9 Cognitive Models of Training Principles and the Instance-Based Learning Tool

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This chapter reviews computational representations of human behavior involving three training principles discussed in preceding chapters (especially chapters 2, 3, and 5): Speed–accuracy trade-off attributable to fatigue, training difficulty, and stimulus-response compatibility. Effects of these three training principles were modeled using the ACT-R cognitive architecture (Anderson & Lebiere, 1998) and the instance-based learning (IBL) theory (Gonzalez, Lerch, & Lebiere, 2003). The use of similar memory principles in all three projects resulted in the implementation of an IBL tool (Dutt & Gonzalez, 2011), which provides a computational framework that facilities building computational models using ACT-R and IBL theory. The last section of this chapter summarizes the IBL tool and concludes with the benefits of using computational representations of learning and training principles: to develop an understanding of the learning process in a variety of tasks; to predict learning effects from training principles; and most importantly, to demonstrate the generality of computational principles and representations from the ACT-R architecture and IBL theory.

Cognitive Architectures: ACT-R

In *Unified Theories of Cognition,* Allen Newell calls for "unification" as an aim of science: "positing a single system of mechanisms—a cognitive architecture—that operate together to produce the full range of human cognition" (Newell, 1990, p. 1). His approach to unification involved a single piece of software representing a theory about the nature of the human mind. ACT-R (Anderson & Lebiere, 1998) is an example of a theory that consists of multiple modules, but that evolved as an integrated cognitive architecture (Anderson et al., 2004). Corresponding to human abilities like perceptual-motor, declarative memory, and the goal, the modules may help make particular predictions about human behavior (Anderson et al., 2004).

ACT-R can be conceptualized as a toolbox of cognitive processes, and a cognitive model is a particular computational representation of the processes involved in executing a concrete task. When a task is to be performed, different cognitive processes may be required in different sequences, along with different intensities and durations to accomplish a task. Thus, a cognitive modeler makes the difficult decisions of which particular sequences are needed. Up to this point, there has been little theory to guide the modeler. In reference to models of human learning that are directly relevant to training principles, however, there have been at least two approaches: (a) learning by means of rules (procedural knowledge, strategies) and (b) learning from particular domain-related events (declarative knowledge, instances; Anderson & Lebiere, 2003). These approaches may use ACT-R's symbolic and subsymbolic knowledge representations in different ways (Anderson & Lebiere, 1998, 2003). The symbolic aspects can be declarative, procedural, or both. Declarative knowledge is represented in chunks, and procedural knowledge is represented in productions (if–then rules). Subsymbolic elements are the neural-like mathematical mechanisms that manipulate the symbolic representations.

ACT-R affords the modeler considerable freedom in which approaches to take when developing an accurate representation of the learning processes involved in a task's execution. Modelers can choose to "think of" or discover the strategies that human beings use in a task, which can be represented in production rules (strategy-based learning or SBL). These production rules "compete" according to the values that are provided through a process of reinforcement learning. In contrast, modelers can also choose to represent knowledge in instances (i.e., task cues are represented as slots of chunks), following IBL theory. Thus, IBL represents the learning process in a generic set of productions and uses mostly declarative knowledge as the basis for learning. In IBL, instances are accumulated and retrieved according to a memory mechanism called activation, which is a function of the recency, frequency of the use of instances, and their similarity to the task's cues. ACT-R models often use a combination of the SBL and IBL approaches. Furthermore, there are also considerable degrees of freedom to decide what parameters and subsymbolic mechanisms are used to "fit" a model to human data.

The IBL theory attempts to provide a framework of the cognitive processes involved in making decisions from experience in dynamic tasks (Gonzalez et al., 2003). As will become clear in the rest of the chapter, this framework helps reduce the degrees of freedom involved in modeling by adopting one particular perspective of learning from experience and exploration, which can be applied to a broad range of dynamic and repeated choice tasks. In modeling, the training effects illustrated in the chapter utilized IBL theory and other proposed ACT-R learning mechanisms. IBL theory will be introduced next, then computational models of three training principles will be summarized: speed–accuracy trade-off, training difficulty, and stimulus-response compatibility. Examples of modeling these three training principles will highlight the common and robust mechanisms of experiential learning used in IBL theory. The chapter will conclude with the presentation of the IBL tool, an easy-to-use computational approach that facilitates and frames the choices that modelers can take with IBL theory.

Instance-Based Learning Theory

IBL theory (Gonzalez et al., 2003; Gonzalez & Dutt, 2011) proposes a particular learning process free of fabricated and specific strategies, as well as concrete guidelines for the symbolic representation of information. The theory also uses a subset of subsymbolic learning mechanisms developed in and adapted from ACT-R. Thus, developing models that follow IBL theory reduces the number of decisions a modeler must make.

IBL theory was initially proposed to demonstrate how learning occurs in dynamic decision-making tasks (Gonzalez et al., 2003). An IBL model was implemented within the ACT-R architecture, and it was demonstrated how IBL theory and ACT-R parameters and processes were needed to account for human decision making in a complex task. IBL theory has more recently been used in other type of tasks, including simple binary choice tasks (Lebiere, Gonzalez, & Martin, 2007; Lejarraga, Dutt, & Gonzalez, in press), two-person game theory tasks (Gonzalez & Lebiere, 2005), and other dynamic control tasks (Martin, Gonzalez, & Lebiere, 2004).

An instance in IBL theory is a triplet containing the cues that define a situation, the actions that define a decision, and the expected or experienced value from an action in such a situation. Simply put, an instance is a concrete representation of the experience that a human acquires in terms of the task situation encountered, the decision made, and the outcome (feedback) obtained in the task. A modeler following the IBL theory must define the structure of a situation-decision-value instance. IBL's generic decision making process involves the following steps:

Recognition (comparison of cues from the task to cues from memory); *Judgment* (the calculation of a decision's possible utility in a situation, either from past memory or from heuristics); *Choice* (the selection of the instance containing the highest utility); *Execution* (the act of making a decision based upon the chosen instance); and *Feedback* (the modification of the expected utility defined in the judgment process with the *experienced* utility after receiving the outcome from a decision made).

In making a choice, the IBL theory selects the alternative with the highest *blended value, V* (Gonzalez & Dutt, 2011; Lejarraga et al., in press) resulting from all instances belonging to an alternative. The blended value of alternative *j* is defined as

$$V_j = \sum_{i=1}^{n} p_i x_i \tag{1}$$

where x_i is the value of the observed outcome in the outcome slot of an instance *i* corresponding to the alternative *j*, and p_i is the probability of that instance's retrieval from memory. The blended value of an alternative (its utility) is the sum of all observed outcomes x_i of corresponding instances in memory, weighted by their probability of retrieval. In any trial *t*, the probability of retrieving instance *i* from memory is a function of its activation relative to the activation of all other instances corresponding to that alternative, given by

$$P_{i,t} = \frac{e^{A_{i,t}/\tau}}{\sum_j e^{A_{j,t}/\tau}} \tag{2}$$

where τ is random noise defined as $= \sigma \times \sqrt{2}$ and σ is a free noise parameter. Noise in Equation 2 captures the imprecision of recalling instances from memory.

The activation of each instance in memory depends upon the *Activation* mechanism originally proposed in the ACT-R architecture (Anderson & Lebiere, 1998). For each trial *t*, the *Activation* $A_{i,t}$ of instance *i* is:

$$A_i = B_i + \sum_j W_j S_{ji} - D_i + \varepsilon \tag{3}$$

The activation A_i of an instance *i* reflects how likely the instance would match a task cue at the current point of time, and the probability and speed of retrieval of that instance (Anderson & Lebiere, 1998). The activation is determined by the base-level activation B_i, the associative activation S_i, the mismatch penalty value D_i, and noise. The base-level activation B_i of the instance i reflects the recency and frequency of that instance's use. S_i reflects the impact of contextual values on the instance's activation, and D_i is the degree to which the instance matches a context (i.e., the extent to which a given instance is similar to previously presented instances in each S slot). The noise parameter ε is a variable value associated with an instance. See detail information regarding each of the terms of the activation equation in Anderson and Lebiere (1998) and in Gonzalez, Best, Healy, Kole, and Bourne (2011).

S_i is defined by the sum of the source activation that an instance receives from the elements currently in attention (i.e., the task cues). W_j represents the attentional weighting of each element's j cues that are part of the current goal instance, and the S_{ji} component represents the strengths of association that measures how often the instance i is needed when cue j is an element of the goal. ACT-R assumes that there is a limited total amount of attention (W, the sum of all W_j) that one can be distributed over source objects. W is an ACT-R parameter that reflects the salience or attention given to an instance's cues. This salience helps create a contrast between relevant and irrelevant cues for the current goal that will help in maintaining information necessary for task performance. Thus, W influences the maintenance and prioritization of goals, attention to relevant and irrelevant information, and the amount of concurrent processing (Lovett, Reder, & Lebiere, 1999). Higher values of W facilitate the retrieval process by increasing spreading activation, whereas lower values reduce activation and increase the likelihood of retrieving incorrect items.

Computational Models of Three Training Principles

This section describes three examples of cognitive models developed to demonstrate the learning processes involved in three training principles (see chapters 2, 3, and 5): speed–accuracy trade-off attributable to fatigue, training difficulty, and stimulus-response compatibility. In each project, behavioral results are used from human experiments and human performance is compared to the results produced by the computational models in the same tasks. Furthermore, all three projects involve fitting human data and predictions on new, unknown conditions, which demonstrate one of the most important benefits of cognitive modeling. Note that a parallel modeling effort using

IMPRINT, rather than ACT-R, is reported in chapter 10 for the first two training principles, and the two sets of models are evaluated and compared in chapter 11.

Models of Speed-Accuracy Trade-Off in a Data Entry Task

Fatigue often results from prolonged work that is manifested as deterioration in performance along with skill acquisition (see chapter 2). On one hand, fatigue effects might be attributed to limitations of cognitive processes such as attention. For example, some models assert that cognitive resources are needed during task performance and that there is a limited amount to expend in the task (Wickens, 1984; see also chapter 4). Thus, monotonous and prolonged perceptual processing depletes this pool of resources, making it harder to maintain attention (Parasuraman, 1986) and often resulting in habituation (Mackworth, 1969). On the other hand, fatigue effects might be explained with arousal theories, which argue that performance decrements are due to the lack of stimulation needed to maintain alertness (Ballard, 1996). Often, sustained repetitive tasks are boring (Hoffman, Sherrick, & Warm, 1998), which produces decreases in arousal (Mackworth, 1969).

Gonzalez et al. (2011) presented a cognitive model representing the cognitive aspects of fatigue (e.g., attention) and fatigue itself as an arousal process. This was a model that followed initial work on fatigue modeling (Fu, Gonzalez, Healy, Kole, & Bourne, 2006; Gonzalez, Fu, Healy, Kole, & Bourne, 2006). The cognitive model was developed in the ACT-R architecture to represent the behavioral pattern observed in a number of experiments incorporating extended task performance, which resulted in both beneficial and deleterious performance effects (Healy, Kole, Buck-Gengler, & Bourne, 2004; Kole, Healy, & Bourne, 2008). Beneficial effects, demonstrated as a decrease in response latency over time, resulted from general skill acquisition and from specific learning or repetition priming attributable to the repeated occurrence of stimuli and responses. Deleterious effects, demonstrated as an increase in errors over time, have causes that are less clear, but might be attributed to *fatigue* or fatiguelike processes such as boredom, task disengagement, or loss of attention that builds across trials.

Following previous work (Jongman, 1998), Gonzalez et al. (2011) developed an ACT-R model of mental fatigue where both arousal and cognitive factors influence performance. The task was data entry, which required subjects to read a four-digit number and then type it on the computer. Two laboratory experiments were examined using the data entry task reported in Healy et al. (2004). Some of the results from this effort that involved comparisons of model predictions to human behavior for average response time and the proportion of correct responses are summarized. Figure 9.1 shows that the ACT-R model was able to capture the primary observation by Healy et al. (2004): that prolonged work resulted in both learning and fatigue effects, with learning effects dominating the speed measure and fatigue effects dominating the accuracy measure. Gonzalez et al. (2011) showed that prolonged work effects are captured by the combination of arousal and cognitive factors corresponding to two ACT-R sub-symbolic parameters in combination with the production compilation mechanism.

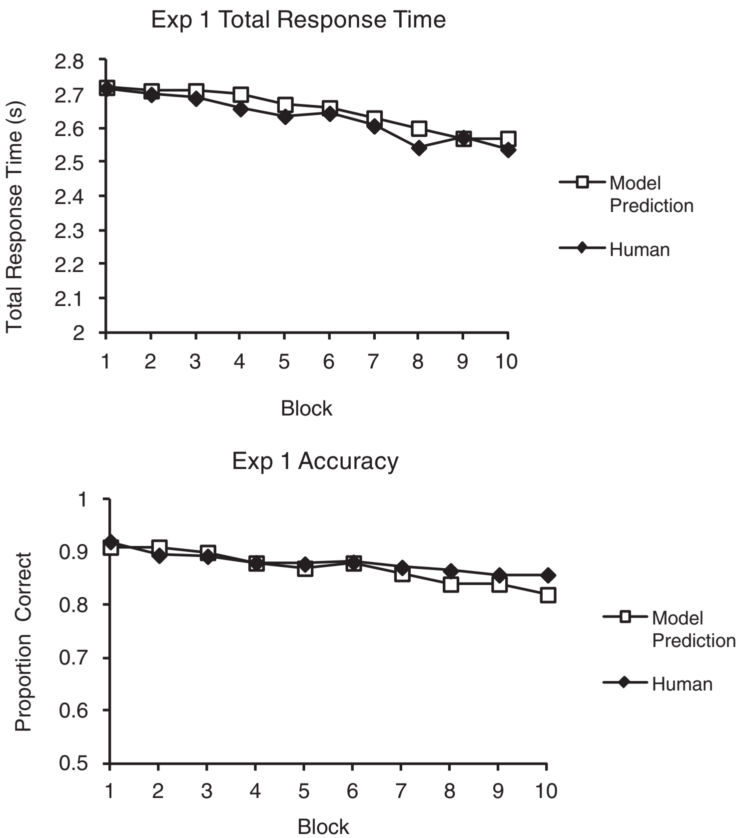


Figure 9.1 Experiment 1 data from Healy et al. (2004) and ACT-R model fits to the data from Gonzalez et al. (2011).

Models of Training Difficulty Principle in the RADAR Task

The training difficulty principle (see chapters 2 and 3) predicts that conditions that cause difficulty during learning would facilitate later retention and transfer. This principle was tested in a RADAR target detection and decision-making task (Gonzalez & Thomas, 2008), using laboratory experiments where, in some cases, the potential targets were nine military vehicles (e.g., submarine, helicopter, and jeep) (Young, Healy, Gonzalez, Dutt, & Bourne, 2011).

The goal in RADAR is to detect and eliminate hostile enemy targets by visually discriminating moving targets among moving distractors. RADAR is similar to military target visual detection devices, in which a moving target needs to be identified as a potential threat or not and a decision is made on how to best destroy that target. The task requires the participant to make both visual and memory searches. The participant must memorize a set of targets and then seek out one or more targets on a radar grid. A target threat may or may not be present among a set of moving blips. The blips—in the form of potential targets or blank masks—begin at the four corners of the grid and approach the center at a uniform rate. Detection of an enemy target must occur before the blips collapse in the center.

Models of the training difficulty principle in the RADAR task were developed under two perspectives, the IBL and SBL approaches, and compared (Gonzalez, Dutt, Healy, Young, & Bourne, 2009). The goal of the model comparison effort was to understand the processes by which behavior is represented, the constraints that the different approaches impose upon the task models, and the comparison of the two approaches' theoretical assumptions (Lebiere, Gonzalez, & Warwick, 2009).

The IBL model was based upon the IBL theory as presented above. The SBL model used four concrete strategies that varied in their effectiveness at performing the target detection task. One strategy was an optimal strategy, and three strategies were suboptimal. These strategies represented practically feasible ways to go about the task. The utility learning mechanism in ACT-R (Anderson et al., 2004) was used, by which the different strategies compete using a reinforcement learning algorithm. This algorithm produces a gradual transition from the suboptimal to the optimal strategies. When the model executes, there is a competition set up between the three suboptimal strategies and the optimal one. Although the suboptimal strategies are executed more often initially, the optimal strategy later picks up in usage because of its increased utility through repeated positive rewards.

The SBL and IBL models were compared along two different dimensions: (a) fit: how well each model fits human learning data in the task; and (b) adaptability: how well each model that has been able to reproduce the way human beings learned in one task scenario behaves in new scenarios that are similar to or different from the training condition. The fit criterion is common in model comparisons, whereas the adaptability criterion is relatively new (Gluck, Bello, & Busemeyer, 2008). The adaptability criterion used here is similar to the generalization criterion method (Busemeyer & Wang, 2000), which divides observed data into two sets: a calibration or training set to estimate model parameters, and a validation or test set to determine predictive performance. However, the models' adaptability was further tested by examining their ability to adapt to new test conditions that are either similar to or different from the training conditions.

Figure 9.2 presents the average times for correct responses during the training phase, in four conditions that varied in the difficulty of target detection (Young et al., 2011). The 1+1 condition indicated the need to memorize one target and the presence of only one item on the RADAR screen. Thus, this was the easiest condition. The 4+4 condition indicated the need to memorize four targets and the presence of four items on the RADAR screen, making it the most difficult condition. The mappings of

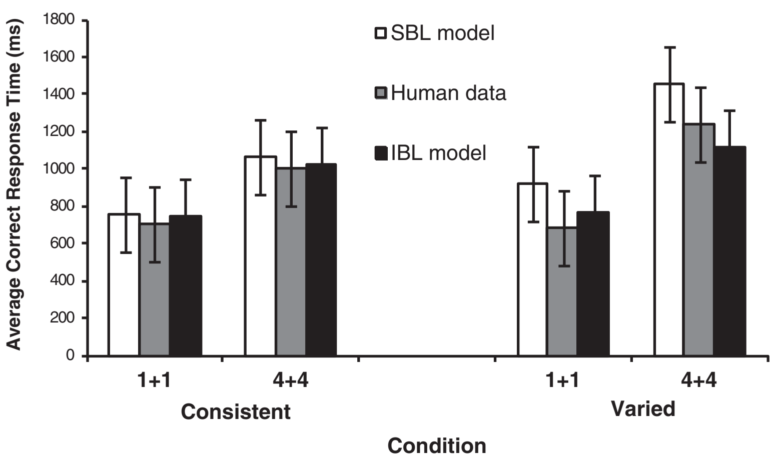


Figure 9.2 Average correct response times (ms) for CM 1+1, VM 1+1, CM 4+4, and VM 4+4 blocks in human data and SBL and IBL models during training. The error bars show 90% confidence intervals.

the targets were either consistent (the target was always a target within a block of trials) or varied (the target was sometimes used as a distractor on a different trial within the same block).

As shown in Figure 9.2, both the IBL and SBL models fit the human data quite well, RMSD = 69 ms for IBL and RMSD = 163 ms for SBL. However, the SBL model seems to generate generally higher time values compared to human data, and it has a higher RMSD. This difference may be because the four strategies in the SBL model execute productions in a fixed time (50 ms per production). There is also no speedup in the correct response times due to this fixed strategy execution time, whereas the IBL model speeds up on account of activation-retrieval time acceleration. The retrieval time decreases if the instances' activation increases over blocks (Anderson & Lebiere, 1998). It is also clear from Figure 9.2 that both models take more time in the more difficult (4+4) blocks than in the easier blocks (1+1) for both consistent and varied target mappings. This finding demonstrates the effects of workload well known from behavioral studies of automaticity (Gonzalez & Thomas, 2008), which result from the extra time taken to process additional items.

Figure 9.3 demonstrates the effects of added difficulty in the task (Young et al., 2011). In the "Tone" condition, participants were required to count deviant tones (low and high frequency) among standard tones (medium frequency) playing in the background during the target detection task. As shown by both models, the tone condition takes slightly more time to process than silent trials because of an extra auditory production in both

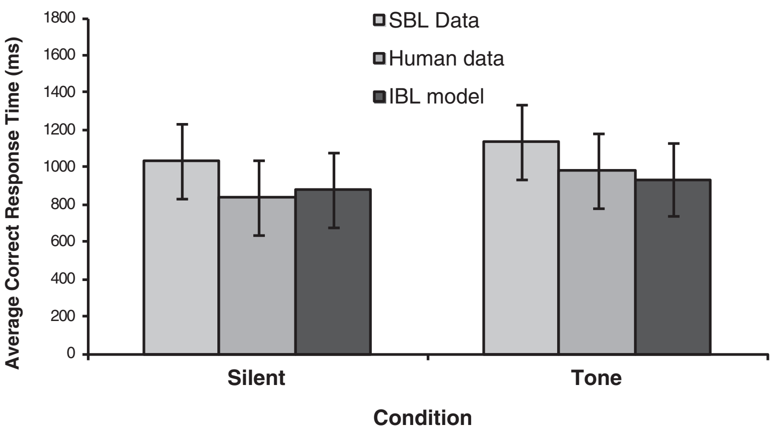
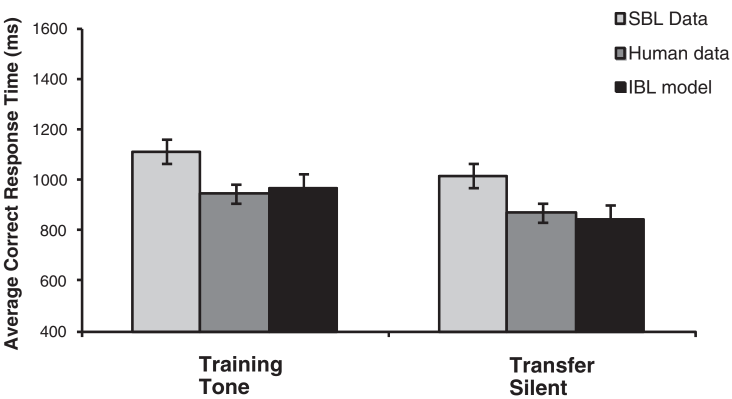


Figure 9.3 Average correct response times (ms) for silent and tone conditions for human data and SBL and IBL models during training. The error bars show 90% confidence intervals.

models that processes the tones. Again, the difference between the time in the SBL model and human data is greater than the difference between the time in the IBL model and human data. The SBL model has no activation-retrieval speedup to compensate for time spent in tone counting, whereas there is such a speedup in the IBL model that reduces the overall time.

To test the adaptability of both models, transfer was compared from difficult to easier conditions (tone-to-silent) and easy to more difficult conditions (silent-to-tone). Figure 9.4 shows these results. The SBL model has an RMSD = 160 ms when it is trained in tone and transferred to silent, whereas the IBL



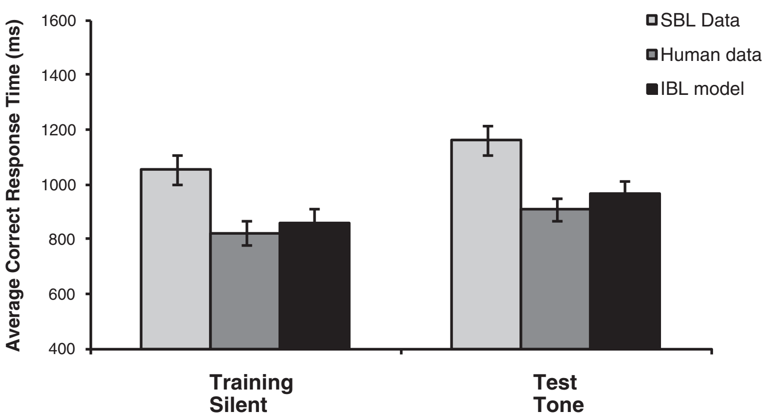


Figure 9.4 Left panel: Average correct response times (ms) for human data and SBL and IBL models for training in the tone and testing in the silent condition. Right panel: Average correct response times (ms) for human data and SBL and IBL models for training in the silent and testing in the tone condition. The error bars show 90% confidence intervals.

model's RMSD = 50 ms. The SBL model's RMSD when trained in silent and transferred to tone is 248 ms, whereas the RMSD for the IBL model is 62 ms. Thus, one can conclude that both models are quite good according to the adaptability criterion, but the IBL model produces values closer to the human data than the SBL model. Although the numerical values are important, the IBL model has other advantages over the SBL model not shown in measurements: the changes in environmental conditions are captured in the instances stored and retrieved from memory, whereas the SBL approach is blind to those changes. The SBL model continues applying the same strategies at test, which might not be as effective as they were during training once the task conditions change. Also, the strategies in dynamic situations are often unknown a priori or difficult to define at all. Human beings are often unable to explain any rules or strategies used to solve a dynamic problem. Thus, the IBL approach is more appropriate for modeling dynamic decision making (Gonzalez et al., 2003) than the SBL approach.

Models of Stimulus-Response Compatibility

The stimulus-response compatibility (SRC) training principle and the Simon effect, as discussed in both chapters 2 and 5, can be modeled using IBL theory (Dutt, Yamaguchi, Gonzalez, & Proctor, 2011; Yamaguchi, Dutt, Gonzalez, & Proctor, 2011). The SRC effect is characterized by faster responses when the stimulus and response locations correspond than when they do not. The effect is so robust that it is found even when stimulus location is irrelevant to the task, a variation known as the *Simon Effect* (Simon, 1990). Both SRC and Simon effects occur for visual and tactile stimuli, verbal and nonverbal symbols that convey location information (e.g., location words; Proctor, Yamaguchi, Zhang, & Vu, 2009), a variety of response modes (e.g., a steering wheel), and in more complex tasks such as flight operations (Yamaguchi & Proctor, 2006).

A dominant cognitive explanation of the faster RT with compatible stimuli and responses is the *dual-route account* (Proctor & Vu, 2006), which assumes two distinct response-selection processes characterized as direct and indirect routes. The indirect route is presumed to activate a response based on the intentions created through the instructed stimulus-response (S-R) mappings. In contrast, the direct route is presumed to activate automatically a response corresponding to the stimulus location, which facilitates response when it is correct but interferes when it is incorrect. Recent findings that the RT speedup can be attenuated or even reversed in mixed-task conditions suggests that the response-selection process that gives rise to these effects is not as purely automatic (e.g., unconditional and independent of task goals) as it is often described in the literature. What is missing in the current literature is an account of the learning mechanism(s) that produce(s) the observed phenomena.

Dutt et al. (2011) provide an explanation of the observed learning effects using a computational model based on IBL theory. The IBL theory has both the direct (automatic) and the indirect (controlled) routes to model human performance in tasks where there is a slow transition from the indirect to the direct route over time. The presence of both routes enables IBL theory to explain how the cognitive processes are used, how SRC and Simon tasks become automatic, and how the performance can be captured when SRC and Simon tasks are intermixed, and to predict the behavior in novel task-mixing conditions. Furthermore, the results of the IBL model were compared to the human data in sequential trials for mixed Simon and SRC tasks, when the compatible (corresponding) or incompatible (noncorresponding) mapping repeats or switches in a SRC (Simon) task and when the Simon or SRC task repeats or switches.

In IBL theory, learning occurs through a progressive accumulation of decision instances in memory and by gradually moving from an exploration phase, where more explicit rules of action are used (the indirect route) to an exploitation phase, where instances retrieved from memory are used. This latter phase involves implicit recognition of familiar patterns and specific retrievals from memory, similar to the gradual process proposed in Logan's (1988) instance theory of automaticity. Thus, an IBL model starts within the indirect route, predicting the application of an action rule. The process then moves to the direct route, such that an instance is retrieved from memory to make a response. Under the direct route, if the task is SRC and the mapping is compatible, an instance closest in similarity to the task and mapping is retrieved from the memory. Because IBL theory works by retrieval of past experiences in the form of instances, a decrease in RT is expected when task and mapping repeat, compared to when either task, mapping, or both switch in mixed SRC and Simon tasks. This result occurs because the retrieval of a past instance is faster when it has been performed recently (recency effect) and/or frequently (frequency effect) under the direct route.

The discussion in Dutt et al. (2010) shows that the calibrated model is able to explain the RT observed in a human experiment. Furthermore, the same model without modification is

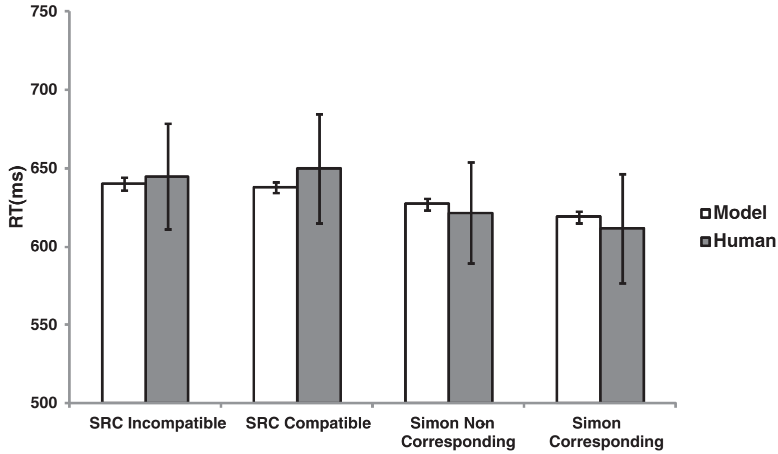


Figure 9.5 The IBL model's fits to human data in different mappings of the SRC and Simon tasks. The error bars show 95% confidence intervals around the point estimate.

used to generate predictions in novel mixed task conditions. The model prediction's fit to human data reveals the role of recency and frequency in the mixed-task paradigm. Figure 9.5 shows that the IBL model results are very close to those of human participants. These fits capture the RTs in four different task trials, and the sequential task and mapping trials. The model fits were generally good with respect to practice and sequential effects in two experiments, suggesting that it provides a good account of the performance in mixed SRC/Simon tasks.

Making Computational Modeling Easy: IBL Tool

Although "unification" as a scientific goal for the cognitive sciences is commendable (Newell, 1990), the representation of a full range of human behavior has proven to be a very complex challenge. Current cognitive architectures that embrace this unification goal are rare (but ACT-R is an exception). The unification goal has turned architectures into very complex systems that are often incomplete and difficult to use.

IBL is not the basis of a unified theory of human behavior. It is only a theory of dynamic decision making. Yet, it has shown robustness across a wide diversity of tasks that vary in their dynamic demands (see Gonzalez & Dutt, 2011; Lejarraga et al., in press) for concrete discussions and demonstrations, and the examples shown in this chapter add to these demonstrations.

This section presents a way in which cognitive modeling and the reuse of IBL theory as a whole can be facilitated: the creation of a simple-to-use tool that represents the unification and constraints of IBL theory. The tool is built upon the ACT-R's subsymbolic mechanisms needed for IBL theory. The construction of a modeling tool will help demonstrate that IBL theory can make general predictions across many diverse tasks; rather than creating multiple, task-dependent models. It will also make the theory more accessible to the community of cognitive modelers and psychologists (a free copy of the tool is available at http://www.cmu.edu/ddmlab/). The tool is motivated and explained further in Dutt and Gonzalez (2011).

Figure 9.6 shows the architecture of the IBL tool, the step-by-step processes from the theory and the interaction with an "Environment," a task for which a model is developed. The IBL tool is an easy-to-use graphical user interface that uses a common mechanism of network communication between two computer applications (i.e., socket communication) to communicate remotely with the task. The tool allows the situation (S) and feedback (U) cues to be retrieved from the task environment, and the processed decisions (D) to be sent from the model to the task. Thus, the task may be developed in any programming language. Using socket interfaces for task communication is the only technical requirement to using the tool.

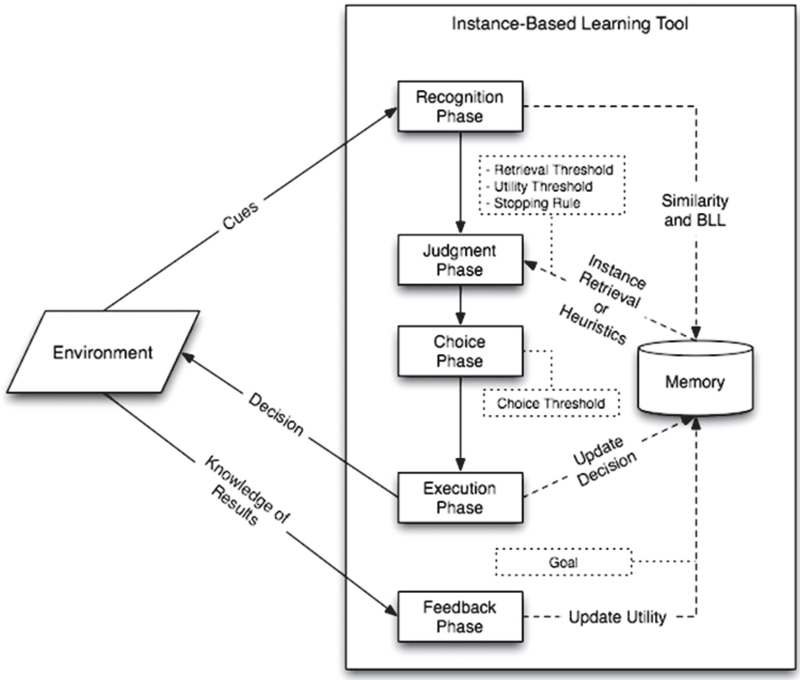


Figure 9.6 The IBL tool with five distinct IBL theory phases (Right) and the task Environment (Left).

The IBL tool takes a modeler step-by-step through the distinct process of IBL theory, making it easy to understand and intuitive for new modelers. Most importantly, these steps are a generic decision-making process that does not depend on the modeler's creativity to define (often complicated) decision-making strategies. Research has demonstrated that this process is generic enough to model most forms of decisions from experience (Gonzalez & Lebiere, 2005; Gonzalez et al., 2003; Lejarraga et al., in press). But the most relevant contribution of the IBL tool is to make the theory more accessible. The IBL tool makes it shareable, by bringing the theory closer to the end users; generalizable, by making it possible to use in different and diverse tasks; understandable, by making it easy to use in cognitive models; robust, by abstracting the specifics of its implementation independent of any specific programming language; communicable, by making the tool interact more easily and in a more standard way with tasks; and usable, by making the theory more transparent.

A step-by-step demonstration of building a cognitive model in the IBL tool for a particular task (the Iowa Gambling Task) is explained in Dutt and Gonzalez (2011). Once a modeler has defined the model's parameters and instance structure, the tool can simulate a number of model participants by connecting it to the task using well-known computer communication standards. These simulations provide the model's predictions regarding human behavior and performance in the task of interest.

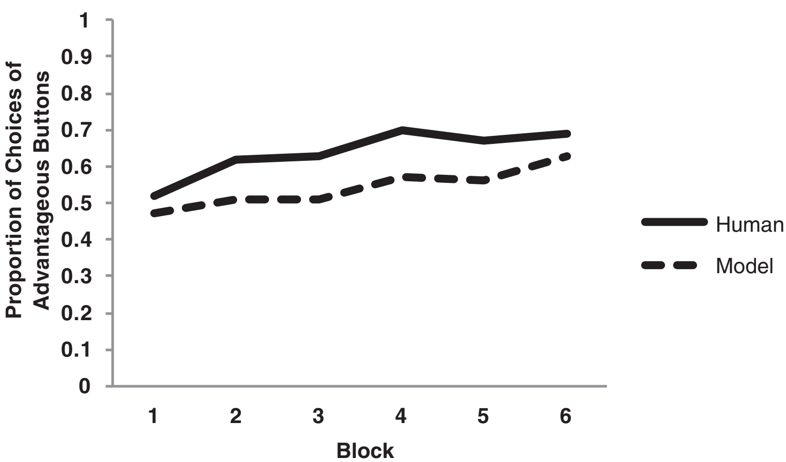


Figure 9.7 The fit of the IBL model developed in the IBL tool to human data for controls in the Iowa Gambling Task. See Dutt and Gonzalez (2011).

Figure 9.7 shows the results obtained from running the IBL model of the Iowa Gambling Task in the IBL tool compared to that of a group of healthy human (control) participants run in the same task, as reported by Bishara et al. (2009). These results were obtained using the default values of the parameters in the tool. Thus, the intention was not to calibrate the model parameters to produce the best predictions for human data, but rather to use the Iowa Gambling Task as an example to explain the IBL tool. Figure 9.7 shows the proportion of choices for the two advantageous alternatives (out of a total of four options in the Iowa Gambling Task) over six blocks of 20 trials each. The proportion of choices has been averaged across all 32 human and model participants. Although the exact level of the values are discrepant, the model in the IBL tool set at default parameter values provides a reasonable prediction of the trend in the observed human behavior over the six blocks of the experiment (MSD = 0.010; $r = 0.86$). In addition to the performance data, running a model in the IBL tool produces data on the values and dynamics of its mechanisms (e.g., activation, base-level learning, noise, and the values of the instance's situation-decision-value slots).

Conclusion

Three projects involving computational representations of human behavior for three training principles are summarized: speed–accuracy trade-off attributable to fatigue, training difficulty, and stimulus-response compatibility. Taken together, these studies show that the ACT-R architecture and IBL theory presents an accurate and robust representation of the learning process in several training paradigms. Because IBL theory has also demonstrated accurate representations in many other tasks (see Gonzalez & Dutt, 2011, for a discussion), the theory is more general than it was initially conceived to be: IBL theory accounts for decisions from experience at many different levels. This ability is illustrated by the precision of the models' predictions in the projects described here. Moreover, the creation of an explicit computer tool that represents the theory can also give rise to interesting demonstrations and new questions and answers. The theory was embodied in the IBL tool, which is available for research purposes. This tool should allow for more widespread from the authors use of IBL theory as it helps facilitate a cognitive modeler's work.

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