Towards Greater Computational Modeling in Neurocognitive Creativity Research

James Lloyd-Cox[1], Alan D. Pickering[1], Roger E. Beaty[2], and Joydeep Bhattacharya[1,#]

[1]Department of Psychology, Goldsmiths, University of London, London, UK
[2]Department of Psychology, The Pennsylvania State University, PA, USA
[#]Correspondence: j.bhattacharya@gold.ac.uk (J. Bhattacharya)

ABSTRACT:

Creative cognition is the driving force behind all cultural and scientific progress. In recent years, the field of neurocognitive creativity research (NCR) has made considerable progress in revealing the neural and psychological correlates of creative cognition. However, a detailed understanding of how cognitive processes produce creative ideas, and how these processes interact differently across tasks and individuals, remains elusive. In this article, we argue that the increased adoption of computational modeling can help greatly in achieving this goal. While the verbal theories guiding NCR have evolved from broader accounts into more specific descriptions of neurocognitive processes, they remain more open to interpretation and harder to falsify than formal models. Translating theories into computational models can make them more concrete, accessible, and easier to compare, and helps researchers to develop causal hypotheses for how variation in cognitive factors leads to variation in creative outcomes. Currently, however, computational modeling of creativity is conducted almost entirely separately from NCR, and few attempts have been made to embody the cognitive theories of NCR in models that can simulate performance on common lab-based tasks. In this paper, we discuss theories of creative cognition and how they might benefit from the wider adoption of formal modeling. We also examine recent computational models of creativity and how these might be improved and better integrated with NCR. Finally, we describe a pathway toward a mechanistic understanding of creative cognition through the integration of computational modeling, psychological theory, and empirical research, outlining an example model based on dual-process accounts.

KEYWORDS: Creativity; theory; psychology; neuroscience; computational modeling

PUBLIC SIGNIFICANCE STATEMENT: This review argues that creativity research would benefit greatly from the wider adoption of computational modeling. We discuss how translating verbal theories of creative cognition into formal computational models can make them more rigorous, accessible, and communicable, and can highlight questions for future research. We examine previous models of creativity and explain how these can be improved to benefit our understanding of human creative cognition and the development of artificial creative systems.

Towards Greater Computational Modeling in Neurocognitive Creativity Research

Creativity, a hallmark of human cognition, has traditionally been considered an elusive target for scientific investigation (Hennessey & Amabile, 2010; Iger, 2019), and even today, there exists considerable variation in how creativity is conceived, operationalized, and assessed across fields (Hennessey & Amabile, 2010; Plucker, 2022; Plucker, Beghetto, & Dow, 2004; Puryear & Lamb, 2020). However, recent decades have witnessed tremendous growth in neurocognitive creativity research (NCR) – research that aims to uncover the neural and cognitive basis of creative thought. While definitions of creativity vary (e.g., Acar, Burnett, & Cabra, 2017; Simonton, 2018), most NCR defines creative cognition as the production of novel and useful ideas (Diedrich, Benedek, Jauk, & Neubauer, 2015; Runco & Jaeger, 2012; Stein, 1953).

Presently, NCR covers a diverse range of research areas, and has begun to uncover how creative cognition relates to cognitive and psychological factors including attention (Frith et al., 2021b; Liu & Peng, 2020; Zabelina, 2018), memory (Benedek, Beaty, Schacter, & Kenett, 2023; Kenett et al., 2018; Madore, Addis, & Schacter, 2016; Storm, Angello, & Bjork, 2011), executive control (Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014b; Camarda et al., 2018a; Chrysikou, 2019; Lebuda & Benedek, 2023), personality (Bonetto, Pichot, Pavani, & Adam-Troïan, 2021; Kaufman et al., 2016; Oleynick et al., 2017), and reward processing (Beversdorf, 2019; Boot, Baas, van Gaal, Cools, & de Dreu, 2017; Lin & Vartanian, 2018). NCR has also made considerable progress in identifying the neural correlates of creative cognition, for example finding that greater creative performance relates to enhanced EEG alpha waves (Agnoli, Zanon, Mastria, Avenanti, & Corazza, 2020; Fink et al., 2018; Rominger et al., 2019; Stevens & Zabelina, 2020), and greater fMRI connectivity between large-scale brain networks (Beaty, Cortes, Zeitlen, Weinberger, & Green, 2021; Chen, Beaty, & Qiu, 2020; Mayseless, Eran, & Shamay-Tsoory, 2015; Sunavsky & Poppenk, 2020).

However, it remains unclear how exactly these neural and psychological correlates lead to the production of creative ideas (see Beaty, Seli, & Schacter, 2018b for an overview of cognitive processes that may relate to the neural connectivity patterns observed during creative cognition). Despite the remarkable progress of NCR, our theoretical understanding of creative cognition is still in its infancy. Over recent decades, the cognitive theories that guide NCR have evolved from more abstract accounts, such as the distinction between convergent and divergent thinking (Guilford, 1959, 1967), to more specific accounts that describe how creative ideas can emerge from, for example, spontaneous and controlled processes (Benedek et al., 2023; Benedek & Jauk, 2018; Volle, 2018) and flexible and persistent meta-control states (Nijstad, de Dreu, Rietzschel, & Baas, 2010; Zhang, Sjoerds, & Hommel, 2020). In addition, significant efforts have been made to formalize and standardize the ontology used by NCR researchers (Gabora, 2018; Kenett et al., 2020; Simonton, 2013, 2022; Sowden, Pringle, & Gabora, 2015). However, considerable work remains to move the field away from loosely defined verbal accounts toward mechanistic theories of creative cognition, complete with causal hypotheses regarding the cognitive operations that produce creative ideas.

We argue that the wider adoption of computational modeling can help greatly in achieving this aim. Computational modeling involves formalizing a theory into a set of algorithmic operations (Farrell & Lewandowsky, 2015; Maia, Huys, & Frank, 2017). This process requires the theory to be fully described in explicit terms, which can expose assumptions that might otherwise remain hidden, and lends considerable clarity, rigor, and reproducibility to the development of theories and hypotheses (Farrell & Lewandowsky, 2015; Guest & Martin, 2021). Computational models also allow causal hypotheses to be formulated and tested, helping researchers to establish relationships between neurocognitive factors and creative behavior (Blohm, Kording, & Schrater, 2020; Wiggins & Bhattacharya, 2014). Indeed, calls for greater modeling within psychology as a whole are growing (Blohm et al., 2020; Guest & Martin, 2021; Smaldino, 2020), yet modeling is rarely used in NCR. Meanwhile, though computational creativity is itself a growing field (e.g., Carnovalini & Rodà, 2020; Gatti, Stock, & Strapparava, 2021; Mekern, Hommel, & Sjoerds, 2019a) with its own annual conference (the International Conference on Computational Creativity), it has developed in relative isolation from NCR, with little cross-pollination between the two fields. Increased collaboration could lead to both a clearer understanding of human creativity and more human-like artificial creative systems (Chateau-Laurent & Alexandre, 2021; Dipaola, Gabora, & McCaig, 2018; Gobet & Sala, 2019). Critically, however, very few computational models exist that both embody a theoretical account from NCR and can perform (and thus, be validated on) common lab-based creativity tasks.

First, we provide an overview of NCR and recent cognitive theories of creativity. We then consider some limitations of purely verbal theories and how NCR would benefit from the increased adoption of computational modeling. Next, we discuss recent computational models of creativity, exploring several models that aim to account for performance in common lab-based creative tasks. Finally, we outline a pathway toward greater computational modeling within NCR, considering ways in which existing models might be improved (including a greater focus on modeling multiple creative tasks) and examining an example of model development.

Neurocognitive creativity research (NCR)

NCR aims to uncover the neural and cognitive processes that underlie creative cognition (Benedek & Fink, 2019). To this end, NCR researchers have explored how creative performance relates to numerous cognitive and psychological factors. Here, we briefly review some of this work. For example, attention research suggests that while real-world creative achievement may relate to leaky attention (Zabelina, 2018), in-lab creative performance may relate to selective (Vartanian, 2009) or flexible attention (Zabelina, O'Leary, Pornpattananangkul, Nusslock, & Beeman, 2015; Zabelina, Saporta, & Beeman, 2016). Meanwhile, research into the link between creative cognition and intelligence has found considerable overlap between the two in terms of lab-based performance (Frith et al., 2021a; Karwowski et al., 2016; Karwowski, Czerwonka, & Kaufman, 2020), and suggests that they may depend on shared neural regions (Benedek, Jung, & Vartanian, 2018; Frith et al., 2021a). Research has also examined relationships between creativity and executive functions, finding that switching (Krumm, Arán Filippetti, & Gutierrez, 2018; Nusbaum & Silvia, 2011; Pan & Yu, 2018; Zabelina & Ganis, 2018), updating (Benedek et al., 2014b; Stolte, García, van Luit, Oranje, & Kroesbergen, 2020; Zabelina, Friedman, & Andrews-Hanna, 2019), and inhibition (Camarda et al., 2018a; Kaur, Weiss, Zhou, Fischer, & Hildebrandt, 2021; Zabelina et al., 2019) all relate to aspects of creative performance.

Considering the relationship between creative cognition and memory, some studies report that creative cognition may benefit from greater working memory (WM) abilities (Benedek et al., 2014b; de Dreu, Nijstad, Baas, Wolsink, & Roskes, 2012; Stolte et al., 2020), while other studies report mixed findings (de Vink, Willemsen, Lazonder, & Kroesbergen, 2021; Krumm et al., 2018) indicating that the role of WM in creative cognition may be task-dependent (Krumm et al., 2018). Meanwhile, studies using network science methods have indicated that more creative individuals may have more flexible and interconnected semantic memory structures (He et al., 2020; Kenett, Anaki, & Faust, 2014; Kenett et al., 2018; Ovando-Tellez et al., 2022). Research has also probed less direct links between creativity and neurocognitive processes, examining how creativity relates to variation in personality traits such as risk-taking (Dewett, 2007; Harada, 2020; Shen, Hommel, Yuan, Chang, & Zhang, 2018) and openness to experience (Batey & Furnham, 2006; Kaufman et al., 2016; Lloyd-Cox, Pickering, & Bhattacharya, 2022b; Oleynick et al., 2017), and how neurodevelopmental conditions including ADHD (Fugate, Zentall, & Gentry, 2013; Hoogman, Stolte, Baas, & Kroesbergen, 2020) and schizophrenia (Sampedro et al., 2020a, 2020b) impact creative cognition.

Further research has explored how creative performance relates to motivation (Benedek, Bruckdorfer, & Jauk, 2020; Xue et al., 2020) and the activities of the dopaminergic (Lin & Vartanian, 2018; Zhang et al., 2020), and noradrenergic systems (Beversdorf, 2019; Boot et al., 2017; Flaherty, 2005). Considering other neural correlates of creativity, fMRI research has consistently found that creative cognition involves increased cooperation between the default mode (DMN), executive control (ECN), and salience networks (Beaty, Benedek, Silvia, & Schacter, 2016; Green, Cohen, Raab, Yedibalian, & Gray, 2015; Lloyd-Cox, Chen, & Beaty, 2022a; Mayseless et al., 2015). In addition, EEG research has found that greater creative performance relates to greater cortical alpha synchronization (Agnoli et al., 2020; Camarda et al., 2018b; Fink et al., 2018; Rominger et al., 2019; Stevens & Zabelina, 2020), while research using transcranial brain stimulation has found that increasing alpha power over the prefrontal cortex can improve the creative quality of ideas (Lustenberger, Boyle, Foulser, Mellin, & Fröhlich, 2015), while stimulation over temporal sites supports the inhibition of non-creative ideas (Luft, Zioga, Thompson, Banissy, & Bhattacharya, 2018).

The theories that guide NCR

Guiding this research is a range of theoretical accounts, providing a conceptual scaffold for researchers to interpret data and develop further hypotheses. These accounts range from being relatively abstract to quite specific in terms of the cognitive processes they describe. For example, an older but highly influential account is Wallas' (1926) four-stage model, which describes the creative process as involving distinct stages of preparation, incubation, inspiration, and verification. This account is broadly suggestive of the processes that might produce creative ideas and can be seen as a precursor to more recent and specific theories.

Another older account (and one that still retains tremendous popularity among NCR researchers) is the distinction between convergent and divergent thinking. These terms were first coined by Guilford (1950, 1959) as two of the (initially) five major intellectual abilities in his Structure of the Intellect model (Guilford, 1967). Guilford defined both kinds of thinking in terms of the number of solutions they produce, with divergent thinking defined as "thinking in different directions" to produce a "variety of responses", and convergent thinking defined as producing "one right answer" (Guilford, 1959). While both modes of thought were described as ways to generate new information from old information, Guilford linked divergent thinking to creativity and convergent thinking to the ability to solve intelligence tests (but see more recent evidence linking divergent thinking to intelligence; Frith et al., 2021a; Karwowski et al., 2016). It is worth noting that the Structure of Intellect model was later criticized due to issues with the factor analytic evidence used to support it, and the model has little support today (Jensen, 1998; Mackintosh, 1998; Undheim & Horn, 1977).

In the years since Guilford, the divergent and convergent thinking constructs have gradually evolved and been reinterpreted, with researchers now arguing that both play important roles in creative cognition (Basadur, 1995; Brophy, 2001; Caughron, Peterson, & Mumford, 2011; Cropley, 2006; Jung, Mead, Carrasco, & Flores, 2013; Runco, 2012, 2014). Indeed, many researchers have shifted away from defining divergent and convergent thinking in terms of the number of solutions they produce, toward defining divergent thinking as a generative process that produces novel ideas, and convergent thinking as an evaluative process that selects and refines ideas (Basadur, 1995; Brophy, 2001; Cropley, 2006; Lee & Therriault, 2013). These generation-evaluation definitions of divergent and convergent thinking can be seen in numerous recent NCR articles (e.g., de Vink et al., 2021; Eskine, Anderson, Sullivan, & Golob, 2020; Gabora, 2018; Jung et al., 2013; Kleinmintz, Ivancovsky, & Shamay-Tsoory, 2019; Lee & Therriault, 2013), although Guilford's original definitions (many solutions vs. a single solution) also remain popular (e.g., Gilhooly, Fioratou, Anthony, & Wynn, 2007; Lu, Akinola, & Mason, 2017; Radel, Davranche, Fournier, & Dietrich, 2015; Runco, 2010; Shamay-Tsoory, Adler, Aharon-Peretz, Perry, & Mayseless, 2011; Volle, 2018). This reinterpretation of divergent and convergent thinking has its roots in another common framework for conceptualizing creativity, which suggests that creative ideas arise from iterative cycles of generation and evaluation (Basadur, 1995; Ellamil, Dobson, Beeman, & Christoff, 2012; Finke, Ward, & Smith, 1992; Jung et al., 2013; Kleinmintz et al., 2019). A prominent theory of this kind is the blind variation and selective retention (BVSR) model, first suggested by Campbell (1960) and later expanded upon by Simonton (2013, 2022). BVSR argues that creative cognition involves cycles of relatively undirected (or partially sighted; Simonton, 2013) processes to produce multiple ideas, and directed processes that select the best idea to develop further.

Among the most popular frameworks for understanding creative cognition that have emerged in recent decades is the dual-process account. This argues that creative cognition emerges from the interactions of spontaneous, associative processes and controlled, analytic processes (Allen & Thomas, 2011; Barr, 2018; Benedek et al., 2023; Benedek & Jauk, 2018; Sowden et al., 2015; Tubb & Dixon, 2014; Volle, 2018). The account is based on wider dual-process theories of cognition (e.g., Evans, 2008; Evans & Stanovich, 2013; Kahneman, 2011), which describe two broad categories of processes which might be termed Type 1 and Type 2 (Evans & Stanovich, 2013). Type 1 processes are typically described as associative, fast, unconscious, and implicit, while Type 2 processes are described as controlled, slow, conscious, explicit, and dependent on WM (Evans, 2008; Evans & Stanovich, 2013; Tubb & Dixon, 2014). NCR researchers have discussed the overlaps between dual-process associative and controlled processes, divergent and convergent thinking, and generation and evaluation (Benedek & Jauk, 2018; Goldschmidt, 2016; Lloyd-Cox et al., 2022a; Sowden et al., 2015), with some highlighting differences between the accounts (e.g., Sowden et al., 2015; Tubb & Dixon, 2014), and others concluding that they are broadly synonymous (e.g., Benedek & Jauk, 2018; Goldschmidt, 2016). Indeed, many NCR articles now define divergent and convergent thinking in terms of associative and controlled processes (e.g., Augello et al., 2016; Cortes, Weinberger, Daker, & Green, 2019; Drago & Heilman, 2012), producing a third interpretation of Guilford's original constructs.

The accounts discussed so far are, for the most part, relatively imprecise, leaving considerable room for interpretation. For example, describing creative cognition as involving divergent and convergent thinking, or cycles of generation and evaluation, does not greatly constrain the space of possible cognitive mechanisms that might underlie creativity. However, as the findings of NCR have grown, more specific theories of creative cognition have emerged. One example is the BVSR theory (Simonton, 2013, 2022), which defines its variational and selective processes in formal mathematical terms. Another is the contextual focus theory (Gabora, 2010, 2018) which builds on suggestions that creative cognition involves switching between narrow and broad attentional states (Bristol & Viskontas, 2006; Dorfman, Martindale, Gassimova, & Vartanian, 2008; Gabora, 2010; Herz, Baror, & Bar, 2020; Zabelina & Robinson, 2010) to define divergent thinking as the broadening of conceptual representations to include more abstract and associative information, and convergent thinking as the narrowing of representations to only the most relevant information (Gabora, 2010, 2018).

Researchers have also suggested more specific cognitive mechanisms corresponding to the associative and controlled processes described by the dual-process account of creative cognition (Benedek et al., 2023; Barr, 2018; Benedek & Jauk, 2018; Volle, 2018). Drawing on evidence linking creative cognition to performance on free-association and verbal fluency paradigms, researchers have suggested that associative creative processes may include the automatic spreading of activation through semantic memory (Kenett et al., 2018; Volle, 2018). Meanwhile, evidence linking creative cognition to intelligence and executive functions has led to suggestions that controlled creative processes may include strategic search processes (Avitia & Kaufman, 2014; Benedek & Neubauer, 2013; Forthmann, Bürkner, Szardenings, Benedek, & Holling, 2019a; Lebuda & Benedek, 2023; Silvia, Beaty, & Nusbaum, 2013), and the inhibition of distracting or unoriginal thoughts (Beaty, Christensen, Benedek, Silvia, & Schacter, 2017a; Camarda et al., 2018a; Volle, 2018). The increased DMN-ECN cooperation observed during creative cognition is also suggestive of interacting associative and controlled processes, and may signify the DMN spontaneously activating ideas (Beaty et al., 2020; Beaty & Lloyd-Cox, 2020), while the executive control network inhibits prepotent ideas (Beaty et al., 2017a; Christensen, Benedek, Silvia, & Beaty, 2021; Lloyd-Cox, Christensen, Silvia, & Beaty, 2021) and implements creative strategies (Benedek & Jauk, 2018). Indeed, DMN-ECN cooperation during creative cognition appears to increase when there is a need for inhibition (Beaty et al., 2017a; Christensen et al., 2021).

Another more specific account distinguishes between two opposing strategies for producing creative ideas: flexibility and persistence. The former involves switching between conceptual spaces to attain more diverse ideas and may depend on striatal dopamine pathways, while the latter involves the persistent exploration of one conceptual space and may depend on prefrontal dopamine pathways (Mekern, Sjoerds, & Hommel, 2019b; Nijstad et al., 2010; Zhang et al., 2020). The account has strong similarities to the distinction between exploration and exploitation in creative cognition (Hart et al., 2017; Lin & Vartanian, 2018), and is primarily supported by measures of clustering (i.e., the generation of similar ideas) and switching (i.e., the generation of ideas from different conceptual categories) in divergent thinking and cognitive search tasks (Mekern et al., 2019b).

How NCR can benefit from the wider adoption of computational modeling

NCR has made considerable progress in uncovering a broad range of cognitive, psychological, and neural correlates of creative cognition, guided by theories ranging from older, broader accounts to more recent and specific accounts. However, a precise, mechanistic understanding of creative cognition remains elusive. We believe that the increased adoption of computational modeling can help greatly towards this goal. While verbal theories are a useful and necessary part of science, they are more ambiguous and open to interpretation than formal computational models, which require all elements of a theory to be explicitly defined (Farrell & Lewandowsky, 2015; Fried, 2020; Guest & Martin, 2021; Smaldino, 2020). Defining theories in explicit and formal terms makes them more falsifiable and easier to compare in terms of their predictions and assumptions. We argue that NCR should continue to move towards more specific cognitive theories supported by computational models.

For clarity, by “computational model”, we refer to dynamic computational models that aim to embody a particular cognitive theory of creativity by representing how creative ideas arise from cognitive processes. As such, we are not referring to statistical models of human fMRI (e.g., Beaty et al., 2018a; Sunavsky & Poppenk, 2020), EEG (e.g., Rosen et al., 2020; Stevens & Zabelina, 2020) or behavioral data (Beaty & Johnson, 2021; Harada, 2020; He et al., 2020; Zioga, Harrison, Pearce, Bhattacharya, & di Bernardi Luft, 2020). Equally, we do not include machine learning models that generate novel or interesting products but in ways that do not seek to emulate human cognition, such as Google DeepDream (Suzuki, Roseboom, Schwartzman, & Seth, 2017), and GPT3 (Floridi & Chiriatti, 2020). Here we examine in more detail the issues that can affect purely verbal accounts, including more recent and specific accounts, and how computational modeling can provide greater clarity, rigor, and reproducibility to the development of cognitive theories (Farrell & Lewandowsky, 2015; Guest & Martin, 2021).

The limitations of verbal theories

At the less specific end of the spectrum of theoretical accounts of creative cognition is the distinction between convergent and divergent thinking. Researchers have defined these constructs in several distinct ways since they first appeared. The first definition separates the two constructs based on the number of ideas or solutions they produce (Guilford, 1959) (i.e., one solution in convergent thinking, but multiple solutions in divergent thinking). A later definition focused on divergent thinking as idea generation and convergent thinking as idea evaluation (Basadur, 1995; Brophy, 2001; Cropley, 2006; Lee

& Therriault, 2013). Finally, a third definition draws on dual process theories of cognition to define divergent thinking as an unconscious, associative process and convergent thinking as a conscious, analytic process (Augello et al., 2016; Cortes et al., 2019; Drago & Heilman, 2012; Gabora, 2010).

The existence of multiple definitions of divergent and convergent thinking suggests that they are likely to be conceptualized very differently across NCR researchers. Indeed, previous researchers have commented on the apparent contradictions that can emerge due to these varying definitions (e.g., Cortes et al., 2019; Dietrich, 2019; Gabora, 2018; Lee & Therriault, 2013). Moreover, none of these definitions are particularly precise. This can make it difficult to develop specific process-level hypotheses regarding these constructs, such as how divergent and convergent thinking might be differentially impacted by WM capacity. The definitional ambiguity of these constructs also makes it difficult to model them computationally, as to do so one would first have to translate one of their broad definitions into a specific set of processes (e.g., Gabora, 2018; Zhang et al., 2020). Whichever processes are chosen could differ greatly from those chosen by another researcher, so any conclusions drawn about these processes need not necessarily apply to the broader constructs. In essence, the reinterpretable nature of divergent and convergent thinking makes them difficult to study or falsify since any specific hypothesis can be easily dissociated from the construct.

Research into divergent and convergent thinking is also affected by inconsistencies between the definitions of these constructs and the tasks used to assess them. For example, convergent thinking is commonly assessed with the Remote Associates Test (RAT; e.g., de Vink et al., 2021; Nielsen, Pickett, & Simonton, 2008; Shang, Little, Webb, Eidels, & Yang, 2021; Zhang et al., 2020), in which participants are shown three unrelated words and must generate a response word that relates to all three. While RAT problems have one correct solution (consistent with the original conception of convergent thinking), they require generating numerous candidate solutions in an associative manner (Cortes et al., 2019), contrary to later definitions of convergent thinking as an analytic, evaluative process (Cropley, 2006; Runco, 2014). Indeed, the RAT was originally developed as a measure of associative processes (Mednick, 1962) and continues to be used as a measure of unconscious insight (e.g., Kounios & Beeman, 2014; Tik et al., 2018; see also Barr, 2018; Benedek & Jauk, 2018).

Meanwhile, divergent thinking is typically assessed with the Alternative Uses Task (AUT; Guilford, 1959, 1967), which requires participants to think of unusual uses for a given object. Since the AUT involves producing multiple ideas, and undoubtedly involves generative and associative thinking, it might appear to satisfy all three definitions of divergent thinking. However, the AUT is also widely considered to engage evaluative and analytic processes to ensure that the ideas generated are task-relevant and original (Beaty, Silvia, Nusbaum, Jauk, & Benedek, 2014; Cortes et al., 2019; Gilhooly et al., 2007;

Nusbaum & Silvia, 2011; Volle, 2018), processes commonly associated with convergent thinking (Cropley, 2006; Sowden et al., 2015). Indeed, both the AUT and RAT are now thought to involve a mixture of associative and controlled processes (Cortes et al., 2019). Given the difficulties in assessing divergent and convergent thinking, their varying definitions, and the fact that they must be translated into more specific accounts when researchers attempt to model or hypothesize about their underlying processes, NCR might seek to replace these constructs with more precise subtypes of creativity defined in terms of more established cognitive processes, such as memory, attention, and cognitive control (Barbot, Hass, & Reiter-Palmon, 2019; Benedek & Fink, 2019; Chrysikou, 2018; Farrell & Lewandowsky, 2015; Kaufman et al., 2016; Plucker, 2022; Wiggins & Bhattacharya, 2014).

As noted, more recent theoretical accounts of creative cognition go much further in suggesting specific mechanisms that might produce creative ideas. Besides BVSR (Simonton, 2022), another recent extension of the generation-evaluation account describes several possible neural and cognitive mechanisms that may underlie both kinds of process (Kleinmintz et al., 2019). Meanwhile, an extension of dual-process accounts has suggested how creative ideas might arise from specific associative and controlled processes operating on a semantic network (Volle, 2018). In addition, several recent review articles have provided in-depth descriptions of the roles of distinct associative (Beaty & Kenett, 2023), memory (Benedek et al., 2023), and metacognitive processes (Lebuda & Benedek, 2023) in creative cognition. Researchers have also proposed neurocognitive mechanisms that might underlie new conceptions of convergent and divergent thinking, relating them to focused and defocused mental representations (Gabora, 2010, 2018) and flexible and persistent meta-control states (Hommel & Wiers, 2017; Nijstad et al., 2010; Zhang et al., 2020). The latter account may soon form the basis of a computational model. Finally, a recent review of the neural underpinnings of divergent thinking, abstraction, and improvisation has argued that all three can arise from dopaminergic novelty-seeking processes, in a framework that may soon be implemented computationally (Khalil & Moustafa, 2022).

For the most part, however, these are still verbal accounts, and thus they retain a degree of ambiguity that can make them difficult to falsify and leaves them open to reinterpretation. Another key issue for verbal theories is that they can be difficult to compare in terms of their predictions or internal consistency. Despite recent efforts (Kenett et al., 2020), there is no commonly accepted ontology for conceptualizing creativity (Kenett et al., 2020; Puryear & Lamb, 2020; Saggar, Volle, Uddin, Chrysikou, & Green, 2021). Researchers tend to employ different accounts to guide their research (Abraham, 2013; Hennessey & Amabile, 2010; Wiggins & Bhattacharya, 2014), and it is not always clear to what extent these accounts are synonymous or overlapping. For example, it is unclear whether associative and controlled processes are synonyms for constructs like generation and evaluation and implicit and explicit thought, or in fact underlie them. Another example is the overlap between theories of flexibility vs. persistence (Nijstad et al., 2010; Zhang et al., 2020) and exploration vs. exploitation (Hart et al., 2017; Lin & Vartanian, 2018), which both distinguish between the tendency to shift between conceptual spaces and the tendency to exploit a single conceptual space. Similarities also exist between accounts linking different forms of creativity to different forms of attention (Gabora, 2010, 2018; Zabelina et al., 2016; Zabelina & Robinson, 2010). However, without formal models, it is difficult to say whether these theories are broadly equivalent or describe fundamentally different kinds of operation.

The benefits of modeling

The benefits that computational modeling can bring to psychology and neuroscience have been discussed at length in several excellent recent articles (Blohm et al., 2020; Borsboom, van der Maas, Dalege, Kievit, & Haig, 2021; Fried, 2020; Guest & Martin, 2021; Maia et al., 2017). A computational model is the explicit formalization of a theory in equations and algorithms (Farrell & Lewandowsky, 2015; Maia et al., 2017), and therefore requires that every aspect of a theory be precisely defined. More precise theories, that describe more specific cognitive processes or operations, are more easily communicated and testable since they make clearer predictions about what should be observed under certain conditions. By contrast, imprecise or ambiguous theories provide no clear mapping to empirical research questions and can be redefined continually, potentially leading different researchers to have very different interpretations of the theory. While NCR is already working toward more rigorous and specific theories (Benedek & Fink, 2019; Gabora, 2018; Volle, 2018; Zhang et al., 2020), the process of translating a theory into a computational model is an excellent way to make it more precise. For example, building a model based on the dual process account would force researchers to be extremely specific about what associative and controlled processes are, how they produce creative ideas, and how they might vary in different creative contexts.

The detail required by computational modeling can also reveal weak points, dubious assumptions, or outstanding questions in theories (Blohm et al., 2020), which can then direct empirical work. For example, modeling creative cognition as involving cycles of generation and evaluation would involve deciding how frequently the model should switch between the two modes. Researchers might also consider whether movement along a continuum between generation and evaluation (or even simultaneous generation and evaluation) is preferable to a binary switch. These decisions might inform, and be informed by, empirical research (e.g., Goldschmidt, 2016; Kleinmintz et al., 2019; Lloyd-Cox et al., 2022a).

In addition, modeling provides a way to demonstrate and test hypotheses for how variation in a neurocognitive factor leads to variation in behavioral outcomes. Indeed, creative cognition is a particularly high-level construct, and there are likely to be a large number of factors that can impact creative outcomes, including a person's attention, memory, cognitive control, and personality (Beaty et al., 2014; Benedek & Fink, 2019; Oleynick et al., 2017). With modeling, these factors can be represented as sets of operations within a computational system, enabling researchers to examine the causal pathways by which they can impact creative performance. For example, researchers might hypothesize that individuals higher in the personality trait openness to experience produce more creative ideas by engaging in broader attentional states (Gabora, 2010, 2018). This hypothesis might then be embodied in a computational model by defining "openness" as a set of parameters governing the propensity to use broad instead of narrow conceptual representations. The hypothesis can then be tested by adjusting the parameters reflecting openness and observing whether the changes in simulated creative outcomes are in line with those observed among human participants with varying openness scores.

Moreover, modeling several contrasting theories can provide researchers with a more concrete basis for comparing their empirical predictions, internal consistency, and theoretical complexity (with less complex models being favorable; Farrell & Lewandowsky, 2015), allowing researchers to combine similar theories and select or reject opposing theories. As noted, there appear to be strong similarities between several accounts of creative cognition, such as those that describe generative and evaluative states (Jung et al., 2013; Kleinmintz et al., 2019), and those that describe associative and controlled processes (Benedek & Jauk, 2018; Volle, 2018), but it is hard to say whether these accounts are equivalent. Translating each account into a computational model could reveal opposing predictions about the role of a particular factor in creative cognition, or might instead indicate that the two accounts are referring to the same underlying mechanisms.

Ultimately, modeling results in more fleshed-out, transparent, and comparable theories (Guest & Martin, 2021). For a more specific example of how computational modeling can bring clarity to verbal theories, consider a creative search task in which participants must think of unusual members of a category (e.g., "uses for a brick", or simply "fruits"). Researchers might debate the processes that govern performance on this task, such as spontaneous association-making, attention, and cognitive control. To provide a concrete foundation for this debate, the task could be modeled as an iterative search through an *n*-dimensional space, with dimensions representing properties that vary across concepts (e.g., the size or exoticness of fruits). Concepts (i.e., fruits or possible task solutions) could be distributed across this space, with the strength of associations between concepts defined by the Euclidean distance between them (smaller distance = stronger association). Common items (e.g., apple, pear) could be clustered around the center, with more unusual items nearer the periphery of the space. Cognitive processes could then be modeled as operations on this space, such as spontaneous processes spreading activation from the center outward and controlled processes strategically pushing activation along one dimension (e.g., thinking of exotic locations to access more unusual fruits; Benedek & Neubauer, 2013).

To further demonstrate how a creative task can be modeled computationally, we have included an implementation of this simple model in MATLAB code in the Supplementary Material, together with a detailed overview. We have made the code accessible to researchers with minimal modeling experience, implementing a major recommendation made by Barton et al. (2022) to enhance the usability of computational models. Of note, this toy model is by no means intended as a definitive model of creativity, but simply as an example of how verbal theories of creative task performance can be translated into formal models for researchers who may have limited or no prior experience in computational modeling.

Once a basic model of a task is implemented, it can serve as a starting point for further models embodying different theories. In the current example, researchers who emphasize associative processes in creative search might adjust certain parameters of the model to reflect this. Others might simulate WM by limiting the number of concepts able to activate at once, or simulate processing speed, attention, or mind-wandering by adding other features. Examining and comparing how these different models fit empirical human data could then help to improve our understanding of the processes underlying creative search (Wilson & Collins, 2019). Of course, evaluating model performance against human data requires reliable and valid measures of the underlying construct, and even then, alternative models may be equally supported by empirical data. As such, models of creative performance might also be compared in terms of their internal consistency and complexity, while researchers continue to develop more fine-tuned assessments of creativity (e.g., Barbot, 2018; Hart et al., 2017, 2022).

Varieties of computational model

Computational models can come in a large variety of forms. However, as noted, we primarily focus on computational models embodying specific theories of human cognition. These are distinct from statistical models used to analyze empirical data, and mathematical models that outline algorithmic hypotheses concerning human cognition, but which are not implemented computationally (though these also help increase the specificity and falsifiability of theories; e.g., MacGregor, Ormerod, & Chronicle, 2001; Simonton, 2013; 2022). Indeed, recent years have seen numerous computational creative systems being developed (see Carnovalini & Rodà, 2020; Gatti et al., 2021; Mekern et al., 2019a), but many of these primarily aim to create products or behaviors that humans would consider creative, such as stories (Concepción, Gervás, & Méndez, 2020), paintings

(Colton, 2012; Yalcin, Abukhodair, & DiPaola, 2020), and music (Anderson, Eigenfeldt, & Pasquier, 2013; Todd & Miranda, 2006; Yang, Choi, & Yang, 2017), without necessarily creating these in a human-like way. By contrast, the models we refer to focus on emulating human cognition, with less regard for the creative quality of the products that are generated (Hélie & Sun, 2010; Olteţeanu & Falomir, 2016; Schatz, Jones, & Laird, 2018; Wiggins, 2020).

Even among computational models of human cognition, however, there is considerable variation in terms of the goals and levels of representation pursued by modelers (Kording, Blohm, Schrater, Kendrick, & Kay, 2020; Palminteri, Wyart, & Koechlin, 2017). Different modelers may have very different aims, leading to considerable variation in how models are evaluated (Kording et al., 2020). For example, some modelers may primarily aim to inspire new empirical research, but could equally be most interested in the efficiency of a model, or how clear and interpretable its predictions are. An important distinction can also be drawn between descriptive and normative computational models. Descriptive models aim to represent our best guess at what the brain is doing, while normative models aim to represent an optimal way to solve a problem based on assumptions of rationality. Existing models of creative cognition arguably fall into both camps, and both are useful to NCR. While descriptive models are crucial for a precise understanding of human creative cognition, normative models can demonstrate how a particular creative task could be optimally performed, inspiring the development of descriptive models and guiding empirical research efforts (Veale & Perez y Perez, 2020).

Models can also vary in their level of representation (Palminteri et al., 2017). Cognitive-level models operate at a high level of abstraction, illustrating how cognitive factors such as attention, inhibition, and associative thought might produce creative ideas (e.g., Lopez-Persem et al., 2022; Schatz, Jones, & Laird, 2018). By contrast, neural models operate at the level of neurons, demonstrating how neuronal populations can give rise to the processes underlying creative cognition (e.g., Kajic et al., 2017). Both levels of representation are important for NCR. However, neural models face greater computational challenges and may not be as useful for making specific predictions about creative cognition, due to the high-level nature of creativity as a construct. Among cognitive-level models, a further distinction can be made between broader models that encompass creativity as well as other cognitive features (e.g., Hélie & Sun, 2010; Wiggins, 2020), and narrower models that focus on how humans perform a single creative task (e.g., Olteţeanu & Falomir, 2016; Schatz, Jones, & Laird, 2018). Again, both types of models are useful. Broader models provide a holistic understanding of how creativity fits together with more general cognition, while narrower models of specific tasks provide an effective means to test cognitive theories of creativity since their performance can be readily compared to human data. While few middle-ground models of creative cognition exist currently (Mekern et al., 2019a), demonstrating how the same cognitive processes can be employed in multiple distinct creative tasks would greatly contribute to our understanding of human creativity. We will consider some existing models of creative cognition in greater detail below.

Challenges for computational models of creativity

One reason why computational modeling has yet to have a significant impact on NCR may be that models of creative cognition face key challenges not encountered by models in other areas of cognitive science. For example, creative cognition is a high-level and complex construct involving many cognitive and psychological factors (Benedek & Fink, 2019; Volle, 2018). While this complexity makes computational modeling all the more important to NCR, simulating creative cognition effectively may be considerably more difficult than modeling processes like memory retrieval. In addition, creative performance can be assessed with a wide range of tasks, across verbal, visual, and auditory domains (Plucker, 2022; Puryear & Lamb, 2020). Consequently, a precise model of creative processing in one specific task or domain may not easily generalize to others, making it difficult to build a comprehensive and cohesive model of creative cognition as a whole.

These challenges, while significant, need not deter NCR researchers from developing new models. Models do not need to account for every factor that might affect creative cognition. All models are simplifications (Smaldino, 2018), and representing a few processes effectively is often more useful than trying to simulate all possible relevant factors, especially when the goal is to create models that are easily understandable and which generate clear predictions (Farrell & Lewandowsky, 2015; Guest & Martin, 2021). Likewise, the diversity of creative tasks implies that NCR may require a corresponding diversity of models, at least initially (Poile & Safayeni, 2016; Wilson & Collins, 2019). While a single model capable of explaining performance across multiple tasks or domains would be a significant advance for the field, models focusing on individual creative tasks have proved highly useful to our understanding of how creative outcomes can arise from cognitive processes (Lopez-Persem et al., 2022; Olteţeanu & Falomir, 2016; Schatz, Jones, & Laird, 2018).

An additional challenge for modeling in NCR relates to the nature of creativity data, which does not readily lend itself to simulation. Computational models of human cognition typically need to simulate data from participants to allow the model to be evaluated. Models of perception or memory often aim to simulate data such as reaction time, perceptual or recall accuracy, or patterns of neural activity (Kahana, 2020; Karimi-Rouzbahani, Bagheri, & Ebrahimpour, 2017; Pramod, & Arun, 2016; Rotaru, Vigliocco, & Frank, 2018). Within NCR, however, the main measure of interest is often the subjective creativity rating of generated ideas, drawings, or musical sequences (Amabile, 1982; Cseh & Jeffries, 2019). While models can be developed to generate such products, which can then also be rated for creativity, this requires incorporating knowledge of sentence construction, or artistic or musical composition into the model. These tasks pose significant challenges even for highly skilled computational modelers.

One alternative for modelers is to simulate specific features of creative output without simulating the output itself (e.g., response times, number of responses made, or number of concepts included in a drawing). Researchers can also focus on simpler creative tasks. For example, paradigms such as free association and the RAT have just single words as input and output, removing the need to model sentence generation. Indeed, several recent models of creative cognition have investigated the generation of single words using semantic networks, as an effective means to study creativity quantitatively (Lopez-Persem et al., 2022; Olteţeanu & Falomir, 2015; Schatz, Jones, & Laird, 2018). Semantic networks are formed of nodes representing concepts, and edges representing associative links, and can simulate how activation spreads from a cue to a response (Beaty & Kenett, 2023).

Fitting semantic networks to participant data can be done in various ways. One approach is to divide participants into low and high creative groups, and then construct group-level semantic networks based on participants' free association data (Kenett et al., 2018). By comparing the properties of these networks, researchers can then identify differences in semantic memory structure between the groups. Another approach is to construct networks from individual participant data, and explore their structural properties in relation to measures of creative cognition (Benedek et al., 2017; He et al., 2021). A further option for semantic network models is to build a single, standard network using free association data (Nelson, McEvoy, & Schreiber, 2004) or distributional semantics methods (Rotaru et al., 2018), and then fit the model to individual participants by modifying the simulated processes that operate on this network (e.g., Lopez-Persem et al., 2022; see also Benedek & Neubauer, 2013; Volle, 2018). This involves defining a set of processes that determine how activation spreads through memory, such as associative and controlled processes, and then adjusting the parameters governing these processes to fit an individual participant's data and mimic their creative behavior. Semantic networks, thus, provide a promising means to examine the production of qualitative ideas as a quantitative process (Beaty & Kenett, 2023; Kenett & Faust, 2019).

In summary, despite the challenges, computational modeling remains a useful and enlightening approach for NCR. While creativity is a complex and multifaceted construct, simple models focusing on specific instances of creativity can still be useful (Smaldino, 2018). Given the diversity of creative tasks, NCR will likely require numerous models to explore how cognitive processes operate in different contexts. In addition, since any task can be modeled in various ways, it is important to develop multiple models of each task and then compare their performance to human data (Poile & Safayeni, 2016; Wilson & Collins, 2019). For example, semantic memory retrieval can be modeled as a random walk (Kenett & Austerweil, 2016; Lopez-Persem et al., 2022) or as an exploratory process of optimal foraging (Hills, Jones, & Todd, 2009). By comparing the goodness of fit of different models to human data, we can determine which model and its underlying hypotheses are more supported, leading to the development of further models and empirical research questions. As models become more sophisticated, identifying commonalities across models of distinct tasks might allow researchers to simulate multiple tasks using a single model, demonstrating how the same cognitive processes operate in different creative contexts. Finally, though creative outcomes are often qualitative in nature and subjectively evaluated, there are methods available for simulating quantitative aspects of creative performance.

Existing computational models of creativity

Having discussed the theoretical accounts that guide NCR and how these might benefit from the increased adoption of computational modeling, we now consider some recent computational models of creativity, and the steps that might be taken to improve these and better integrate them with NCR. Computational models of human creative cognition come in two main forms: broader models and cognitive architectures that focus on creativity as a general feature of cognition (e.g., Hélie & Sun, 2010; Wiggins, 2020), and narrower models that aim to simulate human performance in specific lab-based creative tasks (e.g., Olteţeanu & Falomir, 2016; Schatz, Jones, & Laird, 2018).

Examples of broader models include recent attempts to model conceptual blending - the creative association of ideas or features from two distinct conceptual spaces (Falomir & Plaza, 2020; Schorlemmer & Plaza, 2021), and the simulation of both individual and cultural creativity using autocatalytic networks (Gabora, Beckage, & Steel, 2022; Gabora & Steel, 2020). Other examples include the Copycat (Hofstadter & Mitchell, 1994) and Metacat systems (Marshall, 2006), which focus on simulating analogical thought. Meanwhile, the CLARION cognitive architecture draws on Type 1 and Type 2 processes (Evans & Stanovich, 2013) to model creative thinking as the outcome of both associative, implicit processes and rule-based, explicit processes (Hélie & Sun, 2010). Researchers have also adapted the ACT-R cognitive architecture to simulate aspects of creativity including conceptual blending (Guhe, Smaill, & Peace, 2010). Finally, the IDyOT model, inspired by theories of predictive intelligence (Clark, 2013; Friston, 2010) and global workspace theory (Baars, 1988), focuses on cognition as the hierarchical prediction of perceptual input, with creativity emerging from the system “free-wheeling” in the absence of an external stimulus (Wiggins, 2020).

Although informative, the generality of these broad-focus models means that they are not best placed to model the cognitive theories of NCR, which typically focus on how humans perform specific lab-based creative tasks. For example, Copycat and Metacat operate on a limited set of abstract symbolic concepts, far removed from a human-like associative memory. Meanwhile, CLARION has only modeled elements of cognition relevant to incubation and insight, and must be set up and trained in a specific way for each task. Finally, IDyOT focuses on the perception and generation of sequential information such as music. Critically, these models lack the specific input/output components needed to simulate standard laboratory-based measures of creativity.

By contrast, narrow-focus models aim to simulate the cognitive processes that operate in specific creative tasks (e.g., Kajić, Gosmann, Stewart, Wennekers, & Eliasmith, 2017; Olteţeanu & Falomir, 2016; Schatz et al., 2018). NCR would arguably benefit most from increased modeling of this kind, since NCR and the theories that guide it focus mainly on lab-based creativity, and the performance of such narrow-focus models could be readily compared to large amounts of human data. While such models lack the flexibility needed to account for performance across multiple tasks, they have demonstrated how relatively simple operations on associative memory structures can lead to human-like creative performance on tasks such as the AUT and RAT.

To consider the structure of these narrow-focus models in more depth, one example comes from Kajić et al. (2017), who developed a spiking neural network model of the RAT. The model utilized a distributed memory architecture where each simulated neuron could be part of several concept representations. Words were represented as vectors encoded in neural activity, with word associations defined using the Free Association Norms dataset (Nelson, McEvoy, & Schreiber, 2004). When retrieving solutions, RAT cues were activated in sequence, with only one cue able to activate associations at any one time. Competing associations inhibited each other, and activation gradually decayed over time until a solution was reached. The model produced behavior comparable to human participants in terms of the number of RAT problems it could solve, the number of responses it generated, and the similarities between its responses. By examining the model parameters most relevant to performance, the researchers concluded that two main cognitive processes underlie RAT performance: one that generates potential responses and one that filters responses.

In contrast to the neural-level model of Kajić et al. (2017), Olteţeanu and Falomir (2015) developed a cognitive-level model of RAT performance in which concepts were represented as sets of associations to other concepts. The model's memory was constructed from a database of unique 2-word phrases (i.e., 2-grams), with the strengths of associations between words (i.e., associative strength) defined by the frequency of their co-occurrence in 2-grams. When solving RAT problems, all three cues and their associated concepts were activated in memory simultaneously (again in contrast with the sequential activation employed by Kajić and colleagues, 2017). Solutions were then selected from the most strongly activated associated concepts. While the authors did not directly compare the model to humans in terms of the number of RAT problems it could solve, model performance suggested that the difficulty of RAT items relates to both the strength of associations between cues and solutions, and the number of associations each cue word has (known as “fan”). Since these properties impact how activation spreads automatically between ideas in memory, these findings emphasize the role of automatic associative processes in the RAT.

Building on this work, Schatz, Jones, and Laird (2018) developed a model of the RAT using the Soar cognitive architecture. The authors tested two versions of the model. A baseline model simply searched memory for words that linked to all three cue words. By contrast, a second “free recall model” used spreading activation, which propagated through memory from the three cue words according to both associative strength and fan. The authors also tested two knowledge bases for the model: one formed of 2-grams (following Olteţeanu & Falomir, 2015) and one based on a larger corpus not limited to 2-grams and including several kinds of word association. The authors found that the “free-recall” model and the more sophisticated knowledge base produced the most human-like performance in terms of the number of RAT problems solved, highlighting the important roles of memory structure and associative processes in modeling RAT performance.

Models of the AUT are rare, but one attempt comes from Olteţeanu and Falomir (2016). The model used a knowledge base of 70 objects, each composed of a set of features (manually added by the authors), in a hierarchical memory. These features enabled the simulation of several cognitive strategies that people are known to employ when thinking of unusual uses for objects in the AUT (Gilhooly et al., 2007), including object replacement (matching the cue object to the typical uses of another object with similar features) and object decomposition (breaking the object into components and generating uses for these). The model did not aim to model memory retrieval processes such as spreading activation, but served as a proof-of-concept that matching features of cue objects (and components of objects) to features of other objects can produce solutions to AUT problems.

Another recent model of creative idea generation, this time focusing on free association, comes from Lopez-Persem et al. (2022). The model included separate modules for exploration, valuation, and selection. The exploration module simulated activation spreading through a semantic network using random walks biased by associative strength (defined using a database of word associations). The valuation module then calculated the value of activated ideas based on their novelty and appropriateness (estimated as linear and quadratic functions of the associative strength between each idea and the cue word). Finally, the selection module selected a word from among activated ideas according to their value. The authors then adjusted parameters of the model, and compared the resulting changes in performance to the performance of human participants. They found that certain model parameters were more relevant to the performance of individual modules than others, indicating the processes that may underlie these different components of creative cognition. For example, the exploration module performed well (i.e., matched human performance well) using just associative strength, and was not improved by considering the value of ideas, which only played a role in the subsequent valuation stage. The performance of the exploration module was also unaffected by whether human participants were asked to produce the first response that came to mind or an original but still associated response. These findings indicate that the initial activation of ideas during exploration does not depend on how valuable ideas are, and does not vary depending on the specific task being performed. By contrast, the selection module performed better when considering appropriateness more among first responses, and value more among original responses.

In each of these studies, the authors found evidence that particular computational model structures and parameters can mimic human performance on creative tasks, in some cases finding that certain structures and parameters perform better than others. In this way, models can provide considerable insight into the cognitive operations that underlie performance in creative tasks. However, despite the progress of these models, and the benefits that models of this kind could bring to NCR, computational modeling of creativity is currently conducted largely separately from empirical research. The researchers who build models rarely overlap with those involved in empirical work, and models are rarely mentioned by NCR. One method to increase integration between the two fields would be to improve the value of models to empirical researchers. For example, with some exceptions (e.g., Lopez-Persem et al., 2022; see also Augello, 2016), the models discussed have not explicitly aimed to embody a particular cognitive theory from NCR in a way that would enable researchers to examine the theory's predictions or to test new hypotheses. Indeed, several clear steps could be taken to improve future models of creativity, to increase their ability to simulate human cognition and maximize their explanatory value to NCR.

Future steps for computational models of creative cognition

We have argued that NCR would benefit greatly from the increased adoption of computational modeling. To this end, the neurocognitive theories that guide NCR should, where possible, be formally defined in computational models that can simulate performance in typical lab-based tasks. Hypotheses can then be developed with the aid of computational models, with models adjusted on the basis of empirical data. This approach would bring considerable clarity to our understanding of creative cognition, allowing researchers to rigorously compare different theories and make inferences about underlying processes. Such integration between NCR and computational modeling would, in turn, aid the development of artificial creative systems (Chateau-Laurent & Alexandre, 2021; Wiggins & Bhattacharya, 2014) since a more algorithmic understanding of human creative cognition could inform models of autonomous creativity (Dipaola et al., 2018; Veale & Pérez y Pérez, 2020).

In addition to a heavier focus on modeling theories from NCR, future models of specific creative tasks should aim to meet several additional criteria (see also Mekern et al., 2019a). As already noted, it is highly important that computational models can simulate performance on common creative tasks, to allow model output to be compared to human data. This provides a means to evaluate the structure of the model, and the cognitive theories and hypotheses that the model intends to represent. Different models of the same task can also be compared in terms of how well they fit human data (Guest & Martin, 2021; Wilson & Collins, 2019). We have suggested that smaller, narrow-focus models may be best placed to simulate creative performance on lab-based tasks, though the option also exists to adapt larger cognitive architectures, such as Soar and ACT-R, for this purpose (e.g., Schatz et al., 2018).

Indeed, future models should ideally aim to simulate performance on multiple creative tasks. This is needed to explain how the same cognitive processes can produce creative ideas in different contexts. The first step here would likely be to simulate performance across different verbal tasks, since tasks in different modalities, such as musical composition and drawing paradigms, would require modality-specific components (e.g., memory with visual and auditory representations). Since there is considerable diversity even amongst verbal tasks, which include free-association, metaphor tasks, insight problem-solving in the RAT, and strategic search in the AUT, modeling performance in just some of these tasks would be a good starting point.

Models might also seek to adopt more complex and human-like memory structures. While several studies have modeled human semantic memory as a static network (see, e.g., Kenett et al., 2018; Rotaru et al., 2018), with nodes representing concepts, and edges representing associations, in reality, human memory is far more complex and dynamic. Building more complexity into a model's memory (or “knowledge base”) provides it with more information about concepts and their relationships, enabling more nuanced cognitive processes to be simulated. For example, a simple network in which concepts are represented in a single layer and linked by only a single kind of association does not allow the simulation of search processes that might restrict activation to only one type of concept (e.g., objects), or to concepts that possess a particular property (e.g., roundness) rather than simply being associated with that property.

The benefits of more sophisticated memory structures have already been seen in a model of the RAT, in which a larger memory network with multiple kinds of association produced more human-like behavior than a smaller and simpler network (Schatz et al., 2018). Other examples of more complex memory structures include distributed and hierarchical memory. In distributed memory, concepts are represented as patterns of activity across multiple nodes, where each node can form part of multiple concept representations. This provides a more natural and biologically plausible basis for spreading activation, which now moves between concepts that share nodes (Kajić et al., 2017). In hierarchical memory (e.g., Olteţeanu & Falomir, 2016; Wiggins, 2020), concepts in each layer are represented as sets of concepts in lower layers, which serve as features or properties of higher-level concepts. In both cases, richer conceptual representations provide a basis for more complex and flexible processes to operate on memory.

Other critical goals for future models include the simulation of individual differences and context effects (see also Mekern et al., 2019a). While simulating creative performance allows models to be evaluated in relation to other models, the capacity to model individual differences in a given psychological or cognitive factor (e.g., WM capacity or response inhibition) goes a step further, enabling researchers to develop and test causal hypotheses for how variation in the factor leads to variation in creative performance. To do this, the factor must first be embodied in the model as a set of parameters. These parameters can then be modified, leading to changes in simulated creative outcomes. If these changes align with individual differences observed among human participants (who also vary in the designated factor), then the modeled causal pathway is supported. Indeed, different versions of a model can be designed to reflect contrasting hypotheses regarding how a factor affects creative outcomes. This gives researchers a powerful tool to compare two or more causal hypotheses by examining which model set-up best fits human data.

Finally, modeling context effects allows the conceptual representations stored in a model to be adjusted in response to the current context or sensory input. Concepts in human memory are not equally active at all times, but rather become more activated in certain environments or after certain stimuli. Simulating context effects would thus lead to more realistic models, and might involve allowing activated concepts (such as cue words in the AUT and RAT) to modify the associations, weights, or features that define inactive concepts, thus changing their representations.

Towards greater integration between NCR and computational modeling

Progress toward a more precise, mechanistic understanding of creative cognition cannot be made by modeling alone, but will require the cooperation of theorists, modelers, and experimenters (Dongen et al., 2022; Hitchcock, Fried, & Frank, 2022; Wiggins & Bhattacharya, 2014). How might greater integration between NCR and computational modeling look? We would argue that any research group that proposes a theory of creative cognition should aim to produce a computational model to demonstrate their thinking explicitly. Such models would make theories more rigorous and complete, and could highlight questions for future research. Following the recommendations of Barton et al. (2022), these models should be easily reproducible, with publicly available code that is accessible to those with minimal modeling experience, allowing them to be adapted by other researchers who wish to develop their own hypotheses. As noted, it is also important that future models can simulate performance on common creative tasks, to allow models to be readily compared to both human data and the performance of other models. While we have focused on models of the AUT and RAT, NCR makes use of a large number of other tasks, including metaphor tasks (Beaty, Silvia, & Benedek, 2017b; Benedek et al., 2014a), drawing tasks (Ellamil et al., 2012; Rominger et al., 2018), musical improvisation (Pinho, de Manzano, Fransson, Eriksson, & Ullén, 2014; Rosen et al., 2020), and story writing (Fink, Reim, Benedek, & Grabner, 2020; Prabhakaran, Green, & Gray, 2014). NCR should ideally aim to model all of these tasks computationally to improve our understanding of the cognitive processes that enable creative performance in these different contexts.

Designing a model

Above, we have briefly considered a simple model of creative search, but to show more clearly how theories can be represented in formal models and how modeling can inform empirical research and theoretical debate, we now outline how a more complex model might be built, based on dual-process accounts (Figure 1). A simple starting point would be a semantic network, where nodes are words and edges are associative links, which could be constructed from human free-association data (e.g., Kenett et al., 2018; Schatz et al., 2018) or distributional semantics methods (e.g., Rotaru et al., 2018). The next step is to examine the literature for theoretical processes that might be represented as operations on this network. For example, the spontaneous and deliberate processes described by dual process theories might conceivably be modeled as collections of several computational elements and mechanisms (Table 1).

Spontaneous processes are often described as propagating through memory, reinterpreting information, and activating distant concepts (Benedek & Jauk, 2018; Volle, 2018), and so could be modeled via the structure of memory itself, the automatic spreading of activation through memory, and the spontaneous activation of tangential (i.e., non-task-relevant) ideas. Deliberate processes, meanwhile, are described as inhibiting unoriginal or distracting ideas (Beaty et al., 2017a; Camarda et al., 2018a; Chrysikou, 2019) and directing thought to fulfill strategies (Forthmann et al., 2019b; Gilhooly et al., 2007; Nusbaum & Silvia, 2011). As such, modeling deliberate processes might involve specifying mechanisms that can prevent certain ideas from activating and inhibit certain associative pathways to guide thought in particular directions (Volle, 2018).

Table 1. Summary of cognitive mechanisms that might feature in a computational model of verbal creativity

Broader cognitive construct	Specific feature or mechanism	Example from the literature

Spontaneous Associative Processes	Memory structure	Semantic memory structure relates to creative ability (Kenett et al., 2018).
	Automatic spreading of activation between concepts	Free association and verbal fluency relate to creative performance (Beaty et al., 2014; Marron et al., 2018).
	Spontaneous activation of tangential or task-unrelated ideas	In the absence of cognitive control, distraction and mind-wandering can occur (Fox & Beaty, 2018; Zabelina, 2018).
Deliberate Control Processes	Inhibition of unoriginal and distracting ideas	Less original and distracting ideas require suppression (Camarda et al., 2018a; Chrysikou, 2018; Lloyd-Cox et al., 2021). Inhibition relates to creative ability (Benedek, Franz, Heene, & Neubauer, 2012; Benedek et al., 2014b; Kaur et al., 2021).
	Strategic search processes	Strategic search occurs in the AUT (Gilhooly et al., 2007; Silvia et al., 2013). Search can vary between more flexible and persistent strategies (Lin & Vartanian, 2018; Nijstad et al., 2010).
	Control over WM input	Creativity relates to the breadth of attentional focus (Gabora, 2010; Zabelina, 2018), and WM updating and shifting (Benedek et al., 2014b; Krumm et al., 2018; Zabelina & Ganis, 2018).
Working Memory	A finite set of currently active concepts	WM capacity impacts creative thought (Fugate et al., 2013; Lee & Therriault, 2013). Context effects play a role in creative thought (Gabora, 2018).

To be modeled effectively, these processes seem to require additional features. For example, guiding thought to fulfill strategies suggests the existence of multiple kinds of associative pathway, which could be modeled either with a hierarchical or distributed memory, or by defining the part-of-speech of words (e.g., verbs, nouns) and using these to define different kinds of association. In the context of the AUT, this latter option could allow the simulation of the strategy of object replacement (where the cue object performs the typical use of another object; Gilhooly et al., 2007) by directing activation first along noun-adjective-noun associative pathways (to find an object with similar properties; e.g., brick -> heavy -> hammer) and then noun-verb pathways (to find uses; e.g., hammer -> pound a nail). More importantly, the notion that ideas can be distracting, and require inhibition to allow more relevant or original ideas to activate, implies that active concepts occupy a finite WM, access to which must be managed by cognitive control. Indeed, WM is not often discussed in significant depth by dual-process accounts of creative thought, yet in the context of modeling appears central to the need for controlled mechanisms.

Modeling WM also provides a way to simulate attention. Researchers have suggested that creative performance involves adjusting attention between narrower and broader states (Dorfman et al., 2008; Gabora, 2010; Zabelina, 2018; Zabelina & Robinson, 2010) and shifting between exploratory and exploitative search strategies (Mekern et al., 2019b; Nijstad et al., 2010). Such processes might be simulated by adjusting input to WM. For example, broad or exploratory attentional states might be simulated as a wider input to WM, where activation flows more freely, and tangential ideas can activate spontaneously. By contrast, narrow or exploitative attentional states might involve limiting WM input to only closely related ideas (see Figure 1). Embodying different attention-based theories of creativity in models of this general sort would allow them to be more rigorously compared. Alternatively, if a single model could simulate the behavioral outcomes discussed by different theoretical accounts, that would strongly suggest that the theories are consistent and could be combined into one. Indeed, it is hypothetically possible that all creativity-relevant control processes, including inhibition, adjustment of attentional breadth, and switching between generative and evaluative modes, are based on adjusting WM input, a possibility that could be investigated empirically.

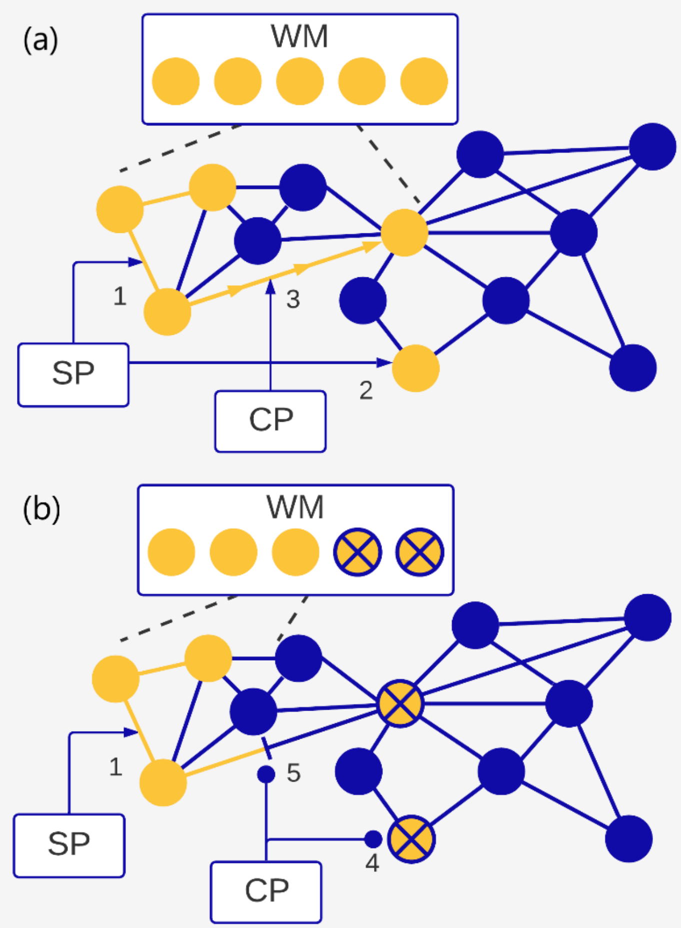

Figure 1. Diagram of an example dual-process computational model of creative cognition. Semantic memory is represented as a network of concept nodes (yellow = active; blue = inactive). Creative performance depends on a combination of spontaneous processes (SP) and controlled processes (CP). Active concepts in working memory (WM) form the current context and can bias the representation of other concepts. Dashed lines indicate the breadth of WM input.

(a) In broad focus attentional states, associative processes, including spreading activation (1), and spontaneous activation of tangential concepts (2), combine with strategic controlled processes that can force activation in specific directions (3), to produce a broader input to WM.

(b) In narrow focus attentional states, cognitive control can suppress distracting concepts (4) and inhibit specific associative pathways (5) to constrain WM input to the most relevant ideas. Different creative tasks may require different attentional states and different combinations of processes.

In principle, such a model could meet many of the requirements for future models noted earlier. Active concepts in WM could form the current context, modifying conceptual representations in memory by changing their associative weights. Individual differences could be simulated by varying parameters governing specific features or operations in the model (e.g., WM capacity or the strength of inhibition). Finally, performance on multiple creative tasks might be achieved using spreading activation to complete RAT problems (e.g., Schatz et al., 2018) and the activation of specific associative pathways to perform strategic idea generation in the AUT.

Implementing a model

Before such a model can actually simulate human data, it needs to be implemented computationally. This process requires several additional steps, which we now describe in more detail. The first step is to construct the memory base of the model, which in the current example is the semantic network. Regardless of whether this is based on human free association data or distributional semantics methods, researchers would have to make several decisions, such as how many words to include, whether to exclude prepositions, articles, and quantifiers, whether to combine singular and plural forms of words, whether to exclude associations below a certain strength threshold, and so on. Researchers also have the option to create multiple semantic networks and tailor each one to an individual participant (e.g., Benedek et al., 2017; He et al., 2021).

Once a memory base is constructed, the next step is to choose which processes to model and how to simulate them. For example, associative processes could be modeled as spreading activation alone, or as both spreading activation and the spontaneous activation of tangential concepts. Each approach requires specifying parameters that determine, for example, how quickly or distantly activation should spread through memory, or how often tangential ideas should activate. Similar decisions need to be made to simulate components such as WM or cognitive control processes (e.g., how strongly inhibition operates to suppress distracting ideas). These parameters can be selected based on existing hypotheses or left open and later adjusted to fit participant data, as described below.

In addition, researchers need to decide how to manage model input and output. For example, in the verbal model described above, one option is to simulate input by activating cue words strongly in memory (e.g., Kajic et al., 2017; Schatz et al., 2018). Activation may then propagate outwards from these cue words to other concepts. The process of selecting concepts as responses for output also requires careful consideration. In tasks like the RAT, this might involve selecting the most strongly activated concept (e.g., Olteţeanu & Falomir, 2015). However, tasks like the AUT may require more sophisticated evaluation and selection processes, potentially based on a specified trade-off between proximity to the cue word (which improves the usefulness of the response) and distance from the cue word (which improves the novelty).

Finally, researchers need to consider how the model will update over time to simulate cognition. One approach is to update the model in discrete time steps. At each time step, activation might spread to new concepts, while the activation of previous concepts gradually decays. Further, each update might involve control processes switching to inhibit different concepts or pushing activation in a different direction. Once all these factors and decision points have been implemented in the code, the model is ready to simulate task performance. As discussed, spreading activation alone might be sufficient to model performance on tasks such as chain association and the RAT (e.g., Lopez-Persem et al., 2022; Schatz et al., 2017). However, simulating performance on the AUT might require a slightly different model setup depending on the particular strategy used, such as object replacement or object decomposition (Gilhooly et al., 2007).

Once the initial model is developed computationally, researchers can refine it and its parameters to fit human data better. One option is to build a model with a specific structure (i.e., with certain components linked by causal pathways) based on theories and hypotheses, and then fit the parameters governing model behavior to human data. For example, the distance traveled by spreading activation processes could be set based on a certain weighting of participants' verbal fluency or chain association data. Researchers could train the parameters of the model using data from one group of participants and then test its ability to predict the creative outcomes of another group. Different hypotheses can then be tested by building different versions of the model with varying causal structures, for example by modifying the process by which inhibition operates (as opposed to how strongly it operates). After testing and training, different model versions can be compared in terms of how well their performance predicts human data. Another option is to specify both the structure of the model and its parameters based on preexisting theories. Different hypotheses, for example regarding how much impact inhibition should have on creative outcomes, can then be tested by defining several sets of parameters and assessing their fit to human data (Lopez-Persem et al., 2022).

This brief sketch of model development clarifies how theories of creative cognition can be translated into formal models. It also demonstrates the potential of modeling to identify new research avenues and the importance of cognitive factors, such as WM, that may have been overlooked in verbal accounts. Importantly, this example highlights that modeling inevitably requires making many reasonable assumptions to "fill the gaps" left by verbal accounts. Verbal theories rarely describe all the details necessary to implement a computational model, leaving the modeler to decide factors such as how exactly to structure semantic memory or simulate inhibition processes. For each of these decisions, alternatives are possible, and so ideally multiple models should be constructed by different research groups and their performances compared (Poile & Safayeni, 2016; Wilson & Collins, 2019). It is crucial to note that the design and implementation of the model discussed here may differ substantially from models focused on the neural level or based on alternative theories of creative cognition, such as flexibility vs. persistence (Mekern et al., 2019b; Zhang et al., 2020). This also highlights the importance of building and comparing multiple models of each creative task.

Concluding remarks

NCR has greatly increased our understanding of creative cognition and its relations to psychological phenomena, including memory, attention, and cognitive control (Beaty et al., 2021; Benedek & Fink, 2019; Chrysikou, 2019; Kenett et al., 2018; Kleinmintz et al., 2019; Volle, 2018). However, the field remains far from a mechanistic understanding of creativity complete with causal hypotheses for how cognitive processes produce creative ideas and how such processes interact differently in different tasks and individuals. We believe that the increased adoption of computational modeling can significantly advance the field and bring it closer to this goal. The verbal theories that guide NCR (and psychology in general) are intrinsically more open to interpretation, more difficult to falsify, and less transparent than formal models (Farrell & Lewandowsky, 2015; Fried, 2020; Guest & Martin, 2021; Smaldino, 2020). By contrast, embodying these theories in computational models can help make them more complete, accessible, and comparable. Modeling forces researchers to exchange abstract constructs for concrete definitions of cognitive processes as operations in a computational system (Benedek & Fink, 2019; Wiggins & Bhattacharya, 2014). Moreover, computational modeling can allow the complex pathways that produce creative ideas to be predicted effectively.

For its part, though several computational models of creativity exist, they have been developed in relative isolation from empirical research, and surprisingly few are well-suited to modeling the cognitive theories of NCR in a way that can be easily compared to human performance. Since a clearer understanding of human creativity could lead to more creative artificial systems, further integration and collaboration between computational modeling and NCR stands to benefit both fields greatly (Chateau-Laurent & Alexandre, 2021; Dipaola et al., 2018; Veale & Pérez y Pérez, 2020; Wiggins & Bhattacharya, 2014).

Indeed, among all areas of cognitive neuroscience, NCR may benefit especially well from computational modeling. After all, creativity is a complex and heterogeneous construct, and its underlying processes undoubtedly vary greatly depending on the specific task, domain, and other contextual and interpersonal factors. Ultimately, science seeks to establish cause and effect relationships, and so to truly advance, NCR needs clear hypotheses about how the same cognitive processes operate in different contexts**,** explicitly demonstrated in computational models. Integrating NCR with computational modeling will require considerable time and coordination between fields. The stakes, however, are high, and we fervently hope this article will help stimulate the necessary dialogue across disciplines (“Theorists and experimentalists must join forces”, 2021).

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Supplementary Information:

Towards Greater Computational Modeling in Neurocognitive Creativity Research

James Lloyd-Cox[1], Alan D. Pickering[1], Roger E. Beaty[2], Joydeep Bhattacharya[1,#]

[1]Department of Psychology, Goldsmiths, University of London, London, UK
[2]Department of Psychology, The Pennsylvania State University, PA, USA
[#]Correspondence: j.bhattacharya@gold.ac.uk (J. Bhattacharya)

The attached code (in MATLAB®; see https://github.com/Alan-Pickering/example-creativity-model) implements a simple toy model of within-category search processes. We have left extensive comments in the code but this supplementary text explains in greater detail how the provided model code works and how one might experiment with it. In the spirit noted in the main article, our primary objective in this exercise is to demonstrate a simple but formal model related to creative cognition. We have tried to do this in the most accessible and transparent fashion. The hope is to enable those new to formal computational modeling to get a clearer insight into the modeling process, rather than making any major claims for the specific features of this particular model. It also makes transparent the process of making assumptions and modeling choices inherent in every formal model.

This model was designed to simulate creativity tasks in which the instructions are to search a conceptual space for an unusual item or response (e.g., trying to come up with an unusual exemplar from the category of "fruit", where unusual is defined as a response that would have been suggested by very few people when asked to generate fruit exemplars).

Concept network as a multidimensional space

The central idea in this model is to represent the concept network (e.g., fruits) as an *n*-dimensional space. In the code provided, we simplify this space to just two dimensions (in the code *ndims*=2). Our first assumption (A1) is that the number of dimensions will not affect the qualitative behavior of the model. We should investigate that assumption by running simulations using higher-dimensional models. In general, we recommend starting with simplifying assumptions but, where possible, one should test the impact of each assumption one makes.

The model's key feature is that each exemplar is represented as a unique point in the space and the Euclidean distance[1] between any two exemplars reflects the overall strength of association

[1] See https://en.wikipedia.org/wiki/Euclidean_distance.

between the exemplars. Our second assumption (A2) is that the free-wheeling, undirected flow of thought in this space will more likely move between exemplars strongly associated with one another (e.g., apple and orange; these examples will have a small Euclidean distance between the points they occupy). The construction of the model as outlined below ensures that the model generally behaves according to assumption A2.

In this model space, the dimensions might be considered features over which items such as fruits might be associated. For example, one dimension might be “size”, and because apple and orange are similar in size, the distance between them on the size dimension would be small; alternatively put, their association in terms of size would be strong. Consider another dimension, “citrus-ness”; here, we expect the distance to be larger as oranges are citrus fruits but apples are not. However, it seems likely that orange and apple would be close together on most of the model dimensions, so the overall Euclidean distance separating them (across dimensions) would be small in our model space. Thus, when one thinks of apple (as an example from the fruit category), one is likely to spontaneously think of orange, and vice versa.

We have used a simple formal feature in our model (the Euclidean distance between items) to capture the relatedness of two items, which seems a “*reasonable*”[2] approach. In defense of this claim, we would argue that the associative strengths of a set of items should have “distance-like” properties. For example, if the associative strength between items apple and orange is 1 (arbitrary) unit and the associative strength between orange and pear is 1.5 units, then the associative strength of apple and pear should be less than or equal to 2.5 units. We would refine/change this basic feature if the model based upon it was shown to be unable to simulate some aspects of observed behavior in creative tasks.

Simulating the concept network using multivariate normal distributions

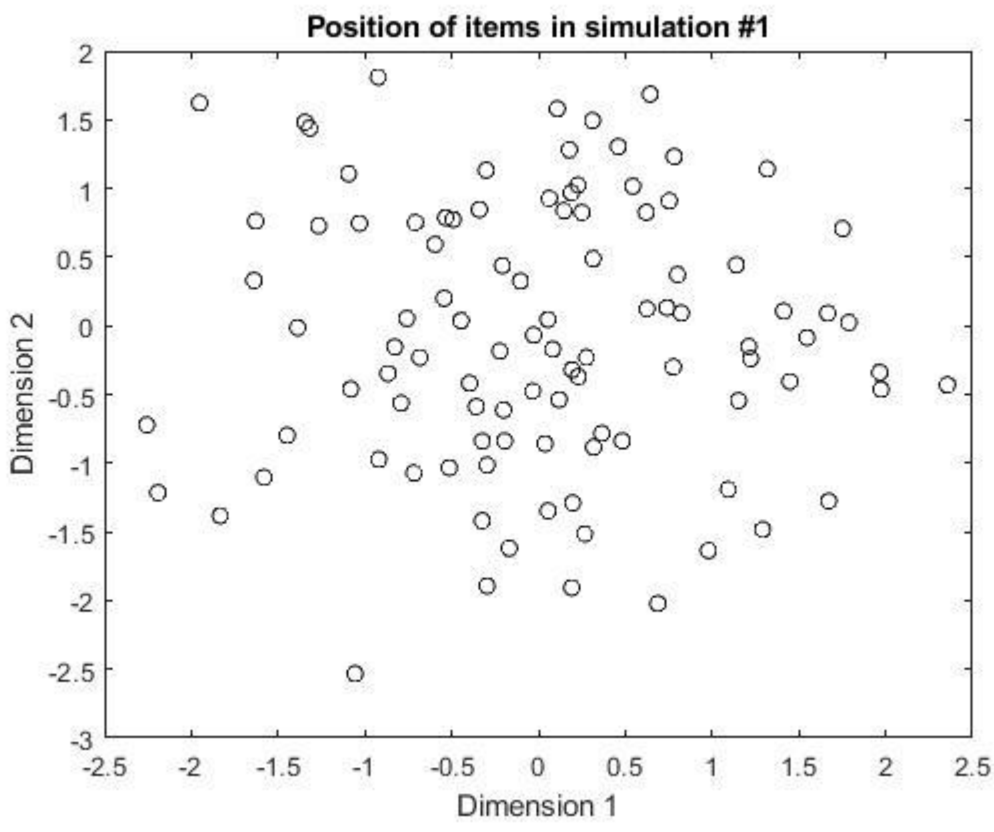
To generate the position of the items in the model space, we use a random number generation process. Specifically, we generated the exemplars using a multivariate normal (MVN) random[3] generator (bivariate in this case as our space has two dimensions). This is a key mathematical choice which we have adopted because it is mathematically simple and well-understood. By doing so, we are not saying that the positions of items in a conceptual space always behave exactly as if they follow a MVN distribution but that it will usually be close enough to the true distribution so as to have little effect on the accuracy of the simulations we are going to perform. If the model simulations fail to capture observed behavior accurately, then we would revisit this choice for our model.

Before explaining the simple implementation procedure to generate an MVN distribution in MATLAB (of note, the procedure will be similarly easy in most other coding languages), we need to

[2] The somewhat subjective notion of reasonableness will crop up more than once and so we will try to give a flavor of how one can justify something as reasonable.
[3] See https://en.wikipedia.org/wiki/Multivariate_normal_distribution

check the reasonableness of our decision to use an MVN distribution. Supplementary Figure 1 (SF1) shows an example of a multivariate normal random sample of 100 items using 2 dimensions. One can see different samples by changing the *plot2show* control variable in the code provided. SF1 was generated using *plot2show*=1 and is the set of items used in simulation number 1.

SF1 shows that most items are clustered close to the center of the space, and the density of items gets less as we move outwards from 0 on either dimension. This implies that the sample items at the center of the space have lots of closely associated items and that as one moves towards the edge of the space, each item has fewer close associates. This seems to capture the associative properties of sets of items such as fruits in a reasonable way: there will be some items in the set with lots of strongly associated items (apple, pear, orange etc.), but others will be associated closely with only a small number of items (jackfruit for example).



Supplementary Figure 1: A random sample of 100 items generated using a multivariate normal random number generation process in 2 dimensions. The distances along each dimension are arbitrary and standardized.

We are trying to use our model to simulate the search for unusual items, where unusual items are those that few other people would think of in a limited period of time. Good answers will be items that have few strong associates because people will generate candidate items by searching associatively through the space. Thus, people will be less likely to come up with items towards the periphery of the space.

In Figure SF1 we used 100 items (in the code, *nitems*=100). Once again, we felt that this was reasonable: it should be roughly equal to the total number of fruits an adult human might be able to name given enough time. Our third assumption (A3) relates to this choice of number; namely, that the precise number chosen is not going to change the way the model would behave, so long as we avoid really small values (<10). Such small values are unreasonable for the sorts of sets of items we might use in the task we are simulating.

The multivariate normal (MVN) random process means that, along each dimension, the distribution of item positions follows a univariate normal distribution. While a univariate random variable has a mean and a standard deviation (0 and 1 respectively, for a standard normal distribution), the MVN distribution has a mean vector and a variance-covariance matrix (*mu* and *sigma,* respectively, in the code). We set the means to be zero on each dimension and the item variances to be 1 (*itemvar* in the code). These are just standardized values and are not important. Nevertheless, they do allow us to scale other parameters in our model easily, given that we know, with these choices, that roughly 5% of our items will lie outside the values of -2 and 2 on each dimension.

We also can choose whether there is any covariation between the values on the separate dimensions of our space. In the model code, this is specified via *itemcov*. Our next assumption (A4) is that these two dimensions are not related; therefore, we set *itemcov* = 0. This ensures that the cloud of points in our 2-d space is roughly circular; non-zero values for the covariance would stretch the cloud of points into an elliptical shape. This is, of course, an initial simplifying assumption which we believe is *almost certainly wrong* even if the other aspects of the model might be useful. Over all of the dimensions on which fruits can vary, we feel confident that the associative distance between pairs of items on some dimensions will be correlated with their distances along some other dimensions (e.g., fruit size will be somewhat inversely correlated with the intensity of flavor, think melon vs blackcurrant or raspberry). Once again, tests of the impact of adopting assumption A4 should be made if the simpler model proves useful. We need to use >2 dimensions to explore this assumption properly; with >2 dimensions, we can arrange it so that the degree of covariation between pairs of dimensions can vary over different pairs of dimensions.

As already noted, generating the MVN distributed items is simple: it is a single line of code once we have the parameters described above. In MATLAB, we use the *mvnrand* command and write (line 105):-

```
itemvals=mvnrnd(mu, sigma, nitems);
```

It is important to note that we do not specify a precise set of fruits in this model or try to set their associative closeness to one another to reflect some objective reality. Our assumptions and model specification create a set of exemplars that we propose could represent any set of exemplars in a category of finite size that is broadly similar to the category of fruits. We could test this by seeing if the real behavior on this task was similar irrespective of the specific set of items being employed (e.g. fruits, or British Olympic gold medalists at London 2012).

An obvious alternative approach would be to create an associative network for a specific category with the weights of association (distances) between items being set to “realistic” values. This could be done by evaluating the associative strength between exemplar pairs for real categories using lexical databases, or by collecting suitable experimental data from human participants. The weights used would then be set to be proportional to the measures of associative strength obtained. This sort of approach has been used in past computational models of creativity see section “Existing computational models of creativity“ in the main text for examples. This is a more complex approach, and we could test whether our simplifying assumptions lead to a model which is capable of producing simulated behavior similar to that produced using a more elaborate model based on “real” associative weights.

Modeling free-wheeling associative thoughts

The next key aspect of the model is our choice for implementing the free association of thoughts. This is intended to capture one facet of the dual-process models discussed in the main text (see Box 1 in particular): the "spontaneous", or "generative", or "automatic" flow of ideas during the search for a creative response. We did this using a random walk[4]. Random walks have been used quite extensively in modeling behavior in varied fields within psychology [1-5]. Once again, this is probably because their basic mathematical processes are well-understood. We leave it to the reader to decide if a random walk is a reasonable choice for this aspect of our model.

In the model, there is a loop of 200 simulations (*nsims*=200), and each simulation can be thought of as a different simulated participant attempting to generate an unusual fruit (one that would be thought of by as few other participants as possible). The choice of 200 is fairly arbitrary but, given the extensive use of random variables in the model, it needs to be large enough to give representative outcomes when aggregated across all simulations. Within each simulation, there is an inner loop of up to 10000 steps (*nsteps*=10000). Each step is one step of the random walk. The number of steps is initially set to be large, although we adjust this to a lower number (1500) for reasons explained below. The length of a timestep is arbitrary, but one could rescale the numbers of steps into response times (e.g., 100 steps equates to 1 second) so that the simulated response times are of the right magnitude. The walk has to start at an initial position. In the simplest version of the model, we assume (A5) that the walk starts at the center of the space: (0,0) in two dimensions (coded as *mystart*). This seems reasonable because, if we are asked to think of fruits, it is highly likely that we would first think of common exemplars at the center of our space.

Another feature is the walk step size, i.e., the amount that the walk might move in each direction on a single step. Bearing in mind that 95% of the items lie along values in the range -2 to 2 on each dimension (see above), we set the step size to 0.05 for each dimension (coded as *stepsize*). To make the walk random, we used a uniform random number generator to create a random move direction for each of the *nsteps* (=10000) steps of a simulation along each of the *ndims* (=2) dimensions. The direction for each step on each dimension was either -1, 0 or +1 (each occurring randomly with equal probability), generating 9 possible moves on each step (3*3 over the two dimensions). To do this, we used the *randi* command in MATLAB to create a matrix of values with 10000 rows and 2 columns for each simulation (called *mymoves*):

```
mymoves=randi([-1 1],nsteps,ndims);
```

The actual walk is thus a combination of the direction specified by *mymoves* multiplied by the amount moved in that direction, specified by *stepsize*. On the *k*-th step of the walk, the variable *currpos* keeps track of the current 2-d position of the walk iteratively, thus:-

```
currpos=currpos+stepsize.*(mymoves(k,:));
```

[4] https://en.wikipedia.org/wiki/Random_walk

Clearly, the larger the values used for *stepsize, the mor*e space will be covered by the random walk. All other things being equal, our *model intuition*[5] is that larger *stepsize* values will enable the simulated participant to encounter more unusual (peripheral) items more quickly.

Retrieval of candidate items

The next aspect of the model is how we interrupt the free-associative process of the random walk with attempts to retrieve candidate items. The way we capture this in our model is that, every so often, the walk pauses and the simulated participant attempts to retrieve an example item from the current position of the random walk in our space of items. The frequency with which this attempt at retrieval occurs is controlled by a parameter in the code called *walkfor* (a default value of 50 steps). This means that after every *walkfor* random walk steps, an attempt at item retrieval is made. This feature of the model embeds another assumption (A6); namely, that the spontaneous free-association processes are in alternating phases with memory retrieval and subsequent evaluative processes. This is a feature present in some theoretical accounts in the literature (see [33] in the main article).

Which items might be retrieved at each attempt? Following the underpinning logic of the model – i.e., that the distance in the model space represents the closeness of the association of an item – we implemented this using a competitive probabilistic retrieval process based on the relative distance of items from the current position of the walk. This means that the items nearest to the current position are compared in terms of their relative distances, and the probability of their retrieval is directly linked to those relative distances (closer items being more likely to be retrieved). The retrieval competition is limited to those items which are within a specific Euclidean distance of the current position. This selection of potential items for retrieval is controlled by a parameter, denoted *closeto* in the code (default =1 distance unit). This parameter is used by computing the Euclidean distance between each item in the space and the current position (computed as *eucdist*, see line 140), and then computing a “logical filter” (*choicefilt* in the code) with value = 1 for those items with a Euclidean distance (ED) less than *closeto*, and 0 otherwise. The filter is used later on in the code to restrict the choice function to apply to only those items with values of *choicefilt*=1. In mathematical terms, we can define a set *S* of potentially retrievable items where the Euclidean distance of item *i* from the current walk position, ED_i is smaller than *closeto* for all items *i* in the set *S*.[6]

The default value of *closeto* represents a wide search radius given that 95% of the items are within a circle of radius 2 units from the center of the space. One might imagine that different individuals might vary in the value of *closeto* that they use. Our next model intuition is that someone with an ability to think more creatively might have a higher value of *closeto*, than their less creative counterpart, and so such a person would include more potential items in their retrieval searches.

[5] A model intuition is what effect we think the model parameter will have. Even if these intuitions seem reasonable, it is important to test these out. Formal modeling allows one to move from intuitions to clear predictions when we run the simulations.

[6] In mathematical notation if item *i* is a member of a set S, this can be written as $i \in S$

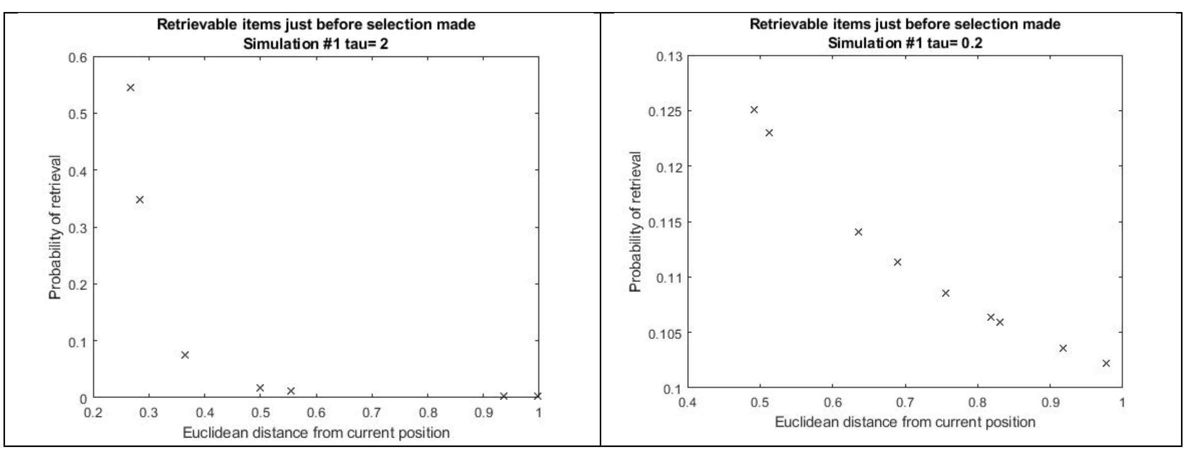
The more creative person (based upon their higher value of *closeto*) would, according to the model, be more likely to alight upon a more creative (unusual) choice of fruit in a fixed amount of thinking time.

The actual formula used to compute the probabilities of retrieval of the items lying within *closeto* distance units of the current position was based upon a widely adopted choice function in psychological modeling: the softmax function.[7] Specifically, the softmax formula used to define the probability of retrieving item *i,* given that *i* is a member of the set S of competing potentially retrievable items, is as follows: -

$$p(R_i \mid i \in S) = \frac{e^{\tau/ED_i}}{\Sigma_{j \in S}\, e^{\tau/ED_j}}$$

The above formula suggests that the smaller the Euclidean distance of a candidate item *i* from the current position, the higher the probability that it is retrieved amongst all the competitor items in set *S*. In the code, it is computed across lines 157-159. The following lines of code (165-167) use a random number generator to retrieve a specific item in accordance with the probabilities returned by the softmax function.

A key parameter in the softmax function is τ (in the code, this is *tau*), and it can take values of zero or greater. This parameter has different names in modeling contexts (e.g., inverse temperature, stochasticity or exploration-exploitation parameter), but it simply controls how noisy the choice process is. As τ gets larger then the closest item is more and more likely to be retrieved (i.e., a more deterministic choice), even when it is only slightly closer than the next nearest competitor. By contrast, as τ approaches zero, all competitor items tend to be chosen with similar probabilities irrespective of their relative distances (more random, noisy choice). We can see this effect of τ in Supplementary Figure 2 (SF2) during one retrieval decision during simulation number 1.



[7] https://en.wikipedia.org/wiki/Softmax_function

Supplementary Figure 2: The effect of parameter τ on retrieval probabilities as a function of Euclidean distance (ED) from the current walk position. Note the difference in y-axis scale across the two panels. In the left panel ($\tau = 2$), there are 7 potentially retrievable items, but the closest two, with EDs < 0.3 have the greatest chance of being retrieved (0.55 and 0.35 approximately). Items with ED ≥ 0.5 have virtually a zero probability of retrieval. In the right panel ($\tau = 0.2$) all 9 potentially retrievable items have a similar probability of being retrieved ($0.1 < p < 0.13$) irrespective of their EDs from the current position, even though the range of EDs goes from just below 0.5 to almost 1.

Once again, one has a strong model intuition that the parameter τ should directly affect the breadth of the search of the category space and thus the ability to generate more creative solutions. When τ is smaller, then more items can be retrieved at any position of the random walk than for higher values of τ. This means that, over a fixed period, the random walk has a greater chance of retrieving more peripheral items (i.e., more unusual, creative choices) for lower values of τ, all other things being equal. We can think of τ in conjunction with the value of *closeto* (already discussed) as opening up the retrieval process to a broader range of possible items. In terms that have been widely used in the creativity literature, one might view these two parameters as reflecting the degree of inhibition in memory retrieval; specifically, the combination of large *closeto* and low τ equates to weak inhibition.

Response selection as a controlled decision process

The final part of the model is the decision process used to decide if a retrieved item is “unusual enough” to be worthy of being given as a response. This represents the other facet of dual-process theories: the “deliberate”, or “evaluative”, or “controlled” process.

If a retrieved item is considered unusual enough, then it will be given as a response (e.g., I have thought of the fruit “durian” and I am happy to give this as my example of an unusual fruit). If it is not deemed unusual enough, then the random walk resumes *from the position of the retrieved item*[8] until a future retrieval attempt is made, *walkfor* random walk steps later. What decision rule might a participant use to decide that a retrieved item was unusual enough? We considered that it must be some simple property of the retrieved item that a simulated participant could use to decide upon unusualness. For example, perhaps after retrieving an item, the participant finds that

[8] The position of the random walk is supposed to represent where one’s thoughts currently are at within the category space. Thus, if one has retrieved an item then the position of that item seems a reasonable choice for the current “position” of your thoughts. In the code the current walk position is moved to the position of the retrieved item on line 177. So, strictly, the model is a random walk punctuated with jumps to retrieved items.

it brings to mind very few close associates, then one might decide that it is worth offering as a creative response. As a simple proxy for this, we used an alternative related decision rule (controlled in the code by the parameter *respmethod* taking a value of 1; *respmethod*=2 has a different effect see below): the retrieved item has to be more than a threshold Euclidean distance from the center of the space. The threshold distance is specified by a parameter called *respthresh* in the code. At the start of each simulation, *respthresh* is set to *respthreshbase* (=2.0 by default). We chose this value in light of the parameters chosen for the multivariate normal distribution of the items (which force 95% of the items to lie between -2 and 2 on each dimension). If the retrieved item has an ED from the center which exceeds the value of *respthresh*, then the response is made and the current random walk stops (controlled in the code by setting *endkflag* to 1). The simulation loop records the response information and then moves on to the next simulated participant.

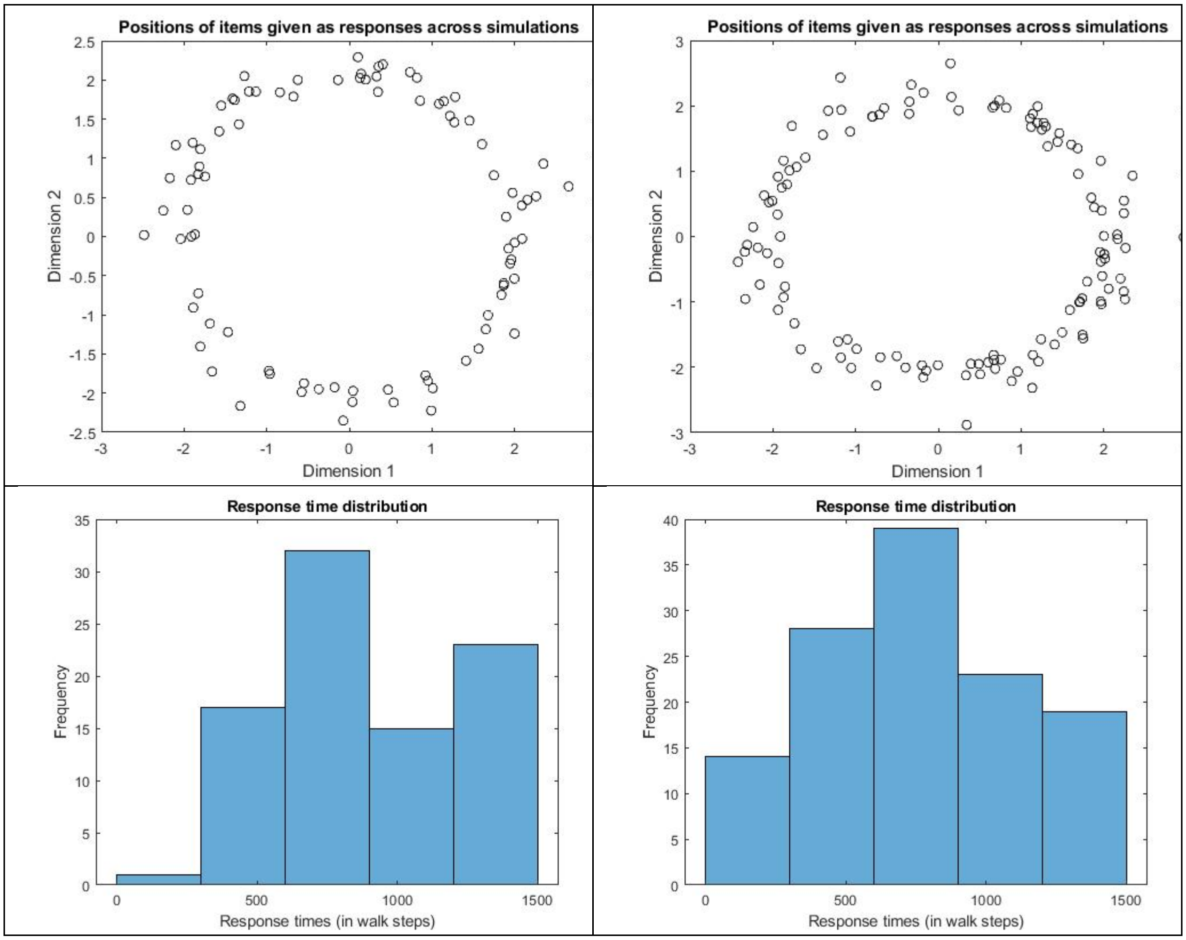
To reflect the potential effect of time pressure on the task we assumed (A7) that participants might relax their decision threshold the longer they could not produce a suitable response. We simulated this by having a decrement to the value of *respthresh* (called *threshdrop* in the code, default value =0.01). The decrement is applied every 100 steps of the random walk if a response has not been made (in the code this is controlled by setting a parameter, *threshtime* = 100). This is a minor feature of the model and we can explore its effect by setting *threshdrop*=0 in the model.

Exploring the effects of parameters

It is relatively easy to explore the effect of the model parameters, which are likely to affect the ability to give more creative responses. As noted above, for example, we have clear model intuitions for the effects of *stepsize*, *closeto*, and *tau*. Thus, it is essential to test these model intuitions, along with the effects of the assumptions listed above. For example, below, we show the effect of changing the value of *tau*.

It was noted above that the maximum number of time steps (*nsteps*) per simulation was set to 10000. This large value was used to develop and set the values of the model parameters. This parameter setting was chosen because it allowed every simulated subject to retrieve an unusual item across the whole range of *tau* values used (0.2 to 2). To test the model, we inspected the response time distributions achieved when 10000 walk steps per simulation were permitted. Based on the mean response times over 200 simulations (generally around 1600-1700 steps), we set the maximum response time to 1500 timesteps in our test simulations. This change was made to reflect our assumption (A8) that, under a small amount of time pressure, not all subjects would be able to select a genuinely unusual response (using the *respthresh* decision rule). That is, they feel that all the candidate responses they thought of in the time allowed are likely to have been thought of by lots of other people as well. The model does not yet implement what response they offer in these circumstances. Perhaps they would give one of the less unusual items previously retrieved but still in their (working) memory. As the simulations below confirm, using the 1500 step maximum per simulation ensures that not every simulated participant can produce an unusual item (i.e., one that passes the decision threshold) in the time allowed.

Supplementary Figure 3 (SF3) shows the simulation results for two very different *tau* values (0.2 vs. 2.0). Our model intuition above was that a lower value of *tau* would lead to more creative responses. In our simulation, this intuition would be confirmed if a higher proportion of the 200 simulated participants (with *tau*=0.2) can give a response that passes the *respthresh* decision rule compared with 200 simulated participants (with *tau*=2). The simulation confirmed our intuition: 88/200 simulated participants (with *tau*=2) were able to generate an unusual response. By comparison, 123/200 simulated participants (with *tau*=0.2) were able to generate an unusual response. The responses made were generally in very similar average positions in the model space see SF3) and were all towards the periphery of the space, in keeping with the nature of the *respthresh* decision rule. In addition to the greater number of responses in the low *tau* condition, SF3 shows that the responses were made more rapidly in the low *tau* simulations (an average of 734 random walk steps, s.d.=358) compared with the high *tau* simulations (average= 878 walksteps, s.d.=364). Thus, in respect of *tau*, our model intuitions are confirmed. We leave it as an exercise for the interested reader to explore the effects of *stepsize* and *closeto* in relation to the model intuitions offered above.



Supplementary Figure 3: The effect of parameter τ on the ability to make an unusual category response in the time allowed. The leftmost panels are for *tau* = 2.0, and the rightmost panels are for *tau* = 0.2. The upper row records the position of the response items made (note the greater number of responses made for the 200 simulations with tau = 0.2). The bottom row records the distribution of response times for the responses given.

Making new predictions with the model and testing them

It is an essential first step to show that the model behaves in the ways our intuitions suggested it would. As already noted, one must also explore, as fully as possible, the impact of the numerous assumptions and choices made in developing the model. However, for the model to be useful, it should lead to novel predictions for real creative behaviors that can be tested in actual human participants. Below we illustrate how even this simple model can generate testable predictions.

The model can easily be made to simulate a fluency task as well (where one has to name as many exemplars of the category as one can in a fixed time). In fact, the provided code already records the number of category exemplars retrieved during the "think of an unusual fruit" simulation. To simulate a fluency task, the "unusual response" decision process must be turned off. This can be achieved by setting *respmethod* to have a value of 2 (instead of the usual value of 1; *respmethod*=2 makes no decision about whether a retrieved item is unusual). Then one can run the code with *nsteps*=1500 (to represent the fixed amount of response time for the fluency task) with *tau*=0.2 vs 2.0. Across 200 simulations, the mean number of unique items retrieved for *tau*=0.2 was 22.1 (s.d.=2.5). For *tau*=2.0, the average number of unique items retrieved was 16.9 (s.d.=3.5). The model thus shows that variation in parameter *tau* can underlie an ability to generate an unusual response more often and be more fluent in generating category exemplars. We leave it as an exercise for the interested reader to see if the same patterns over both tasks can be obtained using variation in the parameters *closeto* and *stepsize*.

Of course, one might argue that by using verbal reasoning alone, one could have arrived at the prediction that more creative people would generate more unusual responses and also be more fluent (i.e., retrieving more exemplars from the category). Having a formal model allows one to explore this predicted effect more rigorously and thoroughly. In the main article, the idea was briefly noted that a strategic search along one dimension of the category might help find unusual items. For example, one might think of exotic locations that one has visited and thereby recall unusual fruits experienced specifically in those locations. A simple way to give dimensional directionality (of this kind) in the search could be to make the step sizes for the random walk different for each dimension. In the code provided, the step size along dimensions 1 and 2 was equal (0.05). With the same average stepsize, a more directed walk would be achieved with step sizes of 0.025 and 0.075 (or vice versa). For low *tau* settings (*tau*=0.2), this had little effect on the number of unusual responses made (in fact, they decreased slightly to 118/200 simulations c.f. 123/200 simulations with equal step sizes). For high tau settings (*tau*=2.0), unequal stepsizes increased the number of unusual responses achieved to 103/200 (c.f. 88/200 with equal stepsizes). This is a novel prediction of the model: in the "find an unusual exemplar task", people with lower creativity (higher *tau*) are more likely than their more creative counterparts (low *tau*) to benefit from a suggestion to use a strategy of focusing their search along one/some specific feature dimension(s). This prediction could be tested with actual participants by testing them under conditions when provided with a dimensional search strategy by the experimenter and comparing the results with performance under a control condition where no such strategy was given. Strictly the prediction applies only to those whose high vs. low creativity stems from processes captured by the parameter *tau* (which controls the noisiness of the exemplar retrieval process).

Model limitations

There are many limitations and unrealistic features of the current model. There is not space here to consider them all. Two striking illustrative examples of limitations are noted. First, the random walk phases in each simulation are of a fixed duration (controlled by the parameter *walkfor*). If these phases are intended to represent periods of mind-wandering around the conceptual space, then it seems unreasonable that these periods would all be of the same duration. An easy fix would be to use a Gaussian random variable (with mean and standard deviation) for *walkfor*, so that in a particular simulation, the number of steps of the random walk between each retrieval attempt would vary randomly about the mean value. The parameters of the random variable could vary across different simulated individuals.

Secondly, and more importantly, the item retrieval process takes no time in the model. Therefore, the model should be extended to include a retrieval time component. Such a component should ensure that the pattern of Euclidean Distances (EDs) of potentially retrievable items influences the time taken for the retrieval in a principled way. For example, one would imagine that a pattern of EDs in the left panel of SF2 (two exemplars with small EDs and high probabilities of retrieval; the rest further away and with very low probabilities of retrieval) would lead to quite different retrieval times than the pattern in the right panel (no close exemplars and all exemplars have a similar probability of retrieval). A pervasive finding is that response times are slower for more difficult decisions [6]. It is relatively straightforward to incorporate retrieval times into the model in a realistic way; for example, one might use a so-called accumulator model [7].

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