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THEORETICAL NOTE

An Entropy Modulation Theory of Creative Exploration

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Compared to individuals who are rated as less creative, higher creative individuals tend to produce ideas more quickly and with more novelty—what we call faster-and-further phenomenology. This has traditionally been explained either as supporting an associative theory—based on differences in the structure of cognitive representations—or as supporting an executive theory—based on the principle that higher creative individuals utilize cognitive control to navigate their cognitive representations differently. Though extensive research demonstrates evidence of differences in semantic structure, structural explanations are limited in their ability to formally explain faster-and-further phenomenology. At the same time, executive abilities also correlate with creativity, but formal process models explaining how they contribute to faster-and-further phenomenology are lacking. Here, we introduce entropy modulation theory which integrates structure and process-based creativity accounts. Relying on a broad set of evidence, entropy modulation theory assumes that the difference between lower and higher creative individuals lies in the executive modulation of entropy during cognitive search (e.g., memory retrieval). With retrieval targets racing to reach an activation threshold, activation magnitude and variance both independently enhance the entropy of target retrieval and increase retrieval speed, reproducing the faster-and-further phenomenology. Thus, apparent differences in semantic structure can be produced via an entropy modulating retrieval process, which tunes cognitive entropy to mediate cognitive flexibility and the exploration–exploitation trade-off.

Keywords: creativity, executive function, network science, entropy

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Creativity is typically defined as the ability to generate ideas that are both novel and appropriate (Runco & Jaeger, 2012). This definition puts a strong emphasis on the product of creative thinking, and less on its process. Recent attention has been given to studying creativity as a complex process that unfolds over time and includes multiple cognitive capacities (Green et al., 2023). This follows a long tradition of theoretical approaches that view creativity as a process, including the geneplore model (Finke, 1996), the blind variation and selective retention model (Simonton, 2023), the dual-system model (Sowden et al., 2015), and the generation and evaluation model (Kleinmintz et al., 2019). However, none of these approaches provide a formal computational account of how and why individuals differ in the creative products they generate.

Extensive empirical research over the past few decades has highlighted how individual differences in creativity are underpinned both by memory structure and executive processes (Beaty & Kenett, 2023; Benedek et al., 2023; Gerver et al., 2023). However, how these processes interact is not yet well understood and recent work has called for an increased application of computational models to bridge this gap (Lloyd-Cox et al., 2023). To date, much computational research in creativity has focused on the role of memory structure in facilitating the generation of novel and appropriate ideas (e.g., Kenett, 2024; Kenett & Faust, 2019; Volle, 2018), and less on the generation process itself.

Here, we attempt to bridge this gap by proposing a formal process model of creative ideation which we call entropy modulation theory. This model offers an approach to integrating structure (e.g., semantic memory) and process (e.g., executive processes or cognitive control), demonstrating how a change in process can generate structural changes concordant with prominent theories in creativity, specifically, the associative and executive theories of creativity, which we describe below.

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This modeling study was not preregistered. Its key insight arose during an informal discussion between the authors Thomas T. Hills and Yoed N. Kenett. All code necessary to reproduce the results presented in this article are available at https://github.com/thomasthills/noisyActivation. The authors have no known conflict of interests to disclose.

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The Associative and Executive Theories of Creativity

The *associative theory of creativity* proposes that structure guides retrieval: "The organization of an individual's associations will influence the probability and speed of attainment of a creative solution" (S. A. Mednick, 1962, p. 222). A common metaphor is that of a rugged landscape (Hills & Kenett, 2022). Ideas sit atop peaks in the mental landscape and the difficulty of traveling from one peak to the next makes up the difference between higher and lower creative individuals. Higher creative individuals, S. A. Mednick (1962) proposed, have more accessible "flat" associative landscapes, while lower creative individuals have less accessible "steep" associative landscapes (but see Benedek & Neubauer, 2013).

When presented with a cue, individuals with flatter landscapes will produce associative targets that are farther away from the cue, on average, because the difficulty of traveling to more distant peaks in the landscape is reduced. The flatness of the landscape therefore provides more cognitive flexibility and leads to more creative products. In addition, flatter landscapes will be less predictable, having greater entropy because the probability distribution is less concentrated on the most likely responses.

This simple metaphor for the distance between ideas has been supported by numerous studies that show that individuals who score higher on various measures of creativity also tend to produce information from memory consistent with differently structured knowledge representations (Beaty & Kenett, 2023; Benedek et al., 2023; Kenett, 2024). For example, when asked to produce associations, higher creative individuals produce more associations more quickly and with more variability than lower creative individuals (e.g., Beaty & Kenett, 2023; Benedek & Neubauer, 2013; Kenett et al., 2014; M. T. Mednick et al., 1964; Vartanian et al., 2007, 2009). Even when asked to provide a single creative word—a verb in response to a noun—the creativity of the response, whose effective distance is measured by latent semantic analysis, correlates with numerous individual creativity measures (Heinen & Johnson, 2018; Prabhakaran et al., 2014).

More recent work has used computational methods to quantify the distance between responses generated in a chain free-association task and relate this score—forward flow—to creativity (Beaty et al., 2021; Gray et al., 2019; Merseal et al., 2023). For example, Merseal et al. (2023) examined the distance of associative responses generated by artists, world-renowned scientists, and a smart comparison group, to three conditions: generating a single common response to a cue word, generating the first word that comes to mind in response to a cue word, or generating a single uncommon response to a cue word. Using forward flow, the authors found that the artists generated significantly more distant responses in the associative and uncommon conditions compared to the other groups, whereas no significant differences were found across the three groups for the common condition (Merseal et al., 2023).

In contrast to the structure-based account of the associative theory of creativity, the *executive theory of creativity* focuses on the relationship between creativity and cognitive control. Here creativity is described as a top-down control process (Beaty, Silvia, et al., 2014; Benedek et al., 2014, 2023; Benedek & Jauk, 2018; Chrysikou, 2019; Silvia, 2015). This process is proposed to involve effortful cognitive control, which influences how the knowledge structure is navigated. In a recent study, Ovando-Tellez, Benedek, et al. (2022) examined the cognitive and neural mechanisms of memory search and how it relates to individual differences in creativity. The authors found that searching one's memory is a goal-directed, effortful task involving neural systems related to attention and cognitive control, each differentially related to various creativity tasks (Ovando-Tellez, Benedek, et al., 2022).

Contributions of effortful control to creativity are supported by a wide variety of evidence. For example, intelligence and other measures of executive function correlate with creativity (Benedek et al., 2014; Nusbaum & Silvia, 2011). General cognitive abilities, such as working memory capacity, are also strongly correlated with the fluency (count) and originality across a number of creativity and retrieval tasks (Unsworth, 2024; Weiss et al., 2024). Neuroimaging research also routinely finds relationships between creativity and activity in brain regions associated with cognitive control (Beaty et al., 2016, 2018, 2019; Frith et al., 2021). For example, resting-state functional MRI activation levels in the brain of higher creative individuals show increased connectivity between key regions of control and representation. Beaty, Benedek, et al. (2014) interpreted this as "pointing to a greater cooperation between brain regions associated with cognitive control and low-level imaginative processes" (p. 92). This is supported by extensive evidence that neural patterns associated with creativity reveal greater interconnectivity between the executive control network and the default mode network (Beaty, Benedek, et al., 2014; Beaty et al., 2018; Evans et al., 2020; Frith et al., 2021; Ovando-Tellez, Benedek, et al., 2022; Ovando-Tellez, Kenett, et al., 2022).

Together, the associative and executive theories of creativity support creative thinking as an outcome of both structure and process (Beaty, Silvia, et al., 2014; Benedek et al., 2017). While previous research has developed computational models to account for the role of semantic memory structure in creativity (Benedek et al., 2023; Kenett, 2024; Kenett & Faust, 2019; Volle, 2018), no such model has been proposed to account for the executive control of variation in the retrieval process.

Recently, Hills and Kenett (2022) considered different theoretical metaphors to the representational nature of semantic memory and the processes that operate over it. They argue that extreme positions—based on either structure or process—need competing alternative accounts to help drive theory development toward more integrative solutions. Thus, our goal here is to advance theory by offering an executive process-model that generates two key empirical observations in creativity research.

The Riddle of Faster-and-Further

The two key empirical observations in creativity research that we would like to address are the following: Compared with lower creative individuals, higher creative individuals (a) produce associations more rapidly and (b) produce less common associations (more creative), on average. This is a general finding across the creativity literature, suggesting a strong relationship between creativity and total production (Jung et al., 2015; Ovando-Tellez, Benedek, et al., 2022; Simonton, 1997; Weiss et al., 2024). As a useful shorthand, we summarize this as being *faster-and-further*.

Faster-and-further presents a riddle for purely structural accounts. That is, if we take one of the most prominent theories for structural activation currently available, spreading activation (Collins & Loftus, 1975; Siew, 2019), then it is not immediately obvious how greater connectivity in memory could lead to faster retrieval. If we

follow standard theory in envisioning that activation moves between potential retrieval targets as a function of their similarity to the cue, then greater connectivity in memory diffuses activation over more targets, leading to slower retrieval (Collins & Loftus, 1975; Klimesch, 1987; Kroll & Klimesch, 1992). Whether we consider random walkers, spreading activation, or some other mechanism, greater connectivity should lead to slower activation of potential targets in memory. This in turn slows the rate at which potential targets would reach threshold levels of activation. Intuitively, if a cue word connects to *N* associates, each with equal associative strength, then spreading activation to each of these associates falls as 1/*N*.

This riddle has empirical support. In the *fan effect*, people are taught many or few relationships with target concepts. The more relationships participants learn, the longer it takes them to retrieve any one of those relationships (Anderson & Reder, 1999). Similarly, substantial evidence supports greater interconnectedness as leading to cognitive slowing, which has been used to explain age-related cognitive decline (Amer et al., 2022; Buchler & Reder, 2007; Hills, in press). Diffusion of associates—by increasing their number—has also been shown empirically to reduce retrieval of goals and social values (Shah, 2003; Thomsen et al., 1996).

Greater numbers of associative relationships also reduce originality. Inspired by the fan effect, Beaty et al. (2023) demonstrated that the richness of semantic neighborhoods—the number of different associations concepts have—impairs originality. In the alternative uses task, participants are required to generate alternative uses to common objects. This measures divergent thinking, a critical component of creativity (Acar & Runco, 2019; Runco & Acar, 2012). Across a series of studies, Beaty et al. (2023) consistently found that alternative uses produced for objects with rich (vs. sparse) semantic neighborhoods were less original. Importantly, participants higher in fluid intelligence were able to generate more original responses in sparse semantic neighborhoods. In sum, learning more associations about a concept reduces speed of retrieval, and areas of semantic knowledge with greater numbers of associations reduce originality.

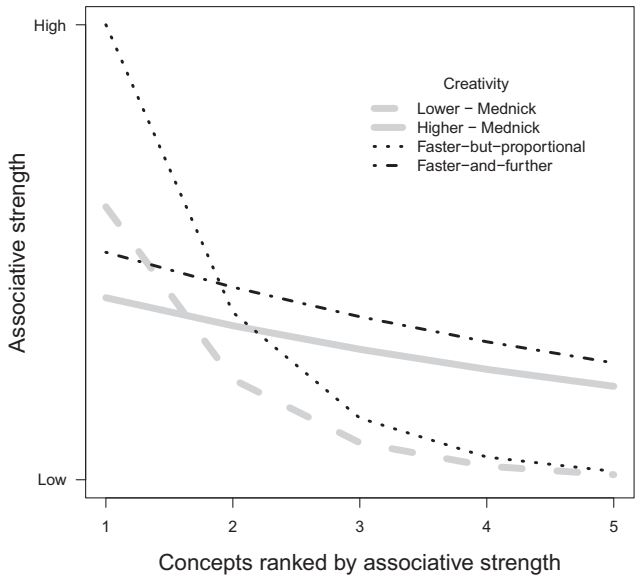
How might we reconcile the riddle of faster-and-further? One hypothesis is that higher creative individuals can adaptively deliver *more* focused activation to associates. This activation could come from cognitive control's enhanced inhibition of attention to alternative tasks, leaving more task-related activation for creativity (Chrysikou, 2019; Chrysikou et al., 2014). However, because cognitive control is often associated with more focused attention (Conway et al., 2001; Kane & Engle, 2002; Unsworth et al., 2021), it is not a priori clear how this activation may be distributed (e.g., more or less focused on the cue) or whether or not it is even needed (as we will see below).

Taken at face value, we might imagine that increased activation is reflected in a raised version of a lower creative individuals' association strength for all items. Retrieval would be faster, but otherwise proportional to that for lower creative individuals. Figure 1 shows the original Mednick associative theory of creativity for "Higher" and "Lower" creative individuals and, alongside this, indicates *faster-but-proportional* retrieval as a raised version of the lower creative's gray dotted line. This would increase the production rate for all items equally, following a pattern suggested by Benedek and Neubauer (2013). According to this *faster-but-proportional hypothesis,* we might need only additional activation to explain creativity (see also Volle, 2018).

However, a faster-but-proportional explanation is insufficient because it fails to explain the flatter tail of higher creative individuals:

Figure 1

A Visualization of S. A. Mednick's (1962) Associative Theory of Creativity Alongside the Proposed Outcomes of Two Process Models



Note. In Mednick's account, higher creative individuals have flatter associative retrieval curves, leading to proportionally greater retrieval of concepts with lower associative strength and greater originality (i.e., entropy). The faster-but-proportional account is a proposed outcome of increasing activation strength during the retrieval process, leading to faster retrieval. Because retrieval is faster, more responses are produced, but the relative originality of retrieval is unchanged. Alternatively, the faster-but-further account visualizes how a flatter tail would potentially require greater activation (raising the curve) plus an additional change to achieve greater production of more distant associations. In this figure we are using association strength as a proxy for speed of retrieval to help visualize the necessary processes. In practice, association strength is normalized by the total number of associations.

More distant associative responses are proportionately more likely. Yet, a structural change involving more interconnectivity—thus facilitating greater creative exploration (Kenett & Faust, 2019)—is also insufficient, because it leads to a decrease in retrieval speed, as noted above. If we are to take the claims of the associative and executive theories seriously, our model must generate both *faster-and-further* phenomenology.

Entropy Modulation Theory

The mechanism proposed by entropy modulation theory is that creative memory retrieval is produced by the executive control of variance in activation. Higher creative individuals are more creative because they can adaptively enlist more variance in the activation of associations. This is in addition to any differences in total activation or structural differences in the way higher and lower creative individuals represent information (Benedek et al., 2023). That is, entropy modulation does not preclude access to more activation or structural differences, but it also does not require them.

Entropy modulation is inspired by a wide variety of evidence, both behavioral and neural, that humans and other animals can

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increase the entropy and unpredictability of their responses in a strategic fashion. For example, humans and other animals can increase random exploration in response to environmental uncertainty and may do so using neural variability (Hills, 2019; Wilson et al., 2014, 2021). Similarly, studies show that executive control can improve random sequence generation (e.g., Baddeley, 1998; Oomens et al., 2021; Towse & Cheshire, 2007; Vandierendonck et al., 1998). Executive control has also been shown to strategically facilitate exploration and dissociative recall (Brown et al., 2022; Cogliati Dezza et al., 2019; Marko & Riečanský, 2023). Executive function has also been proposed as a modulator of exploration and exploitation across a variety of tasks, both in spatial and cognitive search (Hills et al., 2010, 2015). Finally, there is evidence that the shared variance in faster-and-further phenomenology is explained by general cognitive abilities, such as working memory capacity (e.g., Weiss et al., 2024).

Underpinning entropy modulation is the principle that cognitive responses are fundamentally probabilistic. Probabilistic sampling from cognitive representations is a core assumption of many models of cognitive function (Anderson et al., 1997; Bhatia & Loomes, 2017; Faisal et al., 2008; Hills et al., 2012; Luce, 1959; J.-Q. Zhu et al., 2020). Such models account for human variability remarkably well. They also suggest variance in how individuals use stochasticity to mediate exploration (e.g., Yechiam et al., 2005). Moreover, such probabilistic models are the natural outcome of assuming that retrieval from memory is a consequence of spreading activation or random walkers (Abbott et al., 2015; Kenett & Austerweil, 2016; Siew, 2019). Thus, the architecture for probabilistic retrieval is already in place in most cognitive models.

Entropy modulation theory assumes that individual differences in executive function allow some individuals to adaptively modulate the probabilistic entropy of responses by modifying the irregularity of activation of the underlying neural architecture. This is supported by research suggesting that cognitive control can adaptively tune background neural firing in different areas of the brain to mediate the exploration–exploitation trade-off and behavioral flexibility (Aston-Jones & Cohen, 2005; Avery & Krichmar, 2017; Cools & D'Esposito, 2011; Doya, 2008; Eppinger et al., 2021; Gilbertson & Steele, 2021; Lin & Vartanian, 2018; Pezzulo et al., 2015). This modulation may also enhance connectivity between the executive control and default mode networks (Oyarzabal et al., 2022).

Firing irregularity is also observed in the prefrontal cortex to facilitate "flexible and rapid adaptation to ever-changing environments" (Sakamoto et al., 2013, p. 2). Areas of the prefrontal cortex are directly involved in switching to more strategic exploration and may do so by destabilizing frontal "attractors" in response to information about rewards (Cools et al., 2007; Daw et al., 2006; Rolls et al., 2024). Moreover, this modulatory capacity has been directly related to individual differences in executive control (Omidvarnia et al., 2021; Shine et al., 2019) and creativity (Boot et al., 2017). Research also indicates a relation between brain entropy—measured by regional desynchronization—and divergent thinking (Shi et al., 2020).

Entropy modulation theory is designed to capture the above evidence for the cognitive control of stochastic or "entropic" brain activation on creativity, especially in relation to its ability to produce the faster-but-further retrieval curve shown in Figure 1. The formalization of this process is as follows. Starting from the presentation of a retrieval cue (e.g., a concept or question), associates are sampled from memory, each with a probability proportional to their similarity with the cue (S_c). The retrieval probability follows Luce's choice rule (Luce, 1959):

$$P(i|c) = \frac{S_{c,i}}{\sum_j^N S_{c,j}}. \quad (1)$$

The denominator in Equation (1) normalizes the probabilities to sum to 1 over all N possible associates. When sampled, each cue receives an increment to its activation, A, equivalent to δ:

$$A_{i,t+1} = A_{i,t} + \delta. \quad (2)$$

This sampling and activation process is repeated until the activation of one of the associates exceeds a threshold, $A > \tau$. At that time, the associate is retrieved and reported. Here we sidestep the issue of evaluation (e.g., Simonton, 2023; Sowden et al., 2015), though this is an addition that could be made in the future.

Creativity is modeled by assuming that individuals higher in executive function can increase the noise in the activation increment. We model this by letting the activation increment be some base activation, A_b, plus Gaussian noise, $\xi = N(0, \sigma)$ such that

$$\delta = A_b + \xi. \quad (3)$$

Noise, which we take here as shorthand for irregularity, is a common component of many neural models, and recent research also indicates that it may play a critical role in altering brain dynamics (Rolls & Deco, 2010; Touboul et al., 2012). The noise parameter, σ, could be influenced by individual neurons or their pattern of interconnectivity (Deco et al., 2011). Importantly, the addition of noise does not make retrievals uniformly random (for some experimental examples of "random" generation, see Heinen & Johnson, 2018; Rastelli et al., 2022). Rather, noise tunes the impact of retrieval distance so that more distant associates have greater or smaller probabilities of retrieval.

The difference between higher and lower creative individuals lies in the standard deviation of the noise—which we call the noise amplitude—such that higher creative individuals have a greater noise amplitude, $\sigma_{high} > \sigma_{low}$. Formulating the model this way means that higher and lower creative individuals can have the same amount of activation on average, but they distribute it differently by modulating the irregularity of activation.

This framework is a form of evidence accumulation or race model, in which different potential targets compete to reach a threshold level of activation (Busemeyer et al., 2019; Heathcote & Matzke, 2022). The number of iterations required for an associate to reach the activation threshold conveniently provides an indication of response time (Kvam et al., 2015).

An In-Silico Investigation of Entropy Modulation Theory

We conduct an in-silico investigation of entropy modulation theory as follows. We randomly choose 20 cues from the memory representation described below and allow our model to retrieve 5,000 associates for each cue. Each associate is the outcome of sampling and activating targets repeatedly using Equations (1)–(3) until an associate exceeds the threshold, τ.

Producing 5,000 associates per cue allows us to visualize the relative retrieval strengths and thus the flatness of the tail, mimicking that shown in Figure 1. A flatter tail indicates that less common associates are produced proportionately more for higher than lower

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creative individuals. In addition, we can use the number of iterations required to produce an associate as an indicator of the relative response time.

To generate some intuition for this model before we explore the parameters further, we first assume that higher and lower creative individuals share the same memory representation, the same threshold ($\tau = 5$), and the same base activation level ($A_b = 1$), but they differ in their noise amplitude, $\sigma_{high} = 1.0$ and $\sigma_{low} = 0.5$.

To remove the influence of individual differences in memory structure, all individuals sample from the same semantic representation with 500 words. This representation is modeled after the scale-free semantic memory network described in Steyvers and Tenenbaum (2005), such that most words have few associates (connections) and few words have many associates. The representation is constructed by adding one word at a time. The probability of the new word directly connecting to an existing word is proportional to the number of words, k_i, that the existing word already has direct connections with, such that $P(i) \sim k_i$. This follows the model of preferential attachment (Pósfai & Barabasi, 2016). Here we allow each new word to form two new attachments to existing words in the representation.

The resulting semantic memory network and the distribution of similarities from the 20 randomly chosen cue words is shown in Figure 2. As a proxy for associative distance, the similarities between nodes in the network are computed as the inverse of the path distance, where the path distance is equivalent to the number of associations (or edges in the network) required to move from the cue word to the associate.

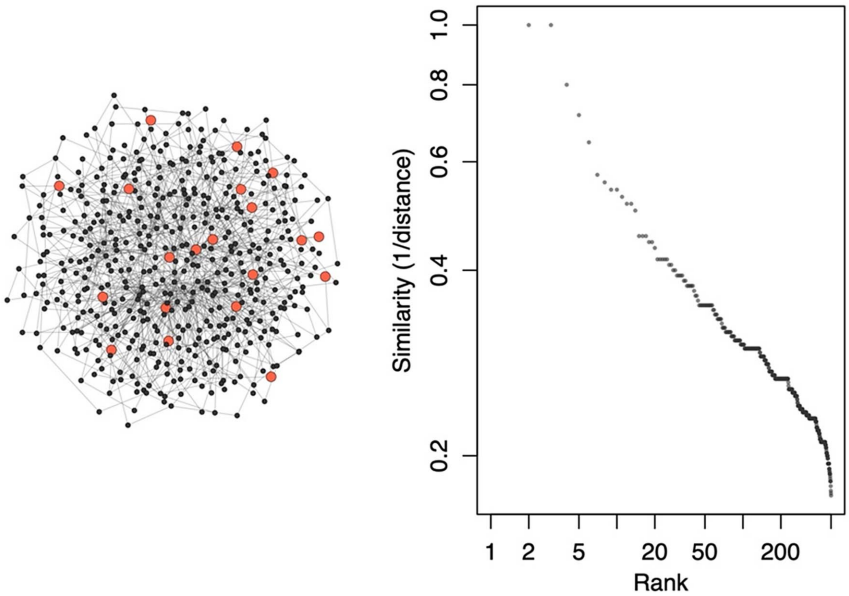
Figure 3 shows the distribution of association strengths and the response times for the simulated higher, $\sigma_{high} = 1.0$, and lower, $\sigma_{low} = 0.5$, creative individuals. The association strengths are produced by dividing the number of times an associate was produced by the total number of associates produced. This produces a probability of production. Response times represent the number of iterations of sampling and activation required to push an associate above threshold.

The results indicate that increasing the standard deviation of the noise leads to both faster-and-further retrievals. The association strengths indicate a flatter tail for noisier retrieval activation and the response times show that noisier is also faster. This pattern closely follows that of the associative theory of creativity (S. A. Mednick, 1962) but also indicates a role for executive function (Silvia, 2015) in curating noise. Importantly for what we show next, flatter distributions have higher entropy, meaning that the associates are less predictable given the cue. Using Shannon's information entropy, $E = \sum_{i=1}^{n} p_i \log(p_i)$, where p_i is the probability of retrieval for associate i, the flatter curve in Figure 3 has $E = 5.72$ and the steeper curve $E = 5.01$.

Figure 4 shows the results for entropy and response time across a range of threshold (τ), noise (σ), and base activation (A_b) values. For each value of each parameter, we recover 500 retrievals from each of the 20 cues and then compute mean entropy and response times for each cue before averaging across all cues. As above, as the noise amplitude increases, entropy rises and the response time falls. The fall in response time with increasing noise follows the intuition

Figure 2

The Semantic Memory Network and the Distribution of Similarities From 20 Randomly Chosen Cue Words



Note. In the semantic memory network, nodes represent words that could be provided as cues or retrieved as associates. Links between nodes indicate direct relationships that activation must pass through to reach potential targets. The 20 randomly chosen cues are indicated by a larger size and red color. Rank-similarity is plotted on log-log axes. Similarities are here approximated by taking one over the path distance in the semantic network, averaged at each rank for the 20 different cues. See the online article for the color version of this figure.

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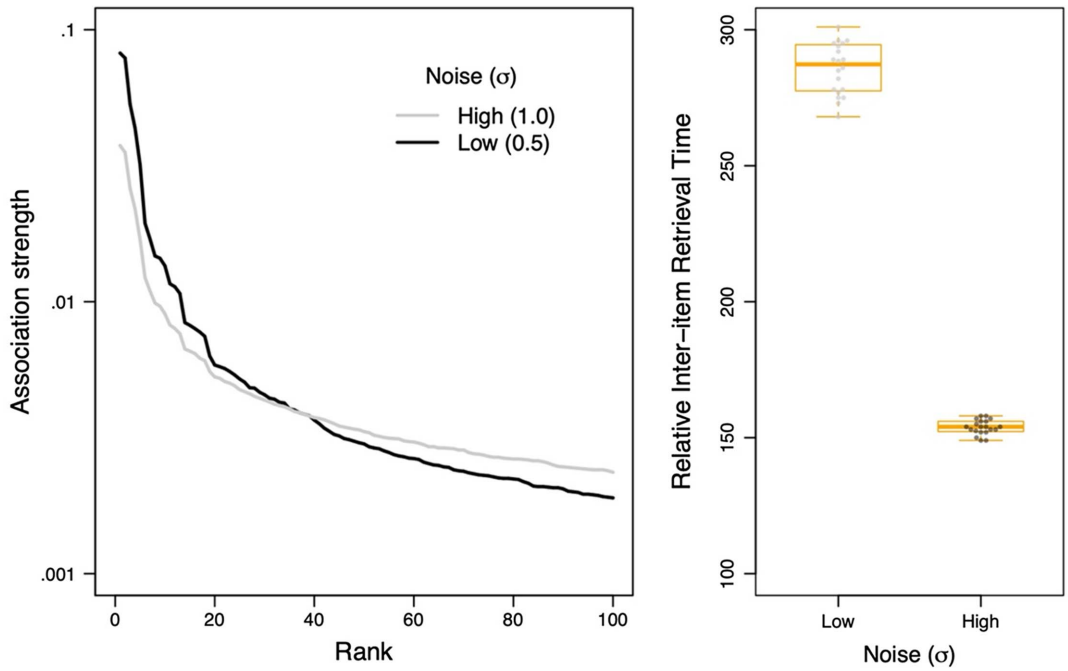
Figure 3

The Distribution of Association Strengths for Higher and Lower Creativity (i.e., Noise) and Their Associated Response Times



Note. Association strengths are computed by ranking associates according to their frequency of retrieval and then dividing frequency by the total number of retrievals over all associates. Values are shown for the top-ranked 100 cue association strengths averaged across all 20 cues. Response times represent the average number of sample-activation iterations before an associate exceeds the threshold. See the online article for the color version of this figure.

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that if the noise is sufficiently high relative to the threshold, the threshold can be reached after fewer samples. As the threshold increases, more retrievals are required, and this reduces the entropy as it more accurately captures the underlying distance distribution. This is a common property of evidence accumulation models (Busemeyer et al., 2019). The relationship between entropy and response time is reflected in the Pearson product moment correlation for the values in the corresponding cells across the top two panels, $r = -.96$, $t(108) = -37.6$, $p < .001$. This follows a classic speed–accuracy trade-off, with both lower thresholds and higher noise producing faster response times but greater entropy of responses.

Varying the base activation, A_b, relative to the threshold (fixed at $\tau = 5$ in the bottom two panels) also influences entropy and response times. Lower base activation requires more samples to reach threshold and is therefore lower entropy and slower. Note that this does not follow the intuition of faster-but-proportional: Greater activation increases entropy as well, which may be another mechanism for entropy modulation. However, for all A_b values investigated, increasing noise increases entropy and reduces response time.

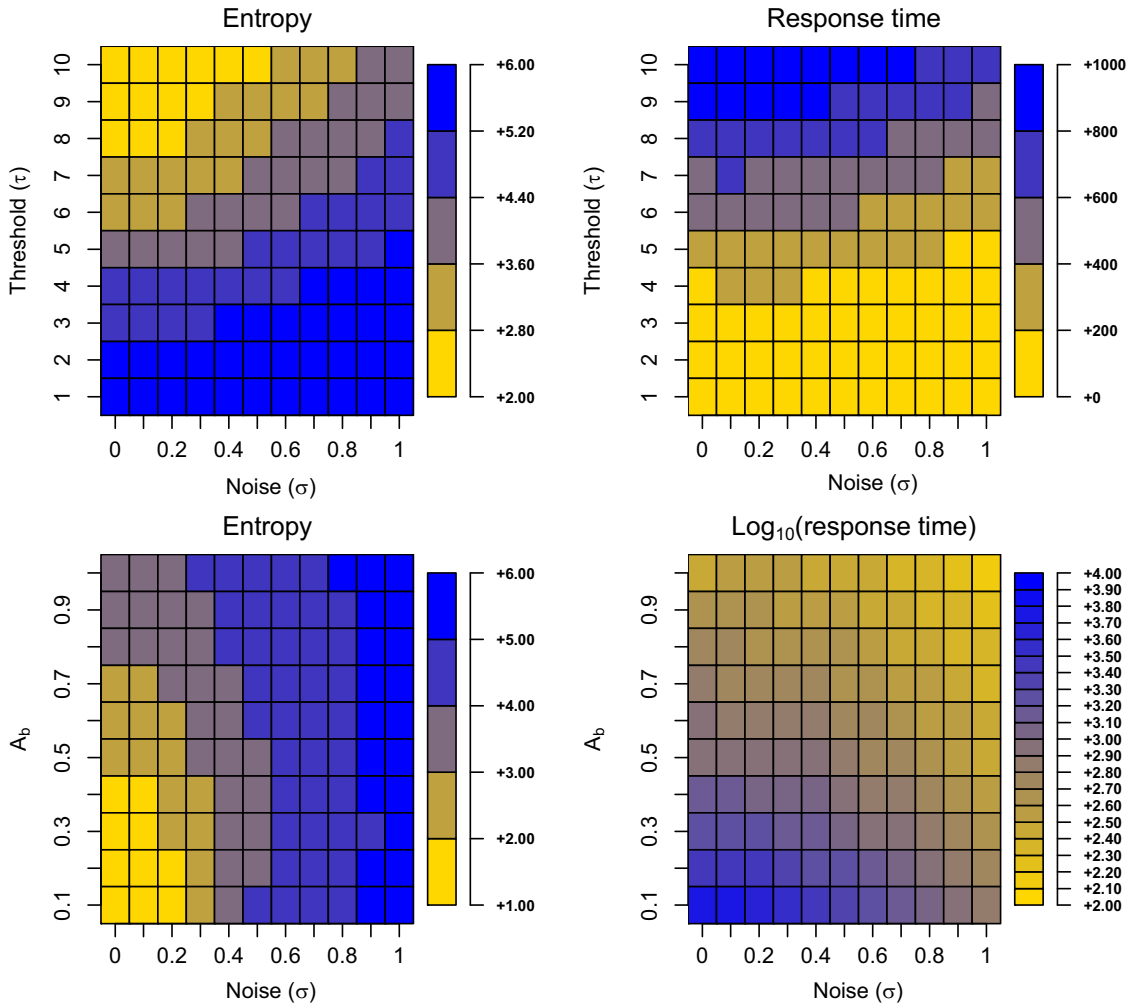
How does the semantic neighborhood of an individual cue affect retrieval? Figure 5 demonstrates how entropy varies in relation to a cue's degree centrality, k, (how many nodes it is connected to) for various values of noise, σ. This figure is produced by generating 50 semantic networks following the same algorithm as described in Figure 2 and sampling five cues (nodes) of each degree value (or as many as are available) from each network. We then retrieve 500 targets for each cue using the appropriate σ value and compute the entropy and response times by averaging their values over all nodes of a given degree as sampled over the 50 networks. In this figure and the next, we hold $\tau = 5$ as it covers a range over which σ has a variable influence on entropy, as shown in Figure 4.

The pattern of results confirms that words with higher degree generally have a higher entropy of recall. This follows the intuition of the fan effect, that cues of higher degree have more potential associates to sample from and are therefore less predictable in their associations. However, higher degree does not show a consistent influence on response times. This is because, unlike noise, higher degree raises entropy by increasing the number of nearby associative targets, not by increasing the variation of activation over targets (e.g., Beaty et al., 2023). Note that this is also not consistent with the fan effect. However, the fan effect compares many versus few close associates—in the present case, there are many potential associates beyond the local neighborhood, and activation is spread among these as well. Nonetheless, as above, increasing noise is consistently associated with the faster-further phenomenon of rising entropy and falling response times.

We can also demonstrate that these effects generalize to a wide range of network structures. To vary this range, we use a rank-based construction method, which ranks nodes and then chooses nodes in proportion to their rank as modulated by a rank-preference parameter (Hills, in press). Using a network of 500 nodes, ranked from 1 to 500,

Figure 4

Entropy and Response Time for Various Noise, Threshold, and Base Activation Values



Note. Each cell in the heatmap is the outcome of 500 retrievals for each of 20 cues with the indicated threshold and noise values. In the top two panels, $A_b = 1$. In the bottom two panels, $\tau = 5$. See the online article for the color version of this figure.

edges are created by randomly choosing pairs of nodes. To modulate network structure, each node is chosen with a probability proportional to its rank, $p(r) \propto r^{-\lambda}$. When $\lambda = 1$, the network approaches a scale-free distribution, like the network described above in Figure 2. Most nodes have few connections, but few (low ranked nodes) have many. When $\lambda = 0$, all nodes are chosen with equal probability, and the network becomes what is called an Erdös-Renyi random graph (Erdős & Rényi, 1960). Thus, over the range from 0 to 1, the network transitions from a random graph to one approaching a scale-free network. For each network type, we construct 20 random network representations, each with 500 nodes and 1,000 random edge allocations. Though pairs can be chosen more than once, all edges are considered equivalent in what follows. For each of the resulting networks, we compute the entropy for 500 retrievals from each of 20 randomly chosen cues. Because some nodes may remain isolated and not connected to the larger network, the cues are always chosen from the giant component in each network, meaning they belong to the largest collection of interconnected nodes.

As shown in Figure 6, for each network type, the results are consistent with the pattern shown in the previous figures. Larger noise values consistently produce higher entropy values for all network types. Networks approaching $\lambda = 1$ are higher entropy than random graphs, but do not show marked reductions in response times.

In sum, the above parameter exploration indicates that entropy modulation—via alterations in stochastic activation, threshold, or baseline activation—can reproduce the faster-and-further phenomenology across a wide range of parameter values and network structures.

Discussion

> The genius of discovery depends altogether on the number of these random notions and guesses which visit the investigator's mind. To be fertile in hypotheses is the first requisite. (James, 1880, p. 456)

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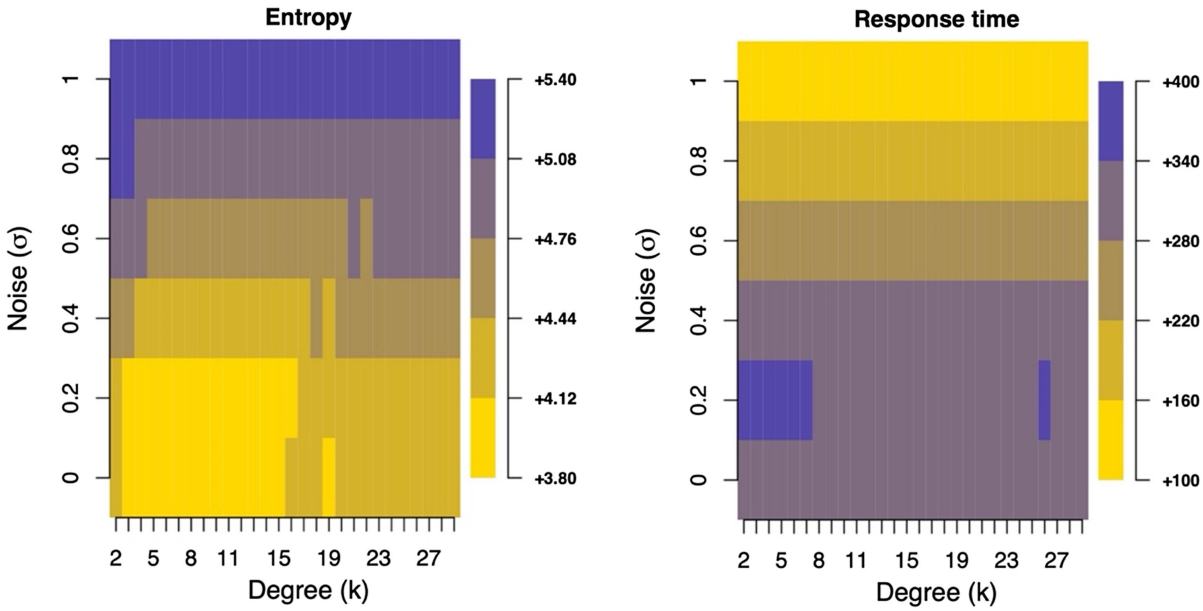
Figure 5

The Influence of Network Degree on Entropy and Response Time as a Function of Noise



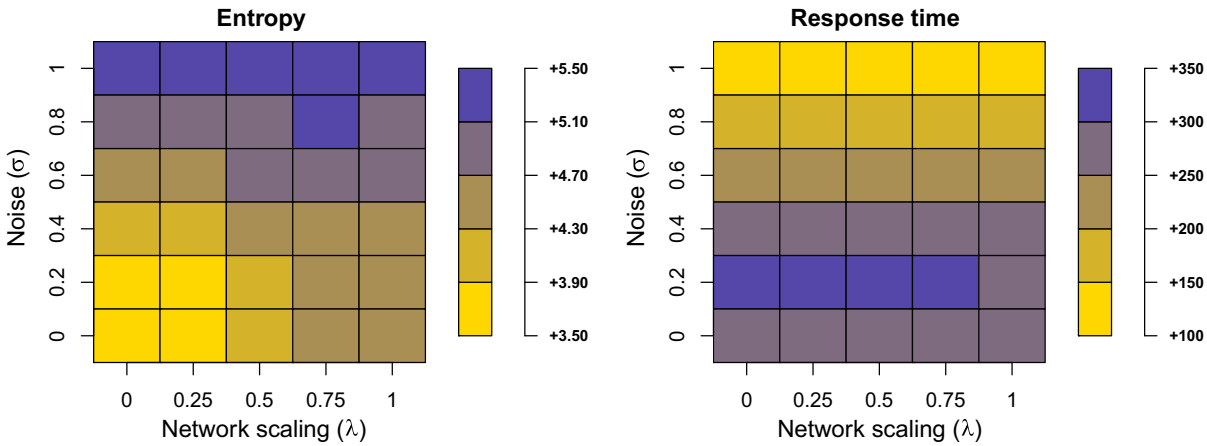
Note. Each cell indicates the entropy or response time of a sample of nodes of a given degree taken from 50 randomly generated networks following the procedure described in Figure 2. Only nodes of degree 29 or fewer are shown as higher degree values have fewer than 10 samples per cell. See the online article for the color version of this figure.

In his lecture on the parallels between social evolution and Darwinian theory, William James portrayed the creative mind as the curator of mental accidents. Social evolution, he proposed, was maintained via the conjuring of conceptual mutations. In the present work, we illustrate how a similar kind of fertility of conceptual exploration can be created by increasing irregularity in the activation process. By increasing the Guassian noise associated with evidence accumulation in the memory retrieval process, the entropy of associations is increased leading to faster and more creative productions, reproducing the faster-and-further phenomenology.

Our model is the first we know of that mechanistically demonstrates how control processes can directly drive the faster-and-further phenomena in creative ideation. Entropy modulation theory also makes novel predictions about the role of executive function in creative memory retrieval. Specifically, executive function should strategically facilitate novel (high entropy) retrieval by upregulating stochasticity during creative exploration.

Figure 6

The Influence of Network Scaling on Entropy and Response Time as a Function of Noise



Note. Each cell corresponds to retrieving 500 targets from 20 cues for each of 20 networks produced with the corresponding rank-based construction method and value of λ. See the online article for the color version of this figure.

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Creativity should be associated with more stochastic processing in areas of the brain associated with accessing cognitive representations. Stochasticity during creative tasks should also lead to more rapid response times. Furthermore, in addition to impacting creativity, the presence of a cognitive load (e.g., a secondary task) should impair executive function and correspondingly impair the network irregularity that predicts creativity. Together, this offers a precise and novel role for executive function that could be tested for in future work.

Entropy modulation does not preclude alternative sources for individual differences in creativity. For example, as the parameter exploration in Figure 4 demonstrates, even if executive function only provided additional activation (or threshold lowering), this would, all other things being equal, increase response entropy, flattening the retrieval curve. Additionally, executive function is likely to guide the use of creative strategies (Lloyd-Cox et al., 2023). Such strategic processes can be learned, for example, learning that creativity can be facilitated by recombining concepts or thinking laterally (Gibbert et al., 2012; Goldenberg & Mazursky, 2002; Malthouse et al., 2022). These represent different routes to creativity than that postulated by entropy modulation. Entropy modulation also does not preclude structural differences in semantic memory. There is ample evidence supporting structural differences in retrieval patterns, including differences in the extent to which higher and lower creative individuals rate the similarity of items (e.g., Benedek et al., 2017; He et al., 2021; Ovando-Tellez, Kenett, et al., 2022). Moreover, educational differences influence semantic structure (Denervaud et al., 2021) as do individual differences in learning ability (Jiménez & Hills, 2022), age (Dubossarsky et al., 2017), and the personality trait of Openness to Experience (Christensen et al., 2018). Going back to Hills and Kenett (2022), a complete account of creativity based on structure or process alone is unlikely. Indeed, the few studies that have examined the roles of both memory structure and executive processes in creativity consistently show they both contribute to creative ideation (e.g., Beaty, Silvia, et al., 2014; Benedek et al., 2017). More concretely, many notable artists like Picasso, Van Gogh, Miles Davis, and Élisabeth Louise Vigée Le Brun, spent years learning from the art of others before they became the sources of originality that we recognize today.

In this article, we demonstrate the feasibility of entropy modulation in modeling the role of executive processes in the faster-and-further phenomenology as envisioned by S. A. Mednick (1962). As we note above, our model can be expanded to include additional variables to generalize across additional cognitive capacities that contribute to the creative process (Benedek et al., 2023; Green et al., 2023). Critically, while we focus here on the faster-and-further phenomenology, we would like to argue that our model formalizes and generalizes across the various creativity tasks that build on creative ideation. For example, Smith et al. (2013) have shown how the Remote Association Test, a convergent thinking task developed by S. A. Mednick (1962) to study this associative theory of creativity, includes an initial divergent thinking phase. Evidence for this was also provided recently by Ovando-Tellez, Benedek, et al. (2022), who found a positive relationship between performance on the Remote Association Test and switching between different semantic senses of a word when retrieving free associates for polysemous words. As this switching was also correlated with a measure of executive function, it provides additional indirect support for entropy modulation. Furthermore, re-analysis of data from Ovando-Tellez, Kenett, et al. (2022) by Hills (in press) finds that higher creative individuals were less similar to one another than lower creative individuals when rating pairs of objects for similarity, providing another potential source of indirect evidence for entropy modulation. In addition, Beaty and Kenett (2023) have recently argued that associative thinking is a general cognitive mechanism at the heart of creative ideation. Thus, our model can serve as a formal starting point to a range of creativity testing paradigms.

Entropy Modulation Theory also helps to align creativity with other literature proposing stochastic sources of mental exploration, such as that experienced through psychedelics or ritual practice (Carhart-Harris et al., 2014; Carhart-Harris & Friston, 2019; Huels et al., 2021; Viol et al., 2017). A common explanation for these altered states is that they are the outcome of critical brain states that lie on the edge between order and disorder, capable of rapid state transitions, and which are highly sensitive (Huels et al., 2021; Lee & Mashour, 2018). This effectively increases the entropy of spontaneous brain activation and thereby tilts the brain toward exploration in its continuous balancing act between exploration and exploitation. Similar adaptive control processes that increase unpredictability, via the addition of noise or entropy, are used in other frameworks as well, such as in the free energy principle (Schwartenbeck et al., 2013), adaptive exploration versus exploitation in decision making (Cohen et al., 2007), animal foraging (Dorfman et al., 2022; Hills, 2019), simulated annealing (Kirkpatrick et al., 1983), and adaptive temperature control in large language models (Y. Zhu et al., 2024). In the domain of cognition, executive control of entropy modulation also connects creativity with the broader literature on cognitive foraging (Hills et al., 2010; Malaie et al., 2024; Todd & Hills, 2020).

In answering the call for further computational modeling in creativity research (Lloyd-Cox et al., 2023), our model offers testable predictions and an alternative to structure-based model predictions. Moreover, our model advances research that may integrate and untangle structure and process effects in creativity. Some of these additional effects include what Benedek and colleagues have highlighted in how additional executive process—such as inhibition, monitoring, updating, and broad retrieval abilities—contribute to creative thinking (Benedek et al., 2014; Benedek, Franz, et al., 2012; Miroshnik et al., 2023; see also Silvia, 2015). Indeed, simply asking people to "be creative" may be sufficient to activate executive control in its various capacities (Benedek et al., 2020; Weinberger et al., 2016). Entropy Modulation Theory offers a modeling framework to which further parameters and structural differences can be added to better understand the complex cognitive processes underlying creativity.

In his seminal article proposing the associative theory of creativity, S. A. Mednick (1962) advocated for terms and ideas that are debated till this day: "flat" versus "steep" associative hierarchies, and the role of an associative process that links remote concepts together to form original and appropriate ideas. These ideas were (and still are) incredibly intuitive and inherent in many other theories on creativity. Yet they are extremely hard to study (Benedek & Neubauer, 2013). Research in creativity has greatly elucidated the role of memory in creativity (Benedek et al., 2023), as well as the general role of associative thinking (Beaty & Kenett, 2023), both underpinned by executive and associative theory. Entropy Modulation Theory provides a parsimonious alternative model that may provide a road to integration. At a minimum, it further demonstrates the need to

develop new, integrative (and creative) models in our attempt to understand the complexity of creative ideation.

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