CHAPTER 25

Beyond Generalization as Search: Towards a Unified Framework for the Acquisition of New Knowledge

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In what has become a landmark article in machine learning, Mitchell showed how generalization – that is, empirical concept formation from multiple examples – could be cast as a search problem, and how a wide range of generalization algorithms could then be described quite simply as search strategies [9]. In this position paper I will attempt to expand on this insight in two distinct ways. The first way is to enlarge the focus from generalization to the principle context within which generalization occurs – the acquisition of new knowledge. The second way is to incorporate explanation-based learning [11, 1] and rote learning into the framework. In another very important sense though, the focus of this article will be considerably smaller than was Mitchell's. Instead of developing a framework within which to fit all of the current work, the analysis will be limited to describing how to fit in some version of each of the major capabilities.

The development of this framework comes out of an attempt to generalize the lessons from research on chunking as a general learning mechanism [5, 6, 15], with a particular emphasis on recent research on knowledge-level learning in Soar [13, 14]. As such, it captures the current point in an evolving understanding of machine learning. This understanding, as well as this paper, is structured around a sequence of five hypotheses, starting with relatively straightforward claims about chunking and building up to the more general claims about learning.

1. *Chunking-functionality hypothesis:* Chunking performs lesson extraction and storage designation.
2. *Chunking-sufficiency hypothesis:* Chunking is a sufficient storage designation mechanism.
3. *Knowledge-reconstruction hypothesis:* Acquisition of new knowledge requires the reconstruction of a copy of the new knowledge, starting from what is already known.
4. *Integrated-learning hypothesis:* Rote learning, empirical generalization, and explanation-based learning arise as variations in the knowledge-reconstruction process.
5. *Knowledge-acquisition hypothesis:* Knowledge acquisition consists of search, lesson extraction, and storage.

[1]I would like to thank Andrew Golding, Haym Hirsh, and Allen Newell for helpful comments on an earlier draft of this paper.

The chunking-functionality hypothesis is based on the workings of the Soar architecture [3, 4] and its learning mechanism, chunking. In Soar, performance is based on search in problem spaces. Chunking creates and stores productions which summarize search episodes. The actions of a chunk production are based on the results of the search. The conditions are based on the supporting information upon which the results depended. The resulting production can directly generate the results from the supporting information. Once the production is created, it is passed to the production compiler for integration into the long-term production memory. The chunking-functionality hypothesis follows fairly closely from this description. Lesson extraction occurs through the determination of the search's results and the results' supporting information. Storage designation – that is, the designation of what material is to be stored – is performed by passing the resulting production to the production compiler.

The chunking-sufficiency hypothesis is a reformulation of the uniform-learning hypothesis, that goal-based chunking is the general learning mechanism (the knowledge-acquisition hypothesis is also a reformulation of this earlier hypothesis) [4]. This earlier hypothesis turned out to be controversial for a number of reasons, including such basic issues as the definition of what is and is not a learning mechanism. The reformulation focuses on the less controversial subissue as to whether any additional architectural mechanisms beyond chunking are required to deal with all of the situations in which information needs to be stored. There are three versions of this hypothesis, of varying strengths. The weak version says that chunking is sufficient, but leaves open whether other mechanisms are also sufficient. The moderate version is identical to the weak version except that it also claims that chunking will turn out to be the "right" sufficient mechanism, in that it will be the one that will fit best within a complete architecture for intelligence. The strong version claims that chunking is the only sufficient mechanism. I will not defend the strong version here; in fact, I find it very unlikely to be true. The weak version is supported, but not proved, by the range of learning behaviors that have been successfully demonstrated in Soar [15]. The moderate version – which will be assumed in the remainder of this paper – requires, in addition to the support for the weak version, a longer-term validation involving comparisons between chunking and other sufficient mechanisms.

Acceptance of both the chunking-functionality hypothesis and the moderate chunking-sufficiency hypothesis implies that the acquisition of new knowledge must involve some form of problem-space search; otherwise, chunking could not be used for storage designation. The knowledge-reconstruction hypothesis places a constraint on what this search does. The first part of the hypothesis says that the search must result in a copy of the new knowledge being created. When chunking is applied to this reconstruction process, a production is learned which can generate the new knowledge in future situations. The second part of the hypothesis says that the reconstruction must be based on existing knowledge, not on the knowledge to be learned. This is necessary to insure that the generation of the new knowledge does not depend on itself; or equivalently, so that the conditions of the new production do not include essentially circular tests for the new knowledge.

The knowledge-reconstruction hypothesis leaves open how the new knowledge is actually reconstructed. One possibility is for it to be derived via a chain of inferences from existing knowledge. For example, the fact that Fido is a mammal can be reconstructed by chaining if the system already knows that Fido is a dog, that dogs are mammals, and that "isa" is transitive. Another possibility is for the new knowledge to be reconstructed by assembling together a set of existing subcomponents. For example, if the system knew the symbols for "Fido", "isa" and "mammal", these pieces could be assembled into a new structure which represents the fact that Fido is a mammal.

The knowledge-reconstruction hypothesis is based on research demonstrating that such an approach can lead to the acquisition of new knowledge in Soar [13, 14][2] – at least if it uses the assembly method – and on a dearth of alternative ways of achieving the same end within the constraints of the first two hypotheses.

The integrated-learning hypothesis states that rote learning, empirical generalization, and explanation-based learning arise as variations in the knowledge reconstruction process. Rote learning can arise when the new knowledge is reconstructed verbatim by the assembly method, as was demonstrated in [13]. Empirical generalization can also arise by the assembly method if: (1) related existing knowledge is retrieved during the reconstruction process, and (2) inductive biases are added to the reconstruction space to specify how the related existing knowledge should lead to the (re)construction of knowledge structures that are different from – that is, generalizations of – the new knowledge that was originally presented. In work in progress, we do have a demonstration of Soar generalizing from multiple examples, but it is not yet completely solid. Explanation-based learning can arise when the new knowledge is reconstructed by chaining from existing knowledge.[3] This has not yet been demonstrated in Soar in the context of acquiring new knowledge, but explanation-based learning has been demonstrated in Soar in other contexts [12].

One of the key ways in which the integrated-learning hypothesis differs from the standard view of generalization as search is that the reconstruction search space is not the same as the conventional hypothesis search space. Instead, the relationship between them is that of a solution space (the hypothesis space) embedded within a problem space (the reconstruction space). A solution space contains only candidate solutions, while a problem space can contain additional states which are not candidates, such as incompletely assembled facts and other ill-formed structures. The use of a problem space rather than a solution space provides a critical source of flexibility in the types of searches that can be performed.

This approach at a synthesis also differs from other attempts at merging empirical generalization and explanation-based learning, such as [2, 7, 10]. The current approach focuses on the low-level issue of how the different methods can arise from the same underlying substrate rather than on the higher-level issues of when to use the different methods and of how results from one are useful for the others. However, if the assembly and chaining approaches to reconstruction can be merged into a single reconstruction problem space – opening up the possibility of intermingling the different learning techniques at a fine

[2]The knowledge-reconstruction hypothesis neglects one crucial but complicating aspect of the work described in these two articles, the acquisition of recognition rules. A more complete rendition of this framework must eventually incorporate this aspect as well.

[3]An interesting variation is to fragment the new knowledge into subparts and to base the reconstruction of some of the subparts on chaining from other subparts. This should yield something like the verification-based learning used in work on learning apprentices [8].

level of granularity – it may be possible to address the higher-level integration issues within this framework as well.

As so far described, there is still one major glitch in the integrated-learning hypothesis. Explanation-based learning involves more than just creating a chain of inferences – it also requires the extraction of an explanation from the chain of inferences and the generalization of the explanation. The knowledge-acquisition hypothesis removes this glitch by claiming that knowledge acquisition involves not only search, but also lesson extraction – extraction and generalization of the explanation – and storage. Storage is not something that is explicitly mentioned in work on explanation-based learning, but is clearly necessary if the new knowledge is to have a lasting effect on the system.

Though the knowledge-acquisition hypothesis solves this particular problem, it also introduces another potential problem. Do rote learning and empirical generalization also involve lesson extraction and storage? These are not explicit parts of most generalization algorithms, but the answer should still be yes. Processing cannot just stop with the end of the search. The result of the search must be determined, along with its supporting information (if any), and then stored away for future use. What really distinguishes empirical generalization and explanation-based learning is not that they use different underlying mechanisms, or that one is inductive and the other is deductive, or even that one is based on multiple examples and the other is based on a single example. Instead it is because one gets its interesting generalization from the search process while the other gets its interesting generalization from the lesson extraction process. When viewed this way, there is also potentially a spectrum of points in between the two extremes.

As mentioned earlier, the knowledge-acquisition hypothesis is a second reformulation of the uniform-learning hypothesis. Unlike the chunking-sufficiency hypothesis, this reformulation retains the grand scope of the original hypothesis, attempting to cover all of knowledge acquisition. To return to Soar-specific terms for a moment, rather than focusing on one architectural mechanism – chunking – this hypothesis attempts to cover the whole path from search to storage: reconstruction (search), chunking (lesson extraction and storage designation), and the production compiler (storage). Even so, this analysis is still almost certainly incomplete. For one thing, an input mechanism is clearly required. For another thing, there may need to be processes which index new knowledge before it is stored so that it can be retrieved when useful but remains in the background when not.

This completes the sequence of five hypotheses with which we started, and this attempt at pointing the way towards a unified framework for the acquisition of new knowledge. The next step is to do better.

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CHAPTER 26

Meta-Levels in Soar

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Soar is an attempt to build an architecture capable of supporting general intelligence. In this article we present an analysis of Soar in terms of the concept of meta-level architecture. In the process, we provide a definition of what it means for something to be a meta-level architecture, and describe how Soar can be viewed as consisting of an infinite tower of meta-level architectures. Each of Soar's meta-level architectures is itself a complex structure that is constructed out of three types of processors: problem-space processors, production processors, and preference processors. In addition to the meta-level architectures themselves, Soar contains a learning mechanism which can modify some aspects of the meta-level architectures.

1. INTRODUCTION

The Soar architecture [1, 2, 3] grew out of an attempt to integrate a set of ideas about what should be included in an architecture for general intelligence. Such an architecture should provide the basis for a system that can work on a wide variety of tasks, employ a wide variety of problem solving methods, and improve its own performance via learning. Some demonstrations of the generality and power of the Soar architecture can be found in [1, 3, 4, 5].

The ideas that went into the design of the Soar architecture included such things as search in problem spaces [6], subgoals, production systems [7, 8], and learning by chunking [9], but did not at that time include the concepts of meta-level architecture [10], introspection [11, 12], or reflection [13]. However, as we now analyze Soar, several aspects of it bear a close resemblance to ideas being investigated in the area of meta-level architecture. In this article, we describe the relationship between Soar and the concept of meta-level architecture. In the process we hope to increase our understanding of both the structure of Soar and the space of meta-level architectures.

In the following sections we specify what we mean by the term "meta-level architecture", give an overview of the Soar architecture (in non-meta-level terms), describe the meta-level architecture embodied by Soar, and conclude.

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