Computational models of creativity: A review of single- and multi-process recent approaches to demystify creative cognition

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Computational models of creativity: a review of single-process and multi-process recent approaches to demystify creative cognition☆

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Creativity is a compelling but heterogeneous phenomenon. As opposed to *big-C* creativity, which is regarded as limited to the rare brilliant mind, *little-c* creativity is indispensable in adaptive everyday behavior, serving to adjust to changing circumstances and challenges. Computational approaches help demystify human creativity by offering insights into the underlying mechanisms and their characteristics. Recently proposed computational models to creative cognition often focus on either divergent or convergent problem-solving, but some start to integrate these processes into broader cognitive frameworks. We briefly review the state-of-the-art in the field and point out theoretical overlap. We extract basic principles that most existing models agree on and desiderata on the way towards a comprehensive model.

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Introduction

Creativity is a compelling phenomenon that has produced admirable ideas and artefacts. A distinction is often made between *big-C creativity*, which allows brilliant minds to create unique and inventive products, and *little-c creativity*, the cognitive functioning that helps even the less brilliant mind adapt to changing circumstances and solve everyday problems [1,2]. Because of its indispensability in everyday functioning, little-c creativity (henceforth *creativity*) is studied widely to understand how creative cognition emerges and why it shows so much interindividual variability.

Since Guilford [3] a distinction is made between divergent and convergent thinking in generating creative ideas. Divergent thinking produces creative ideas by exploring multiple potential solutions to an often vaguely defined problem while convergent thinking serves to identify the single best solution to a well-defined problem. The cognitive operations needed to support divergent and convergent thinking have been associated with possibly antagonistic sets of processes or cognitive control modes, such as flexibility versus persistence [4] or insight versus analytic processing [5]. Yet, actual performance is likely to involve some degree of *interplay* between divergent, convergent, and other cognitive (sub)processes and process-related neural networks (e.g. [6–8]), suggesting that creativity is a complex and heterogeneous phenomenon.

In this short review we consider the most recent (<3 years) computational models of aspects of human creativity. Computational models allow for a mechanistic approach to cognitive processes in healthy and maladaptive cognition [9–11] and thus have the potential to demystify creative cognition. We highlight divergent and convergent processes in these recent computational approaches to creative cognition (see also Table 1), to the degree that they can be distinguished and characterized accordingly. We then briefly consider recent issues with dual-process accounts in modeling creativity (c.f. [12,13]) and propose a unitary approach that might offer a more parsimonious account to recognize the tricky division and adaptivity between antagonistic states underlying creativity.

Recent computational approaches to creativity

Models of divergent creativity

Divergent thinking has been related to associative thinking [13], and can be modeled as spreading activity in neural networks. Three recent publications used a network science approach to study how individual differences in creative associative thinking might arise from structural differences in semantic networks [14,15,16•]. Findings suggested that the semantic networks of highly creative individuals showed more small-world properties, which allows for faster search over a wider network of

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Table 1

Summary of recent computational models applied to creative cognition

Authors	Modeled creativity process	Description computational approach
Benedek *et al*. [14]; Kenett *et al.* [15]; Kenett *et al*. [16•]	Divergent	Network science approach; Percolation analysis
Olteţeanu and Falomir [20]; Olteţeanu [19]; Olteţeanu [21]; Olteţeanu, Falomir, and Freksa [18•]	Divergent	Prototype system (OROC) in CreaCogs theoretical framework
Olteţeanu and Falomir [17]; Olteţeanu, Falomir, and Freksa [18•]; Olteţeanu, Schultheis, and Dyer [23]	Convergent	Prototype system (comRAT) in CreaCogs theoretical framework
Schatz, Jones, and Laird [24]	Convergent	Semantic memory model in cognitive architecture (Soar)
Kajíc *et al*. [25•]	Convergent	Spiking neuron model
Augello *et al*. [32•]	Divergent and convergent*	Cognitive architecture (MicroPsi/Psi)
Wiggins [28]; Wiggins and Bhattacharya [29]	Divergent and convergent	Cognitive architecture (IDyOT)

Note. Asterisks indicate that the authors explicitly modeled these processes in their approach; for the other references we inferred the focus on these processes from the text.

associations, increasing the probability of returning novel associations [15]. Kenett *et al.* [16•] also found that breaking associations in a simulated semantic network led to larger parts of the network breaking apart in low creative individuals, while networks in high creative individuals remained fairly intact. This network science computational approach thus suggests that structural characteristics of semantic networks influence the extent of divergent thinking.

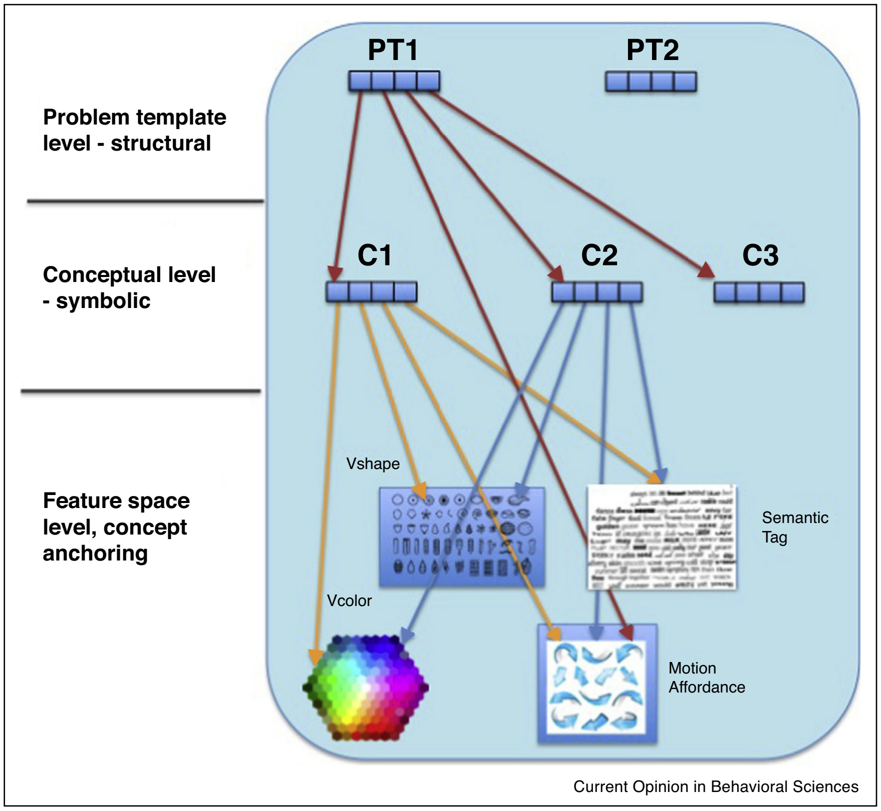
Another recent approach implemented a computational model of a popular task to study divergent creativity, the Alternative Uses Task (AUT [3]). In the AUT, individuals produce as many as possible alternative uses for a common object (e.g. *towel, brick*) within limited time. In the model, performance on this task relies on object replacement and object composition (OROC). The system was modeled within a theoretical framework called CreaCogs [17,18•,19]). CreaCogs-OROC organizes memory into three layers: first, a subsymbolic level where feature spaces (e.g. shape, color, affordance) of objects are represented in a distributed fashion; second, a level of concepts grounded in the subsymbolic level; and third, a problem template level representing known problems and solutions encoded over concepts and relations between them (Figure 1). Each level is grounded in the subordinate level to be able to use, say, features from related concepts to find objects with features that can replace a cue object in the AUT, or *vice versa*. The more feature spaces are considered, the more divergent the search for a replacement use can become, making the divergence of search in the AUT-dependent on the size and number of feature spaces in the CreaCogs-OROC knowledge base — a possible source of interindividual differences. Simulations of the AUT in CreaCogs-OROC show that the system can produce answers comparable to findings in humans [20].

Theoretically, CreaCogs-OROC can be used to construct insight problems [19,21] by taking a simple problem with an existing solution and replacing or (de)composing objects used in the solution to change the problem to a creative problem. The authors suggest an example problem in which the participant should find how to build a seesaw from a surfing board and a bucket to decide who of two people is heavier. Although insight problem construction in CreaCogs has not yet been simulated, the creative (de) composition of objects and object replacement to re-represent a balancing scale is reminiscent of processes in modeling the AUT. The more features or objects are considered in constructing insight problems, the more divergent a search for the solution might have to become. The creative problem-solving (or problem-generating) approach in the CreaCogs framework thus seems to lend itself to model divergent behavior in multiple creativity paradigms.

Models of convergent creativity

While the abovementioned set of models focused on the spread of search, or divergent cognition, similar models are used to study convergent, more targeted search. Another prototype system within the CreaCogs framework (comRAT) simulates performance on the Remote Associates Test (RAT [22]), a convergent-creativity task in which three verbal concepts are presented and a solution word that can be combined with either one is sought for (e.g. *market, glue, man* → *super*). ComRAT was developed as an RAT solver (comRAT-C [17,19]) and a semantic RAT problem generator (comRAT-G [23]). ComRAT-C comprises a knowledge base of word pairs modeled in CreaCogs' concept level. Activation of an

Figure 1



The knowledge base in Creacogs-OROC comprises three levels over which objects are encoded. Each level is grounded in the level below it. The distributed nature of the feature space level might offer dual-states modeling as a unitary approach as suggested by Hommel and Wiers [50•]. Reprinted without changes, with permission from Elsevier based on Figure 1 in 'Object replacement and object composition in a creative cognitive system. Towards a computational solver of the Alternative Uses Test' by Olteţeanu and Falomir [20], *Cognitive Systems Research, 39*, 15–32. Copyright 2016 by Elsevier.

RAT problem activates all words related to the queried word pair, modeling an associative search of the full knowledge base to enable convergence upon one answer found in three word pairs [17,19]. It returns an answer after finding a word that was associated with each of the cue words. Sometimes, the system was also able to converge upon (alternative) answers when only two word pairs in the knowledge base shared a word, indicating that the learned associations structure provides a robust system to solve RAT problems [17].

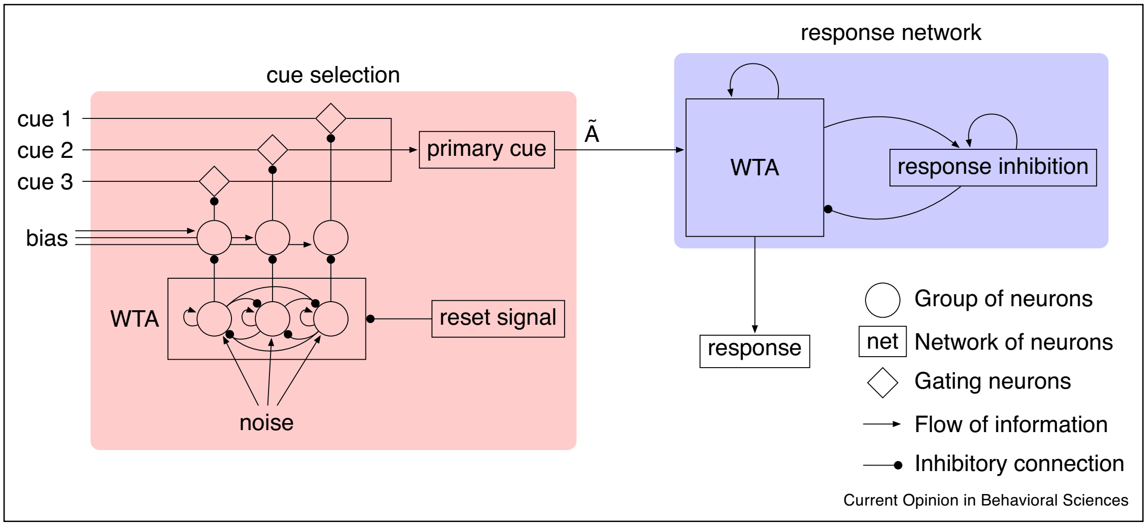
As shown recently [24], spreading activation starting at three RAT cue words can also lead to the correct solution by strongly increasing the activation level of one word of the knowledge base [24]. Free recall, implemented in this computational approach, explained success better than a cued-retrieval approach in which the system was only allowed to return an answer that matched all three problem words. This performance increase thus comes despite the lack of a deliberate query to match the solution word to word pairs of the three RAT cue words [24]. Apparently, a winner-takes-all approach in (divergently) spreading activity over an associative network is sufficient to simulate convergent search process in the RAT.

This was also observed in a biologically plausible spiking neuron model of RAT performance [25•]: a selection network of neurons activates one of three RAT cue words at a time, and randomly switches between cues. Activation spreads from the cue to all neurons that represent the cue word in a distributed fashion. Activation of associated words represented in overlapping neural networks is fed back into a winner-takes-all response network which converges on the most activated word and responds when auto-inhibitory response processes have decayed (Figure 2). Performance of this model matched human performance well [25•] and, again, the success of this model might indicate that spreading activation and a winner-takes-all approach could explain RAT performance.

More integrative computational creativity accounts

While the models described above claim to focus on divergent or convergent creativity specifically, both kinds of models rely on associative search processes or

Figure 2



RAT architecture of a spiking neuron model. One of the three cue words is chosen as a primary cue for which all of its associate words are activated with help of association matrix **Ã**. The winner-takes-all network (WTA) in the response network keeps the most activated word active until a final word is select when response inhibition has decayed. Reprinted without changes, with permission according to CC BY 4.0 from Figure 2 in 'A spiking neuron model of word associations for the remote associates test' by Kajić, Gosmann, Stewart, Wennekers and Eliasmith [25•], *Frontiers in Psychology, FEB*.

spreading of activation. This raises the question whether more integrative models accounting for both divergent and convergent thinking are feasible, an idea that is already apparent in CreaCogs. Some computational approaches have indeed tried to model creativity in the broader scope of cognition.

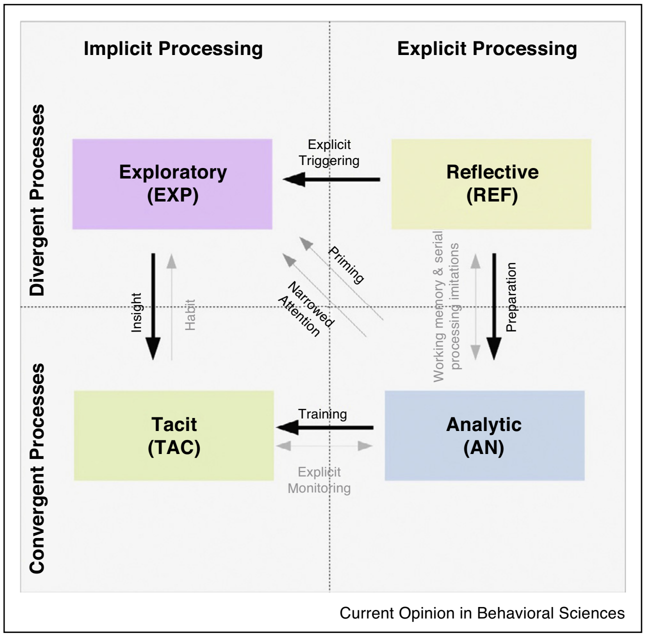
One approach to study creative thinking in a broader cognitive architecture is Information Dynamics of Thinking (IDyOT [26–29]. This model is based on the idea of predictive coding, according to which the brain is constantly occupied with the efficient processing of sensory information by minimizing entropy and unexpectedness. Predictions are produced by generators that compete for attention in a global workspace, implementing Baars' Global Workspace Theory [26,28–30]. Predictions are made from memory, a multiple layer hierarchy including distributed and conceptual representations as well as an intermediate layer of conceptual spaces representing concepts and relations between concepts geometrically, as described by Gärdenfors [31]. According to Wiggins [28], spontaneous creativity arises as a by-product, from the brain 'freewheeling' as it continues prediction in absence of relevant sensory input. A novel idea might be predicted from finding an unvisited point in one of the conceptual spaces [28,29]. So far, no explicit account how this 'freewheeling' leads to more or less divergent ideas was suggested, but the detailed and broad approach might offer a rich simulation of creative cognition.

Interestingly, one recent model by Augello *et al.* [32•] does explicitly model divergent and convergent processes together. Their computational painter is designed within the MicroPsi cognitive architecture [33], and the painter replaces image features with a creative alternative (e.g. a face area with a flower, similar to the human painter Arcimboldo). Augello *et al.* refer to the Four Quadrants Model, which models the interaction between convergent and divergent processes and recognizes that both of these processes can be implicit or explicit (Figure 3 [34]). Long-term memory consists of distributed representations in which each neuron represents the centroid of a pattern cluster representing an image or image detail [35]. The working memory module clusters more abstract representations of image details, enabling feature substitution in one domain (e.g. faces) with features of another domain (e.g. flowers). Cognitive control over these processes allows for more or less divergent search and comes from a resolution network. This network controls for example the permitted distances between centroids in the working memory to allow for broader or narrower search, and the interaction between convergent analytic and tacit processes in deciding whether a replacement is successful or not (Figure 3).

Dual-process modeling

Neurocognitive results have been taken as evidence for distinct neural mechanisms underlying divergent, flexible, or unfocused thinking on the one hand and convergent, persistent, or focused thinking on the other, be with reference to frontal and striatal dopaminergic pathways [36,37], dopamine receptors families [38], or brain networks (e.g. [39–41]). However, dual-process accounts are

Figure 3



The Four Quadrants Model, implementing four (exploratory, analytic, reflective, tacit) strategies, recognizes the crosstalk between implicit and explicit processes on the one hand and divergent and convergent processes on the other. Augello *et al*. [32•] map the four resulting processes onto their creative painter to indicate the importance of interactions between the processes in creative cognition. Highlighted are only the interactions involved in the creative process proposed in the system by Augello *et al*. [32•].
Reprinted without changes, with permission from Elsevier based on Figure 1 in 'Artwork creation by a cognitive architecture integrating computational creativity and dual process approaches' by Augello, Infantino, Lieto, Pilato, Rizzo, Vella [32•], *Biologically Inspired Cognitive Architectures*. This model is based on Figure 1 proposed in 'A four strategy model of creative parameter space interaction' by Tubb and Dixon [34], *Proceedings of the Fifth International Conference on Computational Creativity ICCC*. Copyright 2016 by Elsevier.

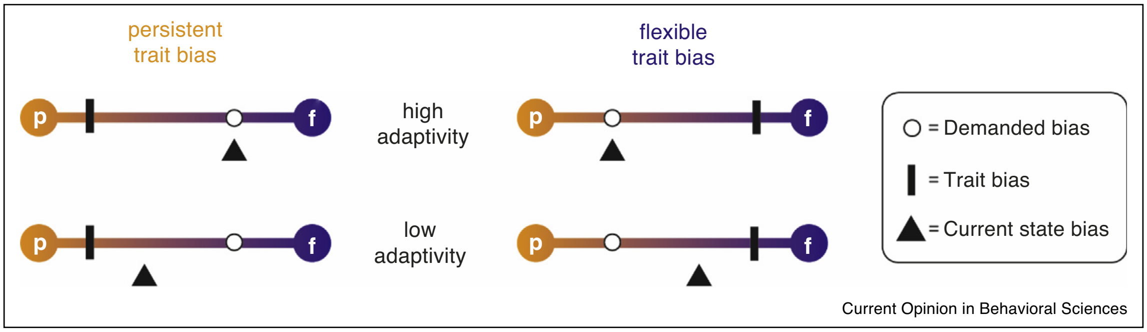
increasingly criticized, often because the processes and/or the outcomes of the two hypothetical pathways are difficult to distinguish or because both types of processes or outcomes rely on some sort of interaction between the two pathways [5,12,13,42–45]. The model by Augello *et al.* [32•] is rather exceptional in trying to integrate divergent and convergent processes in creative cognition (but see CLARION [46–49]). However, the issues mentioned above have led to a call for an even more integrative perspective of creative cognition [12,13,50•].

Towards a unitary account

What basic ingredients should such an even more integrative perspective of creative cognition have? We consider three ingredients essential. First, most of the models that we have discussed agree on the importance of distributed representations of objects or concepts to facilitate replacement or composition, as for instance suggested explicitly in CreaCogs. Such representations also facilitate aspects of creativity that go beyond divergent and convergent thinking, such as the creation of metaphors (creating a connection between two seemingly unrelated concepts that however share some features) or replacement by second-best solutions ('plan b') if best solutions are impossible or not feasible. Second, the degree of flexibility that most aspects of creative behavior require call for the contextualization of representations. Even distributed representations of objects or concepts are relatively static without a means to weigh the possible features according to situational requirements or present goals. It is this contextualization that facilitates the creation of metaphors and the breaking of overlearned associations between concepts. Third, models need to take into account individual differences more. Most models certainly allow for the consideration of such differences but making them an explicit goal of model development would drastically increase our insight into the mechanisms underlying the substantial individual differences in creativity that can be observed in real life. It is important to distinguish between trait-like differences between individuals (resulting from genetic predisposition and/or over learning) that are difficult or impossible to eliminate through interventions, and state-like differences that even the same individual can show in different situations or under different goals.

All three basic ingredients are available from a recent attempt to provide a unitary alternative to conventional dual-route theorizing in action control. As suggested by Hommel and Wiers [50•], both possible and actual events, including concepts and ideas, are represented by distributed networks of the features that characterize these events (so-called event files) — an assumption adopted from the theory of event coding (TEC [51]). While all features of a given event are maintained in the system, the current contribution of features to representing this event in context of the present situation is weighted by its relevance for the present intention and task goal [52]. This implies, among other things, that event files with more task-relevant features compete more strongly for selection for further processing. The feature-based representation principle of event files allows for feature-based selection, competition, and spread of activation, as well as for task-specific selectivity of representation — which covers our first two requirements for a unitary approach. However, to account for individual differences and to allow for modeling both divergent and convergent ways of concept-selection, another principle is required. As Hommel and Wiers [50•] have suggested, the degree of competition between multiple event files can be regulated to make it either weak, as required for divergent thinking and other associative reasoning patterns, or strong, as required for focused in-depth convergent thinking. The idea is that competition and selection is regulated by the present metacontrol state, which reflects a particular balance between extreme persistence, characterized

Figure 4



According to the metacontrol state model (MSM) there are interindividual (trait) biases as well as intraindividual (state) biases in metacontrol state. Each individual is characterized by a certain cognitive control state, dependent on influences due to culture, religion, and genes [50•,53,54]. However, to be able to adapt to changing circumstances individuals should be able to adapt their cognitive control state to situational demands (based on Mekern, Sjoerds & Hommel, in revision).

by strong competition and top–down focus, and extreme flexibility, characterized by weak competition and top–down focus [53]. The particular metacontrol bias on this persistence-flexibility dimension has been claimed to show systematic inter-individual and intra-individual variability; some people tend to be more persistent where others tend to be more flexible, but the same person may also sometimes tend to be more persistent and sometimes more flexible, depending on situational demands (Figure 4, left versus right panel). Moreover, we have recently suggested that people may differ in their *adaptivity*, which refers to the ease with which they keep and readjust their balance between persistence and flexibility in the case of changing environmental demands (Figure 4, top versus bottom panel).

Adopting these three key principles holds promise for developing a unitary computational approach of human creativity that avoids previous problems with dual-process models (as discussed in Refs. [12,13]). A successful unitary approach is likely to help further demystifying creative cognition by coming to grips with the underlying mechanisms.

Conflict of interest statement

Nothing declared.

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