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A Summary of Skill Learning Using A Bottom-Up Model

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We developed a skill learning model CLARION. Different from existing models of mostly high-level skill learning that use a top-down approach (that is, turning declarative knowledge into procedural knowledge) , we adopt a bottom-up approach toward low-level skill learning, where procedural knowledge develops first and declarative knowledge develop s from it. CLARION is formed by integrating connectionist, reinforcement, and symbolic learning methods to perform on-line learning. We compare the model with human data in a minefield navigation task. A match between the model and human data is observed in several comparisons.

The model consists of two main components: the top level encodes explicit declarative knowledge in the form of propositional rules, and the bottom level encodes implicit procedural knowledge in neural networks. In addition, there is an episodic memory, which stores recent experiences in the form of "input, output, result" (i.e., stimulus, response, and consequence). A high-level pseudo-code algorithm that describes CLARION is as follows:

1. Observe the current state x.
2. Compute in the bottom level the Q-value of each of the possible actions (a_i's) associated with the perceptual state x: $Q(x, a_1)$, $Q(x, a_2)$, ..., $Q(x, a_n)$.
3. Find out all the possible actions (b_1, b_2, ..., b_m) at the top level, based on the the perceptual information x and other available information (which goes up from the bottom level) and the rules in place at the top level.
4. Compare the values of a_i's with those of b_j's (which are sent down from the top level), and choose an appropriate action a.
5. Perform the action a, and observe the next state y and (possibly) the reinforcement r.
6. Update the bottom level in accordance with the *Q-Learning-Backpropagation* algorithm, based on the feedback information.
7. Update the top level using the *Rule-Extraction-Refinement* algorithm.
8. Go back to Step 1.

For details, Sun et al (1996).

We compared model performance with human performance in a variety of conditions. In the standard training condition we compared *average* success rates as in Figure 1. Both sets of data were best fit by power functions (for failure rate). The degree of similarity is evident. A Pearson coefficient was calculated which yielded a high positive correlation (r = .82), indicating a high

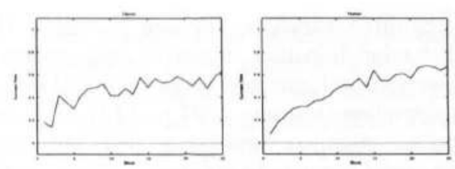

Figure 1: The learning curves in terms of success rates in the standard condition. The right side is the human data and the left side is the model data.

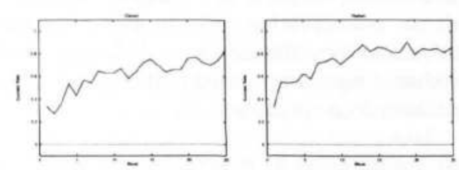

Figure 2: The learning curves in terms of success rates in the verbalization condition.

degree of similarity between human subjects and model runs.

In the verbalization training condition, we compared the average human and model data. We posited that much of the effect of verbalization on learning was associated with rehearsing previous steps and episodes, and thus we use replay to capture verbalization in the model. Again, the two sets of data were highly similar and both were best fit by power functions. We also calculated a Pearson coefficient, which yielded a high positive correlation (r = .84).

A number of other conditions, such as mixed training and over-verbalization, were also used in comparisons. Our detailed protocol analysis further indicated that there was substantial evidence in the verbalization of the subjects for the bottom-up learning process as posited by our model.

References:

R. Sun, et al. (1996). Bottom-up skill learning in reactive sequential decision tasks. *Proc.of 18th Cognitive Science Conference*.