Paul S. Rosenbloom) of the Herbert A. Simon Award for Cognitive Systems
- Laird, J. E., & Mohan, S. (2018). Learning Fast and Slow: Levels of Learning in General Autonomous Intelligent Agents *, National Conference on Artificial Intelligence, AAAI-2018. Senior Track, Winner of Blue Sky Award.*
- Laird, J. E., Lebiere, C. & Rosenbloom, P. S. (2017). A Standard Model for the Mind: Toward a Common Computational Framework across Artificial Intelligence, Cognitive Science, Neuroscience, and Robotics *, AI Magazine 38(4).*
- John E. Laird, Kevin Gluck, John Anderson, Kenneth D. Forbus Odest Chadwicke Jenkins, Christian Lebiere, Dario Salvucci, Matthias Scheutz, Andrea Thomaz, Greg Trafton, Robert E. Wray, Shiwali Mohan, and James R. Kirk (2017). Interactive Task Learning *, IEEE Intelligent Systems, 32(4), 6-21, (invited).*
- Peter Lindes, Aaron Mininger, James R. Kirk, and John E. Laird (2017). Grounding Language for Interactive Task Learning. *Proceedings of the 1st Workshop on Language Grounding for Robotics at ACL.*
- Peter Lindes and John E. Laird (2017). Ambiguity Resolution in a Cognitive Model of Language Comprehension. *Proceedings of the 15th International Conference on Cognitive Modelling (ICCM). Warwick, UK.*
- Lindes & Laird (2017) Cognitive Modeling Approaches to Language Comprehension Using Construction Grammar, AAAI 2017 Spring Symposium on Computational Construction Grammar and Natural Language Understanding
- Prof. John E. Laird is a member of the Games, Exercises, Modeling and Simulation (GEMS) Defense Science Board (2018-2019).
- Prof. John E. Laird is co-organizing a DoD (Basic Research Office - OSD), Future Directions Workshop on the Design of General, Integrated Artificial Systems, July 2019.
- Co-organized with Paul Rosenbloom (USC) and Christian Lebiere (CMU), AAAI Fall Symposium on *Common Model of Cognition. 2018.*
- Co-organized with Kevin Gluck (AFRL) an Ernst Struengmann Forum on “Interactive Task Learning” for Summer 2017.
- Co-organized with Paul Rosenbloom (USC) and Christian Lebiere (CMU), AAAI Fall Symposium on *Standard Model of the Mind. 2017.*