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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* $\rightarrow$ *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