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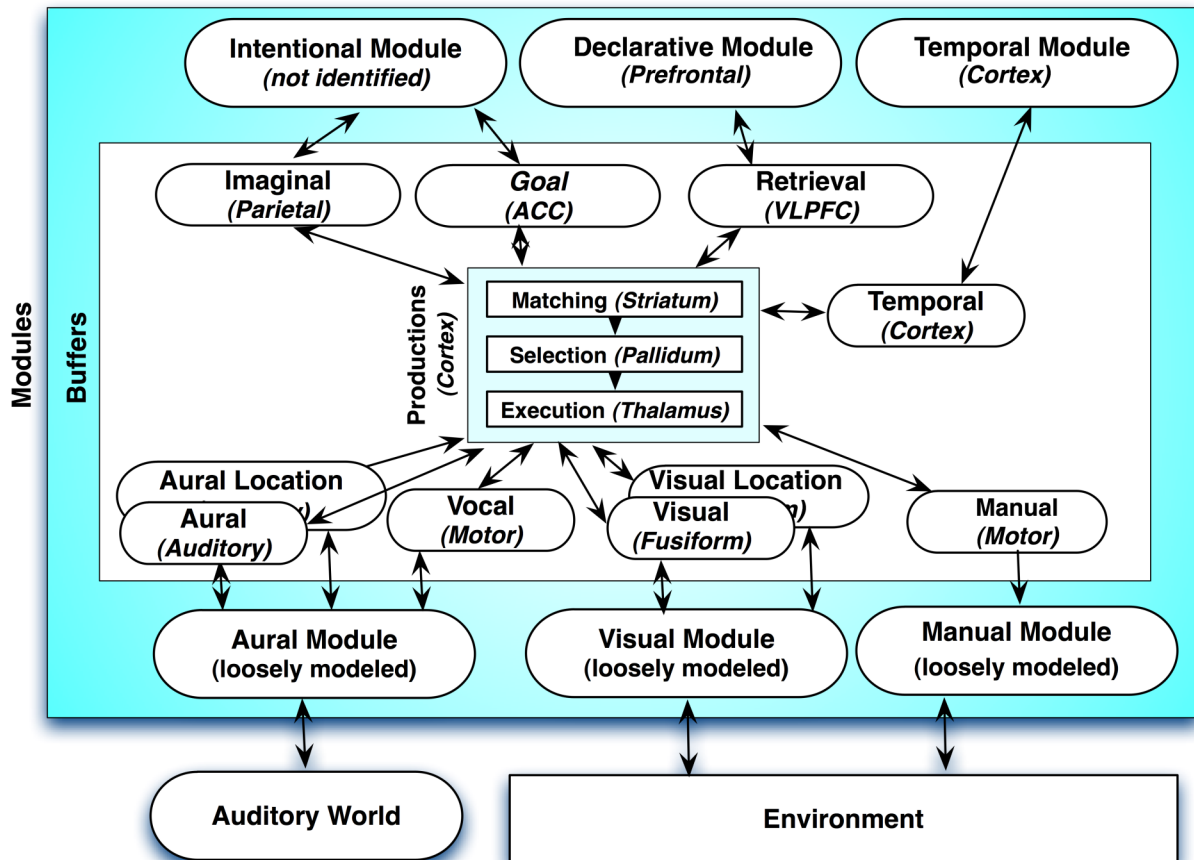
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Abstract

ACT-R is a hybrid cognitive architecture. It is comprised of a set of programmable information processing mechanisms that can be used to predict and explain human behavior including cognition and interaction with the environment. We start by reviewing its history, which shapes its current form, contrasts and relates it to other architectures, and helps readers anticipate where it is going. Based on this history, we then describe it as a theory of cognition that is realized as a computer program. After this, we briefly discuss tools for working with ACT-R, and also note several major accomplishments that have been gained by working with ACT-R in both basic and applied science, including summarizing some of the insights about human behavior. We conclude by discussing its future, which we believe will include adding emotions and physiology, increasing usability, and the use of non-generative models.

Keywords: ACT-R; cognitive architecture; human memory; modeling; simulation;

Graphical/Visual Abstract and Caption

[Figure revised as requested, TIFF available]

Schematic of the ACT-R cognitive architecture and how its components work together to generate behavior. (Figure by authors based on and extending Anderson et al., 2004, the current ACT-R 7 manual, and comments from Dan Bothell).

INTRODUCTION

ACT-R is a theory of the mechanisms that make up cognition, a cognitive architecture. The theory posits a fixed set of mechanisms that use task knowledge to perform a task thereby predicting and explaining the steps of cognition that form human behavior. Thus, it is one example of a unified theory of cognition (Byrne, 2012; Newell, 1990). Currently, it also predicts the activation of brain regions used to generate behavior by using mechanisms that make use of procedural (how to do a task) and declarative (facts about the world) knowledge, and working memory as activation, to perform tasks.

For example, Salvucci (2006) has created a set of declarative and procedural knowledge about how to drive a car (for example, what other cars and lanes are, and when and how to turn). He then added this knowledge to ACT-R that had its vision and motor systems connected to a car simulator. ACT-R when it applies this knowledge of how to drive then provides predictions about the knowledge set, showing that it is sufficient to drive a car. The architecture also provides predictions about how fast the knowledge is applied, when turns and stops are performed, and what parts of the brain are active at each point in time. Additional knowledge can be added about how to dial telephones (what and where are buttons, and how to retrieve a number from memory and then use the memory to push buttons). The combined model can be used to predict the effect of dialing on driving (Salvucci, 2009).

The ACT-R theory has evolved over the course of more than four decades, and so have the acronyms used to describe the theory. ACT-R stands for *Adaptive Control of Thought-Rational*, although in Anderson's (1998) book ACT-R is referred to as *Atomic Components of Thought.*

There are numerous reviews of ACT-R, many noted here. Therefore, in this paper in addition to describing it as a theory, we start by briefly reviewing its history, which explains its current form and helps readers anticipate where ACT-R is going. Similar to most reviews of cognitive architectures, we describe the theory and its structure, and how these are realized as a running computer program; we also briefly discuss tools for getting started and working with ACT-R and major accomplishments in both the scientific and applied science areas. This includes summarizing some of the insights about human behavior that have been gained by working with ACT-R. We conclude by discussing its future, which we believe will include emotions and physiology, usability, and the use of non-generative models. We include explicit lessons for other architectures, but there are many implicit lessons as well.

Sidebar: Key concepts [sidebars are requested by journal, they will format]

Cognitive mechanisms—information processing structures that exist across time and tasks. A set of mechanisms define an architecture. In ACT-R these include a way to see the world, visual memory, working memory, procedural memory, and a way to act upon the world. These modules (which are called buffers in ACT-R) have characteristics, such as how quickly memory decays, what is passed from vision to cognition, and what actions can be taken between buffers.

Productions—if-then rules made up of a pattern to match (if) and actions to take (then). The structures that the patterns can take are defined by the architecture. In ACT-R these patterns match objects (or their absence) in the buffers that make up the mechanisms of ACT-R. These are used to represent procedural task knowledge.

Declarative Memory Elements—these are symbols that represent declarative memory objects that can have attributes and values. They can be linked together. They are used to represent facts about the world and can be used to represent internal state information, such as goals. They have symbolic components that are accessible to the model and subsymbolic information that moderates behaviour and accessibility of the declarative memory. Accessing them increases their activation, which decreases the time to access them. They are also called chunks in ACT-R and cognitive psychology.

Sidebar: Types of architectures in wide use [sidebars are requested by journal, they will format]

There is a wide range of cognitive architectures that have been created. There are several general reviews of architectures available. The first one was perhaps a *SIGArt* review edited by Laird (1991) that noted 38 architectures. Later reviews include the use of architectures in military simulations by Pew and Mavor (1998), which noted 4 major and over 7 minor. In their review, Pew and Mavor examined mostly architectures developed in the US and noted general areas for projects. Ritter et al. (2003) provide a further review of 7 architectures created outside the US and specific projects. In an unpublished but available paper, Morrison (2003) generated a similar broad review of 19 architectures. Langley, Laird, and Rogers (2009) reviewed a select set of 7 architectures and noted several more in an appendix. They included some summary lessons from these architectures and areas that they and most architectures are deficient (e.g., emotions, interaction). Samsonovich (2010) and his colleagues in the BICA Society created an updated and structured review of that has had a web site (http://bicasociety.org/cogarch) with details on a wide range of 26 architectures. More recently, Kotseruba, Gonzalez, and Tsotsos (2016) provide a summary of the history of architectures, noting 55 active architectures. To see which architectures are being actively used, examples can be found in the proceedings of the Cognitive Science Society's annual conference, the proceedings of the International Conference on Cognitive Modelling, and the proceedings of the Artificial General Intelligence (AGI) conference.

Cognitive architectures can be organized in several ways. One way is to group them into five categories based on the goals of the architectures and then the levels of their mechanisms: (a) AI and agent architectures, such as JACK (Busetta et al., 1999) and JESS (Friedman-Hill, 2003), that use high-level knowledge structures such as plans and focus on performance alone; (b) symbolic architectures, which include previous versions of Soar (Newell, 1990) and Icarus (Konik et al., 2009), that use production rules and care somewhat about the match to human cognition; (c) sub-symbolic architectures, such as connectionist networks (e.g., Grossberg, 1999; O'Reilly & Munakata, 2000), where concepts are represented across multiple components or nodes that are organized in networks, and often but not exclusively care about matching human cognition; (d) hybrid architectures, which include both symbolic and sub-symbolic components (Sun & Bookman, 1994), and aim to match human cognition; and (e) non-generative architectures that do not generate behavior, such as IMPRINT (Allender et al., 2005; Booher & Minninger, 2003), and PROCRU (Pew, 2007), that are intended to predict the time and capabilities required to perform a task. These are used as engineering design tools.

ACT-R best fits in the hybrid architecture group because it has rules and declarative memory that are symbolic, but it also has activations that modify how these components are related and used in a sub-symbolic way. The current version of Soar (Laird, 2012) also has sub-symbolic components.

HISTORY

The history of ACT-R is worth reviewing briefly for several reasons. First, the predecessors and previous iterations of the theory continue to shape ACT-R's current form. Second, it shows ACT-R's evolution from early theories of cognition and the influence of contemporaneous cognitive architectures. Third, we hope the history will help readers and future researchers anticipate where ACT-R is going. Finally, the progression shows how cognitive architectures can evolve. The progression from HAM to ACT-R 7, as well as research that influenced ACT-R, is summarized in Figure 1.

Every broad simulation tool has innate strengths attributable to its base simulation's original purpose (i.e., the phenomena that were modelled). For example, the HumMod physiology simulation was initially developed from a heart simulation before being developed into a unified model of human physiology "from birth to death" (Hester et al., 2011). HumMod's heart simulation is its most developed module. ACT-R fits this paradigm as well: ACT-R began as a model of human memory before being developed into a unified theory of cognition. As such, ACT-R is strongest when modelling memory.
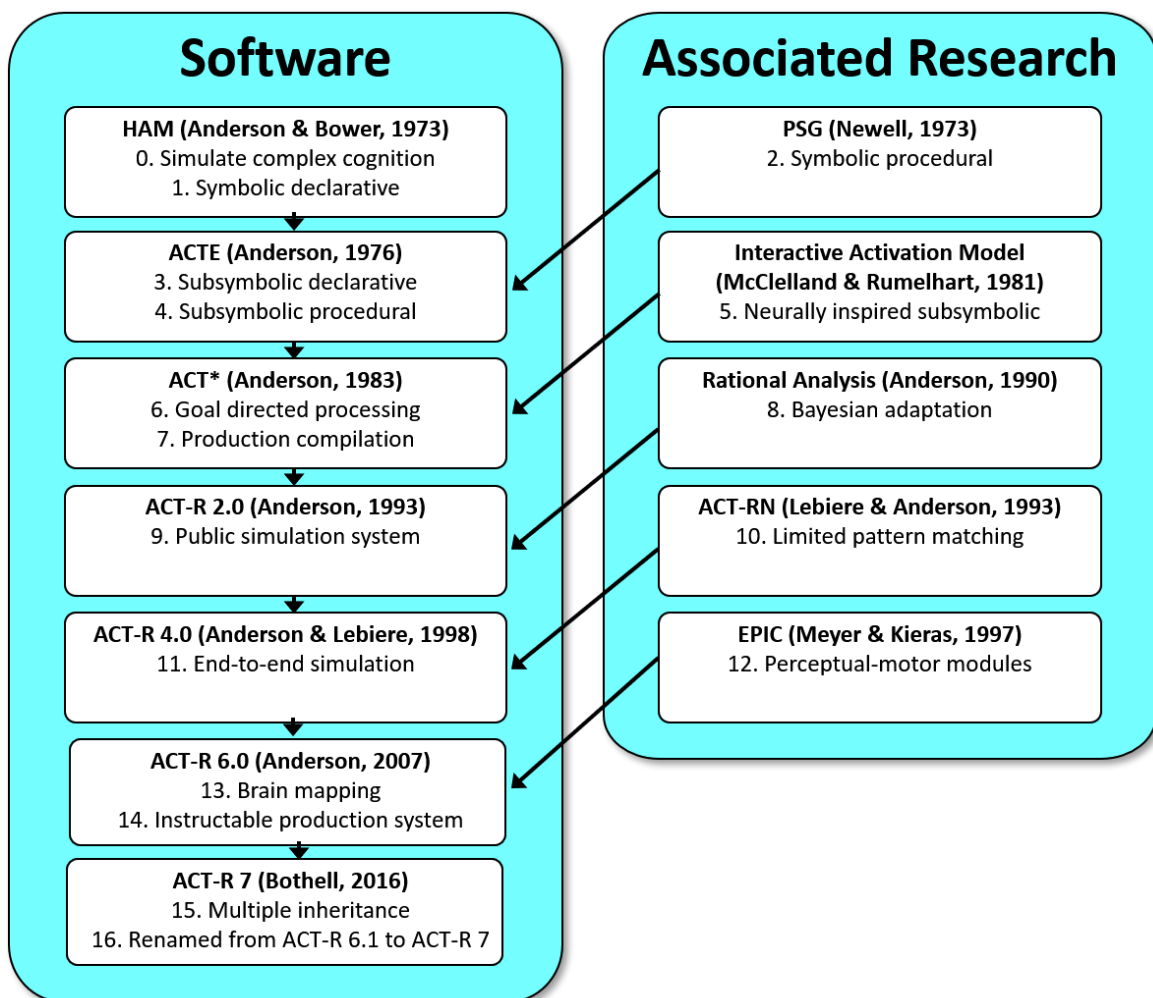

Figure 1. An illustration of the source of ideas and structures in current ACT-R. Figure drawn from Figure 1.11 in Anderson (2007) and extended to include ACT-R 7.

Work based on the ACT-R architecture will, by convention, refer to certain canonical publications to reference a particular implementation of ACT-R. For example, the most recent versions of the theory, ACT-R 7 and ACT-R 6, will typically reference one (or both) of Anderson (2007) and Anderson and colleagues (Anderson et al., 2004). Accordingly, older versions like ACT-R 5 will use older reference points such as Anderson (1993). Our history is drawn from a combination of these primary sources, milestone publications related to the theory (e.g., GRAPES, an early implementation of ACT-R's memory system Sauers & Farrell, 1982), and information disseminated through the annual ACT-R Workshop. A brief review of the history can be found in Anderson's 2007 book, *How can the human mind occur in the physical universe?*, which we also use here.

Predecessors and Early Variations

As a field, research into cognitive architectures is relatively young. Anderson (2007, p. 4) claims that the term itself was introduced by Allen Newell in 1971 (Bell & Newell, 1971). It is worth noting that upon definition of the term, some previous theories could be arguably described as cognitive architectures after the fact (e.g., Hull, 1952). However, the ACT-R theory can specifically trace its lineage to the Human Associative Memory (HAM) model of memory (Anderson & Bower, 1973). This memory simulation model is built around the distributed memory model presented by Hunt (1971). The distributed memory model proposed that information processing operated through buffers that coded and recoded information from outside stimuli into useable chunks, and that these chunks were connected. Although somewhat shallow in its scope, HAM provided the foundational model on which to build a comprehensive theory of cognition.

ACT Theory (1973 to 1993)

Anderson first proposed the ACT theory in 1976 in the book *Language, Memory, and Thought*. ACT was a culmination of several avenues of concurrent research. The ACT theory implemented procedural memory and thus expanded the capabilities of the model to account for many more aspects of cognition. ACT expanded HAM to include procedural memory (from Newell's PSG), alongside HAM's declarative memory. Procedural memory is how to do a task. ACT also included the addition of subsymbolic quantities, that is, numeric activation values for each production rule (sometimes, simply "rule") and declarative memory element. These activation values enabled variation in how and when and how quickly memory elements were used (Collins & Quillian, 1969). Subsymbolic changes in knowledge are represented in smaller increments than whole symbols (e.g., changing the weight of association between two symbols). These mechanisms incorporated the spreading activation model (Collins & Quillian, 1972) for declarative memory and a similar strength measure for the production system. These were the precursors to work on mapping ACT-R processes to their neurological correlates (Anderson, 1976).

In the 1980's the theory was moved into a more complete simulation that included general cognitive processing (ACT-Embodied), and then into ACT* (pronounced Act Star), which was proposed as a general cognitive architecture. Following the initial creation of the ACT theory, Anderson, Sauer, and Farrell (1984) formulated the Goal-Restricted Production System, or GRAPES, to implement these latest developments to the theory. GRAPES is marked as the first true implementation of the ACT theory. GRAPES also marked the final direct contribution of the HAM model's underlying code in the form of the declarative memory system derived from HAM. By acting as a knowledge interpreter built upon the Lisp environment, GRAPES incorporated a dynamic working memory and procedural knowledge bank with weighted values for the importance of different goals which allowed the system to model goal-oriented cognition with a tree structure (Sauers & Farrell, 1982). GRAPES was a more

complete simulation of declarative and procedural memory (Anderson, Farrell, & Sauers, 1984). The GRAPES model provided a goal-oriented model of human cognition that was used as a basis for computer-based tutoring systems.

GRAPES also is important for its implementation of the theory of knowledge compilation. Knowledge compilation is the process of integrating extended computation (multiple rule applications and/or memory retrievals) into a single production rule (Neves & Anderson, 1981). Anderson proposed that task memory was initially encoded as declarative knowledge through learning. However, upon repeated practice, the components of a task (e.g., the memories used to complete the task and the knowledge of what memories to retrieve, and what tasks to perform) are gradually linked together into a single procedural memory, or "compiled". This mechanism is proposed to be how people improve at a procedural task through repeated practice.

The embodiment of this learning mechanism in GRAPES in 1982 provided the basis for Anderson's next revision of the ACT theory: ACT*. ACT* integrated Anderson's (1983) work on knowledge compilation and McClelland and Rumelhart's (1981) Interactive Activation model. Furthermore, this new model also incorporated goal-directed processing within the Goal module and a new model for production learning, both of which are still present within ACT-R today (Anderson, 2007).

ACT-Rational: 1993-1998

Following the release of the ACT* theory, Anderson's work branched out into other applications. As noted in the preface for *Rules of the Mind* (Anderson, 1993), there was a period of uncertainty during the decade following the release of ACT*. During this period, Anderson revised his methodology for understanding cognition through the development of *rational analysis of cognition* (Anderson, 1990). This new methodology led to a significant expansion of the ACT theory. This work culminating in the updated theory, called ACT-R (ACT-Rational), which modified the memory and learning equations to more accurately incorporate use and learning from the environment.

Understanding ACT-Rational requires some explanation of rational analysis. The complexity of the human mind presents a significant "black box" problem, wherein researchers are forced to infer information processing mechanisms from behaviors. Rational analysis provides a solution through the assumption of optimality (that is, rationality) of mechanisms; if multiple mechanisms are possible, the choice of optimal performance suggests which mechanism is most likely. This assumption of optimal mechanisms for human behavior offers a method for reducing the problem space by providing constraints on the gamut of plausible mental mechanisms (Anderson, 1990). The following sources provide further explanation: Chater and Oaksford (1999) provide a retrospective on the first decade of rational analysis. Anderson (1991) provides an in-depth description of its foundation and methodology. Finally, Anderson (1993) provides an explanation of ACT-R, including the integration of the rational analysis methodology.

This addition, as well as including a usable copy of the program on a disc included with *Rules of the Mind*, stimulated the cognitive architecture research community and greatly increased the number of researchers using the theory. This led to the first ACT-R workshop in 1994. Later, annual summer schools were organized to provide a teaching and learning conference for like-minded researchers to discuss their work with ACT-R (Anderson, 2007).

The next iteration, ACT-R 4[a], released in 1998, made several key improvements to the theory and within the program itself as a tool for other cognitive researchers. First, it was presented as a more "polished" form compared to the 1993 release. By incorporating researchers' work outside of Anderson's lab, it promoted a more diverse range of views allowing for even greater collaboration. This version was heavily influenced by connectionism research at that time, and an updated pattern-matching algorithm allowed for increased power of the rule selection system. ACT-R 4 was also improved through the implementation of providing an "end-to-end" simulation tool with the ACT-R distribution—where the model sees the stimuli that participants see and can pass motor outputs into the same simulation participants use—this allowed human participants and cognitive models to interact with the same tasks, thus improving the ability of the program to be tested alongside human participants doing the same tasks (Anderson, 2007; Anderson & Lebiere, 1998).

During this time, other cognitive architectures continued to be developed. One such architecture, EPIC (Kieras & Meyer, 1997), ended up playing a crucial role in ACT-R's development. While sharing some underlying theoretical basis with ACT-R, EPIC used a highly modular structure that incorporated a perceptual-motor system meant to further "embody" the simulation. EPIC's perceptual-motor module would be the core addition of Byrne's ACT-R/PM (Byrne & Anderson, 1997), an offshoot of ACT-R concurrent to the release of ACT-R 4 (Meyer & Kieras, 1997). Figure 2 shows how a perceptual-motor layer was added to the cognitive layer to provide support interaction with the world (similar work was going on with Soar at the same time to provide simulated eyes and hands that were usable across models, Ritter et al., 2000).
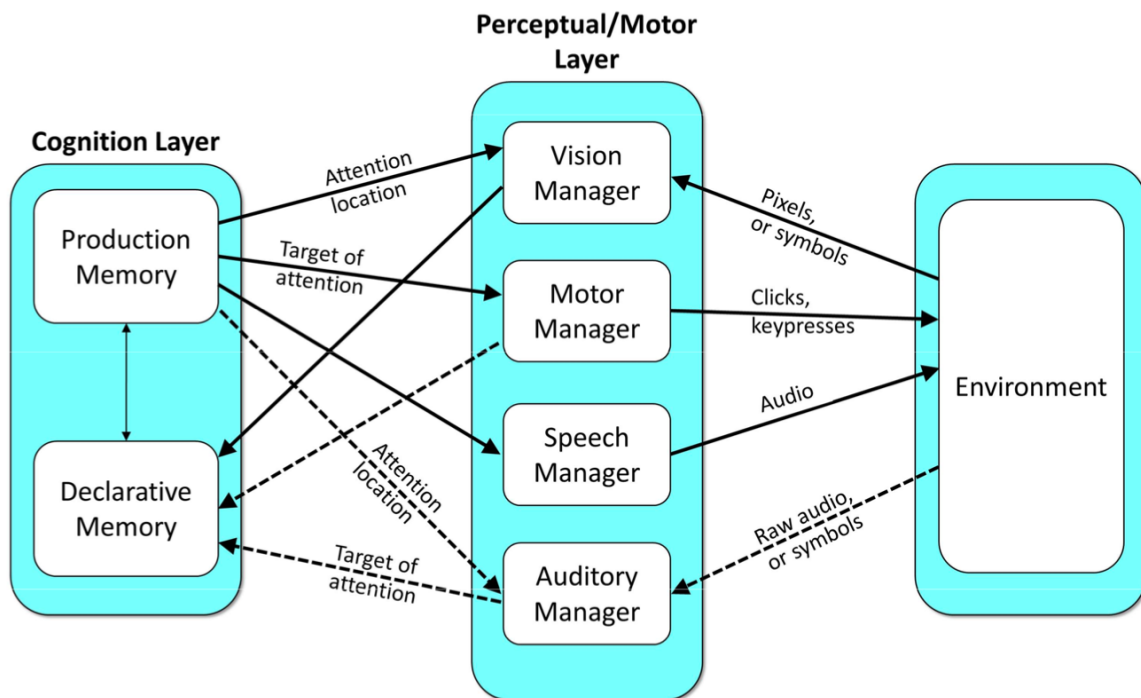

Figure 2. Schematic of the perceptual-motor components for ACT-R, based on Figure 1 in Byrne and Anderson (1997).

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[a] ACT-R versions from v4 are available as software with manuals at
http://act-r.psy.cmu.edu/old-act-r-software/

ACT-R 5, 6, and 7: 1999 to 2018

The release of ACT-R 5 in 2001 once again offered significant advancements in the theoretical framework. As noted earlier, perhaps the most noticeable addition was a perceptual-motor module. This version also reduced the size of the goal module by splitting it into an imaginal module and a smaller goal module. The goal module maintains a chunk for state information and the imaginal module maintains a chunk for context information. In doing so, it brought the theory closer in-line to the minimal inclusion of non-essential information in goals (Anderson, 2005; Anderson & Douglass, 2001).

ACT-R/PM was integrated into ACT-R 5 around 2002 (Fleetwood & Byrne, 2002). It provided a more accurate simulation of human perceptual-motor interaction, providing simulated eyes and hands (Ritter et al., 2000). The basic interaction theory was taken from the EPIC architecture. The software provided a way to interact with an instrumented Lisp window that was included with ACT-R. This work shows how architectures can influence each other.

The perceptual-motor module enhanced the implementation of subgoals within ACT-R by forcing researchers to include additional subgoals to use the perceptual-motor module. Behavioral research on the Tower of Hanoi, a common cognitive task, indicated that the number of subgoals has a significant role on performance of this task (Anderson & Douglass, 2001). Follow up research on this effect using fMRI indicated a neurological basis for subgoal implementation and planning, specifically within the dorsolateral prefrontal cortex (DLPFC), bilateral parietal regions, and the premotor cortex (Fincham et al., 2002). *An Integrated Theory of Mind* (Anderson et al., 2004) offers a detailed overview of the relationship between the modules of ACT-R 5 and its ability to predict and model complex behavior with neurologically compatible mechanisms predictions of brain activity.

ACT-R 6 was released in 2005, though it was first presented during the 2002 ACT-R Summer School[b]. Though very similar to ACT-R 5, it reinforced the modular design by delineating the procedural and declarative mechanisms as modules. It also more closely unified Byrne's Perceptual-Motor module with the architecture and implemented further perceptual/motor components. ACT-R 6 made it much easier for researchers to extend and modify different modules while also speeding up the program relative to ACT-R 5[c], and the community was encouraged to not refer to ACT-R/PM but just to ACT-R.

Over the next ten years, ACT-R 6 was used as a stable base for yearly updates and improvements. In 2014, ACT-R 6.1 was released[d]. This included some changes to make declarative memory chunk-types more useful by allowing for multiple inheritances, as well as some usability fixes. Specifically, memory chunks were given a "type" to identify their contents which improved matching and tying the objects to a theory. Following the 2015 Workshop, ACT-R 6.1 was renamed to 7.0 to alleviate some confusion regarding the numbering of the program. This led to ACT-R 6.1 being considered a "transient

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[b] Lebiere, C. (2002). The Future of ACT-R. Presented at the ACT-R Summer School, CMU. http://act-r.psy.cmu.edu/wordpress/wp-content/themes/ACT-R/workshops/2002/talks/Lebiere-Future.pdf

[c] Bothell, D. (2015) Recent Updates to ACT-R. Presented at the ACT-R Summer School, CMU. http://act-r.psy.cmu.edu/wordpress/wp-content/themes/ACT-R/workshops/2015/bothell-actr2015-updates.pdf

[d] Bothell, D. (2016). ACT-R 6.1 is now ACT-R 7. Presented at the ACT-R Summer School, CMU. http://act-r.psy.cmu.edu/actr7/renaming-6.1-to-7.pdf

transitional version" to help with this[e]. ACT-R 7 is the current version (http://act-r.psy.cmu.edu/software/).

Summary

The history of ACT-R began in 1973 with a memory simulator called HAM and continues with ACT-R 7. It has undergone numerous revisions, and it is extensively documented and applied in several books and over 1,100 publications (most summarized at http://act-r.psy.cmu.edu). The workshops continue, allowing geographically dispersed researchers to gather and collaborate on how ACT-R can evolve. The community surrounding ACT-R provides a cadre of scientists who may not always agree, but all have the same goal: creating a model of the mind. As Newell noted at the beginning of his seminal work:

> *Psychology has arrived at the possibility of unified theories of cognition—theories that gain the power of positing a single system of mechanisms that operate together to produce the full range of human cognition.*
>
> *I do not say that they are here. But they are within reach and we should strive to attain them.* (1990, p. 1).

Though nearly 30 years have passed since those words were written, it may seem that we are no closer to a unified theory of cognition. However, as we have seen over the 50 years of work on cognitive architectures, each new model and theory strives to integrate additional regularities and assimilate prior research. Whether ACT-R is the ideal theory for the creation of a unified theory is yet to be seen. While it may cover many aspects of cognition, there are many other theories that each have strengths and weaknesses. Progress may require the transition into different architectures and models to accommodate existing and future results, but the spirit remains the same. The next section explains the mechanisms in more detail.

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[e] Bothell, D. (2016). ACT-R 7 and Recent Updates. Presented at the ACT-R Summer School, CMU. http://act-r.psy.cmu.edu/wordpress/wp-content/uploads/2016/08/bothell-ACT-R-7-pgss.pdf

Sidebar: ACT-R and Types of Information Processing Cognitive Architectures

Anderson's work on ACT-R aims to create a unified theory of cognition and implement this theory in a computational program. Broadly speaking, cognitive architectures and their underlying theoretical frameworks have been around since around 1960. Herb Simon and Allen Newell (General Problem Solver, Newell, Shaw, & Simon, 1960), and Oliver Selfridge (Pandemonium, Selfridge, 1959) are some of the first researchers to have explored the idea of creating a computational architecture able to explain and predict the human mind. Simon worked with Edward Feigenbaum, his student, to develop what may be the first cognitive architecture, the Elementary Perceiver And Memorizer, or EPAM (Feigenbaum, 1961).

In the following years, many different cognitive architectures have been theorized and developed. A 2016 review of cognitive architectures found 195 different architectures with about 55 active architectures (Kotseruba, Gonzalez, & Tsotsos, 2016). A wide range of architectures are available because each architecture addresses different issues, including topics such as memory, learning, problem solving, emotions, perceptual-motor control, development, language, engineering psychology, errors, and biological, neural, ease of use, and application issues.

The different architectures vary widely, but one commonly used heuristic for organizing them is the information processing and knowledge representation schemes that they use. Figure 3 presents one way to organize architectures, with architectures categorized as symbolic, emergent, or hybrid. Control in symbolic architectures is typically high-level, top-down, and analytic, while for emergent architectures it is low-level, bottom-up, and self-organizing. Hybrid architectures combine features from these two types (Duch, Oentaryo, & Pasquier, 2008; Sun & Bookman, 1994). Elsewhere, based on a reviewer's request, we provide a comparison between ACT-R and Soar, the two most prominent and widely used cognitive architectures (Laird, Lebiere, & Rosenbloom, 2017).
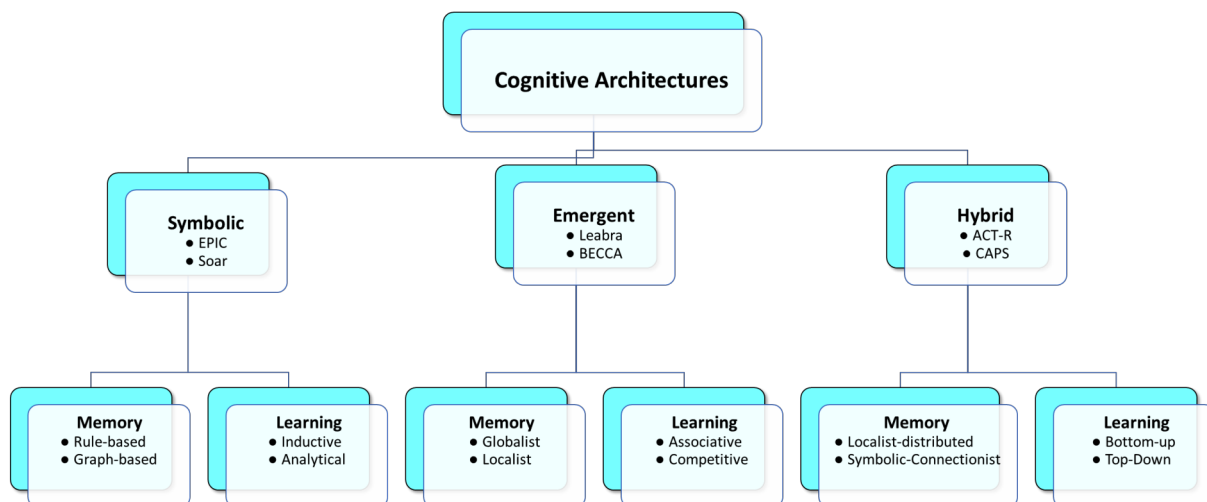

Figure 3: A taxonomy of cognitive architectures based on how information processing occurs in them with examples. These are broadly distinguished by their use of top-down (Symbolic), or bottom-up (Emergent), or a hybrid of these two paradigms. Diagram based on Figure 1 from Duch, Oentaryo, and Pasquier (2008).

Sidebar: ACT-R and Soar

ACT-R and Soar are two prominent cognitive architectures within the field that are often compared and contrasted. However, though they are rooted in the overall idea of creating a unified theory, differences still exist in their approaches. Soar's current development is a result of AI-based research and thus is more theoretically based on assumptions of intelligent agents rather than behavioral phenomena (Laird, 2012; Ritter et al., 2003). Soar combines the heuristic search approach, procedural view of routine problem solving, and a symbolic theory of bottom-up learning designed to produce the power law of learning (Laird, Rosenbloom, & Newell, 1986). ACT-R, on the other hand, is strongly based on detailed experimental data of memory, learning, and problem solving.

There are also numerous similarities, however. Both have two memory types, declarative and procedural, with both architectures maintaining a limitless declarative and procedural memory (although, ACT-R's declarative memory can become difficult to access if the memories are not practiced). Finally, both systems use goal-directed problem solving, although Soar maintains multiple goal states in a hierarchy and ACT-R uses basically a single goal; both Soar and ACT-R are limited to a single, top-level goal.

Soar's decision procedure provides a fundamental difference from ACT-R. Soar uses a decision cycle, where the changing of states only occurs through a decision procedure dictated by the indirect application of rules. Once no more productions apply, the operator is selected or a state is modified. When unable to select an operator, sub-goal creation of choosing the next operator occurs. ACT-R has a more direct state change mechanism through the firing of productions to alter the state or goal stack. Rule firing also differs between the two, while both examine which rules to fire in parallel, Soar fires rules in parallel and ACT-R in serial.

Soar's learning mechanisms also contrast with those in ACT-R. Soar learns in several ways (Laird, 2012). Perhaps the primary way is within production memory through the creation of new rules upon resolving sub-goals (called chunking in Soar), allowing for the learned rule to become the new standard rule for some situations. Soar also learns to compare operators using reinforcement learning and also learns semantic and episodic knowledge, but these are symbolic objects, not objects that have variable activations. Finally, Soar's new rules are immediately available for use (providing in some cases one-shot learning), while ACT-R's new rules start with a specified strength (utility) that must be strengthened (learned multiple times) to compete successfully with the rules that gave rise to it.

ACT-R learns in both declarative and procedural memory through the strengthening of rules upon firing. Productions are rated on their probability of success, cost, and current goal's value, allowing for conflict resolution when choosing between possible productions. Rule strength also influences declarative memory within ACT-R by associating rule strength with declarative memory strength. These differences lead to ACT-R being considered less reactive than Soar, but more cognitively plausible. Thus, Soar tends to be used for larger systems (soar-ware engineering) for AI applications, and ACT-R tends to be used for simulating detailed human behavior.

THEORY COMPONENTS

The mechanisms that make up ACT-R are shown in Figure 4. These components consist of modules and buffers. Each module is responsible for processing a different kind of information. Modules are the mechanisms for modifying and implementing a buffer; buffers store contents that are visible to other modules.

ACT-R has four main modules and a production system: (a) a visual module for identifying objects in the visual field, (b) a goal module for keeping track of current goals and intentions, (c) a declarative module for retrieving information from memory, and (d) a manual module for controlling the hands. A central production system coordinates the communication and performance of these modules through the application of production rules. This central production system is not sensitive to most of the activity of these modules unless the rule being applied is matching against a buffer. However, the central production system has access to the buffers' data and will update the buffers by production rule applications. Thus, the shape, context, and complexity of the rules partially define and are constrained by the architecture.

The manual/motor buffer handles controlling and monitoring hand movement. Visual objects and their identities are located in the visual buffer. The visual and manual systems are the main components in defining interactive ACT-R tasks such as typing on a keyboard or scanning a computer screen.

Figure 4 also shows the current best mapping from the components to brain regions. Since ACT-R 6, researchers have attempted to map the components to brain regions (Anderson, 2007; Anderson et al., 2008; Anderson & Lebiere, 2003; Stocco, Lebiere, & Anderson, 2010). This has primarily been done as predictions of the regions' BOLD (blood flow) responses while doing a task.

Actions in each of these modules take time, although they work concurrently. The time used within models is based on human performance. This time can be provided as a real-time trace where the model runs at the rate predicted in real-time, however most models use a simulated time frame faster than real time. In either case, the predicted times appear in the trace.

The central cycle in ACT–R is one that starts with the buffers holding representations determined by the external world and the internal representations. Patterns in these buffers are recognized using production rules. A production that matches working memory is selected and applied, and the buffers are then updated for another cycle. The assumption in ACT–R is that this cycle takes about 50 ms to complete—this estimate of 50 ms as the minimum cycle time for cognition has emerged in a number of cognitive architectures including Soar, where a value between 30-300 ms is used (Newell, 1990, p. 121, 224). Actions requested from other buffers typically take longer. The manual notes the equations that are used to generate the predicted times to perform actions and how learning occurs through rule learning and changes to chunk activation. The parameters to these equations can be used to model individuals' differences and to explore how the architecture works.

Figure 4 notes several systems. In addition to the systems explained below, the schematic also includes an Aural system that, like the visual system, tracks location and object. The Temporal buffer and module provide time estimations (Taatgen, Rijn, & Anderson, 2004) that can also be used for scheduling when multi-tasking. The Intentional system includes an Imaginal buffer that is used as a scratch pad for holding images and a goal buffer.
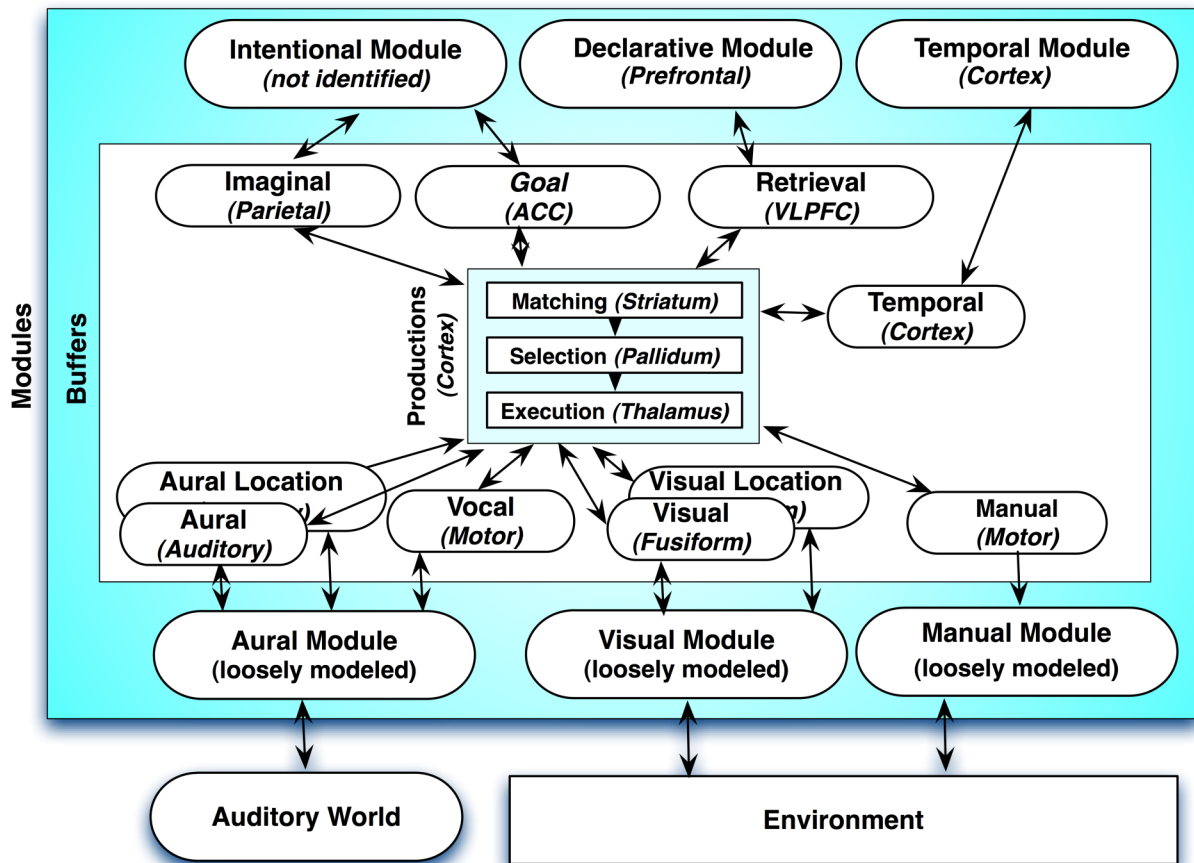
Figure 4: Schematic of the ACT-R cognitive architecture and how its components work together to generate behavior. (Figure by authors based on and extending Anderson et al., 2004, Anderson, 2007, the current ACT-R 7 manual, and comments from Dan Bothell)

Visual

Earlier ACT-R models did not always model the perception and motor aspects of behavior (and some still do not). These models do not include the perceptual-motor components either because they have been difficult to implement or because these aspects are seen as not necessary for insights (e.g., interaction in the task is either trifling, does not lead to learning, or both). Some of the difficulty has been removed by this system and the motor system.

Much of the interaction with the world is done with the visual and motor system[f]. ACT-R's vision module, shown in Figure 4, includes two buffers, one for "Where" information (location) and one for "What" information (visual). The "What" buffer holds a chunk that represents an object in the visual scene, while the "Where" buffer holds the object's location. These two systems are analogous with the dorsal ("Where") and ventral ("What") visual streams in the human visual system (Anderson et al., 2004). The what buffer information is only available if the system focuses on (attends) to a location.

The visual system can attend to a screen location and move its attention around the scene, which is a simulation of fixations and eye movements, and in some systems, lock the eye onto an object so that

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[f] http://chil.rice.edu/projects/RPM/index.html

smooth pursuit eye movements can be performed. This results in chunks representing the location of objects and related chunks holding the semantic context of the object. These visual chunks are then available to central production system to reason about and lead to behavior, for example shifting visual attention.

These perception modules are routinely expanded by researchers to accommodate other capabilities like hearing. These results can be included with the distributed architecture after they have been used and tested several times.

The perceptual and motor components work with an instrumented Lisp window included with ACT-R. Modelers interacting with other systems have created extensions to work with other tasks. For example, SegMan (for Segmentation/Manipulation) has been developed to translate pixel-level input from a computer screen into the objects and symbols that a cognitive model can manipulate. SegMan further translates the manual output of a cognitive model, such as mouse movements and key presses, into a form that can be executed appropriately by a computer (St. Amant et al., 2005; Tehranchi & Ritter, 2018).

Central Production System

During the decision cycle in ACT–R, production rules are used to analyze patterns in all of the buffers that may represent internal and external information. This pattern recognition system determines the next action. While the rules do not have direct access to the modules themselves, they can check some limited state information that has been made available by each module. Production rules consist of a condition and an action, which are also sometimes referred to as the left-hand and right-hand sides of the rule. The pattern structures that the rules can match represent architectural commitments about representations in the buffers and in the simulated mind.

There is a conflict-resolution phase in the rule-based system; a trace of this appears in the ACT-R output trace noting how rules are chosen. In ACT-R, the rules that match the current goal are matched against the central set of buffers connected to the central processing. A rule is selected based on this match (highest utility with noise added), and the action of the rule is applied (the rule "fires," "matches", or is "applied").

The rule can have multiple actions, and these can pass commands to the perception or motor module, or they can modify any buffer's values, updating a declarative or goal memory or putting a command into the visual or motor modules.

Goal Module

The goal module is the simplest module. It provides the system with a goal buffer that is typically used to maintain a model's current task state. The goal buffer also serves as a source of activation for declarative memory retrievals.

It has one buffer named Goal that holds a chunk containing the current control state. The only actions that this module can do are to create a new goal chunk when requested, to update the contents of any slot, and it can clear and save the goal's chunk into declarative memory (Bothell, 2017).

Declarative Memory

The declarative memory architecture in ACT-R is designed to mimic human memory. There are equations (available in the ACT-R manual) that note how quickly the memories are retrieved, which is

based on how often they have been used as well as a threshold (that might vary by individuals or over time) for retrieval, and noise. The fan effect—how well connected the memory is to other memories, particularly currently accessed memories—also influences the time to retrieve a given memory (Anderson & Reder, 1999).

Typically, models will retrieve a memory using search terms, and then use the resulting memory in producing behavior. If a memory cannot be retrieved, the model will need to have strategies to work around this problem, or it will stop running. This approach also helps explain why negative responses are slower than positive responses. There is also partial matching of rules to the current knowledge state (Lebiere, 1999), blending of memory retrievals (Gonzalez, Lerch, & Lebiere, 2003), forgetting (Anderson, Fincham, & Douglass, 1999), and instance-based learning (Gonzalez, Lerch, & Lebiere, 2003) mechanisms, where related memories can be matched or merged, respectively. They are not used in all models.

Manual (Motor)

The motor module receives command requests through the motor buffer. These commands direct the motor module how to output actions to the world. There is a small set of commands for typing on a keyboard and moving the mouse in the window provided with ACT-R, and some researchers have extended this approach with additional code to drive cars and robots. Again, the extensions are typically not included in the ACT-R distribution until they have been used and tested a few times.

The motor buffer can be overwritten by the actions of repeated rule firings, losing action commands, and if too many commands are sent too quickly to the fingers, the commands can jam the system causing no behaviour to occur. This loss of behaviour during a jam is an implementation detail of the software rather than a specific claim regarding motor behaviour (Bothell, personal communication, Sept. 2018).

Learning

There are several types of learning in ACT-R. Not all models use all of these learning mechanisms, and these mechanisms have varied somewhat across ACT-R versions.

Perhaps the mechanism with the largest learning effect is that of declarative memory strengthening. As memories are retrieved and used, they are strengthened; their activation is increased. Retrieval time for a memory is dependent on this activation; higher activation causes lower retrieval times. This approach has been used, for example, to choose strategies in games (West, Lebiere, & Bothell, 2005).

ACT-R also can learn procedural memories. In ACT-R 6 and 7, when two rules fire close enough together, the rules can be merged into a single rule. The times of the rule firings are often influenced by the retrieval of declarative memory. So, these two mechanisms of declarative and procedural knowledge interact in this way.

Notably, there are other areas where learning occurs in humans but does not yet appear in ACT-R. For the most part, ACT-R does not learn to recognize new visual icons, to improve its perceptual-motor capabilities, and to have memories that include synthesis (e.g., smell and sound) or emotions and semantics. These are areas for future work.

Summary

Figure 4 provides a summary of the major components in ACT-R and how they interact. These major components are often found in other cognitive architectures (Laird, Lebiere, & Rosenbloom, 2017). This figure can also be used to see components that are currently missing. For example, it does not have a limbic system and emotions. Further details on the implementation are available in the ACT-R tutorial and ACT-R manual. Further high-level descriptions are available in the canonical reports noted earlier.

TOOLS FOR WORKING WITH ACT-R

As cognitive architectures have gotten more complex, tools for working with them have become more important. Tools also help attract and support a wider range of users for models (Pew & Mavor, 1998; Ritter et al., 2003). There are several resource types that could be usefully provided for each architecture. Most of these tools for ACT-R are provided through the general repository, http://act-r.psy.cmu.edu.

Programming Interface and Other Implementations

The ACT-R distribution includes a graphical user interface (GUI) to help develop models. The primary implementation and realization of the ACT-R theory is in the Lisp version available from the ACT-R website.

The theory has been implemented in other base languages to help with integration with other systems. Their proponents argue that these help to understand what are the fundamental aspects of theory and what are implementation choices caused by the programming language. These implementations currently include two in Java (jACT-R[g] and Java ACT-R[h]).

Instructional Materials

As new people come into a research community, it is useful to have common instructional materials for them. The ACT-R community has several resources, including a manual, which continues to be updated as needed. Importantly, there is also a tutorial (act-r.psy.cmu.edu/software/) with eight units. Each unit notes an example model and has the learner modify the model slightly to learn a modeling paradigm within the architecture (Taatgen, Lebiere, & Anderson, 2006). These tutorials are used in ACT-R summer schools, and in university classes and labs to learn ACT-R.

A list of frequently asked questions (FAQ, acs.ist.psu.edu/projects/act-r-faq/) about ACT-R with answers is also available. The FAQ is posted as a guide for finding out more about ACT-R. It is not comprehensive but can be helpful.

Higher-Level Modeling Languages Based on ACT-R

There have been several high-level behavior representation languages that create ACT-R or ACT-R-like models (Ritter, Haynes, et al., 2006). These high-level languages let users create models in a higher,

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[g] Harrison, A.M. (2008). jACT-R : Making cognitive modelling portable. Retrieved from http://jact-r.org/.

[h] Salvucci, D. (2015). Java ACT-R. A Java Simulation & Development Environment for the ACT-R Cognitive Architecture. http://cog.cs.drexel.edu/act-r/

more declarative representation, such as the Problem Space Computational Model (PSCM) level (Newell et al., 1991) or GOMS (Card, Moran, & Newell, 1983). Herbal creates ACT-R models from PSCM constructs (Cohen, Ritter, & Haynes, 2010) and hierarchical task analyses (Paik et al., 2015). G2A creates ACT-R models from GOMS descriptions (St. Amant, Freed, & Ritter, 2005). ACT-UP provides a more imperative programming approach for creating ACT-R models (Reitter & Lebiere, 2010).

With these tools, users can represent hierarchical or sequential tasks in an ACT-R model more easily. Users can lay out their whole task hierarchically or sequentially, and the relations among tasks are shown in a tree form. Based on these relationships, the ACT-R productions are created by a compiler.

These languages, including Herbal, have all advantages that other high-level languages used in computer science have. These advantages include: (a) smoother integration into systems created in those widely used languages, such as Java, supported by extensive libraries and tools; (b) a perceived and sometimes greater degree of implementation modularity, and thus the ability to more easily investigate changes and extensions to existing cognitive architectures; (c) the opportunity to make comparative analyses; and (d) ease of use through less data manipulation.

Sidebar: How to get started with ACT-R*

How does one get started with ACT-R, or any cognitive architecture? There are several ways. One way that is most common is to use the architecture that is being used locally. This provides support and running example models within your environment. Another approach is to first read about several architectures and then choose one that seems to best support the type of work you are interested in. You can read books, journal articles, conference papers, and manuals to learn about the architectures and how they are used. If you are interested in memory and learning, ACT-R, for example, is a good choice. If you are interested in large system design and problem solving, Soar might be a better choice. If you are interested in neural implementations, then other architectures including Nengo (Eliasmith, 2013) can be good choices.

You might also find that none of the existing architectures suit your purposes, and then you might either create a new architecture or modify an existing one. We would suggest that modifying one is a better option because then you help results cumulate, you can build on existing theory and software, you can save time and effort, and you have more researchers immediately interested in your work who can comment.

When you have chosen your architecture, you can download it and start to use it. You should read the manual (and then can later come back to it once you know what it contains). You should also do some and perhaps all the tutorials that come with the architecture. You can be somewhat selective and choose the tutorials that teach the materials related to your modelling. You should get on a mailing list for the architecture, if there is one, and attend tutorials or meetings with others working with the architecture if you can. Finally, stay in touch with the community working with the architecture to share specific advice and also to learn about changes and uses of the architecture. There are further notes available on how to start using an architecture (Ritter, 2004).

There are several tools to help create ACT-R models. Some have been widely used, such as the GUI provided with ACT-R 6. Others have shown potential. The usability of these theories realized as cognitive architectures, despite their promise and the role of their scientific value, will also be judged by how many people can use them, and how easily the theories are to understand, manipulate, and apply.

ACT-R SUCCESS STORIES AND APPLICATIONS

It is useful to reflect upon ACT-R, and other architectures, by suggesting a Hall of Fame, that is, models within ACT-R that have provided notable insights, styles of models, or results. It is useful to examine places where ACT-R has been used successfully for at least two reasons. The first is that knowing where an architecture has been successful helps define the architecture. The second is that it provides evidence that the architecture is worth taking seriously. Some preference was given to models that are available on the ACT-R website. Here we briefly review some of the success stories. There are more models and other reviews could choose other success stories.

These models are noted because they provide insights about human behavior. They receive support for these insights typically because they match reaction times, but some predict error rates and strategy choices (Daily, Lovett, & Reder, 2001; Marewski & Mehlhorn, 2011). Some show that certain knowledge sets and mechanisms are sufficient to perform a task. Some provide applications that are useful.

Models of Memory

The most classic ACT-R models are of human memory (Anderson et al., 1998; Anderson & Matessa, 1997; Anderson & Reder, 1999; Lebiere, 1999; Pavlik & Anderson, 2005; Stocco & Anderson, 2008). In particular, the Fan effect (e.g., Anderson & Reder, 1999) and the Stroop effect (Juvina & Taatgen, 2009) have been modelled. These models help explain why memory can get stronger with practice, the effect on memory elements of being connected to other memory elements (fan effect), and how automatic processes can dominate less practiced processes (Stroop effect).

Tutors

A cognitive tutor is a computer-based instructional technology that uses a cognitive architecture such as ACT-R. It can use the cognitive architecture for (a) for understanding student's actions and guiding them, (b) for solving the students' problems in a student-like behavior as an illustration (Ritter & Feurzeig, 1988), or (c) used as a basis for the design of the tutor and its strategies. ACT-R has been used to create tutors that use several of these approaches.

A modified version of ACT-R has been used to generate tutors for high school math curriculums (and other topics, typically formal domains with static problems, like programming), including proof generation in geometry and fundamental programming skills in Lisp (e.g., Anderson, Corbett, Koedinger, & Pelletier, 1995; Koedinger, Anderson, Hadley, & Mark 1997). These tutors have a model in a modified version of ACT-R that can recognize student actions in the tutor as steps towards the solution (or not). Rather than generating behavior, they recognize behavior, particularly correct behavior. In studies, students achieve the same level of proficiency as conventional instructions in one third of the time (Anderson et al., 1995) and perform better on standardized tests (Koedinger et al., 1997). ACT-R has also been used to design the ASSISTments tutoring system (Mendicino, Razzaq, & Heffernan, 2009) and been inspirational for the Declarative to Procedural (D2P) tutoring system (Ritter et al., 2013).

Models of Driving

ACT-R has been used to create models of vehicle operators. Salvucci and his colleagues have been creating a series of models of driving behavior and how driving interacts with other tasks (Salvucci, 2001, 2006, 2009; Salvucci & Taatgen, 2008, 2011; Salvucci et al., 2005). Their models have been compared to and predict driver's input to the car and other interfaces, car performance, and eye-

movements. Similar but much simpler models have been created for cars (Ritter, Van Rooy, et al., 2006) and robots (Ritter, Kukreja, & St. Amant, 2007; Trafton et al., 2013). ACT-R has also been used to create a model of airplane operation (Schoppek & Boehm-Davis, 2004; Schoppek et al., 2001) and air traffic control (Schoelles & Gray, 2000; Taatgen, 2002). These models use all the mechanisms in ACT-R to generate behavior, from recognizing objects and the road, to reasoning, to generating commands to drive.

We also include Byrne and Kirlik's (2005) model of airplane taxiing here. In their work, they used ACT-R models of how pilots choose strategies when taxiing planes around a simulation of the runway system of the O'Hare airport. They found suggestions for how to decrease errors when taxiing, a nice application of using a model to suggest system improvements.

Models for Testing Interfaces and Agents

There has been a long interest in creating models of users in ACT-R for use in interface design and as opponents and colleagues in shared interfaces (Anderson, Matessa, & Lebiere, 1997; Byrne & Gray, 2003; Gray & Altmann, 2001; Gray, Young, & Kirschenbaum, 1997). We note a few particular models here, but many of the models of specific regularities are also in service of modelling interface users, or could be, including models of perception and motor output (Ritter et al., 2001).

There are several interesting examples. Paik et al. (2015) created a model of how novice interface users turn into relatively expert users of an interface over four trials based on their task time. This model used the learning mechanisms in declarative memory and rule compilation. Ball et al. (2010) created a synthetic teammate that interacts with natural language and a piloting task, and St. Amant et al. (2007) have created models to evaluate cell phones. These models used all the mechanisms. Also, the previously noted driver and pilot models can be seen as these types of models.

These models have also led to insights about interaction. One is that if the information is not available, neither the model nor the user can do the task. Another is that milliseconds matter, that is, the difficulty of the moves and clicks can change how users process information (Gray & Boehm-Davis, 2000). Models have also explained why users continue to use suboptimal strategies (Fu & Gray, 2004).

Models of How Cognition Changes

The basis of cognitive architectures is to study knowledge and the mechanisms to apply that knowledge, where the mechanisms do not change across tasks, people, or time. There are, however, aspects of how human behavior changes that appear not to be changes to knowledge but appear to be changes to the architecture or architecture parameters, influencing how information is acquired, stored, and processed. ACT-R has been used to represent the effect of sleep fatigue (Gunzelmann et al., 2009), task appraisal stress (Dancy et al., 2015), task appraisal stress and caffeine (Kase, Ritter, Bennett, Klein, & Schoelles, 2017), and development on cognition (Jones, Ritter, & Wood, 2000).

Models of Language

ACT-R has been used to create models of language production and use. They contribute to the psycholinguistic question of how the mind selects words and processes sentences, but they also spell out how general cognition and language can be integrated. Examples include models of how language use co-evolves between users (Reitter, Keller, & Moore, 2011; Reitter & Lebiere, 2011; Trafton et al., 2013), particularly using declarative representations that change with learning, and how architectural constraints (e.g., time to process an utterance) shape language comprehension (Lewis, Vasishth, & Van Dyke, 2006).

Other Notable Models

We include here other notable models that do not fit another category. The ACT-R distribution comes with a small set of models of psychology experiments. These include models of mental arithmetic, subitizing and the Sperling Iconic Task (a visual memory task), several memory tasks, and problem solving. The models are not designed to be a necessary or sufficient set of tasks. They are, however, a useful set and have been used to teach many modellers. Other architectures can either use this set of tasks as a set to model, or they can use the set as an exemplar and provide their own set of example tasks, models, and data. This set can be used to test other architectures, and we know of at least one ongoing effort to model these tasks and behavior in another architecture.

There are also significant models of multi-tasking (Moon & Anderson, 2013; Salvucci & Taatgen, 2008, 2011), decision making (Marewski & Mehlhorn, 2011), and spatial reasoning (Gunzelmann, Anderson, & Douglass, 2004), including how robots reason (Kennedy et al., 2009). There are more models on the ACT-R web site sortable by task, and there are more significant models than there is space to list.

Summary

There are numerous ACT-R models available. The models that are available are a subset of all that are possible. That there are not models for all tasks simply suggests how broad is the range of behavior to model. The coverage also indicates the interests of the modellers using ACT-R. As researchers enter the community they will bring other interests and knowledge, and they will use these to create models in new areas. The sparse coverage could indicate problems with the architecture, but more likely indicates a lack of modellers and time to model.

Table 1 provides a summary of some of the significant models and extensions to ACT-R, a type of Hall of Fame. The ACT-R web site notes many further models, searchable by author and category. These arose initially from ACT-R's core can help summarize further areas where ACT-R models have particular impact.

The work in Table 1 starts with models of memory and moves through applications to model core cognitive psychology tasks. The additional models show that ACT-R can be used in applied ways in psychology and in engineering. Some of the engineering applications then come back and show how core concepts in psychology can be explored in applied settings such as how novice to expert transitions can be modelled and how social networks can be explored with intelligent agents.

Table 1. Some significant models in ACT-R and their implications.

Model	Insights/Implications	Authors
Models of memory effects, e.g., fan effect, spreading activation, priming	Shows how memory effects affect numerous aspects of behavior and provides a foundation for modeling	Numerous
ACT-R/PM (perceptual-motor)	Shows how to incorporate a wide range of micro theories about perception into a cognitive architecture as architectural components.	Byrne & Anderson (1998)
Mapping of ACT-R to brain structures	Shows that the structures in ACT-R can be mapped to blood flow (activation) using fMRI and cognitive models that predict activation (blood flow) in the brain.	Anderson et al. (2004) Anderson (2007)
Driving models	Shows how models can summarize behavior regularities in a complex real-time task.	Schoppek (2001); Salvucci (2006)
Taxiing at O'Hare Airport	Shows how to optimize large processes in large systems using ACT-R.	Byrne & Kirlik (2005)
Herbal/Dismal	Models novice to expert transition on a 20 min. spreadsheet task using a model compiler.	Paik et al. (2015)
Synthetic Teammate	Provides a comprehensive agent to live in a synthetic environment.	Ball et al. (2010)

CONCLUSIONS

This review summarizes and explains ACT-R, a fairly well developed and widely used cognitive architecture that has been used to model behavior in numerous areas. ACT-R's components provide a useful set of broad mechanisms to implement behavior. We conclude by noting insights ACT-R has provided for psychology and cognitive architectures as unified theories of cognition.

Insights for psychology

ACT-R has provided several insights for psychology. One insight is how numerous aspects of cognition are intertwined. There are several interactions worth mentioning, such as how memory and information processing are entwined, and how problem solving and learning are entwined. In many models, the architecture also shows how learning supports memory and vice versa—with learning, memory becomes stronger, with stronger memory, more problem solving can be performed.

Joint work across architectures is starting to show how theories of cognition's mechanisms can be merged, like the perceptual-motor theories in Epic were reused. The theories appear to be easier to merge on the level of the architecture rather than with rules and knowledge, but this could just be what has been able to be merged so far.

Numerous scientists in many fields have encouraged models that make strong predictions that integrate across a wide area (Grant, 1962; Marewski & Olsson, 2009; Newell & Simon, 1972), with a preference for those theories that can do the task (Feynman & Leighton, 1985; Newell, 1990). ACT-R shows that to predict behavior by generating it, mechanisms are required to produce the behavior. Thus, ACT-R models are larger than regression models, and they also produce many predictions including response

items, what knowledge is used, error rates (sometimes), what part of the brain is used to generate the behavior, learning, and forgetting. This approach also provide a principled way to merge theories and an immediate way to apply the theories in simulations and games to test and apply the theories. These advantages are not obtained by small theories that simply describe the results as a single equation.

Insights for cognitive architectures

ACT-R has provided insights about cognitive architectures. ACT-R suggests that cognitive architectures primarily need to be a theory of how behavior is generated through information processing including perception and motor output. ACT-R has shown that it can generate novel predictions and help explain human behavior. Generally, the architecture has been reused rather than the knowledge sets (models).

It also appears that having an interface and tools to help create models, a manual, example models, a summer school, a web site, workshops, and some central technical support are also at least helpful (if not necessary) for architectures to have this level of impact. These resources are useful for building models and supporting a community of researchers who can be more powerful than a single team.

What's Next? The Future of ACT-R

Table 2 notes several future directions we think that ACT-R should and can develop in. Most of these are self-explanatory or have been mentioned earlier in this paper.

One direction that could use more explanation is non-generative models. ACT-R has generally been used to create generative, information-processing models. That is, they perform the information processing required to do the task and they interact with some piece of software to generate behaviour.

A future for ACT-R is to make predictions more quickly and easily without doing the task as a non-generative model, that does not do the task, but only makes predictions. ACT-R is intended to provide a theory of cognition, in the same way that Newtonian physics is intended to explain simple motion and provide direct predictions. In most instances, knowledge of Newton's equations allows physicists and even engineers to use these theories informally and without the use of equations.

While we are strong believers in formal theories and building models, in time, it may be possible for a wider range of folks to use ACT-R by only using the constructs and results of existing models. We are not sure how far this can or should go, but it appears to be a promising approach to extend our understanding for cognition and to extend the application of the theories in ACT-R.

Table 2. Future directions for ACT-R.

Extending ACT-R to model further aspects of motor and sensory behavior

Integration with other task simulations

Learning a task from natural language

Integration of multiple models

Integration of physiology with cognition to support modeling the effects of physiology on cognition (e.g., heat stress) and as a principled way of combining moderators

Usability, so bigger models can be created and can be used by a broader range of users

The use of non-generative models

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FURTHER READING

ACT web site: http://act-r.psy.cmu.edu