

Cognitive Architectures: Research Issues and Challenges

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Abstract

In this paper, we examine the motivations for research on cognitive architectures and review some candidates that have been explored in the literature. After this, we consider the capabilities that a cognitive architecture should support, some properties that it should exhibit related to representation, organization, performance, and learning, and some criteria for evaluating such architectures at the systems level. In closing, we discuss some open issues that should drive future work in this important area.

Keywords: cognitive architectures, intelligent systems, cognitive processes

Draft: Please do not quote without permission; comments welcome.

1. Background and Motivation

A cognitive architecture specifies the underlying infrastructure for an intelligent system. Briefly, an architecture includes those aspects of a cognitive agent that are constant over time and across different application domains. These typically include:

- the short-term and long-term memories that store content about the agent’s beliefs, goals, and knowledge;
- the representation of elements that are contained in these memories and their organization into larger-scale mental structures;
- the functional processes that operate on these structures, including the performance mechanisms that utilize them and the learning mechanisms that alter them.

Because the contents of an agent’s memories can change over time, one would not consider the knowledge and beliefs encoded therein to be part of that agent’s architecture. Just as different programs can run on the same computer architecture, so different knowledge bases and beliefs can be interpreted by the same cognitive architecture. There is also a direct analogy with a building’s architecture, which consists of permanent features like its foundation, roof, and rooms, rather than its furniture and appliances, which one can move or replace.

As we will see, alternative cognitive architectures can differ in the specific assumptions they make about these issues, just as distinct buildings differ in their layouts. In addition to making different commitments about how to represent, use, or acquire knowledge and beliefs, alternative frameworks may claim that more or less is built into the architectural level, just as some buildings embed shelves and closets into their fixed structures, whereas others handle the same functions with replaceable furniture.

Research on cognitive architectures is important because it supports a central goal of artificial intelligence and cognitive science: the creation and understanding of synthetic agents that support the same capabilities as humans. Some work focuses on modeling the invariant aspects of human cognition, whereas other efforts view architectures as an effective path to building intelligent agents. However, these are not antithetical goals; cognitive psychology and AI have benefited from building on the other’s ideas (Langley, 2006), and research on cognitive architectures has benefited from building general intelligence vs an intelligent tool

In some ways, cognitive architectures constitute the antithesis of expert systems, which provide skilled behavior in narrowly defined contexts. In contrast, architectural research aims for breadth of coverage across a diverse set of tasks and domains. More important, it offers accounts of intelligent behavior at the *systems level*, rather than at the level of component methods designed for specialized tasks. Newell (1973a) has argued persuasively for systems-level research in cognitive science and artificial intelligence, claiming “You can’t play 20 questions with nature and win”. Instead of carrying out micro-studies that address only one issue at a time, we should attempt to unify many findings into a single theoretical framework, then proceed to test and refine that theory.

Since that call to arms, there has been a steady flow of research on cognitive architectures. The movement was associated originally with a specific class of architectures known as *production systems* (Newell, 1973b; Neches et al., 1987) and emphasized explanation of psychological phenomena,

with many current candidates still taking this form and showing similar concerns. However, over the past three decades, a variety of other architectural classes have emerged, some less concerned with human behavior, that make quite different assumptions about the representation, organization, utilization, and acquisition of knowledge. At least three invited symposia have brought together researchers in this area (Laird, 1991; VanLehn, 1991; Shapiro & Langley, 2004), and there have been at least two edited volumes (Sun, 2005; VanLehn, 1991). The movement has gone beyond basic research into the commercial sector, with applications to believable agents for simulated training environments (e.g., Tambe et al., 1995), computer tutoring systems (Koedinger, Anderson, Hadley, & Mark, 1997), and interactive computer games (e.g., Magerko et al., 2004).

Despite this progress, there remains a need for additional research in the area of cognitive architectures. As artificial intelligence and cognitive science have matured, they have fragmented into a number of well-defined subdisciplines, each with its own goals and its own criteria for success.

Yet commercial and government applications increasingly require *integrated* systems that exhibit intelligent behavior, not just improvements to the components of such systems. This demand can be met by an increased focus on system-level architectures that support complex cognitive behavior across a broad range of relevant tasks.

In this document, we examine some key issues that arise in the design and study of integrated cognitive architectures. Because we cannot hope to survey the entire space of architectural theories, we focus on the ability to generate intelligent behavior, rather than matching the results of psychological experiments.¹ We begin with a brief review of some sample architectures, then discuss the capabilities and functions that such systems should support. After this, we consider a number of design decisions that relate to the properties of cognitive architectures, followed by some dimensions along which one should evaluate them. In closing, we note some open issues in the area and propose some directions that future research should take to address them.

2. Example Cognitive Architectures

Before turning to abstract issues that arise in research on cognitive architectures, we should consider some concrete examples that have been reported in the literature. Here we review four distinct frameworks that fall at different points within the architectural space. We have selected these architectures because each has appeared with reasonable frequency in the literature, and also because they exhibit different degrees of concern with explaining human behavior. We have ordered them along this dimension, with more devoted psychological models coming earlier.

In each case, we discuss the manner in which the architecture represents, organizes, utilizes, and acquires knowledge, along with its accomplishments. Because we review only a small sample of extant architectures, we summarize a variety of other frameworks briefly in the Appendix. Nevertheless, this set should give readers some intuitions about the space of cognitive architectures, which later sections of the paper discuss more explicitly.

One common feature of the architectures we examine is that, although they have some theoretical commitment to parallelism, especially in memory retrieval, they also rely on one or a few decision modules. We have not included connectionist approaches in our treatment because, to our knowl-

1. Sun (2007) provides another treatment of cognitive architectures that discusses the second topic in greater detail.

connectionist approaches have served as implementation of architecture components

edge, they have not demonstrated the broad functionality associated with cognitive architectures in the sense we discuss here. However, they have on occasion served as important components in larger-scale architectures, as in Sun, Merrill, and Peterson's (2001) CLARION framework.

2.1 ACT

ACT-R (Anderson & Lebiere, 1998, Anderson et al., 2004) is the latest in a family of cognitive architectures, concerned primarily with modeling human behavior, that has seen continuous development since the late 1970s. ACT-R 6 is organized into a set of modules, each of which processes a different type of information. These include sensory modules for visual processing, motor modules for action, an intentional module for goals, and a declarative module for long-term declarative knowledge. Each module has an associated buffer that holds a relational declarative structure (often called 'chunks', but different from chunks in other architectures). Productions comprise ACT-R's short-term memory.

productions are like operators (if-this-then-do-that)

A long-term production memory coordinates the processing of the modules. The conditions of each production test chunks in the short-term buffers, whereas its actions alter the buffers upon application. Some changes modify existing structures, whereas others initiate actions in the associated modules, such as executing a motor command or retrieving a chunk from long-term declarative memory. Each declarative chunk has an associated base activation that reflects its past usage and influences its retrieval from long-term memory, whereas each production has an expected cost (in terms of time needed to achieve goals) and probability of success.

On every cycle, ACT determines which productions match against the contents of short-term memory. This retrieval process is influenced by the base activation for each chunk it matches. ACT computes the utility for each matched production as the difference between its expected benefit (the desirability of its goal times its probability of success) and its expected cost. The system selects the production with the highest utility (after adding noise to this score) and executes its actions. The new situation leads new productions to match and fire, so that the cycle continues.

expected utility

frequency-motivated macro learning

Learning occurs in ACT-R at both the structural and statistical levels. For instance, the base activation for declarative chunks increases with use by productions but decays otherwise, whereas the cost and success probability for productions is updated based on their observed behavior. The architecture can learn entirely new rules from sample solutions through a process of production compilation that analyzes dependencies of multiple rule firings, replaces constants with variables and combines them into new conditions and actions (Taatgen, 2005).

much like macro learning

The ACT-R community has used its architecture to model a variety of phenomena from experimental psychology literature, including aspects of memory, attention, reasoning, problem solving, and language processing. Most publications have reported accurate fits to quantitative data about human reaction times and error rates. More recently, Anderson (2007) has related ACT-R modules to different areas of the brain and developed models that match results from brain-imaging studies. On the more applied front, the framework has played a central role in tutoring systems that have seen wide use in schools (Koedinger et al., 1997), and it has also been used to control mobile robots that interact with humans (Trafton et al., 2005).

if-then rules
much like ops

2.2 Soar

Soar (Laird, 2008; Laird, Newell, & Rosenbloom, 1987; Newell, 1990) is a cognitive architecture that has been under continuous development since the early 1980s. Procedural long-term knowledge in Soar takes the form of production rules, which are in turn organized in terms of operators associated with problem spaces. Some operators describe simple, primitive actions that modify the agent's internal state or generate primitive external actions, whereas others describe more abstract activities. For many years, Soar represented all long-term knowledge in this form, but recently separate episodic and semantic memories have been added. The **episodic memory (Nuxoll & Laird, 2007)** holds a history of previous states, while semantic memory contains previously known facts.

All tasks in Soar are formulated as attempts to achieve goals. The system performs deliberative acts of the system, with knowledge used to dynamically select operators of the current problem space to a problem state, moving ahead one decision at a time. **However, when knowledge about operator selection is insufficient to determine the next operator to apply** or when an abstract operator cannot be implemented, an **impasse** occurs; in response, Soar creates a new goal to determine which operator it should select or how it should implement the abstract operator.

This process can lead to the dynamic generation of a goal hierarchy, in that problems are decomposed into subproblems as necessary. The 'state' of a specific goal includes all features of its supergoals, plus any additional cognitive structures necessary to select and apply operators in the subgoal. Processing in a subgoal involves the same basic processing cycle of selecting and applying operators. Subgoals can also deliberately access episodic or semantic memory to retrieve knowledge relevant to resolving the impasse. The top state includes all sensor data obtained from the external environment, so this information is also available to all subgoals. On any cycle, the states at various levels of the goal hierarchy can change, typically due to changes in sensor values or as the result of operator applications in subgoals. When the system resolves the impasse that generated a goal, that goal disappears, along with all the subgoals below it.

Soar has multiple learning mechanisms for different types of knowledge: *chunking* and reinforcement learning acquire procedural knowledge, whereas episodic and semantic learning acquire corresponding types of declarative knowledge. Chunking occurs when one or more results produced in a subgoal (Laird, Rosenbloom, & Newell, 1986). When this happens, Soar learns a **chunk**, represented as a production rule which summarizes the processing that generated the results. A chunk's actions are based on the results, whereas its conditions are based on those aspects of the goals above the subgoal that were relevant to determining the results. Once the agent has learned a chunk, it fires in new situations that are similar along relevant dimensions, often giving the required results directly and thus avoiding the impasse that led to its formation. **Reinforcement learning adjusts numeric values associated with rules that help select operators** (Nason & Laird, 2004). Episodic learning records the contents of working memory in snapshots, while semantic learning stores individual elements of working memory for later retrieval.

Researchers have used Soar to develop a variety of sophisticated agents that have demonstrated impressive functionality. **The most visible has been TAC-Air-Soar (Tambe et al., 1995), which modeled fighter pilots in military training exercises that involved air combat scenarios.** More recently, Soar has supported a number of intelligent agents that control synthetic characters in

search valley, misleading region of search

related to macro
discussion

lots of applications

interactive computer games (Margerko et al., 2004). Another thrust has involved using Soar to model the details of human language processing (Lewis, 1993), categorization (Miller & Laird, 1996), and other facets of cognition, but the emphasis has been on demonstrating high-level functionality rather than on fits to quantitative measurements.

2.3 ICARUS

ICARUS is a more recent architecture (Langley, Cummings, & Shapiro, 2004) that stores two distinct forms of knowledge. Concepts describe classes of environmental situations in terms of other concepts and percepts, whereas skills specify how to achieve goals by decomposing them into ordered subgoals. Both concepts and skills involve relations among objects, and both impose a hierarchical organization on long-term memory, with the former grounded in perceptions and the latter in executable actions. Moreover, skills refer to concepts in their heads, their initiation conditions, and their continuation conditions.

The basic ICARUS interpreter operates on a recognize-act cycle. On each step, the architecture deposits descriptions of visible objects into a perceptual buffer. The system compares primitive concepts to these percepts and adds matched instances to short-memory as beliefs. These in turn trigger matches of higher-level concepts, with the process continuing until ICARUS infers all deductively implied beliefs. Next, starting from a top-level goal, it finds a path downward through the skill hierarchy in which each subskill has satisfied conditions but an unsatisfied goal. When a path terminates in a primitive skill with executable actions, the system executes these actions to affect the environment. This leads to new percepts, changes in the perceptual buffer, and additional skill paths to achieve the agent's goals.

However, when ICARUS can find no applicable path through the skill hierarchy that is relevant to a top-level goal, it resorts to problem solving using a variant of means-ends analysis. This module chains backward off either a skill that would achieve the current goal or off the goal concept's definition, and it interleaves problem solving with execution in that it carries out selected skills when they become applicable. Whenever problem solving achieves a goal, ICARUS creates a new skill with that goal as its head and with one or more ordered subgoals that are based on the problem solution. If the system encounters similar problems in the future, it executes the learned skills to handle them reactively, without need for deliberative problem solving (Langley & Choi, 2006b).

Researchers have used ICARUS to develop agents for a number of domains that involve a combination of inference, execution, problem solving, and learning. These have included tasks like the Tower of Hanoi, multi-column subtraction, FreeCell solitaire, and logistics planning. They have also used the architecture to control synthetic characters in simulated virtual environments, including ones that involve urban driving (Langley & Choi, 2006a) and first-person shooter scenarios (Choi et al., 2007). Ongoing work aims to link ICARUS to physical robots that carry out joint activities with humans.

2.4 PRODIGY

PRODIGY (Carbonell, Knoblock, & Minton, 1990) is another cognitive architecture that saw extensive development from the middle 1980s to the late 1990s. This framework incorporates two main kinds of knowledge. Domain rules encode the conditions under which actions have certain

e.g., STRIPS planning

interesting statement. macros? reactive? without deliberation?

effects, where the latter are described as the addition or deletion of first-order expressions. These refer both to physical actions that affect the environment and to inference rules, which are purely cognitive. In contrast, control rules specify the conditions under which the architecture should select, reject, or prefer a given operator, set of operator bindings, problem state, or goal during the search process.

As in ICARUS, PRODIGY's basic problem-solving module involves search through a problem space to achieve one or more goals, which it also casts as **first-order expressions**. This search relies on means-ends analysis, which selects an operator that reduces some difference between the current state and the goal, which in turn can lead to subproblems with their own current states and goals. On each cycle, PRODIGY uses its control rules to select an operator, binding set, state, or goal, to reject them out of hand, or to prefer some over others. In the absence of such control knowledge, the architecture makes choices at random and carries out depth-first means-ends search with backtracking.

PRODIGY's explanation-based learning module constructs control rules based on its problem-solving experience (Minton, 1990). Successful achievement of a goal after search leads to creation of **selection or preference rules** related to that goal and to the operators whose application achieved it. Failure to achieve a goal leads to creation of **rejection or preference rules for operators**, goals, and states that did not produce a solution. To generate these **control rules**, PRODIGY invokes a learning method that analyzes problem-solving traces and proves the reasons for success or failure. The architecture also **collects statistics on learned rules and retains only those whose inclusion, over time, leads to more efficient problem solving.**

In addition, PRODIGY includes separate modules for controlling search by analogy with earlier solutions (Veloso & Carbonell, 1993), learning operator descriptions from observed solutions or experimentation (Wang, 1995), and improving the quality of solutions (Pérez & Carbonell, 1994). Although most research in this framework has dealt exclusively with planning and problem solving, PRODIGY also formed the basis for an impressive system that interleaved planning and execution for a mobile robot that accepted asynchronous requests from users (Haigh & Veloso, 1996).

3. Capabilities of Cognitive Architectures

Any intelligent system is designed to engage in certain activities that, taken together, constitute its functional capabilities. In this section, we discuss the varied capabilities that a cognitive architecture can support. Although only a few abilities, such as recognition and decision making, are strictly required to support a well-defined architecture, the entire set seems required to cover the full range of human-level intelligent activities.

A central issue that confronts the designer of a cognitive architecture is how to let agents access different sources of knowledge. Many of the capabilities we discuss below give the agent access to such knowledge. For example, knowledge about the environment comes through perception, knowledge about implications of the current situation comes through planning, reasoning, and prediction, knowledge from other agents comes via communication, and knowledge from the past comes through remembering and learning. The more such capabilities an architecture supports, the more sources of knowledge it can access to inform its behavior.

decreasing the effective breadth of search

Another key question is whether the cognitive architecture supports a capability directly, using embedded processes, or whether it instead provides ways to implement that capability in terms of knowledge. Design decisions of this sort influence what the agent can learn from experience, what the designers can optimize at the outset, and what functionalities can rely on specialized representations and mechanisms. In this section, we attempt to describe functionality without referring to the underlying mechanisms that implement them, but this is an important issue that deserves more attention in the future.

3.1 Recognition and Categorization

An intelligent agent must make some contact between its environment and its knowledge. This requires the ability to recognize situations or events as instances of known or familiar patterns. For example, a reader must recognize letters and the words they make up, a chess player must identify meaningful board configurations, and an image analyst must detect buildings and vehicles in aerial photographs. However, recognition need not be limited to static situations. A fencing master can identify different types of attacks and a football coach can recognize the execution of particular plays by the opposing team, both of which involve dynamic events.

Recognition is closely related to categorization, which involves the assignment of objects, situations, and events to known concepts or categories. However, research on cognitive architectures typically assumes recognition is a primitive process that occurs on a single cycle and that underlies many higher-level functions, whereas categorization is sometimes viewed as a higher-level function. Recognition and categorization are closely linked to perception, in that they often operate on output from the perceptual system, and some frameworks view them as indistinguishable. However, they can both operate on abstract mental structures, including those generated internally, so we will treat them as distinct.

To support recognition and categorization, a cognitive architecture must provide some way to represent patterns and situations in memory. Because these patterns must apply to similar but distinct situations, they must encode general relations that hold across these situations. An architecture must also include some recognition process that lets it identify when a particular situation matches a stored pattern or category and, possibly, measure the degree to which it matches. In production system architectures, this mechanism determines when the conditions of each production rule match and the particular ways they are instantiated. Finally, a complete architecture should include some means to learn new patterns or categories from instruction or experience, and to refine existing patterns when appropriate.

3.2 Decision Making and Choice

To operate in an environment, an intelligent system also requires the ability to make decisions and select among alternatives. For instance, a student must decide which operation will simplify an integration problem, a speaker must select what word to use next in an utterance, and a baseball player must decide whether or not to swing at a pitch. Such decisions are often associated with the recognition of a situation or pattern, and most cognitive architectures combine the two mechanisms in a recognize-act cycle that underlies all cognitive behavior.

how related to
planning? problem
solving?

Such **one-step decision making** has much in common with higher-level choice, but differs in its complexity. For example, consider a consumer deciding which brand of detergent to buy, a driver choosing which route to drive, and a general selecting which target to bomb. Each of these decisions can be quite complex, depending on how much time and energy the person is willing to devote. Thus, we should distinguish between decisions that are made at the architectural level and more complex ones that the architecture enables.

To support decision making, a cognitive architecture must provide some way to represent alternative choices or actions, whether these are internal cognitive operations or external ones. It must also offer some process for **selecting among these alternatives, which most architectures separate into two steps**. The first determines **whether a given choice or action is allowable**, typically by associating it with some pattern and considering it only if the pattern is matched. For instance, we can specify the conditions under which a chess move is legal, then consider that move only when the conditions are met. The second step **selects among allowable alternatives**, after some numeric score and choosing one or more with better scores. Such *conflict resolution* takes quite different forms in different architectures.

preconditions

preferences

Finally, an ideal cognitive architecture should incorporate some way to improve its decisions through learning. Although this can, in principle, involve learning new alternatives, most mechanisms focus on learning or revising either the conditions under which an existing action is considered allowable or altering the numeric functions used during the conflict resolution stage. The resulting improvements in decision making will then be reflected in the agent's overall behavior.

3.3 Perception and Situation Assessment

Cognition does not occur in isolation; an intelligent agent exists in the context of some external environment that it must sense, perceive, and interpret. An agent may sense the world through different modalities, just as a human has access to sight, hearing, and touch. The sensors may range from simple devices like a thermometer, which generates a single continuous value, to more complex mechanisms like stereoscopic vision or sonar that generate a depth map for the local environment within the agent's field of view. Perception can also involve the integration of results from different modalities into a single assessment or description of the environmental situation, which an architecture can represent for utilization by other cognitive processes.

Perception is a broad term that covers many types of processing, from inexpensive ones that an architecture can support automatically to ones that require limited resources and so must be invoked through conscious intentions. For example, the human visual system can detect motion in the periphery without special effort, but the fovea can extract details only from the small region at which it is pointed. A cognitive architecture that includes the second form of sensor must confront the issue of *attention*, that is, deciding how to allocate and direct its limited perceptual resources to detect relevant information in a complex environment.

An architecture that supports perception should also deal with the issue that sensors are often noisy and provide at most an inaccurate and partial picture of the agent's surroundings. Dynamic environments further complicate matters in that the agent must track changes that sometimes occur at a rapid rate. These challenges can be offset with perceptual knowledge about what sensors to

how related to
3.1 on recognition and
categorization

invoke, where and when to focus them, and what inferences are plausible. An architecture can also acquire and improve this knowledge by learning from previous perceptual experiences.

An intelligent agent should also be able to move beyond perception of isolated objects and events to understand and interpret the broader environmental situation. For example, a fire control officer on a ship must understand the location, severity, and trajectory of fires in order to respond effectively, whereas a general must be aware of an enemy's encampments, numbers, and resources to defend against them successfully. Thus, situation assessment requires an intelligent agent to combine perceptual information about many entities and events, possibly obtained from many sources, to compose a large-scale model of the current environment. As such, it relies both on the recognition and categorization of familiar patterns in the environment, which we discussed earlier, and on inferential mechanisms, which we will consider shortly.

3.4 Prediction and Monitoring

Cognitive architectures exist over time, which means they can benefit from an ability to predict future situations and events accurately. For example, a good driver knows approximately when his car will run out of gas, a successful student can predict how much he will score on a final, and a skilled pilot can judge how close he can fly to the ground without crashing. Perfect prediction may not be possible in many situations, but perfection is seldom required. Predictions that are useful to an intelligent system.

A basic
prediction capability
used in larger tasks like
planning

Prediction requires some model of the environment and the effect actions have on it, and the architecture must represent this model in memory. One general approach involves storing some mapping from a description of the current situation and an action onto a description of the resulting situation. Another approach encodes the effects of actions or events in terms of changes to the environment. In either case, the architecture also requires some mechanism that uses these knowledge structures to predict future situations, say by recognizing a class of situations in which an action will have certain effects. An ideal architecture should also include the ability to learn predictive models from experience and to refine them over time.

a part 2 game
manager can enable
monitoring

Once an architecture has a mechanism for making predictions, it can also utilize them to monitor the environment. For example, a pilot may suspect that his tank has a leak if the fuel gauge goes down more rapidly than usual, and a commander may suspect enemy action if a reconnaissance team fails to report on time. Because monitoring relates sensing to prediction, it raises issues of attentional focus when an architecture has limited perceptual resources. Monitoring also provides natural support for learning, since errors can help an agent improve its model of the environment.

3.5 Problem Solving and Planning

Because intelligent systems must achieve their goals in novel situations, the cognitive architectures that support them must be able to generate plans and solve problems. For example, an unmanned air vehicle benefits from having a sensible flight plan, a project manager desires a schedule that allocates tasks to specific people at specific times, and a general seldom moves into enemy territory without at least an abstract course of action. When executed, plans often go awry, but that does not make them any less useful to an intelligent agent's thinking about the future.

Planning is only possible when the agent has an environmental model that predicts the effects of its actions. To support planning, a cognitive architecture must be able to represent a plan as an (at least partially) ordered set of actions, their expected effects, and the manner in which these effects enable later actions. The plan need not be complete to guide behavior, in that it may extend only a short time into the future or refer to abstract actions that can be expanded in different ways. The structure may also include conditional actions and branches that depend on the outcome of earlier events as noted by the agent.

like STRIPS operators

An intelligent agent should also be able to construct a plan from components available in memory. These components may refer to low-level motor and sensory actions but, often, they will be more abstract structures, including prestored subplans. There exist many mechanisms for generating plans from components, as well as ones for adapting plans that have been retrieved from memory. What these methods have in common is that they involve problem solving or search. That is, they carry out steps through a space of problem states, on each step considering applicable operators, selecting one or more operator, and applying it to produce a new problem state. This search process continues until the system has found an acceptable plan or decides to give up.

The notion of problem solving is somewhat more general than planning, though they are viewed as closely related. In particular, planning usually refers to cognitive activities in an agent's head, whereas problem solving can also occur in the world. Especially when a situation is complex and the architecture has memory limitations, an agent may carry out search by applying operators or actions in the environment, rather than trying to construct a plan internally. Problem solving can also rely on a mixture of internal planning and external behavior, but it generally involves the multi-step construction of a problem solution. Like planning, problem solving is often characterized in terms of search through a problem space that applies operators to generate new states, selects promising candidates, and continues until reaching a recognized goal.

real-time search

Planning and problem solving can also benefit from learning. Naturally, improved predictive models for actions can lead to more effective plans, but learning can also occur at the level of problem space search, whether this activity takes place in the agent's head or in the physical world. Such learning can rely on a variety of information sources. In addition to learning from direct instruction, an architecture can learn from the results of problem-space search (Sleeman et al., 1982), by observing another agent's behavior or *behavioral cloning* (Sammut, 1996), and from delayed rewards via *reinforcement learning* (Sutton & Barto, 1998). Learning can aim to improve problem solving behavior in two ways (Langley, 1995a). One focuses on reducing the branching factor of search, either through adding heuristic conditions to problem space operators or refining a numeric evaluation function to guide choice. Another focuses on forming macro-operators or stored plans that reduce the effective depth of search by taking larger steps in the problem space.

Intelligent agents that operate in and monitor dynamic environments must often modify existing plans in response to unanticipated changes. This can occur in several contexts. For instance, an agent should update its plan when it detects a changed situation that makes some planned activities inapplicable, and thus requires other actions. Another context occurs when a new situation suggests some more desirable way of accomplishing the agent's goal; such opportunistic planning can take advantage of these unexpected changes. Monitoring a plan's execution can also lead to revised estimates about the plan's effectiveness, and, ultimately, to a decision to pursue some other course

plan adaptation could also occur in a game context where AI players adapt each others' plans

of action with greater potential. Replanning can draw on the same mechanisms as generating a plan from scratch, but requires additional operators for removing actions or replacing them with other steps. Similar methods can also adapt to the current situation a known plan the agent has retrieved from memory.

3.6 Reasoning and Belief Maintenance

Piazza question. There will be more

Problem solving is closely related to *reasoning*, another central cognitive activity that lets an agent augment its knowledge state. Whereas planning is concerned primarily with achieving objectives in the world by taking actions, reasoning draws mental conclusions from other beliefs or assumptions that the agent already holds. For example, a pilot might conclude that, if another plane changes its course to intersect his own, it is probably an enemy fighter. Similarly, a geometry student might deduce that two triangles are congruent because they share certain sides and vertices, and a general might infer that, since he has received no recent reports of enemy movement, a nearby opposing force is still camped where it was the day before.

To support such reasoning, a cognitive architecture must first be able to represent relationships among beliefs. A common formalism for encoding such relationships is **first-order logic, but many other notations have also been used, ranging from production rules to neural networks to Bayesian networks.** The relations represented in this manner may be logically or probabilistic, but this is not required; knowledge about reasoning can also be heuristic or approximate quite useful to an intelligent agent. Equally important, the formalism may be highly expressive (e.g., limited to propositional logic) or computationally efficient.

what kinds of reasoning methods did you learn in CS x260?

Naturally, a cognitive architecture also requires mechanisms that draw inferences using these knowledge structures. Deductive reasoning is an important and widely studied form of inference that lets one combine general and specific beliefs to conclude others that they entail logically. However, an agent can also engage in inductive reasoning, which moves from specific beliefs to more general ones and which can be viewed as a form of learning. An architecture may also support abductive inference, which combines general knowledge and specific beliefs to hypothesize other specific beliefs, as occurs in medical diagnosis. In constrained situations, an agent can simply draw all conclusions that follow from its knowledge base, but more often it must select which inferential knowledge to apply. This raises issues of search closely akin to those in planning tasks, along with issues of learning to make that search more effective.

Reasoning plays an important role not only when inferring new beliefs but when deciding whether to maintain existing ones. To the extent that certain beliefs depend on others, an agent should track the latter to determine whether it should continue to believe the former, abandon it, or otherwise alter its confidence. Such *belief maintenance* is especially important for dynamic environments in which situations may change in unexpected ways, with implications for the agent's behavior. One general response to this issue involves maintaining dependency structures in memory that connect beliefs, which the architecture can use to propagate changes as they occur.

3.7 Execution and Action

Cognition occurs to support and drive activity in the environment. To this end, a cognitive architecture must be able to represent and store motor skills that enable such activity. For example, a mobile ground robot or unmanned air vehicle should have skills or policies for navigating from one place to another, for manipulating its surroundings with effectors, and for coordinating its behavior with other agents on its team. These may be encoded solely in terms of primitive or component actions, but they may also specify more complex multi-step skills or procedures. The latter may take the form of plans that the agent has generated or retrieved from memory, especially in architectures that have grown out of work on problem solving and planning. However, other formulations of motor skill execution, such as closed-loop controllers, have also been explored.

A cognitive architecture must also be able to execute skills and actions in the environment. In some frameworks, this happens in a completely reactive manner, with the agent selecting one or more primitive actions on each decision cycle, executing them, and repeating the process on the next cycle. This approach is associated with closed-loop strategies for execution, since the agent can also sense the environment on each time step. The utilization of more complex skills supports open-loop execution, in which the agent calls upon a stored procedure across many cycles without checking the environment. However, a flexible architecture should support the entire continuum from fully reactive, closed-loop behavior to automatized, open-loop behavior, as can humans.

Ideally, a cognitive architecture should also be able learn about skills and execution policies from instruction and experience. Such learning can take different forms, many of which parallel those that arise in planning and problem solving. For example, an agent can learn by observing another agent's behavior, by successfully achieving its goals, and from delayed rewards. Similarly, it can learn or refine its knowledge for selecting primitive actions, either in terms of heuristic conditions on their application or as a numeric evaluation function that reflects their utility. Alternatively, an agent can acquire or revise more complex skills in terms of known skills or actions.

3.8 Interaction and Communication

Very relevant in game playing

Sometimes the most effective way for an agent to obtain knowledge is from another agent, making communication another important ability that an architecture should support. For example, a commander may give orders to, and receive reports from, her subordinates, while a shopper in a flea market may dicker about an item's price with its owner. Similarly, a traveler may ask and receive directions on a street corner, while an attorney may query a defendant about where he was on a particular night. Agents exist in environments with other agents, and there are many occasions in which they must transfer knowledge from one to another.

Whatever the modality through which this occurs, a communicating agent must represent the knowledge that it aims to convey or that it believes another agent intends for it. The content so transferred can involve any of the cognitive activities we have discussed so far. Thus, two agents can communicate about categories recognized and decisions made, about perceptions and actions, about predictions and anomalies, and about plans and inferences. One natural approach is to draw on the representations that result from these activities as the input to, and the output from, interagent communication.

A cognitive architecture should also support mechanisms for transforming knowledge into the form and medium through which it will be communicated. The most common form is spoken or written language, which follows established conventions for semantics, syntax, and pragmatics onto which an agent must map the content it wants to convey. Even when entities communicate with purely artificial languages, they do not have exactly the same mental structures and they must translate content into some external format. One can view language generation as a form of planning and execution, whereas language understanding involves inference and reasoning. However, the specialized nature of language processing makes these views misleading, since the task raises many additional issues.

An important form of communication occurs in conversational dialogues, which require both generation and understanding of natural language, as well as coordination with the other agent in the form of turn taking. Learning is also an important issue in language and other forms of communication, since an architecture should be able to acquire syntactic and semantic knowledge for use at both the sentence and dialogue levels. Moreover, some communicative tasks, like question answering, require access to memory for past events and cognitive activities, which in turn benefits from episodic storage.

3.9 Remembering, Reflection, and Learning

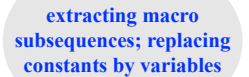
A cognitive architecture can also benefit from capabilities that cut across those described in the previous sections, in that they operate on mental structures produced or utilized by them. Such abilities, which Sloman (2001) refers to as *metamanagement mechanisms*, are not strictly required for an intelligent agent, but their inclusion can extend the flexibility and robustness of an architecture.

e.g., remember a plan

One capacity of this sort involves *remembering* – the ability to encode and store the results of cognitive processing in memory and to retrieve or access them later. An agent cannot directly remember external situations or its own physical actions; it can only recall cognitive structures that describe those events or inferences about them. This idea extends naturally to memories of problem solving, reasoning, and communication. To remember any cognitive activity, the architecture must store the cognitive structures generated during that activity, index them in memory, and retrieve them when needed. The resulting content is often referred to as *episodic memories*.

Another capability that requires access to traces of cognitive activity is *reflection*. It involve processing of either recent mental structures that are still available or older structures the agent must retrieve from its episodic store. One type of reflective activity concerns the justification or *explanation* of an agent's inferences, plans, decisions, or actions in terms of cognitive steps that led to them. Another revolves around *meta-reasoning* about other cognitive activities, which an architecture can apply to the same areas as explanation, but which emphasizes their generation (e.g., forming inferences or making plans) rather than their justification. To the extent that reflective processes lay down their own cognitive traces, they may themselves be subject to reflection. However, an architecture can also support reflection through less transparent mechanisms, such as statistical analyses, that are not themselves inspectable by the agent.

Was the plan helpful?



extracting macro
subsequences; replacing
constants by variables

A final important ability that applies to many cognitive activities is *learning*. We have previously seen the various forms this can take, in the context of different architectural capacities, but we should also consider broader issues. Learning usually involves generalization beyond specific beliefs and events. Although most architectures carry out this generalization at storage time and enter generalized knowledge structures in memory, some learning mechanisms store specific situations and generalization occurs at retrieval time through analogical or case-based reasoning. Either approach can lead to different degrees of generalization or transfer, ranging from very similar tasks, to other tasks within the same domain, and even to tasks within related but distinct domains. Many architectures treat learning as an automatic process that is not subject to inspection or conscious control, but they can also use meta-reasoning to support learning in a more deliberate manner. The data on which learning operates may come from many sources, including observation of another agent, an agent's own problem solving behavior, or practice of known skills. But whatever the source of experience, all involve processing of memory structures to improve the agent's capabilities.

4. Properties of Cognitive Architectures

We can also characterize cognitive architectures in terms of the internal properties that produce the capabilities described in the previous section. These divide naturally into the architecture's representation of knowledge, the organization it places on that knowledge, the manner in which the system utilizes its knowledge, and the mechanisms that support acquisition and revision of knowledge through learning. Below we consider a number of design decisions that arise within each of these facets of an intelligent system, casting them in terms of the data structures and algorithms that are supported at the architectural level. Although we present most issues in terms of oppositions, many of the alternatives we discuss are complementary and can exist within the same framework.

4.1 Representation of Knowledge

One important class of architectural properties revolves around the representation of knowledge. Recall that knowledge itself is not built into an architecture, in that it can change across domains and over time. However, the representational formalism in which an agent encodes its knowledge constitutes a central aspect of a cognitive architecture.

Perhaps the most basic representational choice involves whether an architecture commits to a single, uniform notation for encoding its knowledge or whether it employs a mixture of formalisms. Selecting a single formalism has advantages of simplicity and elegance, and it may support more easily abilities like learning and reflection, since they must operate on only one type of structure. However, as we discuss below, different representational options have advantages and disadvantages, so that focusing on one framework can force an architecture into awkward approaches to certain problems. On the other hand, even mixed architectures are typically limited to a few types of knowledge structures to avoid complexity.

One common tradition distinguishes *declarative* from *procedural* representations. Declarative encodings of knowledge can be manipulated by cognitive mechanisms independent of their content. For instance, a notation for describing devices might support design, diagnosis, and control. First-order logic (Genesereth & Nilsson, 1987) is a classic example of such a representation. Generally

We will also need an experimental method that recognizes the fact that cognitive architectures involve integration of many components which may have synergistic effects, rather than consisting of independent but unrelated modules (Langley & Messina, 2004). Experimental comparisons among architectures have an important role to play, but these must control carefully for the task being handled and the amount of knowledge encoded, and they must measure dependent variables in unbiased and informative ways. Systematic experiments that are designed to identify sources of power will tell us far more about the nature of cognitive architectures than simplistic competitions.

Our field still has far to travel before we understand fully the space of cognitive architectures and the principles that underlie their successful design and utilization. However, we now have over two decades' experience with constructing and using a variety such architectures for a wide range of problems, along with a number of challenges that have arisen in this pursuit. If the scenery revealed by these initial steps are any indication, the journey ahead promises even more interesting and intriguing sites and attractions.

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