The CLARION Cognitive Architecture: A Tutorial

Part 2 – The Action-Centered Subsystem

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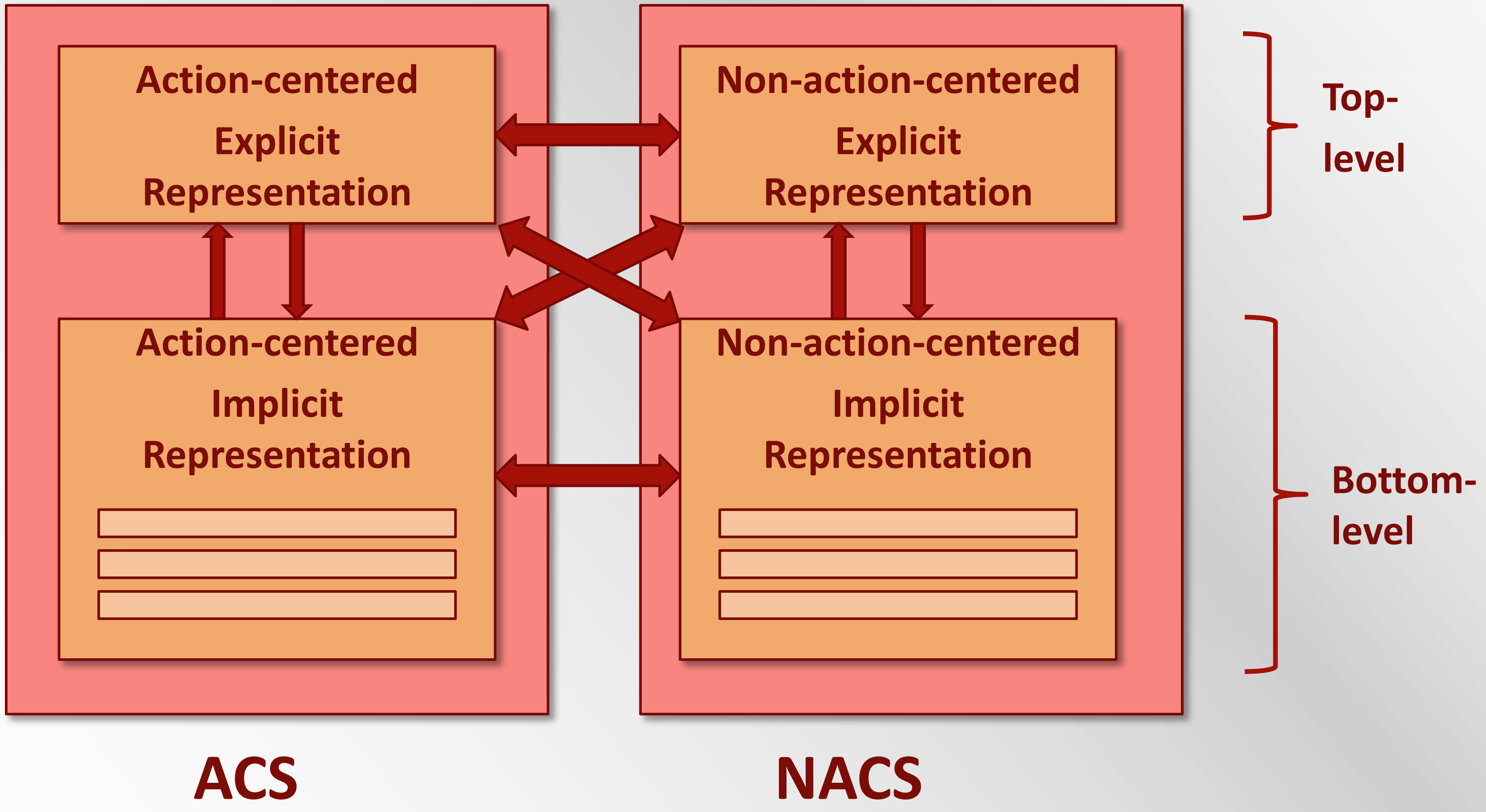
Outline

Representation

Representation



Action-centered Explicit Representation
Non-action-centered Explicit Representation
Action-centered Implicit Representation
Non-action-centered Implicit Representation
Top-level
Bottom-level
ACS
NACS

Representation

Action Decision making process:

1. Observe the current state.
2. Compute in the bottom level the "value" of each of the possible actions in the current state (e.g., Q-values). E.g., stochastically choose one action.
3. Find out all the possible actions at the top level, based on the current state information and the existing rules in place at the top level. E.g., stochastically choose one action.
4. Choose an appropriate action by stochastically selecting or combining the outcomes of the top level and the bottom level.
5. Perform the selected action and observe the next state along with any feedback (i.e. reward/reinforcement).
6. Update the bottom level in accordance with, e.g., reinforcement learning (e.g., Q-learning, implemented with a backpropogation neural network).
7. Update the top level using an appropriate learning algorithm (e.g., for constructing, refining, or deleting explicit rules).
8. Go back to step 1.

Representation

Representation

- Bottom Level
  - Implicit knowledge is:

    Less accessible

    Reactive (as opposed to, e.g., explicit planning); fast decision making
  - Inaccessible nature of implicit (tacit) knowledge (Reber, 1989; Sun, 2002) may be captured by distributed representations

    → a theoretical interpretation (amply argued for before; see Sun, 1994, 2002)
  - E.g., Backpropagation Neural Networks:

    Representational units (in, e.g., hidden layers) are capable of accomplishing tasks but are generally not individually meaningful --- renders distributed representation less accessible.

Representation

- At the bottom level, Implicit Decision Networks (IDNs), implemented with Backpropagation neural networks
- Three types of inputs:
  - Sensory Input (visual, auditory, …., etc.)
  - Working Memory Items
  - Current Goal (an item from the Goal Structure)
- represented as dimension-value pairs:
  - *(dim_1, val_1) (dim_2, val_2) … (dim_n, val_n)*
  - Each pair corresponds to one input node of the network

Representation

- Actions are represented as nodes on the output layer.
- Three types of actions:
  - Working Memory Actions
  - Goal Actions
  - External Actions
- Each action consists of one or more action dimensions
  - in the form:

    (dim_1, val_1) (dim_2, val_2) … (dim_n, val_n)
- Each action may be activated to an extent

Representation

- Chunks are collections of dimension/value pairs that represent either conditions or actions of rules of the top level.
  - Chunk-id$_i$: $(dim_{i1}, val_{i1})\ (dim_{i2}, val_{i2}) \ldots (dim_{in_i}, val_{in_i})$

    e.g., table-1: *(size, large) (color, white) (number-of-legs, 4)*
- Each chunk (as a whole) is represented by a node in the top level
- Each dimension/value pair is represented by a node in the bottom level.

➢ Dual representation: Localist versus distributed representation

Representation

- The level of activation for a node (within an Implicit Decision Network, i.e., ACS bottom level) is calculated using a sigmoid activation function:

$$o = \frac{1}{1 + e^{-\sum_{i=0}^{n} w_i x_i}}$$

where x_i is the value of input *I* (to the node), w_i is the weight of input *i*, and *n* is the number of inputs to the node

- So scaled to [0, 1]

Representation

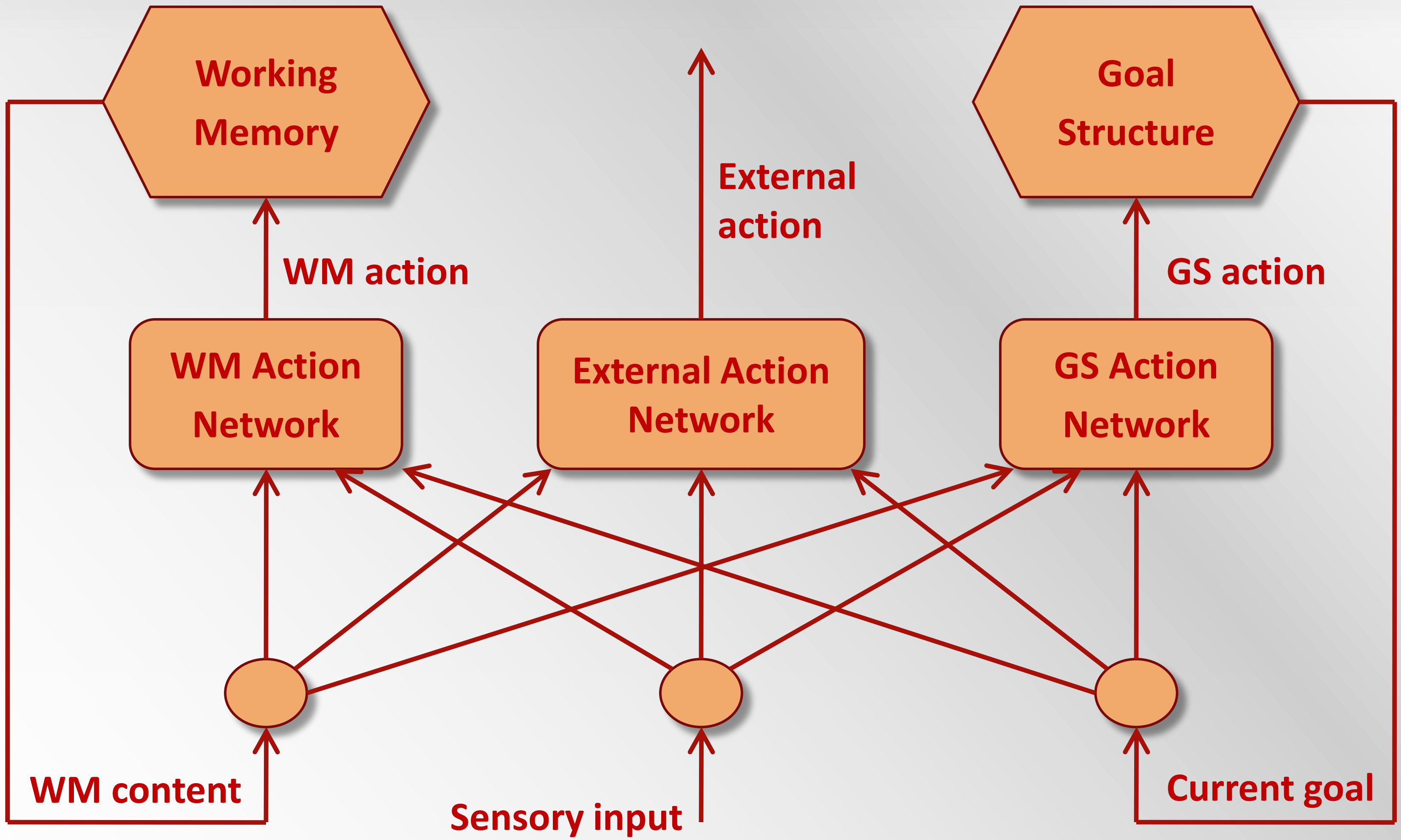
- An action is chosen based on a Boltzmann distribution of the activations of the output-layer nodes.
- The probability of selecting a particular action *i* in the bottom-level is (in accordance with the Boltzmann distribution):

$$p(i \mid x) = \frac{e^{A_i/\tau}}{\sum_j e^{A_j/\tau}}$$

where A_i is the activation of action *i* and τ is the noise (temperature) parameter

Rationale: different levels of stochasticity (randonness or temperature)

Representation



Representation

Questions?

Representation

Representation

- Top Level
  - Explicit Rules:
    - more accessible
    - “consciously” applied; “rationally” deduced actions
    - slower than implicit processes, but also perhaps more precise
    - “Condition →Action” pairs: with Condition Chunk, Action Chunk
  - Rules in the top level come from several sources (more on this later):
    - Extracted and Refined Rules (RER rules)
    - Independently Learned Rules (IRL rules)
    - Fixed Rules (FR rules)
    - (rationale: different types of learning)

Representation

- A top-level rule contains one condition chunk and one action chunk (possibly with multiple dimensions)
    - Chunk nodes connected to bottom-level (micro)features
- Each action chunk is associated with these factors:
    - Rule support and conclusion strength (activation)
    - Base-Level Activation (BLA)

      Recency-based value (for priming; e.g., used for determining RTs)
    - Utility (U)

      Measures the usefulness of a rule based on the cost and benefit of applying the rule (e.g., used for selecting rules)
    - other numerical measures

Representation

- Base-Level Activation (BLA): measures the odds of needing a rule based on the history of its use (Anderson, 1993)

  Can be used to highlight pertinent rules; capture the notion of priming

- BLA: a recency-based value --- gradually decaying "activation":

$$B_j^r = iB_j^r + c \times \sum_{l=1}^{n} t_l^{-d}$$

where t_l is the i^{th} use of rule j and iB_j is the initial value.
By default $c = 2$, $d = 0.5$

Representation

- The activation of the condition chunk is determined by (when using partial match):

$$S^{c}_{c_k} = \sum_i A_i \times W_i^{c_k}$$

where A_i is the activation of the *i*th dimension of chunk *c* and $W_i = 1/n$ (by default), where *n* is the number of dimensions in chunk c_k

- From the activation of the condition chunk node, the support for rule *k* is computed (used for rule selection):

$$S^r_k = S^c_{c_k} ´ \; W^r_k$$

where *k* indicates rule *k* at the top level, S^r_k is the support for rule *k*, S^c_{ck} is the strength of condition chunk c_k (representing the condition of rule *k*), and W^r_k is the weight of the rule *k* (where the default is 1).

- The strength of the conclusion chunk node: combining multiple measures of rule support for the same conclusion chunk node, using *max* (for level combination)

Representation

- Rule selection at the top level:

  based on a Boltzmann distribution of the rule support values, or the utility values of the rules (which may be set to a constant if not needed)

- Utility may be calculated using the following equation:

$$U_j^r = benefit_j - v \times cost_j$$

where υ is a scaling factor balancing measurements of benefits and costs

Representation*

- Benefit:

$$benefit_j = \frac{c_7 + PM(j)}{c_8 + PM(j) + NM(j)}$$

where *PM(j)* = number of positive rule matches and *NM(j)* = number of negative rule matches. By default $c_7 = 1$, $c_8 = 2$

- Cost:

$$cost_j = \frac{execution\_time\_of\_rule\_j}{average\_execution\_time\_of\_rules}$$

where values need to be estimated (domain-specific)

Representation

Questions?

Learning

Learning

- Bottom-Level Learning
  - uses numerical algorithms to perform gradual error correction within the bottom level (IDN's)
  - Three learning methods:
    - Q-Learning (reinforcement learning)
    - Simplified Q-Learning
    - Standard Backpropagation (supervised learning)

- Top-Level Rule Learning
  - Three rule learning methods:
    - Bottom-up rule extraction and refinement (RER)
    - Independent Rule Learning (IRL)
    - Fixed Rule (FR)

Learning

Learning

- Standard Backpropagation (for three-layer network)
  - Calculate error in the output layer using:

$$err_i = target(x,a_i) - Q(x,a_i)$$

where *target(x,a_i)* is the target output for node *i* and *Q(x,a_i)* is the actual output of node *i*

  - Output weights are updated as follows:

$$\Delta w_{ji} = \alpha x_{ji} \delta_j$$
$$\delta_j = err_j o_j (1 - o_j)$$

where x_{ji} is the *ith* input of output unit *j* and o_j is the output of unit *j*

Learning*

- Standard Backpropagation (cont.)
  - Weights are updated in the hidden layer by:

$$\Delta w_{ji} = \alpha \delta_j x_{ji}$$

$$\delta_j = o_j(1 - o_j)\sum_k \delta_k w_{kj}$$

where x_{ji} is the *ith* input to hidden unit *j*, α is the learning rate, o_j is the output of hidden unit *j*, and *k* denotes all of the units downstream (in the output layer) of hidden unit *j*

Learning

- Q-Learning
  - A reinforcement learning method (as opposed to supervised learning)
  - Updating based on the temporal difference in evaluating the current state and the current action chosen
  - May be implemented using backpropagation, except error is calculated in the output layer using:

$$err_i = \begin{cases} r + \gamma e(y) - Q(x, a_i) & \text{if } a_i = a \\ 0 & \text{otherwi} \end{cases}$$

where $r + \gamma e(y)$ estimates the (discounted) total reinforcement to be received from the current point on.

Learning

- Q-Learning (cont.)
  - *Q(x,a)* approaches:

$$Q(x,a) = \max_{a_i : i=1,2,3,\ldots} \left(\sum_{i=0}^{\infty} \gamma^i r_i\right)$$

where γ is a discount factor, a_i is an action that can be performed at step *i*, and r_i is the reinforcement received at step *i*

  - *e(y)* is calculated using:

$$e(y) = \max_b (Q(y,b))$$

where *y* is the new state resulting from action *a* in state *x*

Learning

- Simplified Q-Learning
  - Basic form (atemporal) reinforcement learning
  - Temporal credit assignment is not involved
  - Most useful when immediate feedback is available and sufficient
  - Error is calculated in the output layer using:

$$err_i = \begin{cases} r - Q(x, a_i) & \text{if} \, a_i = a \\ 0 & \text{otherwis} \end{cases}$$

Learning

- Context for Reinforcement Learning --- Two loops:
  - Sensory Input → Action (e.g., by implicit reactive routines within the ACS, formed by, e.g., reinforcement learning)
  - Sensory Input → MS → MCS → *Reinforcement signal* (to be used in the ACS for reinforcement learning)
- In addition to other loops

Learning

Questions?

Learning

Learning

- Top Level Learning
  - Bottom-up learning --- rule extraction and refinement (RER)

    "Condition → Action" pairs are extracted from the bottom level and refined (generalized, specialized, or deleted) as necessary
  - Independent rule learning (IRL)

    Rules of various forms are independently generated (either randomly or in a domain-specific order) and then refined or deleted as needed
  - Fixed Rules

    Rules are obtained from prior experiences, or provided from external sources

Learning

- Rule extraction and refinement (RER)
  - Basic idea of the algorithm:

    If an action decided by the bottom level is successful (according to a criterion), then a rule is constructed and added to the top level

    In subsequent interactions with the world, the rule is refined by considering the outcome of applying the rule:

    - If the outcome is successful, the condition of the rule may be generalized to make it more universal
    - If the outcome is not successful, then the condition of the rule should be made more specific

Learning

- Rule extraction
  - Check the current criterion for rule extraction

    If the result is successful according to the current rule extraction criterion, and there is no rule matching the current state and action, then perform extraction of a new rule

    - "Condition → Action"
    - Add the extracted rule to the action rule store at the top level

Learning

- Rule extraction (cont.)
  - A rule is extracted based on a (domain-specific) positivity criterion

    e.g., $\gamma \max_b (Q(y,b)) + r - Q(x,a) > threshold_{RER}$
  - This determines whether or not action *a* is reasonably good (Sun and Peterson, 1997, 1998)
  - In cases where feedback is immediately available (and there is no temporal sequences), the positivity criterion can be simplified

    e.g., $r > threshold_{RER}$

Learning

- Refinement
  - Extracted rules (or Independently learned rules) have rule statistics that guide rule refinement --- for each rule and its variations:
    - Positive Match *PM:=PM+1* when the positivity criterion is met
    - Negative Match *NM:=NM+1* when the positivity criterion is not met
    - At the end of each episode (e.g., a game, an action sequence, etc.), PM and NM are discounted by multiplying them by .9

Learning

- Refinement (cont.)
  - Based on PM and NM, an information gain measure (IG) may be calculated:

$$IG(A,B) = \log_2\left(\frac{PM_a(A)+c_1}{PM_a(A)+NM_a(A)+c_2}\right) - \log_2\left(\frac{PM_a(B)+c_1}{PM_a(A)+NM_a(A)+c_2}\right)$$

where *A* and *B* are two different rule conditions that lead to the same action *a*, c_1 and c_2 are constants (1 and 2 respectively by default)

  - Essentially compares the percentages of positive matches under different conditions: A vs. B

    If *A* can improve the percentage to a certain degree over *B*, then *A* is considered better than *B*

Learning

- Generalization
  - Check the current criterion for Generalization
    - If the result is successful according to the current generalization criterion, then generalize the rules matching the current state and action
    - Remove these rules from the rule store
    - Add the generalized versions of these rules to the rule store (at the top level)

Learning

- Generalization (cont.)
  - A rule can be generalized using the information gain measure:
    - If $IG(C, all) > threshold_1$ and $max_{c'} IG(C', C) \geq 0$, then set

      $argmax_{C'} (IG (C', C))$ as the new (generalized) condition of the rule

      where C is the current condition of the rule, *all* is the match-all rule, and C' is a modified condition such that C' = *"C plus one value"*
    - Reset all the rule statistics

  - Other possibilities: one-or-all, etc.

Learning

- Specialization
  - Check the current criterion for Specialization
    - If the result is unsuccessful according to the current specialization criterion then revise all the rules matching the current state and action
      - Remove the rules from the rule store
      - Add the revised (specialized) rules into the rule store (at the top level)

Learning

- Specialization (cont.)
  - A rule can be specialized using the information gain measure:
    - If $IG(C,all) < threshold_2$ and $max_{C'} IG(C',C) > 0$, then set

      $argmax_{C'} (IG\ (C', C))$ as the new (specialized) condition of the rule

      where *C* is the current state condition of the rule, *all* is the match-all rule, *C'* is a modified condition such that *C'* = "C minus one value"
    - If any dimension in *C* has no value left after specialization then the rule is deleted
    - Reset all the rule statistics

Learning

- Example

  SRT Task (Curran and Keele, 1993)

  - Repeating sequence of X marks each in 1 of 4 possible positions; press corresponding buttons
  - Subjects learn to predict new positions on the basis of preceding positions

    Learn the sequential relations embedded in the sequence

    Leads to faster responding

Learning

- Example (cont.): modeling
  - Learning (by iterative weight updating) in the bottom level promotes implicit knowledge formation (embedded in weights)
  - Resulting weights specify a function relating previous positions (input) to current position (output)
  - Acquired sequential knowledge at the bottom level can lead to the extraction of explicit knowledge at the top level

Learning

- Example (cont.)
  - The initial extraction step creates a rule that corresponds to the current input and output (as determined by the bottom level)
  - Generalization adds more possible values to the condition of the rule so that the rule may have more chances of matching new input
  - Specialization adds constraints to the rule (by removing possible matching values) to make the rule less likely to match new input
  - Applicability of these steps determined by the IG measure (discussed before)

Learning

- Example (cont.)
  - Suppose sequence is:

    1 2 3 2 3 4
  - Initially extracted rule may be:

    1 2 3 2 3 --> 4
  - Generalization may lead to a simplified rule:

    * 2 3 2 3 --> 4 (where * stands for “don’t care”)

    * 2 * 2 3 --> 4

    and so on
  - Continued generalizations and specializations are likely to happen, as determined by the IG measure (which is in turn determined by the performance of the rule)
  - Incorrect generalization may occur (e.g., 2 3 → 4), which may then be revised

Learning (RER)

Questions?

Learning

- Independent Rule Learning (IRL)
  - A variation of rule extraction and refinement
  - In which, the bottom level is not used for initial rule extraction.
  - Rules are generated either randomly or through a domain-specific order
  - Then these rules are tested through experience using the IG measure
  - If the rule IG measure is below a threshold, then the rule is refined or deleted.

Learning

- Independent Rule Learning (cont.)
  - Positivity criterion can be based on information from the bottom level (similar to RER):

    e.g., $\gamma \max_b (Q(y,b)) + r - Q(x,a) > threshold_{IRL}$

  - Positivity criterion can also be based on information from external sources (such as immediate feedback/reinforcement)

Learning

- Independent Rule Learning (cont.)
  - One possible information gain measure for IRL rule testing is:

    If $IG(C, random) < threshold_3$ then delete the rule

    This is equivalent to:

    $$\text{If } IG(C) = \log_2\left(\frac{PM_a(C) + c_5}{PM(C) + NM(C) + c_6}\right) < threshold_4 \text{ then delete rule C}$$

  - Specialization/generalization are also possible (similar to RER); assuming the most general (match-all) condition to begin with.

Learning

- Fixed Rules (FR)
  - Externally given or acquired from prior experiences (or by pre-endowment)
  - Enables top-down learning (assimilation)

    Rules in the top level may guide implicit learning in the bottom level.
  - Can represent more than just propositional structures

    More complex interaction, and more complex action sequences between conditions and actions, akin to:
    - Schemas (Arbib, 1980; Dretcher, 1989)
    - Abstract behaviors (Mataric, 2001)

Learning (IRL and FR)

Questions?

Level Integration

Level Integration

- Several level integration methods:
  - Stochastic Selection
  - Combination

      Bottom-up Rectification

      Top-down Guidance
- Assumes one bottom-level network and one top-level rule group
- Details on coordinating multiple bottom-level networks and top-level rule groups can be found in the technical descriptions (Sun, 2003)

Level Integration

- **Stochastic Selection**

  At each step, the probability of using any given rule set is:

  P_{RER} = probability of using RER rule set

  P_{IRL} = probability of using IRL rule set

  P_{FR} = probability of using FR rule set

  The probability of using the bottom level is:

  $P_{BL} = 1 - P_{RER} - P_{IRL} - P_{FR}$

Level Integration

- Selection probabilities may be:
  - Fixed (pre-set/constant; e.g. set by the Meta-Cognitive Subsystem)
  - Variable (see later)
- Deterministic selection of either the top level or the bottom level:
  - is a special case of stochastic selection --- probability=1/0
  - Selection probabilities in this case may be chosen by the Meta-Cognitive Subsystem (discussed later)

Level Integration

- Variable selection probabilities: may be calculated using "probability matching", as follows:

$$P_{BL} = \frac{\beta_{BL} \times sr_{BL}}{\Phi}$$

$$P_{RER} = \frac{\beta_{RER} \times sr_{RER}}{\Phi}$$

$$P_{IRL} = \frac{\beta_{IRL} \times sr_{IRL}}{\Phi}$$

$$P_{FR} = \frac{\beta_{FR} \times sr_{FR}}{\Phi}$$

where *sr* stands for success rate, β is a weighting parameter, and $\Phi = \beta_{BL} \times sr_{BL} + \beta_{RER} \times sr_{RER} + \beta_{IRL} \times sr_{IRL} + \beta_{FR} \times sr_{FR}$

Level Integration

- **Combination**
  - Combining activations from the top level with activations (Q-values) in the bottom level, in some way
  - Top-down guidance vs. bottom-up rectification
    - Positive conclusions reached in the top level can add to action recommendations in the bottom level; Negative conclusions reached in the top level can veto actions in the bottom level
    - Or, bottom-level selections are verified by the top-level rules
  - Then selecting an action based on the combined values using a Boltzmann distribution

Level Integration

- Bottom-up Rectification:
  - Bottom-level outcome is sent to the top level
  - The top level rectifies and utilizes outcomes from the bottom level with the knowledge in the top level
  - Likely to happen in reasoning situations, where final outcomes are explicit (Nisbett and Wilson, 1977)
  - (One possibility: weighted sum combination)

Level Integration

- Top-down Guidance:
  - Top-level outcome is sent down to the bottom level
  - The bottom level utilizes the outcome of the top level, along with its own knowledge, in making action decisions
  - Most likely happens in skill learning and skilled performance
  - (One possibility: weighted sum combination)

Overview

Action Decision making process:

1. Observe the current state.
2. Compute in the bottom level the “value” of each of the possible actions in the current state. E.g., stochastically choose one action.
3. Find out all the possible actions at the top level, based on the current state information and the existing rules in place at the top level. E.g., stochastically choose one rule and hence one action.
4. Choose an appropriate action by stochastically selecting or combining the outcomes of the top level and the bottom level.
5. Perform the selected action and observe the next state along with any feedback (i.e. reward/reinforcement).
6. Update the bottom level in accordance with, e.g., reinforcement learning (e.g., Q-learning, implemented with a backpropagation neural network).
7. Update the top level using an appropriate learning algorithm (e.g., for constructing, refining, and deleting explicit rules).
8. Go back to step 1.

Level Integration

Questions?

Working Memory

1. Representation
    1. Bottom-Level Representation
    2. Top-Level Representation
2. Learning
    1. Bottom-Level Learning
    2. Top-Level Rule Learning
3. Level Integration
4. **Working Memory**
5. Simulation Examples
6. Summary

Working Memory

- For storing information on a temporary basis
  - Facilitating subsequent action decision-making and/or reasoning
- Working memory involves (cf. Baddelay, 1995):
  - Action-directed ("deliberate") encoding of information

    (as opposed to automatic encoding)
  - Gradual fading of information
  - Action-directed re-encoding ("refreshing") of information
  - Limited storage capacity
  - Multiple stores

Working Memory

- May be divided into multiple sensory related sections:
  - Visuospatial information
  - Auditory/verbal information
  - Other types of information
- Each section consists of a certain number of slots
  - Each can hold the content of a chunk
- Capacity is limited

Working Memory

- **Working memory actions** may:
  - Add items into working memory

    Set i: the content of a chunk is stored in working memory slot *i*

    Set {i}: the content of multiple chunks are stored in multiple slots in working memory
  - Remove items from working memory

    Reset i: the content of the *i*th working memory slot is removed

    Reset-all-WM: removes all items from working memory

    Do-nothing
- Working Memory actions can be performed by either or both levels of the ACS

Working Memory

- Base-level activation (BLA) for WM:
  - Determines how long past information should be kept around (when there is no reset action)
  - Recency-based:

$$B_i^w = iB_i^w + c \times \sum_{l=1}^{n} t_l^{-d}$$

where *i* indicates an item in working memory, *l* indicates the *l*th setting of that item, t_l is the time since the *l*th setting, and *iB* is the initial value of *B* (*c* and *d* are constants)

Working Memory

- If the base-level activation of working memory item *i* is above a threshold:

$$B_i^w > threshold_{WM}$$

then the working memory item *i* is used as input to the bottom level and the top level (otherwise invisible)

Working Memory and NACS

- Working memory may be used to transmit information between the Action-Centered (ACS) and the Non-Action-Centered (NACS) subsystem (discussed later)
- Working memory is minimally necessary for storing information from the non-action-centered subsystem,
    - Must be able to retrieve and hold conclusions from reasoning so it can be used for action decision-making.
    - Must be able to extract additional declarative information related to the current state and action (including related past episodes, which is also stored in the NACS)

Working Memory

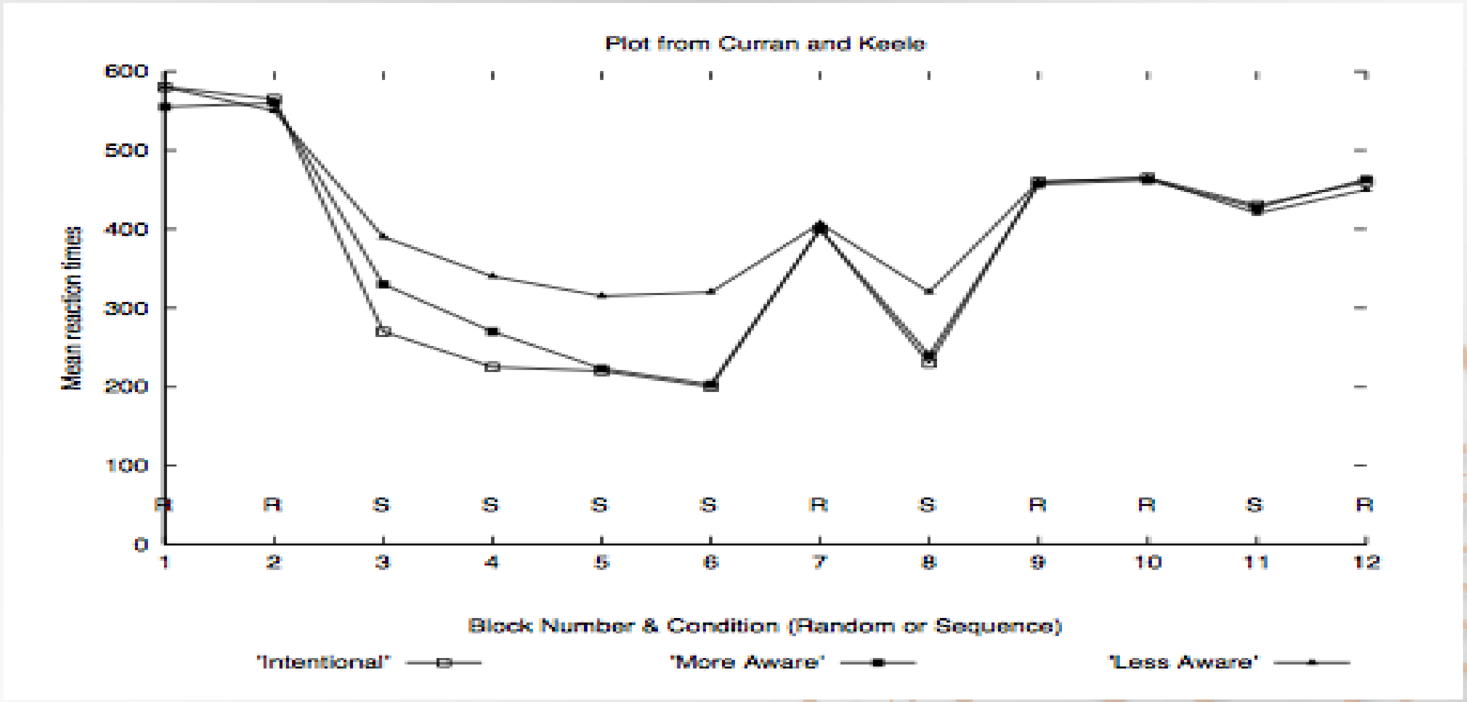
Questions?

Simulation Examples

Simulation Examples

- Serial reaction time task (Curran and Keele, 1993)
  - A sequence of X marks
  - Two phases:
    - Single task learning
    - Dual task transfer
  - Three groups of subjects:
    - Less aware
    - More aware
    - Intentional

Simulation Examples



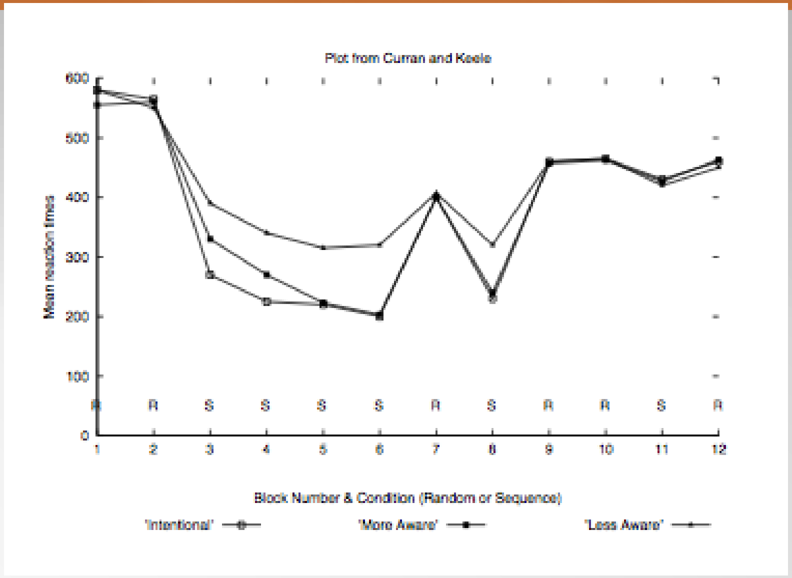
3 (intentional vs. more aware vs. less aware) X 2 (sequential vs. random) ANOVA:

- significant difference across groups during the STL phase
- No difference across groups during the DTT phase

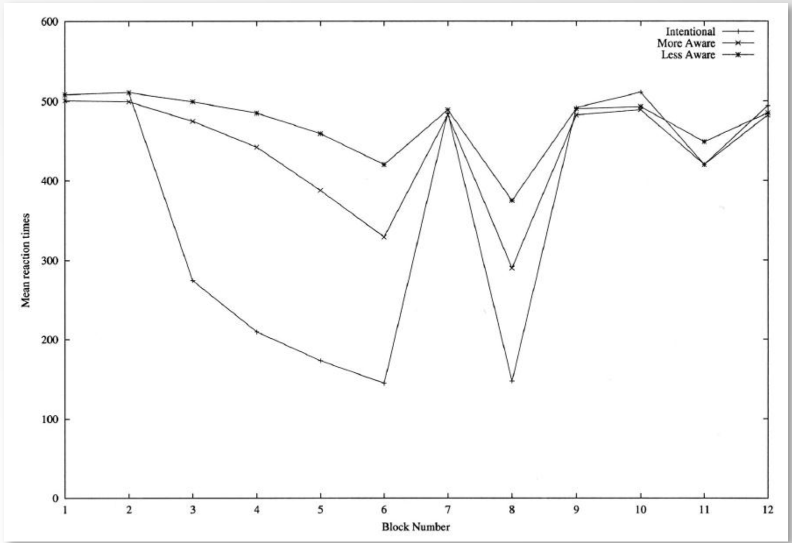
Simulation Examples

- Model Setup
  - Simplified Q-backpropagation learning at the bottom level
  - 7x6 input units (both primary and secondary tasks) and 5 output units
  - RER rule learning at the top level
  - Three groups:
    - Less aware: use higher rule learning thresholds
    - More aware: use lower rule learning thresholds
    - Intentional: code given knowledge in the top level
  - Linear transformation: $RT_i = a \times e_i + b$
  - ANOVA confirmed the data pattern

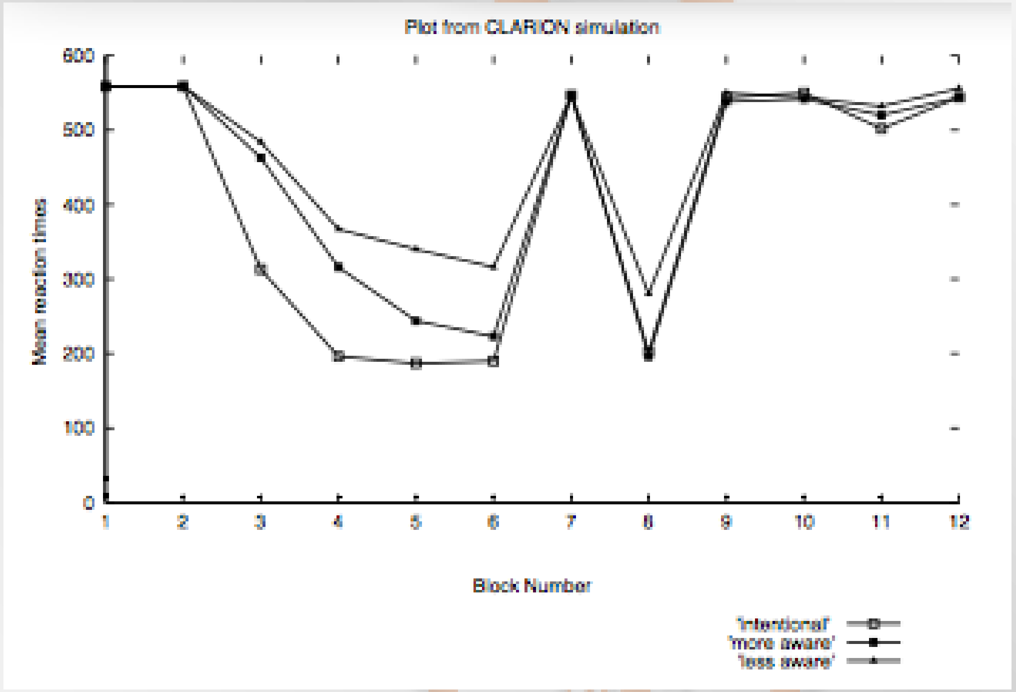
Simulation Examples



Human data from Curran & Keele



Plot from Cleeremans (1993) Simulation



Plot from CLARION Simulation

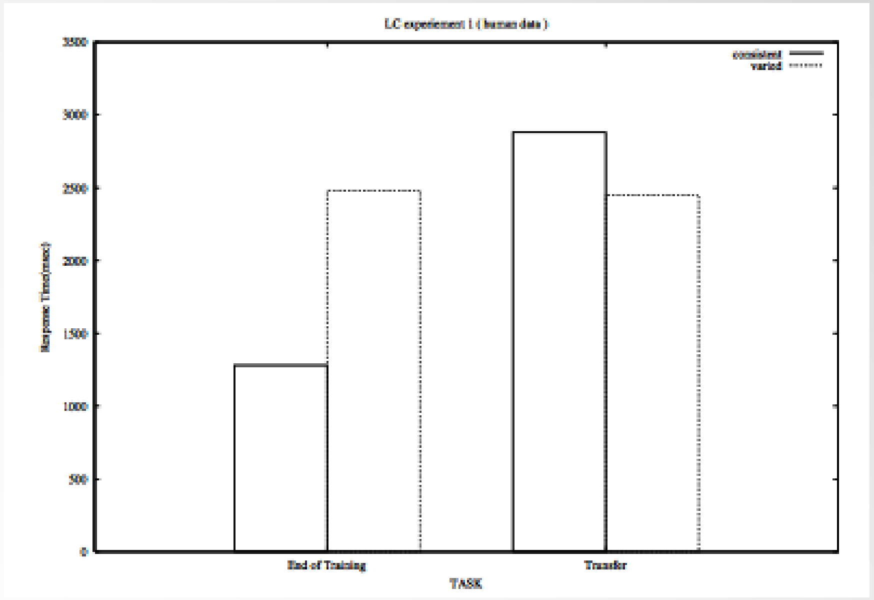
Simulation Examples

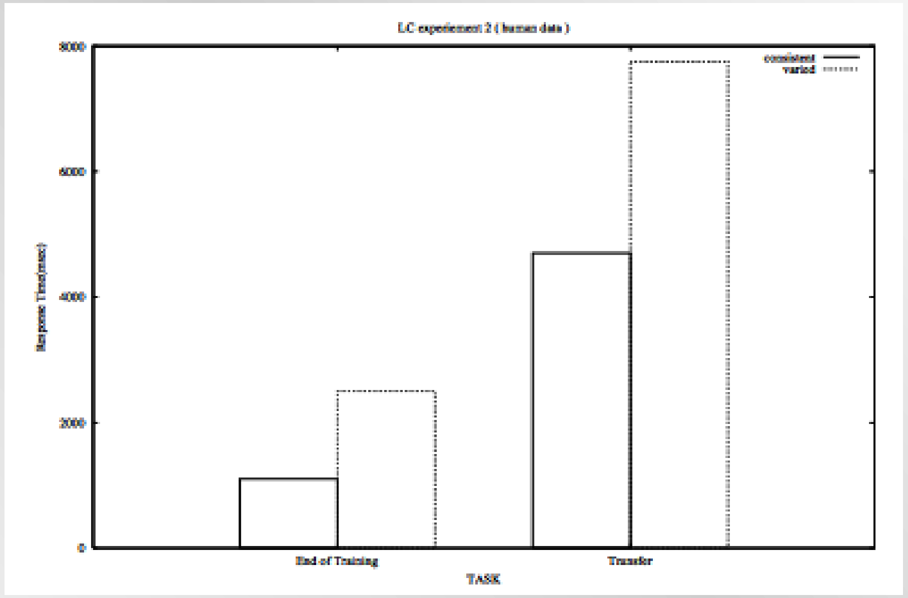
- Letter counting task (Rabinowitz and Goldberg, 1995)
  - Experiment 1
    - *letter1 + number = letter2*
    - The consistent group:
      - 36 blocks of training (the same 12 addition problems in each)
    - The varied group:
      - 6 blocks of training (the same 72 addition problems in each)
    - Transfer phase:
      - 12 new addition problems (repeated 3 times)

Simulation Examples

- Letter counting task (cont.)
  - Experiment 2
    - Same training
    - Transfer:
      - 12 subtraction problems (repeated 3 times)
      - *letter1 - number = letter2 (reverse of addition problems)*

Simulation Examples





- Experiment 1
- Experiment 2

Simulation Examples

- Model Setup
  - Simplified Q-backpropagation learning in the bottom level ACS (IDNs)
  - 36 input units, 26 output units, and 30 hidden units
  - Fixed Rules
    - If goal=addition-counting, start-letter=x, number=y, then starting with x, repeat y times counting up
    - If goal=subtraction-counting, start-letter=x, number=y, then starting with x, repeat y times counting down

Simulation Examples

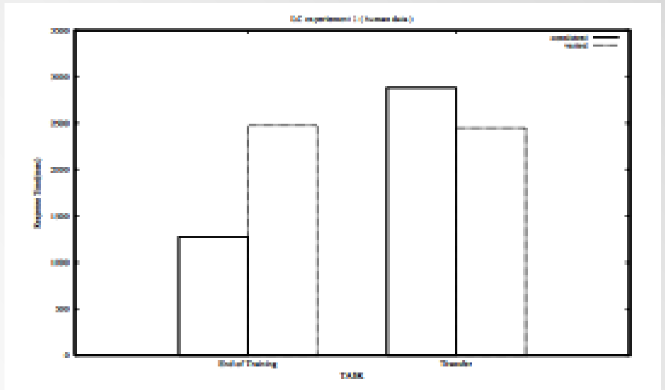
- Model Setup (cont.)
  - Rule utility (used for rule selection) and rule base-level activation (used for response time)
  - Response Time:

$$DT_{TL} = y \times t_{counting} + c \times \frac{1}{BLA(rule)}$$

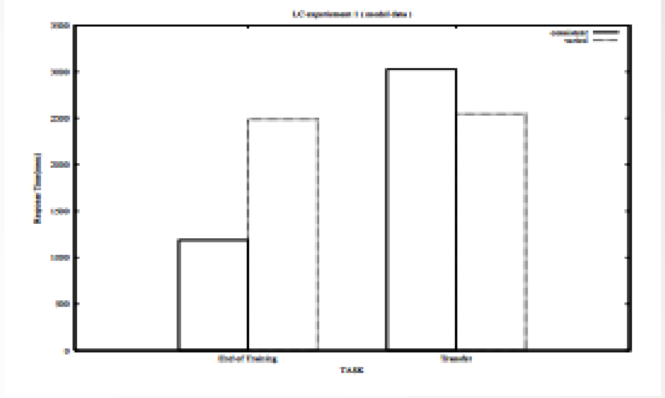
$$DT_{BL} = constant$$

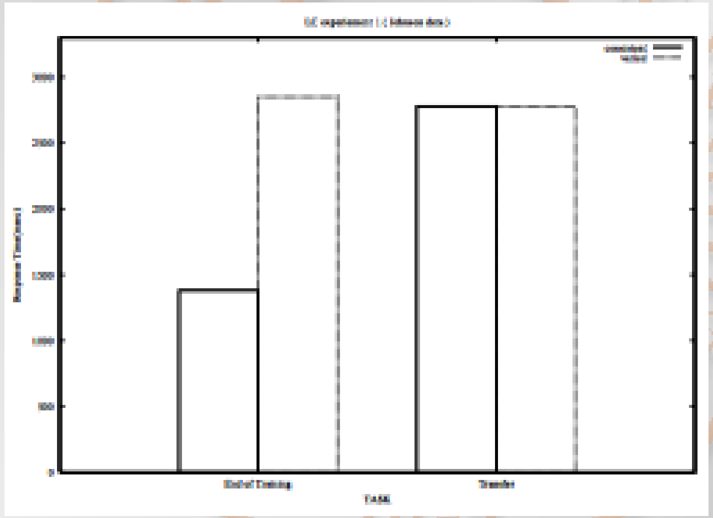
Simulation Examples

- Experiment 1: CLARION vs. ACT-R



Rabinowitz and Goldberg Experimental Results



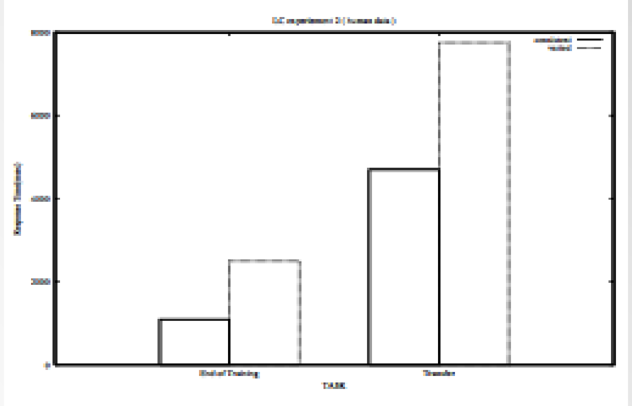


CLARION Simulation Results

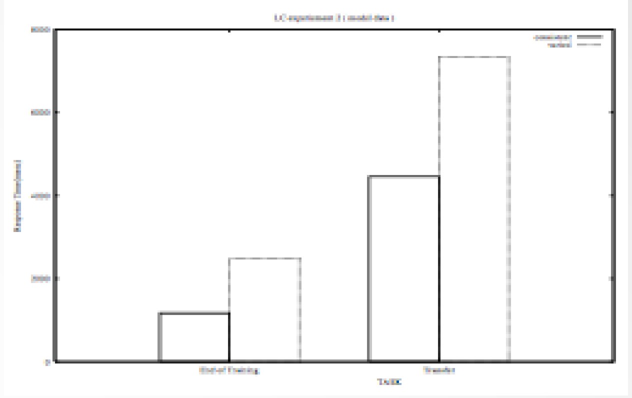
ACT-R Simulation Results

Simulation Examples

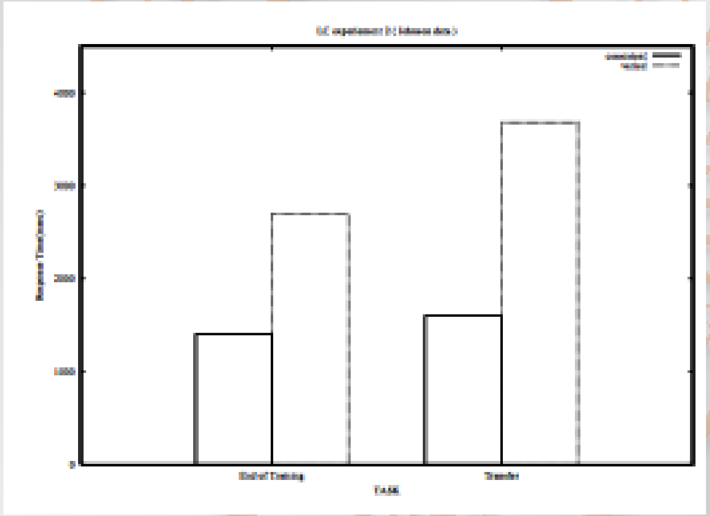
- Experiment 2: CLARION vs. ACT-R (cont.)



Rabinowitz and Goldberg Experimental Results

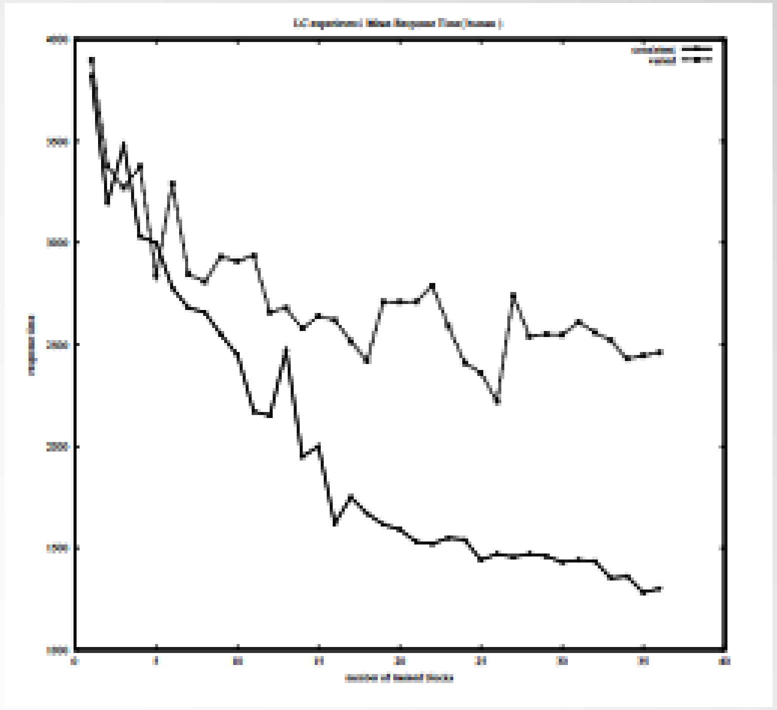


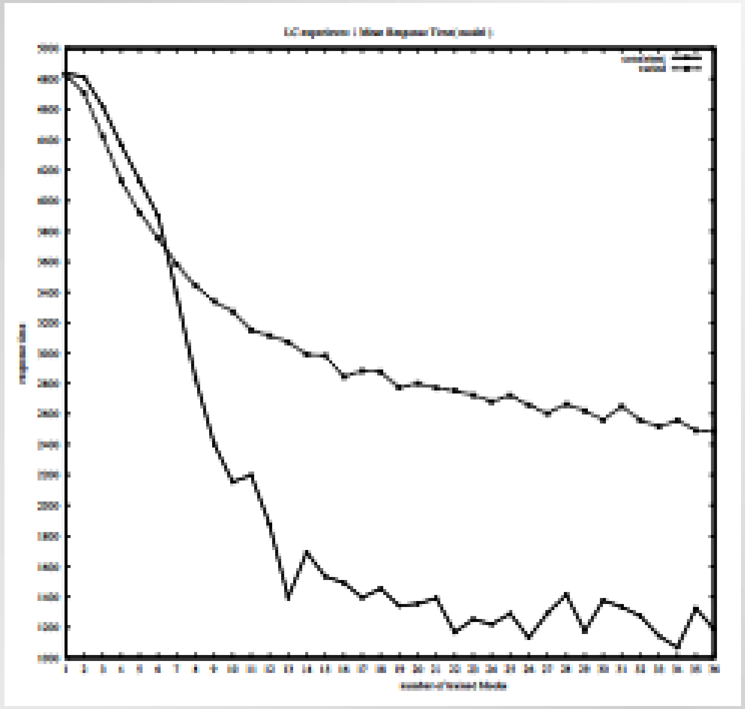
CLARION Simulation Results



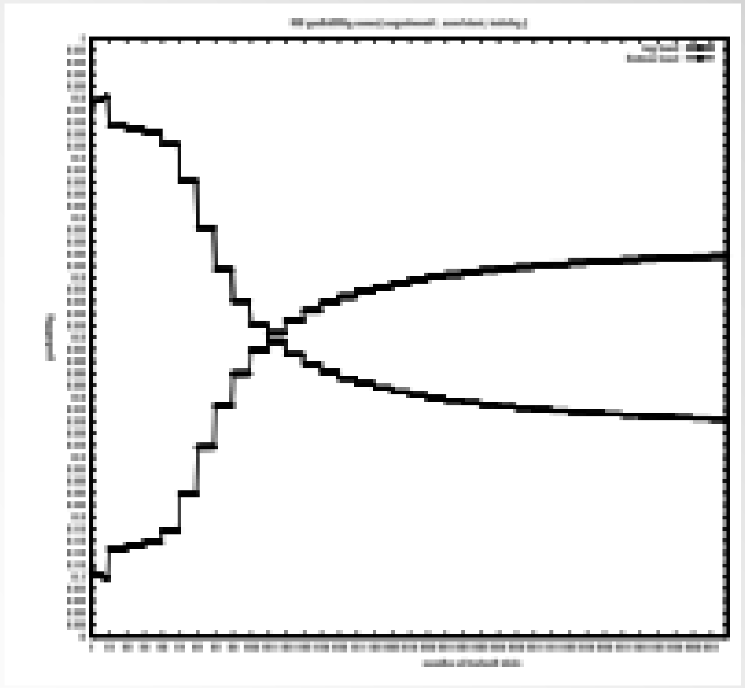
ACT-R Simulation Results

Simulation Examples

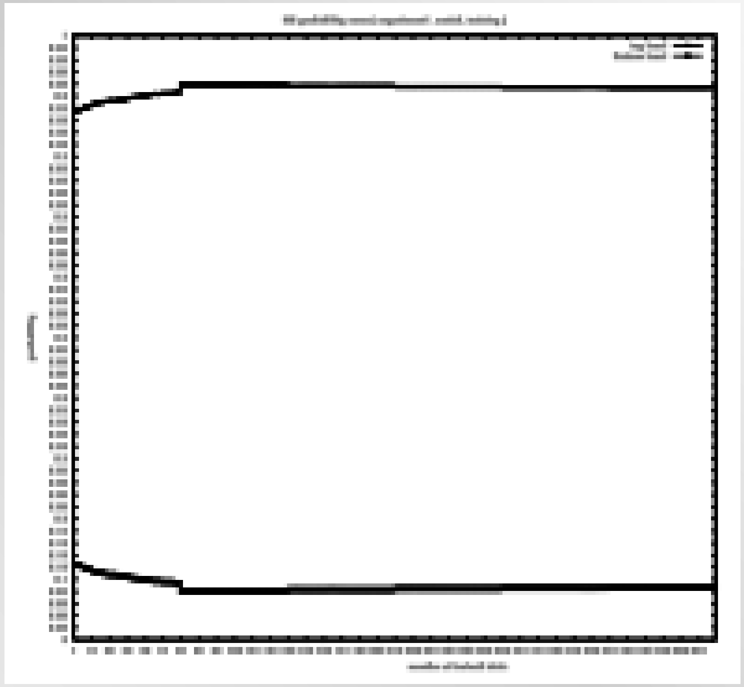

Learning curve of Rabinowitz and Goldberg (1995)


Learning curve during the simulation

Simulation Examples



Level selection probability of the consistent group during training in the simulation



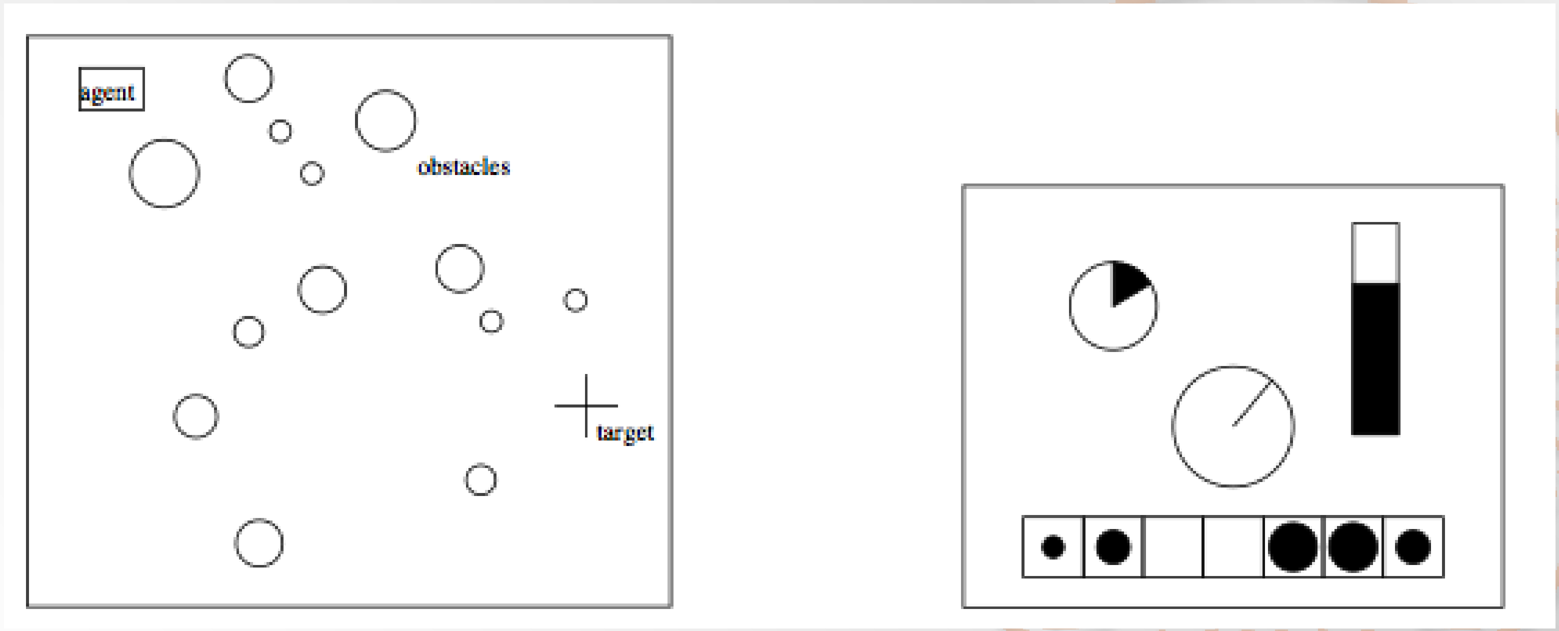
Level selection probability of the varied group during training in the simulation

Simulation Examples

Questions?

Simulation Examples

- Minefield navigation task (Sun et al 2001)



Simulation Examples

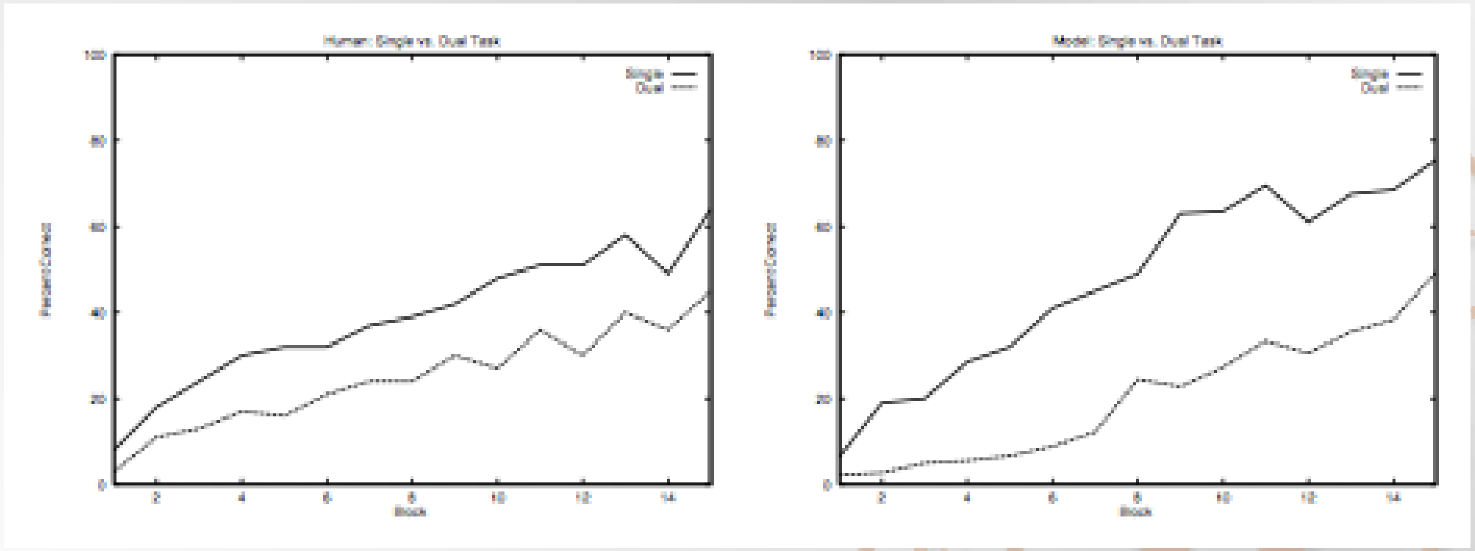
- Four training conditions:
  - Standard training condition
  - Verbalization condition
  - Dual-task condition
  - Transfer conditions

Simulation Examples

- Model Setup
  - The effect of the dual task is captured by reduced top-level activities (through raised rule learning thresholds)
  - The effect of verbalization stems from heightened rule learning activities (through lowered rule learning thresholds)
  - The model starts with no more a priori knowledge about the task than a typical human subject
  - 10 human subjects were compared to 10 model subjects in each experiment

Simulation Examples

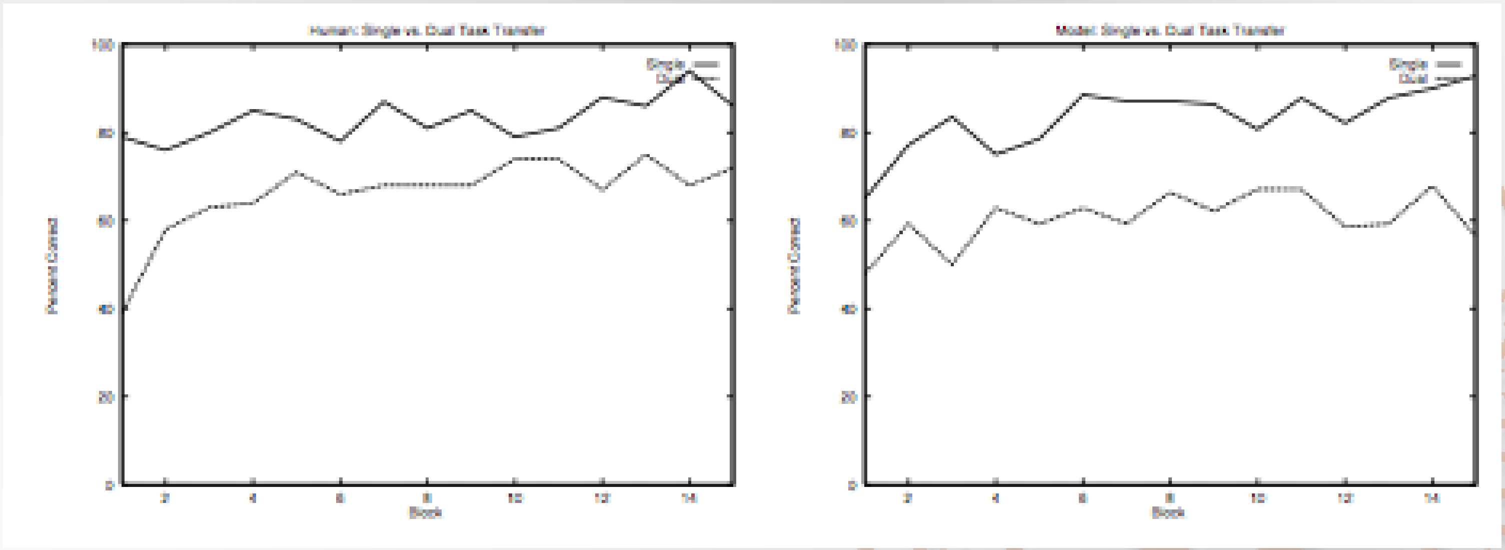
- The effect of the dual task condition on learning:



  - 2 (human vs. model) X 2 (single vs. dual task) ANOVA indicated a significant main effect for single vs. dual task ($p < .01$), but no interaction between groups and task types

Simulation Examples

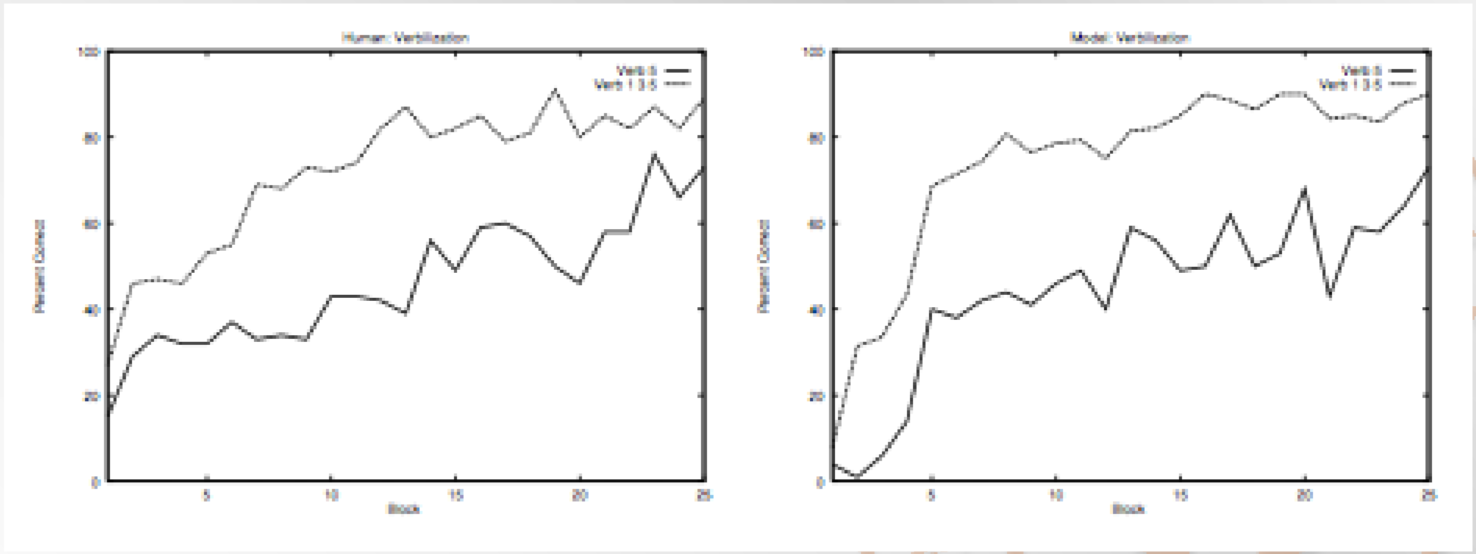
- The effect of the dual task condition on transfer



  - 2 (human vs. model) X 2 (single vs. dual task) ANOVA revealed a significant main effect of single vs. dual task (p < .05), and no interaction between groups and task types

Simulation Examples

- The effect of verbalization



  - 4 (days) X 2 (human vs. model) X 2 (verbalization vs. Standard) ANOVA indicated that both human and model subjects exhibited a significant increase in performance due to verbalization ($p < .01$), but that the difference associated with verbalization for the two groups was not significant

Simulation Examples

- Academic science task (Naveh and Sun, 2006) --- Lotka's law
- Number of authors contributing a certain number of articles follows an inverse power law: a Zipf distribution (Lotka, 1926)
- Simon (1957): a simple stochastic process for approximating Lotka's law
  - The probability that a paper will be published by an author who has published *i* articles is a/i^k
- Gilbert (1997) simulated Lotka's law
  - Assumed that authors were non-cognitive and interchangeable; it neglected a host of cognitive phenomena that characterized scientific inquiry (e.g., learning, creativity, evolution of field expertise, etc.)

Simulation Examples

- Setup for simulating academic publishing data:
  - Multiple agents: with limited academic life spans (in part, depending on productivity)
  - Each paper: based on combining past ideas (from past papers), with local optimization
  - Action sequences in generating papers: decided based on implicit and explicit knowledge, with learning from experiences
  - Evaluated based on a set of criteria (i.e., refereed)

Simulation Examples

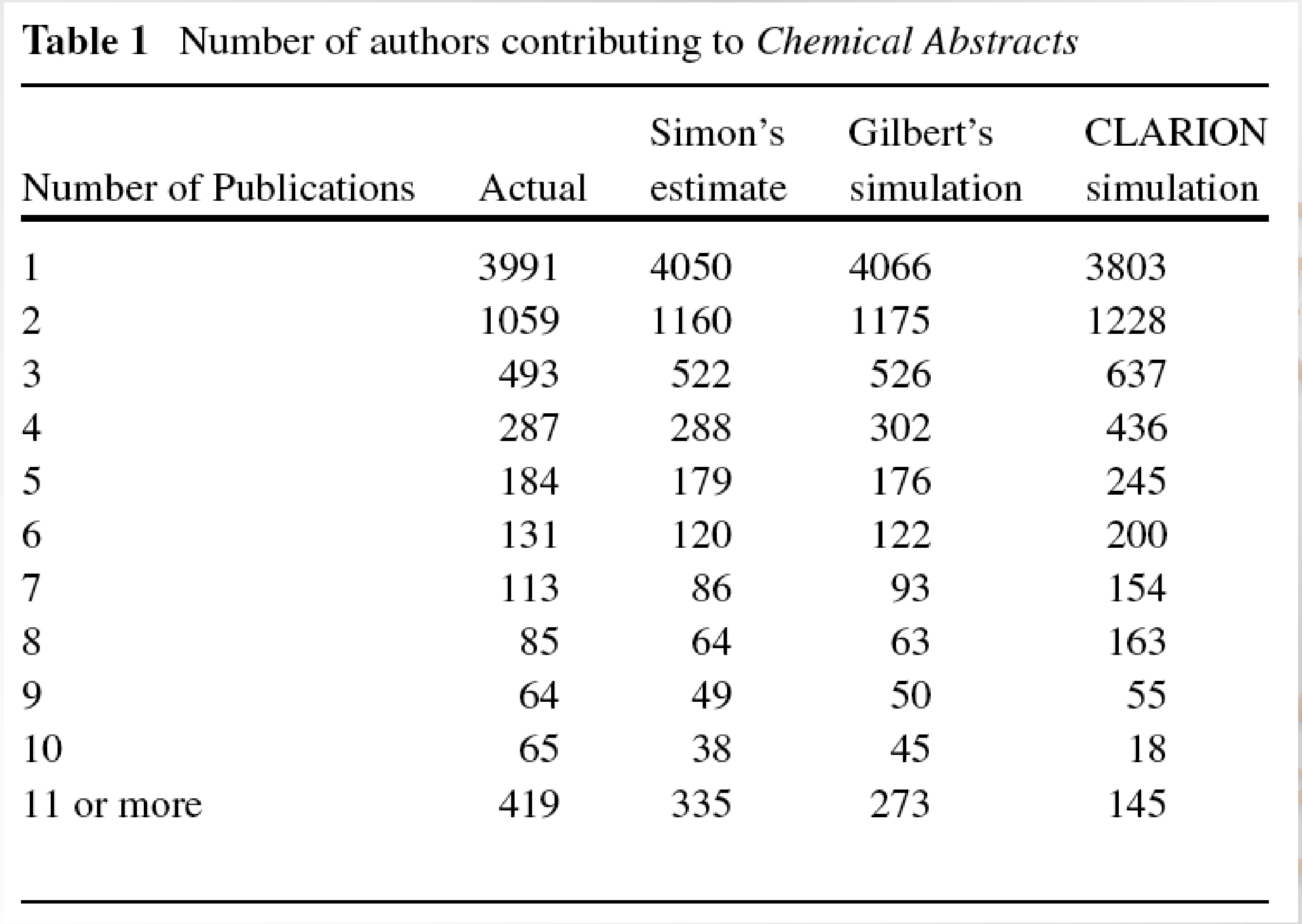


Table 1 Number of authors contributing to *Chemical Abstracts*

Number of Publications	Actual	Simon's estimate	Gilbert's simulation	CLARION simulation
1	3991	4050	4066	3803
2	1059	1160	1175	1228
3	493	522	526	637
4	287	288	302	436
5	184	179	176	245
6	131	120	122	200
7	113	86	93	154
8	85	64	63	163
9	64	49	50	55
10	65	38	45	18
11 or more	419	335	273	145

Simulation Examples

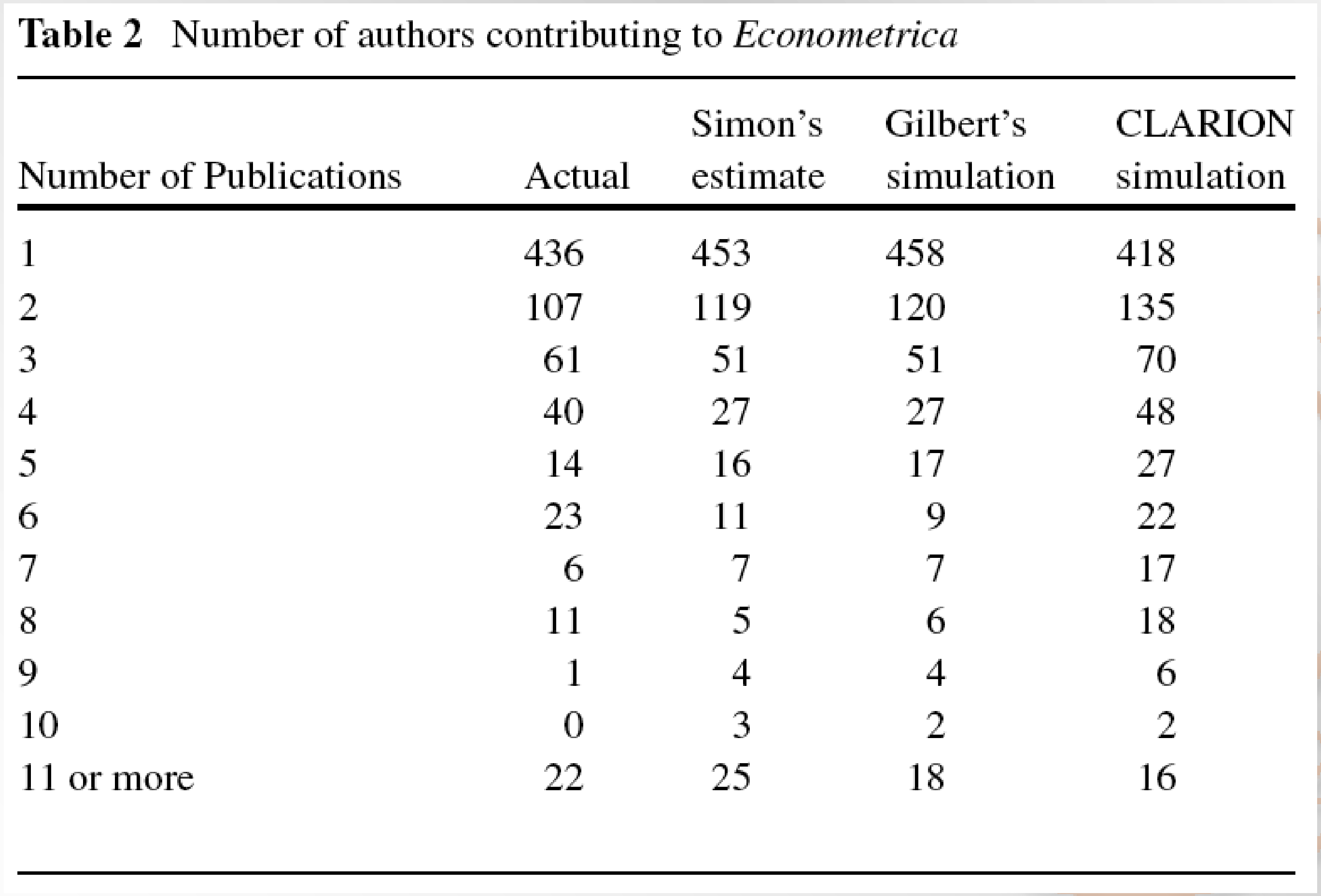
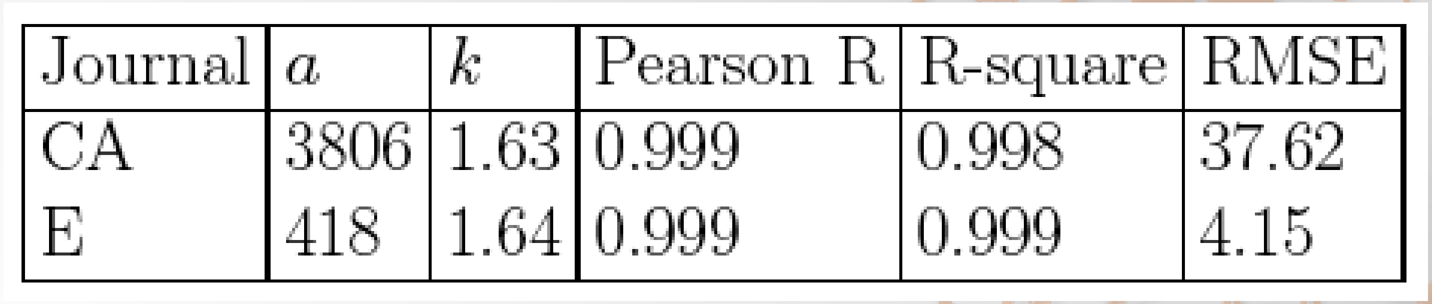


Table 2 Number of authors contributing to *Econometrica*

Number of Publications	Actual	Simon's estimate	Gilbert's simulation	CLARION simulation
1	436	453	458	418
2	107	119	120	135
3	61	51	51	70
4	40	27	27	48
5	14	16	17	27
6	23	11	9	22
7	6	7	7	17
8	11	5	6	18
9	1	4	4	6
10	0	3	2	2
11 or more	22	25	18	16

Simulation Examples*

- The CLARION simulation data for the two journals matched the real-world data well
- The CLARION simulation data for the two journals could be fit to the power curve $f(i) = a/i^k$ (as in Simon's, but not built in)



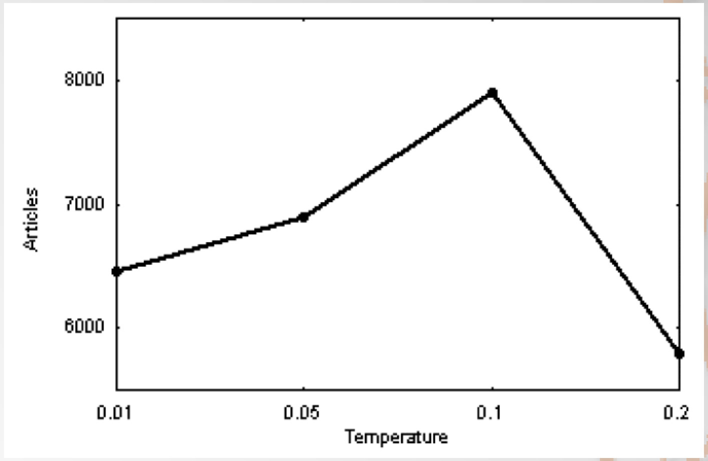
Journal	a	k	Pearson R	R-square	RMSE
CA	3806	1.63	0.999	0.998	37.62
E	418	1.64	0.999	0.999	4.15

Simulation Examples

- The number of papers per author reflected cognitive processes of authors, as opposed to being based on auxiliary assumptions
- Emergent, not a result of direct attempts to match the human data
- More distance between mechanisms and outcomes, to come up with deeper explanations

Simulation Examples

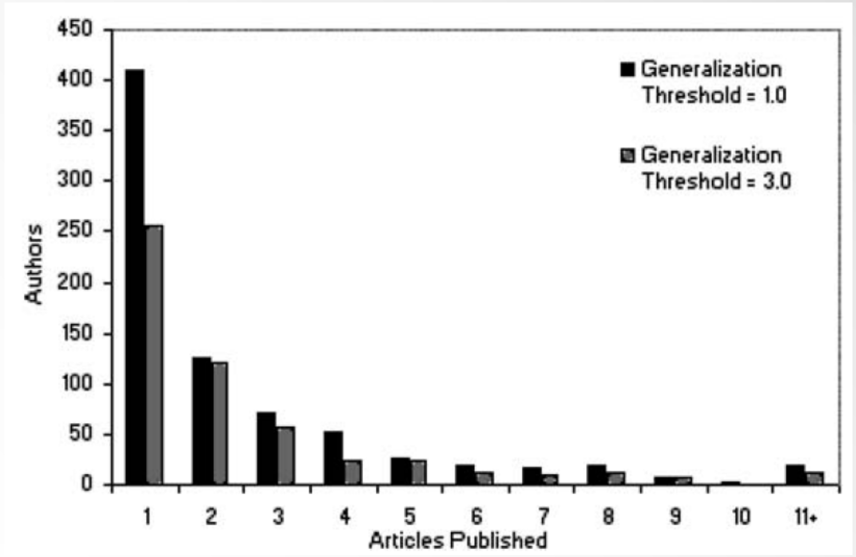
- Varying cognitive parameters:
  - Most prolific under a moderately high temperature setting:

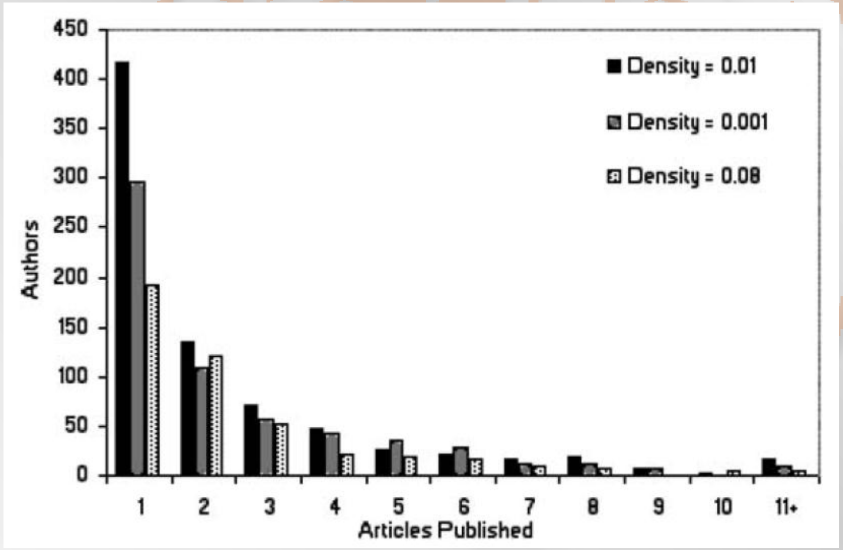


  - **Serendipity** in scientific discovery!

Simulation Examples

- Varying cognitive parameters:
  - Generate different communities producing different numbers of papers, by varying cognitive parameters
  - Power curves are obtained under different cognitive parameter settings





Simulation Examples

- Varying cognitive parameters:
  - Cognitive-social invariance
  - General applicability and validity of the model
  - Generate new theories and hypotheses
  - Reduce the need for costly (or impossible) human experiments

Simulation Examples

Questions?

Summary

Summary

- ACS Bottom level: implicit representation
  - Implemented by

    e.g., backpropagation networks
  - Bottom-level learning modes:
    - Q-learning
    - Simplified Q-learning
    - Etc.

Summary

- ACS Top level: explicit representation
  - Rules: “condition chunk node $\rightarrow$ action chunk node”
  - Types of top-level rules:
    - Rule extraction and refinement (RER)
    - Independent Rule Learning (IRL)
    - Fixed Rules (FR)

Summary

- Level Integration
  - Stochastic Selection
    - Level is chosen probabilistically
  - Combination
    - Bottom-up rectification
      - Bottom-level outcome rectified at the top level
    - Top-down guidance
      - Top-level outcome assists action decision-making at the bottom level

    - Both may boil down to weighted-sum in the simplest case

Summary

- Working Memory
  - Involves:
    - Action-directed encoding of information (as opposed to automatic encoding)
    - Gradual fading of information (using BLA)
    - Action-directed re-encoding ("refreshing") of information
    - Limited storage capacity
  - Working memory is also used to transmit information between the action-centered and non-action-centered subsystems.

Summary

Thank You

Questions?