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The Central Role of Cognition in Learning

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Abstract

In this essay, I review the early history of artificial intelligence and cognitive psychology, including reasons for their initial deprecation of learning. This topic has received increasing attention since the 1980s, but, unfortunately, most current research makes little contact with results on cognition, having stronger links to pattern recognition and behaviorism. I argue that these approaches ignore the most interesting aspects of knowledge acquisition, organizing my points around distinctive features of the cognitive systems movement. In closing, I reiterate the need to study both cognition and learning, not in isolation but as interacting elements within integrated intelligent systems.

1. Historical Retrospective

In 1981, Herbert Simon and I co-authored a book chapter that was titled *The Central Role of Learning in Cognition*. In this essay, I argue for the converse position: that cognition plays a central role in learning. To provide context, I must explain briefly why we wrote that essay and why recent trends in artificial intelligence and cognitive science call for a similar piece that inverts many of the points we presented then. This requires, in turn, that I review two interconnected threads of historical events in these related fields.

By 1960, the behaviorist paradigm had dominated American psychology for almost two decades. Research in this tradition focused strongly on learning for sensori-motor tasks, with typical experiments conditioning rats to press levers or training pigeons to peck buttons. Moreover, behaviorists rejected any use of mental structures or processes as theoretical constructs; scientists were to focus only on observed behavior and to eschew internal elements as unnecessary baggage. It is difficult to overstate the influence this movement had on research during this period, not only on what psychologists examined but on what they explicitly ignored.

In contrast, the 'cognitive revolution' of the late 1950s – which Miller (2003) recounts as a counterrevolution against behaviorism – redirected attention to higher-level abilities for reasoning, problem solving, and language. Researchers who aligned themselves with this new movement concentrated their studies on human behavior rather than that of rats and pigeons, and they hypothesized internal structures and processes that could be modeled on the digital computers then emerging. For understandable reasons, these cognitive psychologists initially downplayed the role of learning and instead emphasized human performance on complex tasks. Initially this focused on general, domain-independent abilities, but by the 1970s the field had come to devote much of its energies to the study of knowledge and expertise.

The rise of cognitive psychology occurred at the same time as the launch of artificial intelligence. As I have explained elsewhere (Langley, 2012a), this was not an accident. Two of the field's founders, Allen Newell and Herbert Simon, viewed themselves as computational psychologists who were using computers to model human thinking. This offered a way to make theories of the mind both precise and testable, and thus to counter the behaviorist argument that discussions about internal structures and mechanisms were unscientific. Along the way, they developed the first implemented AI system – the Logic Theorist – whose design was directly influenced by their studies of human problem solving (Newell, Shaw, & Simon, 1958).

As evidenced by the edited volume *Computers and Thought* (Feigenbaum & Feldman, 1963), early AI was also closely associated with work on pattern recognition. Researchers in both areas adopted the computational metaphor and implemented running systems on digital computers. However, by 1970 the two movements had diverged. Pattern recognition focused on techniques for perceptual processing, with typical tasks being object classification in images and word recognition in speech. Most systems incorporated numeric representations and relied on statistical learning to induce classifiers from training examples. In contrast, AI emphasized central cognitive processing for high-level tasks like reasoning, problem solving, and language understanding. These systems typically adopted symbolic notations and learning became at most a minor player.

Nevertheless, by the late 1970s, some researchers in both cognitive psychology and AI had recognized that theories of cognition and intelligence were necessarily incomplete without an account of learning. Research on concept attainment (Winston, 1975; Mitchell, 1982), grammar acquisition (Anderson, 1977; Berwick, 1979), and strategy learning (Anzai & Simon, 1978; Langley, 1983) explored this idea using formalisms and mechanisms developed in models of human cognition and AI. When machine learning declared itself as a field at the 1980 Carnegie Mellon workshop, it viewed itself primarily as an offshoot of symbolic AI and cognitive psychology that was focused on the acquisition of expertise. However, the community also saw itself as a splinter group that felt learning deserved more attention than it had received from either of its parent disciplines.

This was the intellectual setting in which Simon and I wrote our 1981 chapter. At the time, it seemed worthwhile to organize and present arguments that learning had a central role to play in the study of cognition, both human and machine. We noted that, despite the great variations observed in human behavior, invariants might still exist and learning mechanisms were natural suspects. We discussed desirable features of explanations that incorporated acquisition processes, aspects of cognition that are known to improve with experience, and candidates for general principles of learning. We made frequent reference to adaptive production systems, a framework that researchers were exploring actively and that offered new ways to approach these issues.

The chapter was timely, appearing in a book titled *Learning and Cognition* that John Anderson (1981) edited in conjunction with the annual Carnegie Symposium on Cognition. Since then, the computational study of learning has received ever increasing attention and, indeed, it has come to be widely viewed as the most important topic in AI and cognitive science. But we never imagined that so many researchers would retreat – as I have discussed in another essay (Langley, 2011) – to the tenets of behaviorism, associationism, and pattern recognition, or forget how much learning revolves around cognitive representations and mechanisms.

This essay aims to remind readers that the key insights of AI and the cognitive revolution are highly relevant to the computational study of learning. For this reason, I have organized it around five themes of cognitive systems research that I have discussed elsewhere (Langley, 2012b). In each section, I introduce one of the themes, present claims that it suggests about the nature of learning, and provide supporting examples. In closing, I consider the implications of these statements for the research agenda in cognitive systems. Each claim revolves around ways that high-level cognition interacts with learning, but they do not dismiss the reality of other noncognitive forms. Like rats and pigeons, people improve their ability to recognize objects and exhibit conditioned responses, yet this appears to happen in an unconscious way that bears little relation to intelligent behavior. They seem far less interesting forms of learning than ones that interact with the mental structures and processes that make us distinctively human.

2. Learning and High-Level Cognition

One important feature of cognitive systems research lies in its focus on high-level behaviors that underlie what we commonly refer to as *intelligence*. This includes a number of distinctive abilities:

- *multi-step reasoning*, which draws inferences about a given situation from available facts;
- *planning*, which generates possible courses of action that will achieve an agent's goals;
- *design*, which formulates new structures from components that satisfy given criteria; and
- *language use*, which lets agents communicate beliefs, goals, and intentions to each other.

Taken together, these and related high-level cognitive activities separate humans from other mammals.[1] They endow us with an intellectual prowess that is useful across a broad range of settings, letting us pursue mathematics, art, and science, engage in complex and extended goal-oriented activities, and coordinate with our fellows to achieve shared aims.

With these observations about the nature of intelligence as background, I can return to the essay's main topic and state its first claim:

- *Learning occurs in the context of high-level cognition.*

Of course, humans benefit from low-level learning of the type studied by the behaviorists, for which research on inducing classifiers for pattern recognition and reactive controllers for execution is quite relevant. But improvement also occurs on tasks that require high-level mental processing, and these appear to involve very different structures and processes – for both performance and learning – than the ones that we share with rats and pigeons.

For example, natural language relies on syntactic, semantic, and pragmatic knowledge structures, as well as mechanisms that operate over each type of content. Language understanding involves the incremental construction of meaning from sentences and previous context, whereas language generation operates in the opposite direction, translating intended meaning and context into sentences. Language acquisition is responsible for mastering these abilities. In humans, this clearly involves lower-level processes for learning to recognize words and specific turns of phrase, but it also depends centrally on the acquisition of new grammatical structures, semantic descriptions, and pragmatic constraints. Similar arguments hold for the less well-studied topics of learning in reasoning, planning, design, and other facets of high-level cognitive processing.

1. Although some other species exhibit limited versions of plan generation, artifact design, and even language use, we observe their fully expressed forms only in *Homo Sapiens.*

There is no question that learning occurs in each of these arenas or that it accounts for the gradual shift from novice behavior, which is often halting and characterized by search, to expert performance, which is typically rapid and guided by knowledge. Our understanding of high-level cognition will be incomplete until we account for the improvement of these abilities with increasing experience. Again, the existence and importance of learning on high-level tasks does not mean that lower-level forms do not occur, but the former should be a primary concern for cognitive systems research, while the latter are mainly distractions from its agenda.

3. Learning and Cognitive Structures

A second key feature of the cognitive systems paradigm lies in its emphasis on the representation and use of rich mental structures. For example, reasoning mechanisms typically generate proof trees that specify how one can derive a conclusion from given elements through a series of inference steps. Similarly, planning methods produce chains of actions that, if carried out, would transform initial states into ones that achieve specified goals. And language understanding transforms one or more sentences into a representation of their meaning, including implied elements that were left unsaid. These processes use formalisms like logic, production rules, and frames as the building blocks for composing these interconnected structures.

As already noted, knowledge can aid performance in every area of high-level cognition, but early efforts to introduce this knowledge manually raised practical issues. They also failed to address questions about where such knowledge originated. This leads to our second claim:

- *Learning involves the creation of new cognitive structures*.

This is a familiar idea in the educational community, which views teaching as the communication of knowledge and which assumes students acquire mental structures that they can use in the future. This is reflected in textbooks' attempts to state explicit principles that underlie topics in mathematics, science, and engineering, along with clear procedures for solving problems in each area. Different fields adopt distinct principles and methods, with the stability of chemical compounds following different rules from those for structural loads on bridges, but they can both be stated in formal terms that involve relations among interacting elements.

Moreover, people seldom acquire such knowledge entirely from scratch, whether in the context of classroom instruction or based on their own initiative. This suggests a third postulate:

- *Learning builds on existing cognitive structures*.

In other words, human learning is *cumulative* in that it takes advantage of existing knowledge and extends it. This contrasts drastically with the popular view that learning is primarily about finding regularities in large data sets in the absence of background knowledge. Both humans and synthetic cognitive systems exist over time, so later learning can and should take advantage of structures that have been acquired from earlier experiences.

The notion of cumulative acquisition is far more constraining than the one of *incremental* learning, although the latter also differs from the batch approaches that are popular currently. An incremental system updates its mental content after each training case or experience, but this may involve only statistical updates, as in the naive Bayesian classifier or reinforcement learning. Cumulative learning is incremental, but each training case can lead to new cognitive structures that become available for processing later experiences. This underlies an important form of *transfer*, in which learning on an earlier task enables more rapid or effective learning on a later one.

Examples of this cumulative form of transfer arise in many different contexts. For instance, we learn to solve algebra problems only after we become able to handle basic arithmetic, and we learn to solve physics problems only after we have mastered algebra. In each case, acquiring new cognitive skills depends on the presence in memory of structures that encode component abilities. Textbooks assume such dependencies in the way they order educational content for presentation, with more basic materials preceding topics that rely on them.

Similarly, people acquire language skills in stages. They start by learning to comprehend and produce individual words, which they must master before they can acquire the ability to compose them into sentences. This capacity in turn is necessary before they can communicate complex relationships and chains of reasoning to others. Many studies of child language acquisition attest to its gradual, incremental, and cumulative nature (e.g., Brown, 1973). But high-level structures can also aid the acquisition of low-level ones, as when we use knowledge about syntactic structure to infer the meanings of new words from their surrounding context. Previously learned cognitive structures provide important scaffolding for the acquisition of language.

The cumulative character of learning holds even in the arena of complex motor skills. We must first acquire the ability to grasp a baseball before we can master throwing it, and we must learn to throw, catch, and run before we can contribute to an infield play. We cannot drive a car to the office until we have first learned to follow traffic lights and signs, and these depend on more basic skills for accelerating, decelerating, turning, and changing lanes. This does not mean that such tasks involve no parametric learning; such numeric updates appear to happen when people practice a new skill after they have acquired its basic form. But this only takes place once they have created such structures, which happens rapidly because learning composes them from established units.

In summary, many types of learning involve both the generation of rich cognitive structures and the utilization of existing mental elements to support the process, with content acquired earlier providing the scaffolding for later acquisition. The great majority of learning in humans is structural and cumulative, and we have every reason to believe that our cognitive artifacts will need to acquire knowledge and expertise in the same manner.

4. Embedded Learning in Cognitive Systems

A third important feature of our paradigm is its emphasis on the study of system-level artifacts. These incorporate a number of processing elements that interact in synergistic ways to demonstrate behavior that none could produce in isolation. Although this approach was common among early AI researchers, who often developed composite systems, it contrasts markedly with the field's current operating procedure, which nearly always studies component algorithms apart from their potential roles in integrated intelligent agents.

The system-level approach both offers opportunities for learning and places requirements on its operation. These lead directly to another claim:

- *Learning operates over the traces of high-level cognition.*

In a limited sense, some incremental methods for concept learning incorporate this idea. Fisher's (1987) COBWEB used categorization of new training cases to alter the structure of its conceptual hierarchy, and even the perceptron algorithm used classification errors to drive revision of numeric parameters. However, traces of higher-level cognitive processes offer richer types of trace information to drive more sophisticated forms of learning. For example, some cognitive architectures, including Soar (Laird, 2012) and PRODIGY (Carbonell, Knoblock, & Minton, 1990) use traces of success and failure during search to acquire control rules that guide future problem solving. Similarly, O'Rorke (1989) describes a variation on the early Logic Theorist that analyzes its own successful reasoning to improve efficiency at generating proofs. More recently, Winkler, Tenorth, Bozcuoglu, and Beetz (2014) have presented an episodic memory for physical activities that can store and retrieve rich traces to drive robot learning.

Moreover, the cognitive systems paradigm's assumption that intelligent behavior results from synergistic interactions among processing components offers other ways to close the loop between performance and learning. This in turn suggests a fifth claim:

- *Cognitive processes can utilize knowledge learned from traces of other processes.*

For instance, another cognitive architecture, ICARUS (Li, Stracuzzi, & Langley, 2012), uses traces from successful problem solving to learn hierarchical skills, which its execution module then uses for reactive control. The framework also uses these traces to acquire new conceptual predicates, which a separate mechanism then uses to draw relational inferences. Recent work on learning from instruction and demonstration (Hinrichs & Forbus, 2014; Kirk & Laird, 2014) shows how a learner can combine traces from multiple sources to acquire complex game-playing skills.

To recapitulate, our community's focus on system-level artifacts has clear implications for the study of learning. In particular, many processes for acquiring new knowledge rely on inspection of traces generated by high-level cognitive mechanisms, which provide the training experiences to drive improvement. In addition, the resulting structures need not be used by the same module that produced the traces; other elements can use them to increase their own effectiveness. In other words, learning mechanisms are best viewed as additional components that interact with other elements in an integrated cognitive system.

5. Learning in Humans and Machines

Another primary characteristic of cognitive systems research is its incorporation of ideas from psychology. Human behavior offers many hints about structures and processes that produce intelligence, and it makes sense to take advantage of these insights when devising cognitive artifacts. Naturally, this includes not only mechanisms for carrying out high-level cognitive tasks, but also techniques for improving their performance through learning.

I have already touched on some of these notions, such as the incremental and cumulative nature of acquisition, in earlier sections. But perhaps the most important feature of human learning lies in its diversity, which leads directly to another claim:

- *Humans learn from many different sources of information and in many different ways.*

Unlike most statistical learning systems, people are not one-trick ponies. For example, we can acquire new skills by observing another person's activities, although this typically involves more than simple imitation. Creating general skills means inferring the role model's goals, which means that learning depends on cognitive analysis. But, as discussed previously, we can also learn from our own problem solving by examining traces of decisions that led to desirable and undesirable outcomes, as demonstrated by work on PRODIGY (Carbonell et al., 1990), Soar (Laird, 2012), and other systems that acquire knowledge to guide search.

Moreover, once we have determined and stored the basic structure of a skill, by whatever means, we can improve its execution through repeated practice, which in turn allows more rapid and accurate performance. This variety of learning is most obvious in skills for physical activities, like playing golf or driving a car, and Iba (1991) reports one approach to acquiring complex motor skills by observing sample traces and then improving their execution through practice. But it can also arise in more abstract settings, including social ones, where we infer the general rules of conversation by watching others interact but must still engage in similar dialogues ourselves, sometimes making errors, before we become truly proficient.

Of course, people can also acquire knowledge and expertise from formal instruction. We learn procedures in arithmetic, algebra, and physics from worked out solutions to problems, as modeled by VanLehn and Jones (1993), but this is similar to observational settings. More explicit transfer of content occurs during reading of educational material, including textbooks that describe not only procedures, but also principles that underlie them, as Barbella and Forbus (2011) describe in their work on this topic. We can also learn new capabilities through interactive forms of instruction, an approach to knowledge acquisition on which both Kirk and Laird (2014) and Hinrichs and Forbus (2014) have made recent progress. Research during the 1980s and 1990s reflected this variety, with the 'multistrategy learning' movement (Michalski, 1993) making it an explicit target. Our field should continue work in this important tradition.

The availability of many different forms of learning also raises the issue of which variety to invoke in the current situation. In some cases, there seems little choice, as the setting may rule out some forms of acquisition, but in others there is room for choice about which technique to use. This suggests a seventh claim:

- *Some aspects of human learning operate under strategic control.*

For instance, a student who is attempting to master geometry theorem proving may read passages in a textbook, analyze the steps in a sample solution, try to solve an exercise problem on his own, or even ask the instructor for clarification. Similarly, someone trying to learn a second language can choose to read a dictionary to increase her vocabulary, watch a video to observe conversations, practice her skills with another speaker, or ask an expert to comment on such practice. The underlying mechanisms that support learning may be automated and unconscious, but the decision about which activity to pursue is under deliberate cognitive control. Cox and Ram (1999) describe Meta-AQUA, a system that addresses this challenge by treating learning methods as operators and composing them into plans to achieve the agent's learning goals.

To summarize, the cognitive systems movement looks to results from psychology for ideas about the construction of intelligent artifacts, and two well-established features of human learning suggest directions for future research. One concerns the ability to acquire knowledge from many types of sources and to utilize a variety of different mechanisms. Another is that, in many cases, people have strategic control over which form of learning they invoke. Both facilities reflect the diversity, adaptability, and sophistication that we associate with human intelligence and that we desire for synthetic cognitive systems.

6. Heuristics and Learning

Many computational treatments of learning view the process in terms of search through a space of structures or hypotheses. This is a longstanding idea that goes back at least to Simon and Lea's (1974) proposal for a General Rule Inducer, but other early proponents included Mitchell (1982), who relied on breadth-first search, and Langley, Gennari, and Iba (1987), who instead cast learning as as an incremental variety of hill climbing. The latter's view requires the learner to make some *choice* about how to update cognitive structures in response to each training experience, although they assumed such decisions were automated and unconscious.

The need to make repeated choices during learning maps directly onto another feature of cognitive systems research – its use of heuristics – and suggests another claim:

- *Learning involves heuristic search through a space of candidate cognitive structures.*

This statement comes with the standard caveats associated with heuristic methods: they offer no guarantees of producing optimal results, but they are often effective in practice, reducing effort greatly over nonheuristic alternatives. In the context of learning, this translates into substantial increase in learning rates and corresponding reduction in the number of training cases needed to acquire useful structures.

Heuristics have also figured prominently in nonincremental approaches to learning, which must explore similar hypothesis spaces even if they can inspect more training instances for regularities. But the need to incorporate experiences incrementally, an ability associated with agents that operate in an environment over time, makes the need for heuristic guidance even more important to the acquisition of effective cognitive structures. Incremental learners can suffer from order effects, a natural consequence of operating over limited data, that lead them astray. Heuristics that mitigate such order effects include adoption of restricted hypothesis languages, utilization of background knowledge, and even benevolent training regimens (Langley, 1995).

However, incremental hill climbing is not the only metaphor for learning. Another perspective, even more relevant to cognitive systems research, is that learning relies on the generation of explanations. This process combines existing knowledge elements to interpret each experience and uses this understanding to generate new long-term structures. Some researchers in this tradition treated the explanation process as deductive, but others viewed it as abductive, introducing default assumptions to complete accounts when background knowledge is incomplete. For example, VanLehn and Jones (1993) took this approach to model the acquisition of rules for physics problem solving from sample solutions. Because default assumptions may be incorrect, it aligns more directly with the classic notion of heuristics, which are not guaranteed to work but which are often useful in practice.

Learning in the Soar, PRODIGY, and ICARUS architectures has a similar flavor, as they produce new structures by compiling the results of problem solving, which itself relied on heuristic search. Moreover, the resulting structures themselves aid future search efforts, which leads to a final claim:

- *An important form of learning is the acquisition of heuristic knowledge about a domain.*

As noted at the outset, research in AI and cognitive science once focused on the differences between novice and expert behavior, with domain-specific knowledge, often heuristic in nature, being the standard account. One of the earliest efforts on computational learning, by Samuel (1959), showed how one can acquire numeric evaluation functions during search, but many heuristics take the form of symbolic structures. Later research by Anzai and Simon (1979), Langley (1983), and others reported mechanisms for learning such heuristics incrementally from the results of problem solving, with ensuing work on Soar and PRODIGY building on their ideas.

To reiterate, heuristics are essential not only to a cognitive system's performance elements, but to guiding choices during learning. Moreover, acquisition processes themselves can produce new rules of thumb that make performance modules more accurate or efficient. Such methods offer no guarantees, but in practice they let cognitive systems, both natural and synthetic, tackle difficult tasks that would otherwise be impractical or impossible.

7. Concluding Remarks

Taken together, the claims and examples in the previous sections offer a compelling argument for studying learning from the cognitive systems perspective. We need computational artifacts that improve their performance not only on sensori-motor tasks but on ones that require high-level cognitive processing. Such learning should not only produce rich mental structures that arise from the traces of interacting cognitive mechanisms but also benefit from knowledge elements acquired earlier. Our intelligent systems should reflect both the diversity and the strategic control observed in human learners, and they should utilize and acquire heuristics that guide search effectively.

Yet none of my comments in this essay contradict any of the points we made in the 1981 chapter. Learning is an essential part of intelligence, and any account of high-level cognition that omits it will be incomplete. We need more research on this intriguing topic, as we urged 35 years ago, but it should incorporate the field's many insights about cognitive structures and processes, and it should embed its treatment of acquisition within system-level accounts of the mind, rather than approaching it in isolation. Learning is far too important to leave in the charge of associationists and behaviorists, and cognition has a central role to play in its understanding.

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