Modeling Uncertain Reasoning with Stochastic Simluation in ACT-R

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In many tasks, humans must make inferences about sequences of events that each have more than one possible outcome. At first glance, ACT-R has two difficulties modeling reasoning in such tasks. First, ACT-R does not provide a method for representing that an event, state or relation that a chunk represents has a probability (not certainty) of being true. Second, it does not have facilities that combine these probabilities to compute likely outcomes in complex tasks according to the laws of probability. This would seem, again at first glance, to require at least a major retrofit of ACT-R. Some researchers have therefore decided to use Bayesian Networks (BNs) to model uncertain reasoning. BNs can represent uncertain states and, given prior and conditional probability distributions for these states, compute the likelihood of unobserved states, all in accordance to Bayes Theorem. BNs have several shortcomings as cognitive modeling tools, however. In many tasks, subjects do not behave according to normative probability theory at it is not clear how to explain such behavior in BNs. Further, BNs are not very expressive. Unlike ACT-R, a BN has no chunk-like way of representing relations among objects. Because BNs their representational paucity, BNs do not explain how uncertain reasoning in domains that has so far been best modeled with chunks, productions, attention, spatial maps, etc. interacts with probabilistic representations. Either ACT-R requires a major reworking to accommodate models of probabilistic inference or there must be a relatively simple way of modeling probabilistic inference in ACT-R.

We propose a method of modeling probabilistic inference in ACT-R without significant modifications and in particular without introducing numerical probabilities to ACT-R. The method is based on the class of techniques called "stochastic simulation", which are similar to Monte Carlo simulation. To illustrate this approach, we describe a method of converting any BN into an ACT-R model.

In our approach, an ACT-R chunk is created for each state variable represented by a node in a BN and a production is created for the conditional probability relationship represented by the edges of the BN. We also introduce the notion of a "world" in which copies of these chunks exist. Each chunk is given a slot whose value is the world in which that chunk is said to exist. Probabilities in a BN are estimated as follows: N (a parameter provided a priori) worlds are created and a copy of each chunk is created in each world. As productions match in these worlds, they elaborate the representation of (or "simulate" a) world. Because in many cases multiple productions can match, the worlds will differ from each other. In order to make the productions fire as often as the conditional probabilities in the BN they represent require, we create copies of each production so that their relative number reflects the relative conditional probabilities specified by the BN. To estimate the probability that the state a particular chunk represents is true, we simply compute the proportion of worlds that include a chunk representing that state.

This technique provides a method for estimating probabilities (that provably converges on the true probabilities) in a task without adding a probabilistic apparatus to ACT-R. The involvement of ACT-R processes such as chunk retrieval and conflict resolution in production matching suggests possible explanations of biases in probabilistic inference. Perhaps most importantly, because no new exotic machinery is introduced, existing ACT-R models of cognitive processes can be used to help explain behavior in tasks where probabilistic inference is required.

We briefly discuss some empirical work we have conducted that offers evidence that humans use this kind of stochastic simulation in a probabilistic qualitative physics task.