Simulating Knowledge Reuse in Skill Acquisition using the Clarion Cognitive Architecture

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Introduction

Skill acquisition is a major concept in cognitive science, because it sheds light on how individuals learn to perform tasks and how they integrate newly acquired skills into their existing behavioral repertoire. Initially, skill acquisition was framed as a gradual process where individuals build new skills in isolation. However, more recent theories state that this process is not simply incremental, but it involves the integration of new skills with pre-existing knowledge and skills, facilitating faster learning and reducing errors (Newell, 1990). This perspective aligns with the idea that knowledge reuse plays a critical role in accelerating learning, as it allows individuals to leverage their prior experiences to perform tasks more effectively in new contexts (Singley & Anderson, 1989).

The concept of knowledge reuse states that individuals do not learn new tasks from scratch but instead apply previously learned skills to similar, novel tasks. For instance, someone who has learned to drive a car may apply that knowledge to learn how to operate a motorcycle. According to Salvucci (2013), skill acquisition involves proceduralizing knowledge (i.e. transforming declarative knowledge into actions) and integrating new knowledge with already learned skills, facilitating faster learning and reduced error rates. These principles are central to understanding how knowledge reuse enables more efficient skill acquisition.

Building on these insights, this article aims to explore the role of knowledge reuse in skill acquisition by simulating two learning conditions using the Clarion Cognitive Architecture. Building on these insights, the present work extends Salvucci's dual-systems framework by using a full-scale cognitive architecture to simulate knowledge reuse. The Clarion model is a dual-process cognitive architecture that integrates explicit (symbolic, rule-like) representations with implicit (sub-symbolic, distributed) learning systems. The research question central to this study is: How does the reuse of prior knowledge, facilitated by the explicit system in the Clarion Model, influence the speed of learning and the number of errors made during skill acquisition?

The hypothesis driving this study is that learners who can access and reuse prior knowledge through the explicit system will learn new tasks more quickly and make fewer errors than learners who must start from scratch using only the implicit system. This hypothesis is consistent with the notion that knowledge reuse reduces cognitive load and allows learners to apply pre-existing knowledge representations to new contexts, which ultimately leads to faster learning and fewer mistakes (Salvucci, 2013).

To explore this hypothesis, this study simulates two distinct learning conditions using the Clarion Cognitive Architecture. In one condition, the model is initialized with prior knowledge in the form of explicit symbolic rules and associations; In the other, the model begins without this pre-loaded structure and learns entirely through trial-and-error interactions. While prior knowledge can exist in both implicit and explicit forms, this study operationalizes it as structured symbolic representations stored in Clarion's explicit subsystems. By observing how the model behaves under these different initializations, we aim to characterize the impact of structured prior knowledge on learning speed and error reduction. Rather than testing a sharp directional hypothesis, the goal is to better understand the range of learning trajectories that emerge from distinct knowledge configurations within a dual-process cognitive system.

Model

The Clarion Cognitive Architecture is designed to model cognitive processes by simulating both explicit and implicit learning systems. It is built on a dual-process framework that simulates how people integrate conscious, rule-based knowledge with non-conscious, experience-based learning (Sun, 2002). In this study, the focus is on how explicit knowledge, facilitated by pre-learned production rules, influences the rate of skill acquisition. The Clarion Model can be broken down into the following parts, which work in conjunction with each other:

- **Explicit System:** The explicit system stores and applies production rules, which are essentially if-then statements that describe how to perform tasks. These rules represent conscious knowledge, which can be retrieved and applied when needed. For example, in a typing task, the explicit system might contain a rule like “if the letter ‘A’ is displayed, press the corresponding key.” When novel tasks share structural similarities with previously learned ones, such as similar input-output mappings or subgoals, the explicit system can support transfer by reusing or recombining existing rules. This ability to apply known procedures to related problems can accelerate the learning process, especially in domains with overlapping task components (Taatgen, 2002).
- **Implicit System:** The implicit system learns gradually from experience through repeated exposure and feedback. In Clarion, this is implemented via reinforcement learning mechanisms in the bottom level of the Action-Centered Subsystem (ACS), where distributed representations (such as neural weights) are adjusted based on success or failure. For example, in a typing task, the implicit system might learn to associate specific key presses with letter stimuli by refining internal connections over time, leading to

faster and more automatic responses. While the implicit system handles fine-tuning through trial and error, it's important to note that the explicit system (top level) also learns from experience, albeit in a symbolic fashion, such as by extracting new rules or modifying existing ones in response to repeated patterns. Together, these systems allow the model to improve both procedurally and declaratively as it gains experience (Huber & O'Reilly, 2003; Sun, 2005).

- **Action-Centered and Non-Action-Centered Subsystems:** The Action-Centered Subsystem (ACS) focuses on motor actions (e.g., pressing a key or steering a car), while the Non-Action-Centered Subsystem (NACS) supports cognitive functions such as memory retrieval and semantic reasoning. These subsystems collaborate to perform tasks, enabling the integration of cognitive and motor processes. This cooperation is central to Clarion's dual-process framework and illustrates how both symbolic and sub-symbolic knowledge interact during skill acquisition (Sun, 2005; Sun, Merrill, & Peterson, 2001).

A central feature of Clarion is its ability to integrate both implicit and explicit knowledge through ongoing interaction between its subsystems. As the model practices a task, implicit experience in the Action-Centered Subsystem (ACS) can support the formation or refinement of explicit rules in the top level, a process known in Clarion as bottom-up learning (Sun, Merrill, & Peterson, 2001). Over time, this allows the model to improve its performance by aligning symbolic knowledge with patterns learned through experience, leading to smoother and more efficient behavior. This mechanism reflects how skills can become more fluid and coordinated through practice, even though Clarion does not implement production compilation per se.

In this study, the explicit system will be used to simulate the reuse of prior knowledge. By drawing on pre-existing production rules, the model will apply learned skills to new tasks, facilitating faster learning and fewer errors. The comparison between learning with prior knowledge (explicit system) and learning without prior knowledge (implicit system) will demonstrate the impact of knowledge reuse on task performance.

Methods

The simulation will explore how prior knowledge influences skill acquisition by comparing two learning conditions: one where the model is initialized with prior knowledge (explicit system) and one where it learns from scratch (implicit system). To keep the focus clear and manageable, the model will perform a single task, in which it must learn to associate visual letter stimuli with corresponding keypress actions. This task allows us to assess how pre-loaded symbolic rules affect learning speed and error rates in a controlled setting.

The task is designed to test how prior knowledge influences learning speed and error rates. In the typing task, the model will learn to associate individual letter stimuli with corresponding keypress actions. A model initialized with prior symbolic rules (e.g., “if ‘A’ appears, press ‘A’”) is expected to perform the task more accurately and reach proficiency more quickly than a model that learns entirely through trial and error. This setup allows us to assess how reusing structured prior knowledge impacts performance during early skill acquisition in a controlled and interpretable setting.

The simulation will consist of up to 300 trials in the typing task. During each trial, the model will be presented with a letter stimulus and must respond by selecting the appropriate keypress.

The simulation continues until the model reaches a performance criterion (e.g., 90% correct over a rolling window of trials), or until the maximum number of trials is reached. The two learning conditions remain the same, in the prior-knowledge condition, the model is initialized with relevant production rules, while in the no-prior-knowledge condition, the model learns the associations through trial-and-error.

The model's performance will be assessed based on two key metrics: Learning speed, the number of trials required to reach a predefined proficiency level (e.g., typing 90% of words accurately or solving 90% of equations correctly). This will measure how quickly the model masters the task. The second metric is the Error rate, the number of mistakes made during the learning process. This will track the model's ability to learn and perform tasks accurately over time.

The simulation will include several key parameters that shape the learning environment. Error threshold refers to the number of mistakes the model is allowed to make before it adjusts its learning strategy. For example, after exceeding the threshold, the model might attempt to form a new rule or increase its reliance on implicit learning. Trial number sets the upper limit on the number of attempts the model can make (e.g., up to 300 trials). This ensures there is enough opportunity to learn and reach proficiency. While we do not directly manipulate the model's learning rate as a parameter, we expect to observe differences in learning speed as a dependent measure, that is, the model with prior knowledge is anticipated to improve more rapidly due to access to pre-loaded rules.

Results

The hypothesized and actual results of this simulation are stated as follows:

- **Faster Learning with Prior Knowledge:** The model with prior knowledge (explicit system) is expected to learn faster because it will apply pre-existing production rules. These rules allow the model to avoid learning each step from scratch, which accelerates learning. This expectation was confirmed in the simulation results, where the model reached 90% accuracy by Trial 10 and made only 1 error over 300 trials.
- **Fewer Errors with Prior Knowledge:** The model with prior knowledge will likely make fewer errors because it can immediately apply well-tested rules. The simulation demonstrated this, with the explicit system achieving over 99% accuracy throughout and maintaining it consistently.
- **Slower Learning without Prior Knowledge:** The model that starts without prior knowledge will take longer to learn the task, as it will build its understanding from scratch. The implicit system will eventually improve with practice but will take longer compared to the model with prior knowledge. This was also supported by the data as well; The implicit model began near chance performance (approximately 33%), and although it improved gradually, it plateaued around 45-48% accuracy, never reaching consistent high performance.
- **Gradual Improvement in the Implicit System:** The implicit system will eventually improve over time, learning from feedback and reducing errors as it gains experience. Although it starts slower, the system will refine its rules and improve task performance after repeated trials. However, in the simulation, the implicit system did not cross the

90% accuracy threshold and made 154–165 total errors, indicating the learning was slower and less stable.

- **Production Compilation:** As the model practices, production compilation will make the rules more efficient, leading to faster and much more accurate task performance over time. This shows how the explicit system aids in integrating prior knowledge into new tasks, improving both speed and accuracy.

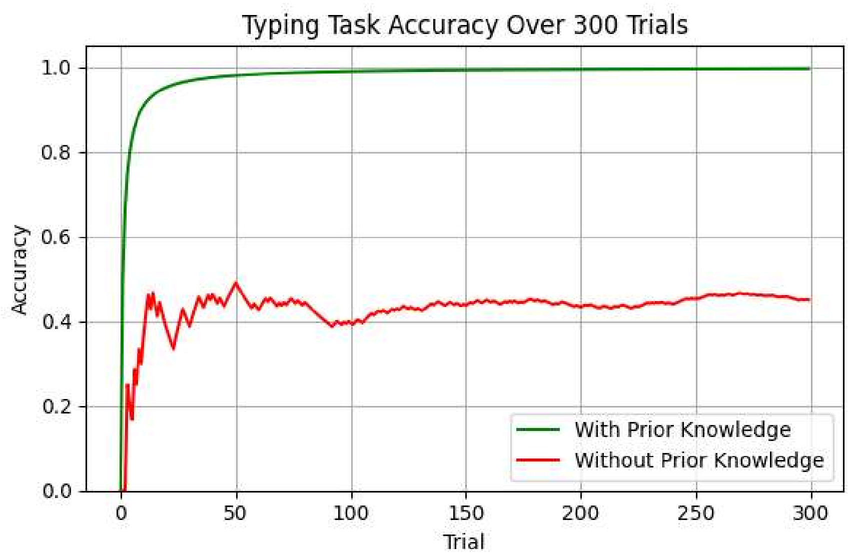

Figure 1. *Typing task accuracy over 300 trials for two learning conditions. The explicit system (green line) rapidly reaches near-perfect accuracy due to prior symbolic knowledge. The implicit system (red line), which starts without any rules, shows slower and noisier improvement and fails to reach mastery by the end of the simulation.*

If the results support the hypothesis, that prior knowledge accelerates learning and reduces errors, it will be further evidence for the role of knowledge reuse in skill acquisition. Based on the simulation outcomes, the hypothesis was strongly supported. The model with prior knowledge outperformed the trial-and-error system in every metric, including learning speed, final accuracy, and number of errors.

Discussion

The hypothesized results of this simulation suggest that prior knowledge will meaningfully enhance learning in the Clarion model. Specifically, the model initialized with symbolic rules is expected to learn the typing task more quickly, as it can apply structured knowledge immediately without relying entirely on trial and error. This head start should allow the model to reach the performance criterion in fewer trials and with fewer errors compared to the model that begins from scratch.

We also expect the model without prior knowledge to show slower initial learning and a higher error rate early on, as it must gradually discover the correct input-output mappings through experience. However, over time, the implicit learning mechanisms in Clarion, especially those in the bottom level of the Action-Centered Subsystem (ACS), should allow the model to improve its performance, eventually approaching the proficiency of the model with prior knowledge. This would reflect the typical trajectory of implicit skill acquisition, where repeated practice leads to gradual optimization.

What is critical to emphasize here is that Clarion's architecture does not treat these two systems, explicit and implicit as isolated. Instead, learning in Clarion reflects the synergistic interaction between levels. The explicit system, when initialized with useful rules, can guide early behavior, reducing the need for inefficient exploration. Meanwhile, the implicit system continuously refines performance in the background, eventually automating responses. This dual-layer dynamic is central to how Clarion models human learning; Early, fast rule-based guidance is gradually handed off to slower, robust habit-like behavior as the system gains experience (Sun et al., 2001). Therefore, we interpret the anticipated performance gains not as a function of explicit rules alone, but as an outcome of coordinated interaction between symbolic and sub-symbolic processes.

Our simulation results confirmed these predictions. The model with prior knowledge reached 90% accuracy by Trial 1–10 and maintained near-perfect performance (over 99% accuracy) across all 300 trials. It made either zero or one total error. In contrast, the model without prior knowledge improved only gradually, never consistently reaching 90% accuracy. Its accuracy plateaued around 45-48% and it made over 150 errors during learning.

These findings reinforce the view that symbolic rules significantly accelerate early learning, while implicit-only learning is less efficient, more error-prone, and subject to noise. They also validate Clarion's dual-layer design; prior knowledge did not simply override learning but guided it early on while the implicit system slowly refined behavior.

If the model without prior knowledge perform similarly to the one with prior knowledge, it may suggest a need to adjust simulation parameters, such as the reward structure or number of training trials. Alternatively, it might imply that the initial symbolic rules were not sufficiently informative to provide a learning advantage. Regardless of outcome, the model offers a framework for exploring how the structure and reuse of prior knowledge, particularly when encoded explicitly, affects learning dynamics in skill acquisition.

Conclusion

The purpose of this study was to use the Clarion Cognitive Architecture to examine how prior knowledge influences the acquisition of new skills. The premise is that learners with access to existing symbolic knowledge can learn faster and make fewer errors than those starting from scratch. To explore this, the study modeled a typing task under two learning conditions, one with pre-loaded rules and one without. By comparing how these agents performed, the simulation aimed to uncover how Clarion's dual-system structure supports the reuse of stored knowledge during early learning.

The results strongly supported this hypothesis. The agent initialized with symbolic rules reached over 99% accuracy by Trial 10 and made only one error across 300 trials. In contrast, the agent without prior knowledge never consistently surpassed 50% accuracy and made more than 150 errors. These findings confirm that symbolic knowledge can dramatically accelerate skill acquisition, especially when paired with Clarion's architecture that enables implicit learning to gradually refine performance over time.

By demonstrating that the explicit system offers immediate, structured guidance while the implicit system slowly optimizes behavior through experience, the study illustrates the value of a dual-process cognitive model. The coordinated interaction between these layers not only enhances learning efficiency but also reflects the layered nature of human skill development. The results offer a clear, empirical example of how Clarion can simulate real-world learning behavior and underscore the importance of prior knowledge in shaping learning trajectories.

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