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Supraarchitectural Capability Integration: From Soar to Sigma

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Abstract

Integration across capabilities, both architectural and supraarchitectural, is critical for cognitive architectures. Here we revisit a classic failure of supraarchitectural capability integration in Soar, involving *data chunking*, to understand better both its source and how it and related integration issues can be overcome via three general extensions in Sigma.

Keywords: Cognitive architecture; integration; declarative learning; Soar; Sigma.

Many of the most important early results from Soar concerned how integration across a small general set of architectural mechanisms, plus appropriate knowledge above the architecture, could yield a wide variety of problem solving and learning capabilities (Laird, Newell & Rosenbloom, 1987). Because these capabilities all intrinsically involved forms of knowledge above the architecture, in addition to mechanisms within the architecture, they are on the whole most appropriately considered *supraarchitectural*; i.e., above the architecture.

Some supraarchitectural capabilities, such as lookahead search across metalevels, became part of the toolkit available for routine use in more comprehensive systems – in this case via a set of default rules that were loaded whenever Soar was initialized and usable whenever a tie occurred among operators proposed for selection. However, others of these capabilities – such as declarative learning via what came to be called *data chunking* (Rosenbloom, Newell & Laird, 1991) – proved impossible to deploy routinely in combination with other capabilities, and thus never amounted to more than standalone demonstrations.

Such failures in *supraarchitectural capability integration* loomed over Soar for years as one of its most significant flaws. In the case of declarative learning, the inability to integrate it routinely with other capabilities was ultimately accepted as a fundamental limitation in Soar, triggering a dramatic shift to an approach in which new declarative memory and learning modules were implemented in Soar 9 for routine use in conjunction with other capabilities (Laird, 2012). This move then helped trigger an even broader shift in Soar from its early emphasis on uniformity to its more diverse present state, while also aligning it more closely with ACT-R's long-term approach (Anderson *et al*., 2004).

Sigma (Rosenbloom, 2013) is a more recent architecture that is based on combining what has been learned from over three decades of separate work in cognitive architectures – Soar in particular – and graphical models (Koller & Friedman, 2009). One of the three key desiderata driving the development of Sigma – *functional elegance* – is a reformulation of Soar's earlier notion of uniformity. Sigma maintains many of the high level concepts from Soar, yet it has revealed an ability both to embody a wider variety of supraarchitectural capabilities and to integrate them together routinely. Here we analyze what has enabled Sigma to overcome this earlier fundamental limitation in Soar.

The key to integration of supraarchitectural capabilities is to fit them naturally within the system's overall processing and control structure, which for both Soar and Sigma can range from reactive to deliberative to reflective. Reactive processing can be thought of as parallel, memory driven, automatized, or System 1. It may include basic forms of perception, memory access, reasoning and decisions, but it is limited to what can be accomplished within a single cognitive cycle; i.e., ~50 msec in people. Deliberative processing can be thought of as algorithmic, knowledge intensive, or controlled. It comprises routine sequential behavior based on sufficient expertise to always know what to do. Reflective processing deals with situations that are problematic – yielding impasses and metalevels – and can be thought of as search driven or System 2.

Both of the supraarchitectural capabilities mentioned earlier – lookahead search and data chunking – are implemented reflectively in Soar; that is, an impasse must occur that halts normal processing before the metalevel processing necessary for the capabilities can proceed. In the former case, hypothetical reasoning about the future occurs, as necessary, across metalevels. In the latter case, declarative knowledge structures must be explicitly assembled within a metalevel in order for chunking – Soar's sole learning mechanism at the time – to learn new rules from them. Although chunking can occur each decision, it is an inherently reflective learning mechanism because it learns from traces of rules that fire in metalevels.

Reflective integration is unproblematic for lookahead search because an impasse has already brought normal processing to a halt. However, normal processing could continue in the absence of data chunking, and an artificially induced impasse is in fact required to enable it. Thus, reflective integration is natural in the former case, but both artificial and intrusive in the latter case, where reflection is in service of learning for the future rather than solving the current problem. This is not to say that deliberate reflective learning can't be appropriate or natural, as in after-action review or post-problem metacognition, or that reflective learning can't occur naturally as a side effect of metalevel problem solving – as with chunking – but it can be inappropriate and intrusive when pursued deliberately during task performance.

Yet, declarative learning – both semantic and episodic – must be able to occur continually on a routine basis. Since data chunking could not achieve this, and Soar's formulation of supraarchitectural reactivity – in terms of parallel knowledge access (i.e., rule firing) until quiescence, followed by a decision – could support no other approaches, distinct semantic and episodic memories and learning mechanisms were added in the Soar 9 architecture to enable declarative learning to proceed reactively and in parallel.

Sigma, in contrast, succeeds because of three general extensions to the reactive level. The first extension is to support a more general form of knowledge structure – one that is *hybrid* (discrete + continuous) and *mixed* (symbolic + probabilistic) – and thus also a more general form of reactive reasoning. This enables Sigma not only to perform symbolic reasoning in parallel – as was supported by Soar's parallel rule system – but also probabilistic reasoning and signal processing. Data chunking was a purely symbolic approach to declarative memory, but declarative memory in Soar 9, and in ACT-R before it (Anderson *et al*., 2004), has a strong activation-based subsymbolic component. This aspect is provided in Sigma's supraarchitectural declarative memories via reactive probabilistic reasoning.

The second extension is that, instead of only making decisions about which action to perform next, Sigma can in parallel make decisions about any of the values in working memory. This enables not only reactive retrieval of distributions from declarative memory, but also reactive selection of the best choices from these distributions. In Sigma, declarative retrieval is thus inherently reactive, with deliberative retrieval arising only as necessary (through explicit manipulation of cues across decisions). Declarative retrieval in Soar has traditionally been deliberative, even in Soar 9, although a more reactive mode has recently been introduced (Li & Laird, 2015).

The third extension is the inclusion of a reactive learning mechanism based on *gradient descent* that updates parameters everywhere in long-term memory once per cognitive cycle (Rosenbloom, Demski, Han & Ustun, 2013). Instead of embodying one general reflective learning mechanism, as in the early days of Soar, or this plus multiple memory-specific reactive learning mechanisms, as in Soar 9, Sigma supports a single general reactive learning mechanism. This is adequate for learning not only the contents of semantic and episodic memory (Rosenbloom, 2014), but it can also acquire: *Q* functions in reinforcement learning; models of actions that are experienced; maps (as part of SLAM); and perceptual and transition functions in speech recognition (Joshi, Rosenbloom & Ustun, 2014). Moreover, because it operates in parallel over all parameters in Sigma's long-term memory, multiple reactive supraarchitectural learning capabilities can proceed without interference with each other or with other capabilities.

These three extensions together enable a full reactive path from perception through memory access, reasoning, decisions and learning (and, hopefully, ultimately affect and motor control as well). In the process they yield a major expansion of what can occur in general via parallel reactive processing, in moving from Soar to Sigma, and thus which reactive supraarchitectural capabilities can be implemented and integrated together in a routine manner. Declarative – semantic and episodic – memory and learning provide compelling examples, but so do perceptual memory and learning – as in speech recognition and parameter learning – and imagery (e.g., mental map) memory and learning.

None of this implies that Sigma will not eventually need additional learning mechanisms – such as for acquiring new types of memory structures rather than just new instances of existing types – but it does imply that a suitably general reactive cycle can support much broader supraarchitectural capability integration than was previously thought.

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