Accounting for creativity within a psychologically realistic cognitive architecture

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Abstract Creativity research, computational or otherwise, can benefit from a detailed understanding of human creative problem solving. The psychological processes of human creative problem solving have been tackled using computational modeling and simulation based on the CLARION cognitive architecture. CLARION, in general, attempts to provide a unified explanation of a wide range of psychological phenomena using (mostly) five basic principles. By using these CLARION principles, the Explicit-Implicit Interaction (EII) theory of creative problem solving was derived, which provides a unified framework for understanding creative problem solving. A list of key phenomena that can be accounted for by the EII theory and simulated using the CLARION cognitive architecture is presented. This work represents a step in the development of unified process-based theories of creativity encompassing incubation, insight, and various other related phenomena. Beyond EII, the roles of motivation, personality, emotion, and social interaction in creativity may also be explored using CLARION.

Introduction

Creativity research, computational or otherwise, can benefit from a detailed understanding of human creative problem solving, including the detailed psychological processes and mechanisms involved therein. Psychological processes of human creative problem solving have been tackled with a variety of means, including computational modeling and simulation, for example, based on the CLARION cognitive architecture (Sun 2002, 2014).

Cognitive architectures, in general, are becoming increasingly important in cognitive science, in psychology, and in artificial intelligence (AI) (Langley, Laird, and Rogers 2009). Among these cognitive architectures that have been proposed, the CLARION cognitive architecture (Sun 2002, 2003, 2014) tries to provide a more unified explanation of a wide variety of psychological phenomena using mostly five basic principles: 1) The co-existence of, and the difference between, explicit and implicit psychological processes; 2) The simultaneous involvement of implicit and explicit processes (in most tasks); 3) The “redundant” representation of explicit and implicit knowledge; 4) The integration of the results of explicit and implicit processing; and 5) The iterative (and possibly bidirectional) processing. This cognitive architecture has already been used to account for many psychological phenomena (such as implicit learning, bottom-up learning, cognition-motivation interaction, creativity, and so on) and to simulate a great deal of relevant human behavioral data (e.g., with respect to low-level skill learning, high-level cognitive skill acquisition, and reasoning; see, e.g., Sun, Merrill, and Peterson 2001, Sun, Slusarz, and Terry 2005, Sun 2002).

In relation to problem solving, some existing psychological theories of problem solving and reasoning have highlighted a role for implicit cognitive processes. For instance, implicit processes are often thought to generate hypotheses that are later explicitly tested (Evans 2006; Gabora 2010; Helie and Sun 2010). Also, similarity has been shown to affect reasoning through processes that are mostly implicit (Sun 1995). Yet, most theories of problem solving have focused on explicit processes that gradually bring the problem solver closer to the solution in an explicit, deliberative way. However, when an ill-defined or complex problem has to be solved (e.g., when the initial state can lead to many different interpretations, or when the solution paths are highly complex), the solution is often found by sudden 'insight' (Bowden et al. 2005, Pols 2002), and theories of regular problem solving are, for the most part, unable to account for this apparent absence of deliberative processes. Hence creative problem solving needs to be examined specifically.

Research on such creative problem solving has tried to tackle more complex, more ambiguous problems. However, psychological theories of creative problem solving tend to be fragmentary and usually concentrate only on a subset of phenomena, such as focusing only on incubation (i.e., a period away from deliberative work on the problem; for a review, see Smith and Dodds 1999) or insight (i.e., the sudden appearance of a solution; for a review, see Pols 2002). The lack of detailed process models (e.g., detailed process oriented computational models) has resulted in their limited impact on the field of problem solving and creativity (Duch 2006).

In this chapter, we explore an integrative theory of creative problem solving that is based on a psychologically realistic cognitive architecture, that is, the CLARION cognitive architecture. The integrative theory and the cognitive architecture on which it is based will hopefully transcend the shortcomings of many existing models/theories, and address many relevant aspects of creative problem solving, from incubation to insight, and from motivation to personality.

The remainder of this chapter is organized as follow. First, we discuss the relevance of psychologically realistic cognitive architectures to AI, cognitive science, and psychology. Second, the

CLARION cognitive architecture is sketched. Third, the Explicit-Implicit Interaction (EII) theory of creative problem solving, derived from the CLARION cognitive architecture, is briefly explained. Fourth, we present a summary of phenomena that are captured by the EII theory and simulated by CLARION. Fifth, going beyond EII, we examine the relevance of motivation, personality, emotion, and social interaction to creative problem solving, and how CLARION may account for them. We conclude with a discussion of the advantages of using integrative frameworks (such as cognitive architectures) in AI and cognitive science.

Why is a Cognitive Architecture Important?

In cognitive science as well as in AI, a cognitive architecture is the specification of the essential structures, mechanisms, and processes in the form of a domain-generic computational cognitive model, which can be used for a broad, multiple-level, multiple-domain analysis of cognition and behavior (Sun 2004). Its function is to provide a framework to facilitate more detailed modeling and understanding of various components and processes of the mind. In this way, a cognitive architecture serves as an initial set of assumptions to be used for further development of models and theories.

While there are all kinds of "cognitive architectures" in existence, we focus specifically on psychologically oriented cognitive architectures (as opposed to software engineering oriented ones). For cognitive science, the importance of such cognitive architectures lies in the fact that they are highly beneficial to understanding the human mind in many ways. Researchers who use cognitive architectures must specify cognitive mechanisms in sufficient detail to allow the resulting models to be implemented on computers and run as simulations. While it is true that more specialized, narrowly scoped models may also serve this purpose, they are not as generic and as comprehensive and therefore do not provide unified accounts (Sun 202, 2004).

For the fields of AI, the importance of cognitive architectures lies in the fact that they support its central goal—building artificial systems that are as capable as human beings (or more). Cognitive architectures help to reverse engineer the only truly intelligent system around currently—the human mind. The use of cognitive architectures in building intelligent systems may also facilitate the interaction between humans and artificially intelligent systems because of the similarity between humans and cognitively/psychologically grounded intelligent systems.

The CLARION cognitive architecture

CLARION (Sun 2002, 2014; Sun et al. 2001, 2005) is an integrative, comprehensive cognitive architecture consisting of a number of distinct subsystems for distinct psychological functionalities, with a dual representational structure in each subsystem (implicit versus explicit representations).

The subsystems within CLARION include the action-centered subsystem (the ACS), the non-action-centered subsystem (the NACS), the motivational subsystem (the MS), and the meta-cognitive subsystem (the MCS). The role of the action-centered subsystem is to control actions, regardless of whether the actions are for external physical movements or for internal mental operations. The role of the non-action-centered subsystem is to maintain general (declarative) knowledge. The role of the motivational subsystem is to provide underlying motivations for perception, action, and cognition, in terms of providing impetus and feedback (e.g., indicating whether an outcome is satisfactory or not). The role of the meta-cognitive subsystem is to monitor, direct, and modify dynamically the operations of the other subsystems. See Figure 1.

Generally speaking, within each subsystem, a dual representation exists, which is made up of two “levels”. The top level encodes explicit knowledge in a localist fashion, while the bottom level encodes implicit knowledge in distributed connectionist representation.

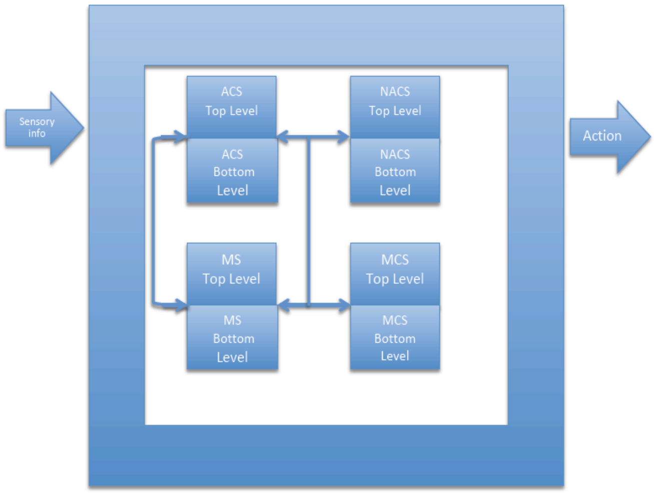

Fig. 1. The CLARION cognitive architecture. The major subsystems are shown.

Given the length limit of this chapter, a detailed mathematical/algorithmic description of the CLARION cognitive architecture cannot be presented. Instead, some of the most basic general principles are briefly reviewed below. The reader interested in detailed specifications of the cognitive architecture is referred to the cited papers above (in particular, Sun 2002, 2014).

Principle #1: The Co-existence of, and the Difference Between, Explicit and Implicit Knowledge

CLARION assumes the existence of two different types of knowledge, namely explicit and implicit, residing in two separate stores (Sun 2002). Explicit knowledge is easier to access and to verbalize, crisper, more flexible, and usually symbolic (Sun, 2002). However, using explicit knowledge requires more attentional resources. In contrast, implicit knowledge is relatively inaccessible, harder to verbalize, often more vague, and usually "subsymbolic" (Sun 2002). However, using implicit knowledge does not tap much attentional resources. Explicit and implicit knowledge is processed differently. According to CLARION, explicit processes often perform some forms of rule-based reasoning (in a very generalized sense) and result in relatively crisp and exact processing (often involving hard constraints), while implicit processing is "associative" and often involves soft-constraint satisfaction (Sun 1995, 2002).

Principle #2: The Simultaneous Involvement of Implicit and Explicit Processes in Most Tasks

Explicit and implicit processes are involved simultaneously in most tasks under most circumstances (Sun 2002). This can be justified by the different representations and mechanisms involved with the two types of knowledge respectively (Sun 2002). As such, each type of processes can end up with similar or different conclusions that contribute to the overall output (see, e.g., Sun et al. 2005).

Principle #3: The "Redundant" Representation of Explicit and Implicit Knowledge

According to CLARION, explicit and implicit knowledge are often "redundant": They frequently amount to a re-description of one another in different representational forms. For example, knowledge that is initially implicit may be later re-coded to form explicit knowledge (e.g., through "bottom-up learning"; Sun et al. 2001). Likewise, knowledge that is initially learned explicitly (e.g., through verbal instructions) is often later assimilated and re-coded into an implicit form, usually after extensive practice (top-down assimilation; Sun 2002). There may also be other ways redundancy is created, for example, through simultaneous learning of implicit and explicit knowledge.

Principle #4: The Integration of the Results of Explicit and Implicit Processing

Although explicit and implicit knowledge are often re-descriptions of one another, they involve different forms of representation and processing, which may produce similar or different conclusions; the integration of these conclusions is necessary, which may lead to synergy, that is, overall better performance (Sun et al. 2005).

Principle #5: The Iterative (and Possibly Bidirectional) Processing

According to CLARION, processing may be iterative and potentially bidirectional. If the integrated outcome of explicit and implicit processing does not yield a definitive result (i.e., a result in which one is sufficiently confident), another round of processing may occur, which may often use the integrated outcome as a new starting point. Reversing the direction of reasoning may sometimes happen (e.g., using abductive reasoning; Johnson and Krem 2001). Alternating between forward and backward processing has been argued to happen in everyday human reasoning (Rips 1994). Of course, time constraints may limit the number of iterations.

The EII theory of creative problem solving

CLARION led to an integrative theory of creative problem solving. The theory has been termed the EII (Explicit and Implicit Interaction) theory (Helie and Sun 2010).

The EII theory, in part, attempts to integrate and thus unify existing theories of creative problem solving in two senses. First, most theories of creative problem solving have focused on either a high-level stage decomposition (e.g., Wallas 1926) or on a process explanation of only one of the stages (Lubart 2001). Second, the process theories of incubation (e.g., Smith and Dodds 1999) and insight (e.g., Pols, 2002) are usually incomplete and often mutually incompatible. EII attempts to integrate the existing theories each of which tends to describe only a part of creative problem solving to provide a detailed description of the processes involved in the key stages of creative problem solving. EII starts from Wallas' (1926) stage decomposition of creative problem solving and provides a detailed process-based explanation that is ready for a coherent computational implementation. However, EII is not just an integration and implementation of previously existing theories, but it is a new theory, which emphasizes the importance of implicit processing and implicit-explicit integration in problem solving.

The EII theory relies mainly on the five basic principles of CLARION, as explained above, plus a few (relatively minor) auxiliary principles. In addition to the five basic principles presented so far, three auxiliary principles should be mentioned here. These principles are less important and alternative principles may be equally viable. Therefore they are not central to the fundamental theoretical framework. First, Principle #5 implies that a 'definitive result' needs to be achieved in order to terminate the iterative process. This stopping criterion assumes a primitive form of meta-cognitive monitoring that can estimate the confidence in a potential solution (Bowers et al. 1990). In CLARION, this meta-cognitive measure is termed the *Internal Confidence Level* (ICL). Second, there must be a threshold that defines what is meant by a ‘definitive result’. This threshold can vary as a function of task demands, and there might be several thresholds for different levels of confidence (Bowers et al. 1990). Lastly, a negative relationship between the ICL and the psychological response time might be assumed (Costermans, Lories, and Ansay 1992).

Creativity in Problem Solving

This section presents the EII explanations and the corresponding CLARION-based simulations of well-established psychological paradigms (e.g., free recall, lexical decision, and problem solving) and their results.

In what follows, the emphasis is not on the fine-grained details involved (which is inevitable given the summary nature of this chapter). Detailed explanations and simulations can instead be found in prior publications, for example, in Helie and Sun (2010).

Modeling Incubation within EII

Incubation (i.e., a period of not thinking about a given problem consciously) is one of the major stages of creative problem solving, according to Wallas (1926). EII stipulates that incubation occurs mostly through implicit processes, thus usually without conscious awareness (Helie and Sun 2010).

In CLARION, incubation is mostly captured within the bottom level of the NACS, which is implicit. The bottom level of the NACS consists of fully recurrent connectionist attractor networks (e.g., Hopfield-type networks) with distributed representations of implicit knowledge. Such networks are known to perform soft constraint satisfaction through gradual, iterative activation propagations. Therefore potential solutions may be formed gradually, resulting from an iterative process of soft constraint satisfaction (Sun 2014).

Within the bottom level of the NACS of CLARION, the search is generally more diffused due to soft constraint satisfaction, and thus may be more remote. As a result, less likely associations may be retrieved, leading to creative solutions.

Example of Simulating Incubation in a Lexical Decision Task

Yaniv and Meyer (1987) asked human subjects to perform two tasks sequentially. First, in a rare-word association task, they showed subjects word definitions that were weakly associated with their definienda. The subjects had a limited time to find a definiendum for each definition. If the subject found the definiendum, they were transferred to a lexical decision task, where they had to classify briefly presented strings of letters as ‘word’ or ‘non-word’. If the subject did not produce a definiendum, they were asked to rate their feeling of knowing (FOK) and then started the lexical decision task also. The results of the second task show that those definitions that allowed for the retrieval of the correct definienda by the subjects or generated high FOKs from the subjects produced priming in the lexical decision task (i.e., faster reaction times).

According to the EII theory, a rare-word association trial produces a simultaneous search at the explicit and the implicit levels (Principle #2). Because the target association is rare in this task, explicit memory search is not likely to yield a satisfactory solution within the allotted time (because the existing set of hard constraints does not necessarily lead to solutions in this case). In contrast, according to EII, implicit memory search is more likely to retrieve the desired association if given enough time, because soft constraint satisfaction can allow partial match that can be iteratively improved. However, implicit memory search is often cut short by the experimenter who then asks the subject to take part in lexical decision trials (for those subjects who did not produce a definiendum). At the beginning of the lexical decision trials, implicit knowledge is still in the same state as it was at the end of the corresponding rare-word association trial. Hence, if the association was retrieved or nearly retrieved during the rare-word association trial (i.e., with high FOK), the preceding memory search is relevant and the target word (related to the definiendum in question) is thus primed for the lexical decision trial (i.e., leading to faster reaction times). In contrast, the recognition of unrelated words (distractors) is not affected by the previous state of implicit knowledge, because the rare-word association trial was irrelevant to these words.

This conceptual explanation by EII led to a detailed computational model that produced simulations in line with Yaniv and Meyer’s (1987) results. The results of 3,000 simulations with a CLARION-based model are shown in Figure 2, which capture the corresponding human data (Helie and Sun 2010).

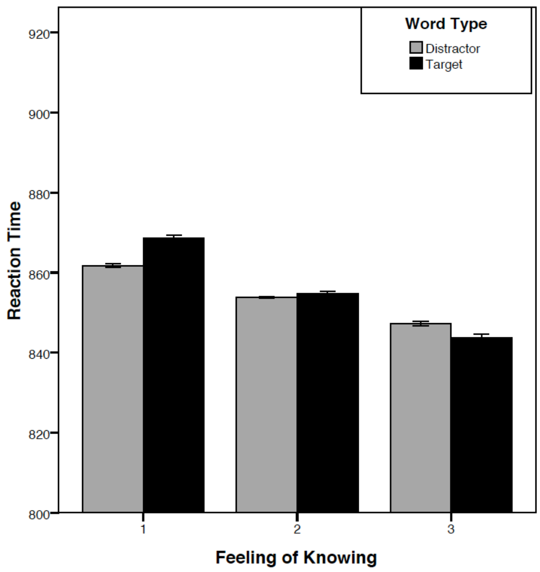

Fig. 2: Simulated response times in the lexical decision task for subjects who did not produce a definiendum in the rare-word association task.

Modeling Insight within EII

According to Wallas (1926), insight, the sudden emergence into consciousness of a potential solution, is another major stage of creative problem solving, normally following the incubation stage. According to EII, insight results from the transferring of the activation of implicit knowledge (e.g., as a result of incubation) to that of the corresponding explicit knowledge; hence the sudden appearance of insight.

Correspondingly, CLARION captures insight computationally through the emergence of activations from the bottom level of the NACS to the top level of the NACS (bottom-up activation flows). That is, insight amounts to activating explicit (easily accessible) representations at the top level by implicit, distributed, not so easily accessible representations at the bottom level. The result is an explicitly accessible solution emerging into the mind.

Example of Simulating Insight in Problem Solving

Durso, Rea, and Dayton (1994) asked human subjects to explain stories like the following one:

> A man walks into a bar and asks for a glass of water. The bartender points a shotgun at the man. The man says 'thank you', and walks out.

The subjects' task was to explain why the sight of the shotgun replaced the man's need for a glass of water (i.e., because he had the hiccup). To explain this story, the subjects had two hours to ask the experimenter yes/no questions. When the time elapsed, each subject was classified as a 'solver' or as a 'non-solver' and his/her knowledge graph was drawn. Solvers' and non-solvers' knowledge graphs were shown to have different connectivity.

According to EII, reading the story results in both explicit memory retrieval and implicit memory search (incubation). However, explicit processing (mostly rule-based; Principle #1) brings up stereotypical semantic associations from the story. In contrast, the gradient of associations is flatter in implicit memory (Mednick 1962) and weak associations are recorded. The search is thus more diffused, and more remote ("creative") associations can be retrieved with soft constraint satisfaction. According to the EII theory, implicit processing allows for the retrieval of more approximate, more hypothetical associations that differ from those retrieved explicitly. These implicit associations are then integrated with the result of explicit processing (Principle #4). If the chosen integrated association is deemed plausible (i.e., if the ICL is high enough), a question concerning the validity of this association is put to the experimenter. If the experimenter confirms the association, it is added into explicit knowledge; otherwise, it is removed. This process is iterated; explicit and implicit processing are restarted with the new state of the knowledge. This iterative process ends when the subject finds the solution or the allowed time elapses.

The results of 8,000 CLARION-based simulations show that, consistent with the EII explanation above, the probability of solving the problem increases with the stochasticity of the implicit association retrieval. See Helie and Sun (2010) for details.

Motivation, emotion, personality, and social interaction

Beyond the interaction between implicit and explicit processes as stipulated by the EII theory, creativity involves many other aspects of the human mind. Below, a number of important psychological aspects are discussed. CLARION may be used to provide interpretations to these aspects in relation to creativity.

For instance, it has been known that motivation has a lot to do with creativity. One of the most relevant findings is that intrinsic motivation is correlated with creativity. However, intrinsic motivation may lead to generating new ideas, but new ideas will not be judged as creative unless they are also useful (as defined by some communal standards). Individuals with prosocial motivation and good at perspective taking should be better at generating useful ideas. Grant and Berry (2011) tested experimentally whether or not intrinsic motivation and prosocial motivation combined result in greater creativity and their results confirmed the expectation.

It is also known that anxiety has debilitating (or facilitating) effects on routine cognitive or motor tasks. Byron and Khazanchi (2011) performed a meta-analysis and found that anxiety was significantly negatively related to creative performance --- Anxiety and creativity present competing cognitive demands. Other emotions are also known to have significant effects on creativity (see, e.g., Akinola & Mendes, 2008; Amabile et al., 2005).

As explained earlier, the CLARION cognitive architecture contains four major subsystems, which include the motivational subsystem (the MS, as mentioned earlier; see Figure 1) that captures various innate, essential motives as well as acquired motives, in the form of *drives* (both primary and secondary drives; Sun, 2009). With the MS, different motives (drives), such as *achievement and recognition*, *affiliation and belongingness*, and *similance*, exist and may be activated by situations (Sun, 2009). Therefore, with CLARION, it is possible to explore effects of motivation on creativity, including effects of intrinsic achievement orientation, prosocial tendency, and so on. There is also an account of emotion within CLARION, largely on the basis of motivation, including capturing a variety of major emotions (e.g., anxiety; Wilson and Sun, 2009). Thus, CLARION can also be used to capture the effects of emotion on creativity.

Personality, as extensively studied in personality psychology, is also known to have a lot to do with creativity. There have been various studies concerning the effects of personality on creativity. For instance, based on a meta-analysis of data, Feist (1998) argued that, in general, creative individuals were more open to experiences, less conventional and less conscientious, more self-confident, more driven, ambitious, and dominant, and so on. There also appeared to be temporal stability of these distinguishing characteristics among creative individuals. These characteristics corresponded well with the five-factor model of personality (commonly known as the Big Five), and their detailed facets (see McCrae and Costa 2010; Sun and Wilson 2014a).

Furthermore, Feist and Barron (2003) reported a longitudinal study. At age 27, a sample of 80 male graduate students was assessed on potential, intellect, personality, and creativity. At age 72, personality and career outcome data were collected again. Intellect, potential, and personality at age 27 were expected to predict lifetime creativity. It was also predicted that personality would explain unique variance in creativity over and above that explained by intellect and potential. Results supported these expectations. They concluded that certain personality traits such as openness to experiences, tolerance, and self-confidence might serve as a relatively direct link to creative behavior.

The role of personality can be captured within CLARION, as has been shown before (e.g., Sun and Wilson 2011, 2014, 2014a). As mentioned earlier, the CLARION cognitive architecture emphasizes four major subsystems, including the motivational subsystem (the MS), as shown in Figure 1. These subsystems together capture various dimensions of human personality, as demonstrated in detail by Sun and Wilson (2014, 2014a). Among these subsystems, the MS plays an especially important role in determining personality. The various essential motives within the MS capture major aspects of personality dimensions, such as the Big Five (Sun and Wilson, 2014, 2014a). Various simulations have been carried out to date to explore the effects of personality dimensions such as openness to experiences and conscientiousness

In relation to the role of social interaction in creativity, Ashton-James and Chartrand (2009) emphasized behavioral mimicry as a social cue for creative thinking. Specifically, being mimicked by an interaction partner cues convergent thinking and a social opportunity for collaboration, while not being mimicked cues divergent thinking and a social demand for improvisation and innovation. They experimentally manipulated whether individuals were mimicked or not and subsequently measured their capacity for convergent and divergent thinking. The results showed the importance of understanding how social relationships influenced the creative processes. Relatedly, Tadmor et al. (2012) showed that multicultural experience among members of a collective would enhance joint creativity in a super-additive fashion. The results showed that in terms of creativity, the social whole might be greater than the sum of its parts.

Correspondingly, CLARION emphasizes modeling and simulating social interaction and social processes in understanding the mind. Social simulation with a cognitive architecture such as CLARION enables the exploration of the mutual influence of the social and the psychological (Sun, 2006). Many different social situations have been simulated, using CLARION as the model of the individual mind involved in social interaction. For instance, Naveh and Sun (2006) showed that growth of academic science was closely related to not only individual cognitive processes but also social processes and social institutions. Together they determined the level of creativity of a society.

Therefore, CLARION appears to provide a comprehensive framework for capturing human creativity, including its many different aspects and components. Some of these aspects, such as motivation, emotion, personality, and social interaction, although downplayed or ignored in many previous theories or models of creativity, may nevertheless be captured and explained within CLARION.

Conclusion

The work described in this chapter summarizes how a psychologically realistic cognitive architecture, namely, CLARION (Sun 2002, 2014; Sun et al. 2001, 2005), can lead directly to a theory of creative problem solving (e.g., EII; Helie and Sun 2010). Cognitive architectures such as CLARION generally integrate many cognitive/psychological mechanisms and processes in order to produce intelligent behavior in a psychologically realistic way. In the EII theory (as derived from CLARION), the key ingredient is the interaction of explicit and implicit processing. By incorporating both explicit and implicit processing, the EII theory is able to provide a unified framework for re-interpreting and integrating some important (but fragmentary) psychological theories of incubation, insight, and creativity (see Helie and Sun 2010 for details of the re-interpretation and integration).

The EII theory is, however, not complete yet. For instance, it needs to move on to account for real-world cases of creative problem solving. Such cases would inevitably involve motivation, personality, and emotion. Social interaction is also important in this regard. However, the EII theory is currently more complete than previous theories (especially previous computational theories/models). We have shown that the roles of motivation, personality, emotion, and social interaction can all be accounted for within CLARION, and therefore can be added to EII.

In relation to AI, a unified computational model (based on CLARION) is shown to be capable of capturing creative problem solving in widely differing settings (e.g., free recall, lexical decision, problem solving, and so on), demonstrating its computational capacities. Computationally, the model involved different types of neural networks to simulate, respectively, explicit processing (with localist, feedforward networks) and implicit processing (with distributed, fully recurrent, attractor networks). Integrating these components was essential in capturing creative problem solving. A computational cognitive architecture is an important way of exploring the advantage of synergistically combining several specialized computational models, because so far no single computational model can capture human intelligence by itself. Future work should be devoted to tackling more complex real-world creative problem solving situations involving additional factors as detailed earlier.

Better, more integrated computational models of creative problem solving that are psychologically realistic are needed for both AI and cognitive science. In relation to AI, they may spur corresponding research on computational creativity. They may influence and/or challenge common perceptions of where the limits of creativity may lie and consequently where the limits of intelligent machines may ultimately lie. In the process, psychologically realistic models of creative problem solving may help to push the boundaries further, one step at a time.

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