## INSTANCE-BASED COGNITIVE MODELS OF DECISION-MAKING

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#### I. INTRODUCTION

'Cognitive architectures' are computer algorithms designed to model human behavior and to function in a way similar to the workings of the human mind. The breadth of cognitive architectures is one of their primary strengths. Rather than serving as special-purpose models engineered specifically for individual tasks, cognitive architectures provide general computational mechanisms and constraints that are applicable to the development of models for all kinds of tasks.

ACT-R is a widely researched cognitive architecture that accounts for hundreds of empirical results obtained in the field of experimental psychology (Anderson and Lebiere, 1998). ACT-R is a hybrid architecture of cognition that combines a production system (to capture the sequential, symbolic structure of cognition) with a subsymbolic, statistical layer (to capture the adaptive nature of cognition). A goal of ACT-R researchers is to investigate the overall integration of cognition by building models designed to explain how all the components of the mind work together (Anderson, 2002).

Although cognitive architectures like ACT-R can offer flexibility and precision in human-like behavior representation, they have rarely been used to study economic decision making. A reason for this state of affairs is that ACT-R has mistakenly been

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conceptualized as a rule-based static theory that does not provide the flexibility necessary for uncertain decision situations, like economic settings. This chapter will demonstrate the potential of ACT-R to model economic decision making.

Economic decision making should be modeled as a learning process, involving more than calculation of expected values, accounting for human cognitive limitations and abilities, and allowing for flexibility in transfer of knowledge. This chapter summarizes evidence of successful ACT-R modeling of decision making processes of this kind. Several examples of ACT-R decision making models show that the same architecture can be used in a variety of tasks including dynamic control tasks, backgammon players and simple 2 x 2 gamers like in the Prisoner's Dilemma. We argue that for economic decision making settings as well as for many other tasks in which learning and decision making occur in unison, instance-based decision making is the most plausible learning mechanism (Gonzalez, Lerch and Lebiere, 2003). Other researchers have also theorized that instance-based decision making is a general mechanism used for all types of decision making under uncertainty (Gilboa and Schmeidler, 1995). All the models reported in this chapter have successfully used this instance-based approach in ACT-R, concluding that ACT-R can provide an integrated account of the psychology of decision making.

The rest of this chapter is organized as follows: Section 2 presents an introduction to the ACT-R cognitive architecture, its knowledge representation structures and memory and learning mechanisms. Section 3 summarizes the instance-based decision making

# II. ACT-R COGNITIVE ARCHITECTURE

ACT-R 5.0 (Figure 1) is a modular, neurally plausible architecture structured as a

for which declarative memory and the central production system are the modules of foremost importance.

ACT-R incorporates a symbolic system in which declarative knowledge and procedural knowledge interact in discrete cycles. Declarative structures called 'chunks' are used to store factual knowledge in the declarative memory. Chunks encode knowledge as structured, schema-like configurations of labeled slots. 'Productions' are modular, condition-action rules that encode procedural memory by representing potential actions to be taken when certain conditions are met. ACT-R also incorporates a subsymbolic system in which continuously varying quantities are processed simultaneously to produce many of the graded characteristics of human cognition. These subsymbolic quantities participate in neural-like activation processes that determine the speed and success with which decision makers access chunks in the declarative memory and resolve conflicts among productions. Finally, ACT-R also incorporates a set of learning processes that can lead to the creation of new symbolic knowledge structures.

The subsymbolic activation processes believed to be implicated in instance-based decision making make a memory chunk available for retrieval to the degree that the similarity between a past experience and a current context (as defined by a current goal) indicates the usefulness of the chunk at that particular moment. Retrieving a chunk results in its immediate reinforcement (due to its frequency of use) through ACT-R's base-level activation learning mechanism. Activation (1) reflects, in Bayesian terms, the log posterior odds that a chunk is relevant in a particular situation. The activation

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that the base-level learning equation produces both the Power Law of Forgetting and the Power Law of Learning. Strengths of association are determined by using a similar mechanism that records the statistics of co-occurrence between sources and retrieved chunks (see Anderson and Lebiere, 1998 for more detail).

When retrieving a chunk (3) to instantiate a production, ACT-R selects the chunk with the highest activation  $A_i$ . However, some stochasticity is introduced within the system by adding Gaussian noise of mean 0 and standard deviation to the activation  $A_i$ of each chunk. To be retrieved, the activation of a chunk needs to reach a fixed retrieval threshold that limits the accessibility of declarative elements. If the Gaussian noise is approximated with a sigmoid distribution, the probability *P* of chunk *i* being retrieved by a production is determined as follows:

 $\frac{A_i}{s}$ Р

i

condition to the greatest degree, according to a similarity function. Specifically, the chunk with the highest match score is retrieved, where match score  $M_{ip}$  is a function of the activation of chunk *i* in production *p* and its degree of mismatch to the desired values:

$$M_{ip} \quad A_i \quad MP \quad 1 \quad Sim(v,d) \tag{5}$$

In the above formula MP

Blending also represents a generalization of well-known AI techniques. Neural networks have a similar ability to learn in their connection weights a number of training patterns and produce an output that reflects the constraints of the entire training set rather than any specific pattern. The Bayes Optimal Classifier produces the most likely outcome weighted over all hypotheses (ACT-R chunks), rather than simply the most likely hypothesis (most active chunk). Linear weighted regression is an instance-based machine learning algorithm that produces the answer that minimizes the squared error between a fitted function and a set of data points, with each data point being weighted by its distance to the query point. The blending mechanism combines attributes of all these techniques.

In summary, the ACT-R cognitive architecture incorporates a set of mechanisms that can be used to develop models of learning and performance. The assumptions described in this section are not arbitrary; they are supported by years of work resulting in the accurate modeling of a broad range of results in experimental psychology.

#### III. INSTANCE-BASED DECISION MAKING

Making decisions based on instances basically means that courses of action are chosen through the use of accumulated experience. Observations in real-world, complex situations (e.g., military battle executions and firefighting) support the notion that under conditions involving stress, uncertainty, or task overload, people's decision making is mostly experience-based (Klein, Orasanu, Calderwood and Zsambok, 1993; Pew and Mavor, 1998; Zsambok and Klein, 1997). Two theories, one from economics and the other from psychology, crystallize this form of decision making. The economists Gilboa and Schmeidler (1995) proposed a theory called 'casebased decision theory' (CBDT) (Gilboa and Schmeidler, 1995) designed to explain decision making under conditions of uncertainty. Like expected-utility theory, CBDT derives a functional representation of preferences from a set of axioms about individual behavior. But, in contrast to expected-utility theory, CBDT posits that decision makers rely on their experience by choosing alternatives that have worked best in the past. Central to the theory is the concept that memory consists of a finite set of past instances or cases and that similarity to past cases is the *only* guide to decision making. Cases in CBDT are triplets (q, a, r) where q is the problem situation, a conditions of uncertainty (e.g., CBDT). Like CBDT, IBLT proposes that instances (or cases) accumulate in the memory as individuals make decisions, and incorporates the concepts of similarity and utility. But, in

decisions. Thus, decision makers confronted with similar situations while performing a task gradually abandon general heuristics in favor of improved instance-based decision-making processes.

The different mechanisms used to retrieve instances, evaluate alternatives, and apply feedback are central to IBLT. A similarity mechanism plays an integral role in individuals' recognition of decision-making situations. If the situation is relatively common, then the use of past experience might enable individuals to make accurate,

### IV. ACT-R INSTANCE-BASED MODELS OF DECISION MAKING

This section summarizes a set of ACT-R models of decision-making tasks performed by either individuals or small teams. Researchers have developed these models in accordance with the instance-based approach and have validated them by using human data. We briefly summarize how accurately data generated through the use of each of these models describe actual human behavior.

The sugar factory task (Berry and Broadbent, 1984) is an instance-based ACT-R model. Sugar factory is a computer-simulated task in which participants are told to imagine that they are factory managers and can control the production of sugar sp by determining the number of workers w employed on each of a number of trials. Unbeknownst to the participants, the following equation governs the behavior of the system:

$$sp_t \quad \mathbf{2} \quad xw_2 \quad sp_t \quad \mathbf{1} \tag{7}$$

Sugar production is proportional to the number of workers employed, a concept that is intuitive enough, but is inversely related to the sugar production at the previous step, a relationship that is difficult and counterintuitive to infer. The value entered for the workers hired ( $w_t$ ) can be varied in 12 discrete steps (1  $w_t$  12), while the sugar production  $sp_t$  changes discretely within the range 1  $sp_t$  12. To allow for a more realistic interpretation of w as the number of workers and sp as tons of sugar, the actual computer simulation multiplies these values by 100 and 1000, respectively. If the result according to the equation is less than 1000, sp is simply set to 1000. Similarly, a result greater than 12000 always leads to an output of 12000 tons of sugar. Finally, in two-

thirds of all trials a random value of ±1000 is added to the result derived from the equation above.

Dienes and Fahey (1995, 1998) developed two models of the sugar factory task using either rules or instances and found that the former model reproduced human behavior more closely than the latter. In addition, they found that subjects that displayed the best control performance of the system also exhibited the lowest amount of system knowledge, as determined by a post-task test.

Wallach and Lebiere developed an ACT-R instance-based learning model of the sugar factory and compared it to a models proposed by Dienes and Fahey (Dienes and Fahey, 1995, 1998; Wallach and Lebiere, 2003). The ACT-R model is quite simple, consisting of a single heuristic rule (taken from the Dienes and Fahey model) to bootstrap the system and another rule to retrieve past instances. Nonetheless, in comparison with the models of Dienes and Fahey it provides at least as good of a fit to human data without making any unwarranted assumptions. The ACT-R model also explains lowest amount of system knowledge in best performers: the model's knowledge of the system consists only of instances rather than any general, abstract understanding of the system's dynamics.

Because the sugar factory task has only a few discrete states (a single input control variable and a single output variable), Wallach and Lebiere (2003) tested the generality of the ACT-R modeling approach by applying it to Broadbent's transportation task (Broadbent, 1977; Broadbent and Aston, 1978). Participants performing that task can adjust two continuous input variables to try to achieve target values on two continuouslyvarying output variables. Like the sugar f1978adben1.7193 TD01289 Tw0.2296 Tw[Because th039dge of [J-13.3ar

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output values without explicitly encoding structural knowledge about causal relationships between variables—to successfully control the task (Berry and Broadbent, 1987). The model makes use of the ACT-R blending mechanism that retrieves the value or values that best satisfy the constraints expressed by an entire set of chunks, with each chunk weighted by its probability of retrieval.

Figure 2 shows that the model's ability to control the system is quite comparable to that of the test subjects', with  $r^2$  of .73. Control performance was measured by the number of trials necessary to achieve the respective target value pairs. The average number of errors, defined as an increase in the distance to the required target values from trial *n* to trial n+1, was within the empirically observed range.



FIGURE 2: A VERAGE NUMBER OF ERRORS AS A FUNCTION OF PROBLEMS

The ACT-R model of the transportation task has an intriguing characteristic: A set of instances representing each subject's exploration phase is used instead of a general heuristic rule to initialize the instance-based model. Thus each model run constitutes an individualized version of the general instance-based model, adjusted to the knowledge of each individual subject.

Researchers also have applied the instance-based models of learning by individual decision makers to decision making by two-person teams. The mechanisms used to model decision making in multi-player game settings are the same as those used to model individual decision making. Instead of using theories specially developed for the task, such as game theory, we have built models based on the same general-purpose mechanisms of the ACT-R cognitive architecture (e.g., learning and memory).

Researchers use game-like tasks to evaluate team decision making because the competitive aspect of game playing is a good tool by which to ensure maximal effort by subjects and to test the limits of the subjects' cognitive abilities. Because these multiperson adversarial games involve a finite, often small number of choices that are repeated for a certain number of iterations, they allow for instance-based learning to occur.

Instance-based decision making is largely dependent on an individual's ability to match current situational patterns with past situations and the associated decisions stored in memory. In team decision-making situations, memory consists of one's own instances and those of the opponent. Thus, the quality of one player's decisions often depends strongly upon her awareness of the opponent's instances and upon her ability to analyze them to infer her opponent's plans.

To identify the essence of team tasks, Lebiere and West (1999) studied human decision making in the classic game of paper-rock-scissors. This game embodies the essence of adversarial decision-making: It offers each player a finite set of options, has simple, well-defined zero-sum<sup>2</sup> rules that define the outcome of those options, and allows

<sup>&</sup>lt;sup>2</sup>A zero-sum game is one in which every gain by one of the players has to be offset by an equivalent loss by another. It has been recently argued that many real-world situations can in fact be

the most direct expression of the dynamic character of move and countermove, as each player tries to anticipate the other's moves and preempt them. Rather than attempting to create a model specifically tailored for this particular task, in accordance with the architectural approach we re-used a model previously developed for the basic human skill of learning sequences of events. The ACT-R Sequence Learning Model learned sequences of stimuli by building instances encoding short pieces of sequences (Lebiere, Wallach and Taatgen, 1998). Although the model accumulates instances straightforwardly through experience, the procedural knowledge is quite trivial and consists basically of a pair of production rules that match the most recent move against instances in memory, retrieve the most active instance with its prediction of the next move, then lead to selection of the move that counters the predicted one.

Figure 3 presents a time course of model and subject performance for a number of sample runs. The model stored the opponent's moves as sequences of different lengths zligure 3 pp.cskill

game, playing it well is by no means trivial. This generalized ACT-R model was entered in an international competition<sup>3</sup> and placed in the top tier, holding its own against specialized AI programs designed specifically for the game. than by trying to maximize their own separate outcomes. Lebiere, Wallach and West (2000) present a model of the PD directly based upon the paper-rock-scissors model. They argue (as detailed above) that the chun

(A) HUMAN					(B) MODEL				
Subject Pair	A1A2	A1B2	B1A2	B1B2	Model Run	A1A2	A1B2	B1A2	B1B2
1	1	1	1	97	1	10	13	12	65
2	7	1	1	92	2	1	0	2	97
3	14	1	2	83	3	4	19	12	65
4	04	5	5	86	4	92	4	3	1
5	21	4	3	72	5	93	3	3	1
6	24	5	5	66	6	1	1	2	96
7	54	12	7	27	7	95	3	2	0
8	34	2	52	11	8	13	21	18	48
9	58	25	5	12	9	2	9	2	87
10	83	9	4	3	10	5	4	10	81
Mean	30	7	8	55	Mean	32	8	6	54

Two ACT-R models were run in pairs, interacting with each other for the same number of trials completed by the human subject pairs (10). Table 1B shows the corresponding frequencies for the model. Remarkably, the model matched not only the mean percentage of outcomes over the 10 pairs, but also the distribution of outcomes across pairs, with approximately the same number of pairs cooperating and defecting (and even a mixed outcome pair). Figure 4 indicates that the model also reproduced the time course of the human subjects' gradual shift in decisions from the original preponderance of defection toward more cooperation.



# V. SCALING UP TO COMPLEXITY, UNCERTAINTY, AND DELAYED FEEDBACK

Although most of the situations confronted by the previously described models were not trivial and clearly captured some fundamental aspects of human decisionmaking, they shared a certain simplicity that is not reflective of real-world complexity. At each decision point, subjects (or the model) had a small number of discrete options (typically 2 or 3). The decision makers also received immediate feedback from their actions, which greatly aided in the learning process. Finally, although the decisionmaking process itself may have added a measure of uncertainty, the actual tasks were entirely deterministic. When studying human cognition it is essential to ascertain if the instance-based decision-making approach can indeed deal with more complex situations. Researchers have documented the use of this approach in complex tasks at the individual level (Gonzalez *et al.*, 2003).

The IBLT process has been implemented in the ACT-R architecture in the context of a dynamic task requiring resource allocation and scheduling (Gonzalez *et al.*, 2003). This dynamic decision-making task, known as the 'Water Purification Plant' (WPP), involves uncertainty and feedback loops generated by the interrelationship of a user's decisions. WPP requires individuals to "purify" water via different treatment processes while acting under a deadline. They make these decisions while a simulation clock runs and must react as water arrives in different tanks and in unknown patterns.

This ACT-R model of IBLT relies heavily on the symbolic representations of ACT-R, but also reflects the subsymbolic processes described by the activation equation (and thus, the base-level learning equation), partial matching, and blending. Each instance has an activation value that depends on attention, base-level activation and learning, and other probabilities. Thus, rather than relying solely on past instances to

guide decision making, IBLT incorporates many cognitive phenomena and mechanisms for decision making.

Researchers have used human data to

Although the ACT-R model of WPP addresses issues of decision making in complex environment, many decision making tasks in the real world are performed in a team. The instance-based approach also suits team decision making. The well-known game of backgammon presents a slightly

of the activation equation, which allows retrieval of closely matching chunks. This sort of similarity-based generalization essentially captures the effect of distributed representations in connectionist networks.

Starting with this general representation, the model gradually builds its declarative knowledge based on the experience gained by playing against a relatively strong opponent. A publicly available evaluation function (Tesauro, 1992) was used to play with the ACT-R backgammon model. The model was trained for 1000 games against the 'expert' opponent. Figure 6 displays the percentage of games won over the 1000 games for the ACT-R model and the opponent's model. The results indicate the model requires approximately 100 games to learn to play relatively well and almost matches the performance of its strong opponent by 1000 games (See Sanner et al., for further analyses).



FIGURE 6: (A) PERCENTAGE OF WINS (O) AGAINST OPPONENT (X)

## VI. CONCLUSION

This chapter describes ACT-R as a cognitive architecture that facilitates the development of decision-making models. In

Models of economic decision-making settings can benefit from a cognitive architecture like ACT-R. Not only is ACT-R a powerful computational architecture that combines most of the mechanisms required for economic settings, but compared to other computational approaches, ACT-R also provides a more realistic characterization of the flexibility and adaptability of human behavior. ACT-R's learning mechanisms supported by psychological research can effectively explain and represent transfer of knowledge.

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