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"Forward Flow": A New Measure to Quantify Free Thought and Predict Creativity

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Keywords: Free thought; Default network; Methodology; Creativity; Mind wandering

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Abstract

When the human mind is free to roam, its subjective experience is characterized by a continuously evolving stream of thought. Although there is a technique that captures people's streams of free thought—free association—its utility for scientific research is undermined by two open questions: 1) How can streams of thought be quantified? and 2) Do such streams predict psychological phenomena? We resolve the first issue—quantification—by presenting a new metric, "forward flow," that uses latent semantic analysis (LSA) to capture the semantic evolution of thoughts over time (i.e., how much present thoughts diverge from past thoughts). We resolve the second issue—prediction—by examining whether forward flow predicts creativity in the lab and the real-world. Our studies reveal that forward flow predicts creativity in college students (Study 1) and a representative sample of Americans (Study 2), even when controlling for intelligence. Studies also reveal that membership in real-world creative groups—performance majors (Study 3), professional actors (Study 4) and entrepreneurs (Study 5)—is predicted by forward flow, even when controlling for performance on divergent thinking tasks. Study 6 reveals that forward flow in celebrities' social media posts (i.e., on Twitter) predicts their creative achievement. In addition to creativity, forward flow may also help predict mental illness, emotional experience, leadership ability, adaptability, neural dynamics, group productivity, and cultural success. We present open-access online tools at www.forwardflow.org for assessing and visualizing forward flow for both illustrative and large-scale data analytic purposes.

Keywords: Free thought; Default network; Methodology; Creativity; Measurement; Mind Wandering

"Forward Flow": A New Measure to Quantify Free Thought and Predict Creativity

Williams James (1890) argued that the human self is defined by "thoughts connected as we feel them to be connected" (p. 141). This mental flow is characterized by both continuity and change, in what he called a "stream of thoughts, of consciousness" (p. 141). Although the term "stream of consciousness" is now in everyday use, psychological research is very different today than in the 19th century. In contrast to James—who wrote introspective, holistic, and qualitative accounts of the mind—psychology journals today typically publish quantitative experiments that investigate specific mental processes underlying circumscribed phenomena. This increased focus on measurement and mechanism is natural, and even desirable, as a science matures. However, increased precision and specificity may sometimes neglect some important elements of subjective experience (Varela, Thompson, & Rosch, 1991)—such as the dynamics of free thought.

Like James's proverbial stream, our "free" thoughts—i.e., thoughts unbound to specific stimuli—flow forward through time, constantly evolving. However, few studies examine this dynamic unfolding, instead assessing thoughts at a single time point toward a single referent (e.g., via Likert scales). Although much can be learned from these static assessments, there is an approach that captures freely flowing thoughts: free association. Free association is a simple psychological technique in which people report the thoughts that spontaneously arise in connection with previous thoughts. In one popular version of free association—"targeted" free association—people hold a seed concept (e.g., mother) or image (e.g., an inkblot) in mind and report all the thoughts that stem from this target thought. This version of free association was widely used in psychoanalysis to reveal unconscious associations[1] with important psychoanalytic elements (Farber, 2005; Freud, 2013), and is still sometimes used today to exhaustively map out conceptual associations (Stark, Kogler, Gaisbauer, Sedmak, & Kirchler, 2016).

Another version of free association—"chain" free association—better represents James's idea of a "stream of thought." Participants are given a seed concept (thought 1) and report their first association (i.e., thought 2); then their first association from thought 2 (i.e., thought 3); then their first association from thought 3 (i.e., thought 4); and so on. In other words, each thought x_n is the direct association from thought x_{n-1}. Chain free association—hereafter simply called "free association"—gives researchers a rich picture of dynamic subjective experience, revealing how a person's thoughts evolve over time (Marron & Faust, 2018).

Despite its great potential within psychological research (De Deyne et al., 2016; Joffe & Elsey, 2014; Nelson, McEvoy, & Dennis, 2000), free association—and the stream of thoughts it reveals—is often overlooked in modern studies, likely because of two issues. The first issue is methodological: It is unclear *how* to use free association in modern quantitative studies. The second issue is conceptual: It is unclear *why* free association is scientifically useful (in other words, what exactly do streams of thought predict?). We first review a potential solution to the

[1] Although these associations are not "unconscious" in the strict sense (Epstein, 1994), they may nevertheless provide insight into otherwise hidden dimensions of patients' mental lives (Westen, 1999).

methodological issue—latent semantic analysis—before suggesting one area where free association might offer predictive power—creativity.

From Qualitative Experience to a Quantitative Metric

Free association yields a rich picture of subjective experience, illustrating thoughts as they meander through a multi-dimensional semantic space. But this richness can also be a curse. Modern psychological studies often seek to represent people's characteristics and behaviors with small sets of discrete numbers, such as an IQ score for intelligence or Big Five scores for personality. We can debate whether such reduction is desirable, but it is a fact of much contemporary science. The practical question for us is whether the stream of thoughts captured by free association can also be distilled to a small set of values, or perhaps even a single number.

The technique of latent semantic analysis provides a potential solution to this problem. Latent semantic analysis (LSA; Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990) computes the semantic similarity—or inversely, the distance—between two words based on the frequency of their co-occurrence within some corpora of text. For example, "snow" and "white" often appear together in books, magazines, and newspapers, and so have a small semantic distance. Conversely, "snow" and "carburetor" seldom co-occur and so have a large semantic distance. LSA can be applied to any list of words and returns the set of semantic distances between all pairs of words ranging from 0 (minimally different) to 1 (maximally different). For example, analyzing a list of 5 words (e.g., bear, honey, sugar, frosting, cake) with LSA would return a symmetric 5 x 5 matrix (with zeroes along the diagonal because a word has zero semantic distance from itself). The cell x_{ij} gives the semantic distance between the *i*th word and the *j*th word. In our example, $x_{1,5}$ would give the semantic distance between the first word (bear) and the fifth word (cake), which is .66 (calculated at lsa.colorado.edu).

While objections have been raised against LSA (e.g., dependency on the specific text corpora and the specific number of dimensions used to calculate semantic space) it is still widely applied to study memory and language (Kenett, Levi, Anaki, & Faust, 2017). Here, LSA can be used to analyze free association because free association yields a sequential list of words, one for each thought in a stream of consciousness. Of course, a matrix of semantic distances is not simple to use, especially as lengthier lists of N words produce proportionately large N x N matrices. We outline a new composite measure that reduces this complexity (regardless of list length/matrix size) and may also predict diverse psychological phenomena. We call this metric *forward flow* because it captures the extent to which people's streams of thought "flow forward" in semantic space.

The Forward Flow of Thought

In simple terms, forward flow quantifies how much current thoughts semantically depart from previous thoughts within free association. In the metaphor of a stream of thought, forward flow is how far "downstream" later thoughts are compared to earlier "upstream" thoughts. For example, the free association sequence "candy, sugar, delicious, yummy, treat" would have low forward flow because later thoughts are semantically similar to previous thoughts. That is, rather than flowing away from earlier thoughts (e.g., "candy"), the later thoughts in this sequence (e.g., "yummy" and "treat") remain relatively close to them. Conversely, the free association sequence "candy, store, warehouse, forklift, safety" would have higher forward flow because later thoughts are semantically dissimilar to previous thoughts ("forklift" and "safety" may be semantically near, but they are both quite distant from "candy"). Importantly, then, forward flow is not just about the association between any two adjacent thoughts, but rather a holistic measure that captures the dynamics of an *overall* sequence of thought, regardless of length.

The instantaneous forward flow of any particular thought is calculated by its average semantic distance from all preceding thoughts, as given by Equation 1 (where D is semantic distance between thoughts and *n* is the numerical location of a thought within a stream).

$$\text{Equation 1: } \frac{\sum_{i=1}^{n-1} D_{n,i}}{n-1}$$

The dynamic forward flow of an entire thought sequence—what we call "forward flow"—is calculated by the average of Equation 1 across all thoughts in a sequence, as given by Equation 2 (where again D is semantic distance between thoughts, and *n* is the total number of thoughts within a stream).

$$\text{Equation 2: } \left(\sum_{i=2}^{n} \frac{\sum_{j=1}^{i-1} D_{i,j}}{i-1}\right) / (n-1)$$

This "forward flow" is not the "flow" of Csikszentmihályi (1990)—being present in the moment—but instead captures the degree of change within a stream of thought, similar to the idea of "mental progression" (Mason & Bar, 2012). In the words of James (1880, p. 456), forward flow distinguishes between those who have "thoughts of concrete things patiently following one another in a beaten track of habitual suggestion" (low forward flow) from those who have "abrupt cross-cuts and transitions from one idea to another...[who make] the most unheard-of combinations of elements." (high forward flow). Of course, no single number can fully capture the dynamic richness of subjective experience, but forward flow allows researchers to quantify streams of thought as they unfold via free association. Forward flow is also straightforward to measure, requiring only a minute or two at the beginning of a study for people to free associate a list of thoughts.

In order to make forward flow accessible to researchers, we have developed an open-access online suite of resources (www.forwardflow.org) that provides LSA distances and forward flow metrics for both individual lists and arbitrarily large datasets of word sequences (see supplementary materials for development materials).[2] These resources also provide a way to graphically depict thought sequences—the "thought plot." In a thought plot, each thought is sequentially listed in equal intervals along the x-axis, with its instantaneous forward flow

[2] Our LSA engine is trained on similar corpora as the Colorado engine and yields similar similarity metrics. However, the Colorado engine does not allow for high-throughput or integration with other applications, and so we needed to develop our own engine.

depicted on the y-axis. These graphs illustrate an individual's stream of thought, as can be seen in Figure 1, which compares two thought plots drawn from Study 1.

So far, we have suggested that forward flow is an easy-to-use metric that quantifies streams of free thought. However, a second question is this tool's utility: What phenomena, if any, are predicted by the kind of free-varying thought captured by forward flow?

Is Free Thought Useful?

Free association is a rich technique because it generates relatively unconstrained thoughts. These "free" thoughts stand in contrast to those measured during modern psychology experiments, which are almost always bound to a specific referent (i.e., they are "task-bound"). When we assess someone's personality, hopes about the future, or thoughts about another person, we are directing their attention to that focal object, and there are certainly benefits to this focus: Task-bound thoughts about a phenomenon are—by definition—more relevant to that phenomenon than are thoughts in general. However, assessing only task-bound thoughts can give a biased picture of mental life, neglecting important psychological phenomena tied to free thought (e.g., mind wandering Smallwood, McSpadden, & Schooler, 2007, Zedelius & Schooler, 2015).

Recent neuroscience research reveals that many phenomena may be tied to the dynamics of unconstrained thoughts (Christoff, Irving, Fox, Spreng, & Andrews-Hanna, 2016). For many years, neuroscience studies focused exclusively on task-bound thoughts by measuring brain activity during experimental tasks, which typically involve reading or viewing images (for a review, see Gruberger et al., 2011). These tasks are typically clustered into blocks with "inactive" time between them, during which participants simply lay staring into the dark. However, participants' brains remained quite active during this inactivity, in what researchers have since termed "default network" activity (Buckner, Andrews-Hanna, & Schacter, 2008).

Default network activity corresponds to daydreaming (Kucyi & Davis, 2014), mind wandering (Mason et al., 2007), and other phenomena associated with less-constrained thought (e.g., Mazoyer et al., 2001). Studies reveal that this activity is linked to performance in a variety of important domains, including autobiographical memory (Spreng & Grady, 2010), theory of mind (Spreng, Mar, & Kim, 2009), episodic thought (Andrews-Hanna, Reidler, Huang, & Buckner, 2010), event construal (Tamir & Mitchell, 2011), and understanding both fiction and other minds (Tamir, Brickler, Dodell-Feder, & Mitchell, 2016). Most importantly for this paper, default network activity also predicts creativity (Beaty et al., 2018; Kühn et al., 2014), likely because relatively unconstrained thinking is important for the generation and retention of novel ideas (Jung, Mead, Carrasco, & Flores, 2013).

Although important, these neuroscience studies connecting creativity to unconstrained thought have limitations. Measuring default network activity requires access to an expensive fMRI scanner, and the exact content of these default network activity-related thoughts is unclear. It is also unclear what specific aspects of unconstrained thought predict creativity. We suggest that free association provides a cheap and easy way to reveal the contents of unconstrained thought, and that its quantification via forward flow that may predict creativity.

Forward Flow and Creativity

Both anecdotal and scientific evidence suggest a potential link between forward flow and creativity—in particular, divergent thinking.[3] Anecdotally, creative people are often good at generating works that leave behind the past: Jackson Pollock moved beyond easels and brushes and Einstein moved beyond Newtonian mechanics. This "forward movement" appears in many artistic and scientific creative works as visionaries eschew tradition for originality. Indeed, Walt Disney's recipe for creativity makes this connection explicit: "Around here… we don't look backwards for very long. We keep moving forward, opening up new doors and doing new things." As thinking is for doing (Fiske, 1992), those who complete more "forward-moving" creative actions might also have more "forward-moving" thoughts.

Recent studies support the idea that creativity is related to individual differences in memory organization (Hass, 2017; Heinen & Johnson, 2017)—differences that allow more creative participants to connect ideas that are further apart in memory (Kenett, Anaki, & Faust, 2014). Most relevant to the current work, associative dynamics appear related to both creative performance and default network activity (Marron et al., 2018). However, one limitation of these studies is that they all assess task-bound thoughts, measuring cognitive processes while participants are engaged in creative tasks or are explicitly instructed to be creative. Although many real-world situations entail conscious efforts to be creative, here we examine whether features of unconstrained thought—free association *without* instructions to be creative—might also predict creativity across diverse settings and populations. Can forward flow predict divergent thinking and perhaps even the choices and outcomes related to people's careers?

Importantly, we do not claim that forward flow is the "best" predictor or measure of creativity. Creativity is predicted by expertise (Baer & Kaufman, 2005), personality (Kaufman et al., 2016), attentional control (Beaty, Benedek, Silvia, & Schacter, 2016), one's social network (Perry-Smith & Shalley, 2003), and the broader cultural milieu (Rudowicz, 2003). There are also many measures of creativity which predict creative performance. Nevertheless, revealing the predictive power of forward flow in creativity would both contribute to this important body of work and point to the general methodological utility of assessing streams of free thought.

Research Plan

Six studies (plus one pilot study) examine whether forward flow predicts creativity. In the first two studies, we compute forward flow from free association sequences and test whether it predicts performance on divergent thinking tasks within a college sample (Study 1) and a representative sample of Americans (Study 2). In the next three studies, we use a known groups

[3] Divergent thinking tasks are widely applied creativity measurements, requiring participants to generate novel responses to open ended questions (Runco & Acar, 2012). Convergent thinking, an alternative measure of creativity, requires participants to respond to closed ended questions (Simonton, 2015).

paradigm to examine whether membership in real-world creative groups—performance majors (Study 3), professional actors (Study 4) and entrepreneurs (Study 5)—can be predicted by forward flow, even when controlling for performance on divergent thinking tasks. Finally, we treat social media posts as streams of consciousness unfolding over time and test whether forward flow on Twitter predicts creative achievement (Study 6). All data and analysis syntax is available at osf.io/a4hc9.

Measures and Methods

Methods Used Across Most Studies

The studies presented here build sequentially on each other, providing systematic replication and extension. As such, they share many methods in common; we summarize them here to avoid redundancy.

Assessing Forward Flow

Thought Collection. In Studies 1-5, forward flow was assessed to capture relatively unconstrained thought. It was always assessed first to avoid contamination from other measures. Participants received a seed word followed by 19 blank lines, with these instructions: "On this page, starting with the word '[seed word]', your job is to write down the next word that follows in your mind from the previous word. Please put down only single words, and do not use proper nouns (such as names, brands, etc.)." Seed words—which varied both within and across studies to enhance generalizability—ensured all participants had the same "starting place" in thought, allowing for controlled comparisons between streams of thought. See supplementary materials for all seed words. Importantly, participants were *not* instructed to be creative.

Forward Flow calculation. To calculate forward flow, we used our custom LSA engine, whose development—including training corpora and calculation techniques—is documented at forwardflow.org and in the supplementary materials. The LSA engine used a 300 dimensional space (as in Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990) to generate a symmetric 20 x 20 matrix for each participant, representing the semantic distance (i.e., the inverse of semantic similarity) between each pair of words. Forward flow was calculated via Equation 2.

Assessing Creativity via Divergent Thinking

In Studies 1-5, participants completed a set of divergent thinking tasks. Responses in each task were coded for creativity by multiple raters (details below). Regardless of the task, participants were always instructed to be as creative as possible. (For complete materials, see supplementary materials). For generalizability, we sampled from a diverse set of tasks:

Novel Uses Task. Participants generate three novel uses for a common item (Guilford, 1950)—a box of popsicle sticks. A less creative response might be "making popsicles" and a more creative response might be "building a raft for beetles."

Draw an Alien Task. Participants are given a blank page and some crayons and are asked to draw an extraterrestrial (Ward, 1994). A less creative alien might look like a human with an oblong head and a more creative alien might look nothing like a human at all.

Charity Idea Task. Participants come up with three ways for a hypothetical charity to raise money from the community (Lucas & Nordgren, 2015). A less creative idea might be to call people on the phone and a more creative idea might be to sell tickets to puppy races.

Caption Task. Participants write a caption for each of three abstract images, such as intersecting lines or an array of circles (Torrance, 1972). A less creative response to an array of circles might be "spots" and a more creative response might be "a galaxy of stars."

Similarity Task. Participants see word pairs (e.g., train/tractor) and come up with a way in which the pair is related (Wallach & Kogan, 1965). A less creative response to this example might be "vehicles" and a more creative response might be "links in the food production chain."

Coding Creativity

All responses on divergent thinking tasks were rated by at least two coders, who assigned a number from 1 (least creative) to 4 (most creative) to each response by considering both the novelty and relevance of responses. (For example, saying that a set of popsicle sticks could be used as "a piranha fight" would be novel but not relevant.) In all studies, coders first discussed a random sample of 10 responses for calibration before independently rating all responses. Responses within each task were averaged together to form a total task score. Reliability across coders for all tasks was above $\alpha = .81$ across all studies, and typically much higher (see supplementary materials). In all studies, creativity ratings between tasks were significantly correlated and so were collapsed into an overall creativity index for each participant.

Exclusions

Participants were excluded from analyses if they generated two or more unprocessable words during free association (e.g., "Nike," "Matthew," or "Schnizzle"), if their forward flow was more than 3 standard deviations from the mean (often because they wrote the same words over and over), or if they left large portions of the survey unfinished (e.g., all the cognitive capacity measures). The number of exclusions for each study is detailed within that study.

Methods Used Across Some Studies

Assessing Cognitive Capacity

As creativity is often linked to general cognitive capacity (i.e., intelligence; Silvia, 2015), cognitive capacity was assessed in the first three studies as a control variable using some combination of three tasks. All tasks are detailed in full in the supplementary materials.

GRE Verbal. As forward flow is a verbal task, it is especially important to control for general verbal ability. We used problems from the GRE verbal to assess this ability.

Cognitive Reflection Task (CRT). In this three-item task, wrong answers spring quickly to mind whereas correct answers require more reflection (Frederick, 2005).

Raven's Matrices. This standard intelligence task asks people to complete a series of incomplete visually patterned matrices (Raven, 2000).

In all studies in which cognitive capacity was assessed, measures were significantly correlated and so were collapsed into a single cognitive capacity index for each participant.

Assessing Convergent Thinking

In Study 1, we assessed convergent thinking via the Remote Associates Task (RAT; Mednick, 1962; Simonton, 2015). In the RAT, respondents are given a set of triplets (e.g., cottage/swiss/cake) and asked to find a word that unites them (e.g., cheese). These triplets have only one solution and participants are not instructed to be creative. Convergent thinking was not assessed beyond the first study because it showed no significant correlations with other measures.

Creativity Achievement Questionnaire

In Study 6, we used a modified Creative Achievement Questionnaire (CAQ; Carson, Peterson, & Higgins, 2005) to measures real-world creative accomplishments in 10 domains: visual arts, music, dance, architectural design, creative writing, humor, inventions, scientific discovery, theater/film, and culinary arts. In our version of the CAQ, coders simply noted the presence or absence of clear success in a given domain.

Pilot Study: An Initial Test of the Link between Forward Flow and Creativity

We first conducted a small pilot study that measured forward flow (as assessed by LSA analyses of a free association sequence) and creativity (as assessed by three divergent thinking tasks: novel uses, draw an alien, and charity ideas) among 35 amateur actors (54.3% female, $M_{age} = 41.03$, $SD_{age} = 17.24$, 3 exclusions) attending a workshop. As predicted, forward flow predicted creativity ratings on divergent thinking tasks, $r(30) = .46$, $p = .008$, providing initial evidence for an association between the forward motion of free thought and creativity.

Studies 1 and 2: Correlation Between Forward Flow and Creativity

These studies assessed whether forward flow predicted creativity in divergent thinking tasks for college students (Study 1) and a representative sample of Americans (Study 2).

Study 1: College Students

Undergraduate University of North Carolina (UNC) students (N = 277, 55% female, $M_{age} = 19.76$, $SD_{age} = 2.65$, 60 exclusions) were recruited from high-traffic areas of campus until we achieved a sample size of at least 194, which would give us 80% power to detect an effect size of $r = .2$. Participants completed the forward flow measure and the “novel uses” and “draw an alien” tasks to measure creativity. Convergent thinking was assessed with the RAT and cognitive capacity was assessed with GRE Verbal questions and the CRT.

Results. As predicted, forward flow was positively associated with creativity, $r(215) = .24$, $p < .001$, even when controlling for cognitive ability, $\beta = .24$, $p < .001$. Figure 1 contrasts the thought plots of participants with high and low creativity ratings. Forward flow did not significantly correlate with convergent thinking, $r(215) = -.00$, $p = .96$, demonstrating some divergent validity (i.e., forward flow does not correlate with everything).

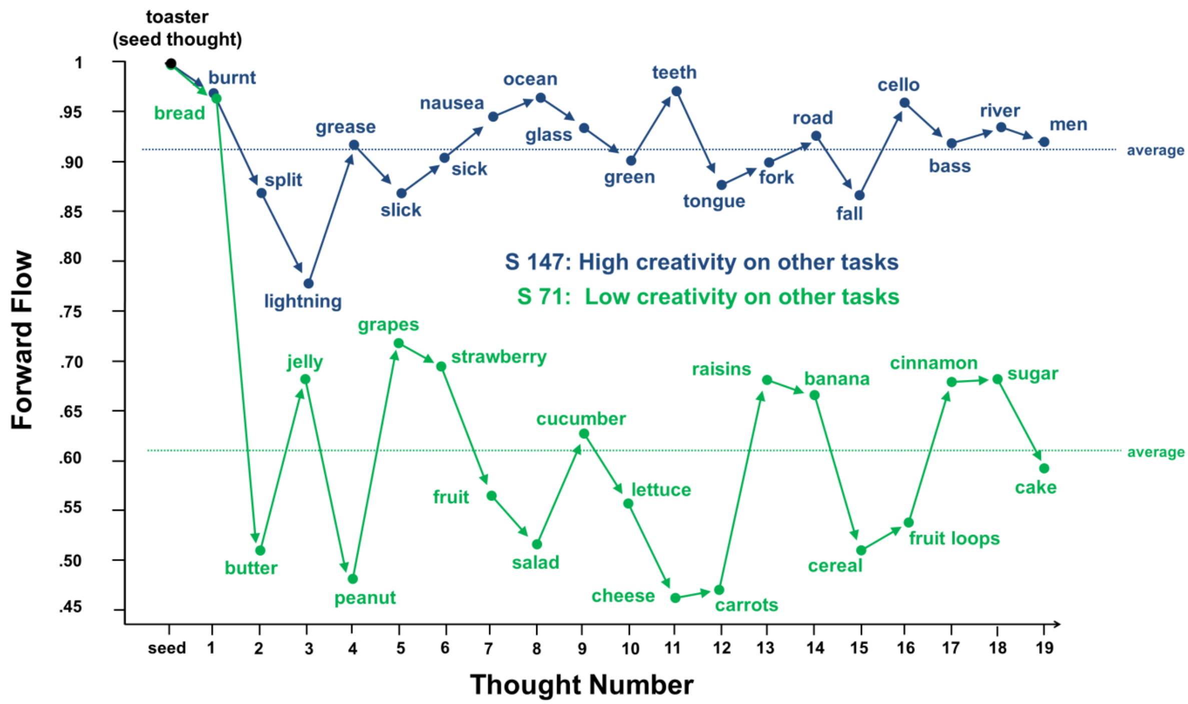

Figure 1: Thought plot comparing two participants from Study 1. The responses of S 147 (blue) on divergent thinking tasks were rated as more creative than those of S 71 (green).

Study 2: A Representative Sample of Americans

A representative sample of Americans in terms of age and socio-economic status completed the study via Qualtrics, who provided the sample via a "panel" (N = 581, 76% female, $M_{age} = 45.15$, $SD_{age} = 15.69$, 62 exclusions). Because we expected more measurement noise in the general public, we sought at least 80% power to detect an effect size between $r = .1$ and $r = .15$, achieved with approximately 500 participants. An online survey assessed forward flow and creativity—via the "novel uses," "caption," "similarity," and "charity idea" tasks. Cognitive capacity was assessed with GRE Verbal questions and Raven's matrices.

Results. As predicted, forward flow was positively associated with creativity ratings, $r(517) = .12$, $p = .009$, even when controlling for cognitive ability, $\beta = .09$, $p = .036$.

Studies 3-5: Known Creative Groups Validation of Forward Flow

Across the first two studies, forward flow in unconstrained thought was positively associated with creativity. Although many studies use these tasks, they have been criticized for not reflecting real-world creativity (Silvia et al., 2008). Studies 3-5 therefore use a known-groups paradigm to test links between forward flow and creativity in the real world: Do people with more real-world creativity have higher forward flow? And, can forward flow predict real-world creativity even when controlling for divergent thinking responses? We examined student performers (Study 3), and professional actors (Study 4) and entrepreneurs (Study 5).

Study 3: Comparing Performance Students with Non-performance Students

This study tested whether students in a traditionally “creative” major—dramatic performance majors who take acting, directing, and playwriting classes—have higher forward flow than non-performance students enrolled in a theatre history class.

Participants were recruited from UNC Drama classes (N = 254, 57.6% female, M_{age} = 19.44, SD_{age} = 2.72)—122 from performance-major classes (e.g., Acting, Playwriting) and 132 from a non-performance-major lecture-oriented class (Theatre History). Participants completed forward flow and the “novel uses” and “draw an alien” creativity tasks. Cognitive capacity was assessed with GRE Verbal questions and the CRT. There were 29 exclusions. For exploration, we collected forward flow at the semester’s end to examine test-retest reliability.

Results. As hypothesized, participants in performance-oriented classes had higher forward flow (M = .79, SD = .04) than participants in a lecture-oriented class (M = .76, SD = .05), $t(223) = 4.93$, $p < .001$, $d = 0.66$. Participants in performance-oriented classes also had more creative responses on the divergent thinking tasks (M = 2.02, SD = .62) than participants in the lecture-oriented class (M = 1.54, SD = .43), $t(223) = 6.80$, $p < .001$, $d = .91$, despite the fact that the two groups did not differ in overall cognitive ability, $t(223) = 1.18$, $p = .24$.

A logistic regression revealed that major type (performance vs. lecture) was significantly predicted by both forward flow, B = -10.10, SE = 3.44, $p = .003$, and rated creativity, B = -1.52, SE = .32, $p < .001$, but not cognitive capacity, $p = .73$. Exploratory analyses suggest test-retest reliability in forward flow across the semester, $r(167) = .40$, $p < .001$, with end-of-semester forward flow higher in performance students compared with lecture students, $t(167) = 3.49$, $p = .001$. Forward flow is higher in creative (vs. non-creative) college majors, even controlling for cognitive capacity and divergent thinking responses.

Study 4: Comparing Professional Actors with Internet Workers

This study attempted to replicate the results of Study 3 with another creative group—professional actors. As professional actors are required to be creative on a daily basis, we predicted they would have higher forward flow than a comparison group of internet workers.

We recruited working actors (N = 52, 48% female, M_{age}= 38.89, SD_{age} = 11.83) from the listserv of the Miller Voice Method Studio, a New York City company that trains people in presence, vocal clarity, and strength. Its listserv reaches 1000+ professional actors, with experience ranging from Broadway and Off-Broadway to Television and Film. We emailed the listserv 3 times to maximize sample size. As a comparison group, we recruited 100 Amazon Mechanical Turk workers (AMT; 29% female, M_{age} = 32.88, SD_{age} = 9.06—although 102 completed the study). Power analyses suggested 80% power to detect an effect size of $d = 0.43$, but as the effect size in Study 3 was higher ($d = 0.66$), we felt we had sufficient power. Given the difficulty of recruiting professional actors, a condensed survey assessed only forward flow and creativity (via the “novel uses” and “caption” tasks). There were 48 exclusions.

Results. As predicted, professional actors had higher forward flow ($M = .83$, $SD = .04$) than AMT participants ($M = .79$, $SD = .04$), $t(104) = 4.34$, $p < .001$, $d = 0.88$, and scored higher on creativity measures ($M = 2.16$, $SD = .51$) than AMT participants ($M = 1.70$, $SD = .38$), $t(104) = 5.33$, $p < .001$, $d = 1.08$.

A logistic regression revealed that sample group (actor vs. AMT) was significantly predicted by both forward flow, B = 20.29, SE = 6.56, and rated creativity, B = 2.11, SE = .56, *p*s < .003. Of course, actors and AMT participants likely differ on many characteristics, but professional actors also have higher forward flow than our sample of amateur actors from the pilot (M = .78, SD = .054), $t(68) = 4.38$, $p < .001$, $d = 1.05$. As professional and amateur actors performed similarly on divergent thinking tasks, $t(68) = 0.06$, $p = .96$, $d = 0.01$, forward flow seems more strongly associated with professional acting success than standard creativity measures.

This study again suggests that forward flow helps distinguish between highly creative and less creative groups of people, even when controlling for standard creativity measures.

Study 5: Comparing Professional Entrepreneurs with Professional Accountants

This study compared samples of entrepreneurs and accountants. Both groups were mid-career business professionals with similar education and financial standing (see below). However, because entrepreneurs often undertake creative ventures (Amabile, 1996; Schumpeter, 1934), we predicted they would have higher forward flow than accountants.

We recruited 159 entrepreneurs (25.8% female, $M_{age} = 54.53$, $SD_{age} = 12.38$) and 169 accountants (44.4% female, $M_{age} = 50.73$, $SD_{age} = 12.92$) via emails to UNC business school alumni, giving us 95% power to detect an effect size of $d = 0.36$. There were 28 exclusions.

Participants completed an online survey that assessed forward flow and creativity—via the “novel uses” and “charity” tasks. A manipulation check assessed how much they self-identified as an entrepreneur (Liñán & Chen, 2009): entrepreneurs did self-identify more ($M = 4.47$, $SD = .67$) than accountants ($M = 2.20$, $SD = 1.24$), $t(296) = 19.46$, $p < .001$, $d = 2.26$.

Participants also self-reported the importance of creativity, risk-taking, pivoting in business, financial performance, and financial wellbeing. A Varimax factor analysis revealed that these five measures formed two factors with eigenvalues above 1. The first three formed a risk/pivoting factor and the last two formed a financial success factor. All measures are listed in supplementary materials.

Results. As predicted, entrepreneurs had higher forward flow ($M = .81$, $SD = .04$) than accountants ($M = .79$, $SD = .05$), $t(296) = 3.70$, $p < .001$, $d = 0.43$. Entrepreneurs also scored higher on creativity measures ($M = 1.88$, $SD = .47$) than accountants ($M = 1.77$, $SD = .34$), t(296)

= 2.43, *p* = .016, *d* = 0.28. Entrepreneurs scored higher (M = 3.38, SD = .58) than accountants (M = 2.92, SD = .56) on risk/pivot, *t*(296) = 6.93, *p* < .001, *d* = 0.80 but not on financial success, *p* = .17.

A logistic regression revealed that membership in the entrepreneur (as opposed to accountant) career group was significantly positively predicted by forward flow, *B* = 9.21, *SE* = 3.04, and risk/pivot, *B* = 1.39, *SE* = .25, *p*s < .003, significantly negatively predicted by financial success, *B* = - .39, *SE* = .19, *p* < .04, and was not predicted by rated creativity on divergent thinking tasks, *p* = .36.

As in Studies 3-4, forward flow was higher in a real-world creative group (entrepreneurs vs. accountant) and predicted this group membership even controlling for other variables.

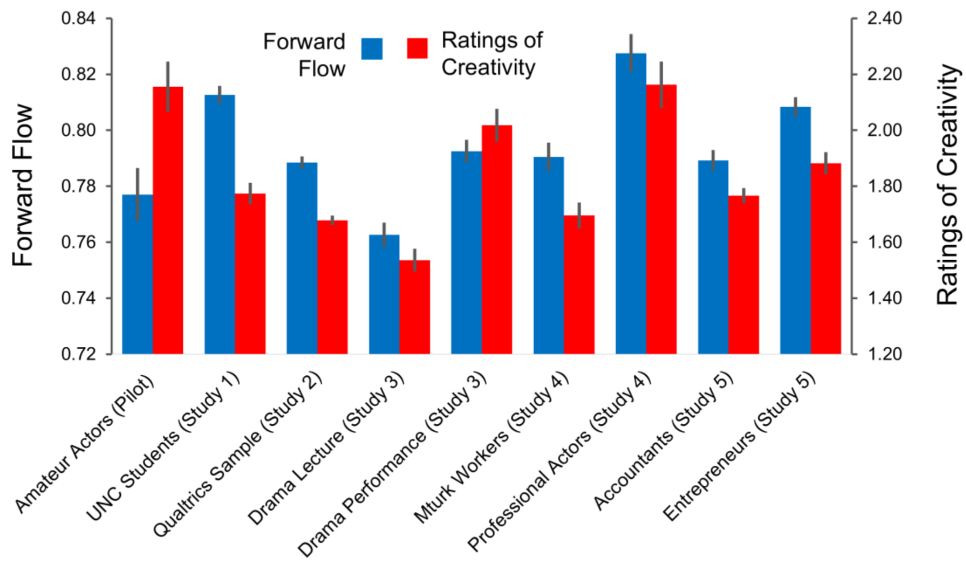

Figure 2. Average forward flow and rated creativity on divergent thinking tasks, by sample and study (Studies 1-5).

Super-analysis: Combining All Data

Given the variety of effect sizes across our previous studies, we now report results of a “super analysis” that includes all participants from Studies 1-5 as well as the pilot study. Unlike a traditional meta-analysis, which combines effect sizes of individual studies, this analysis combines all forward flow and creativity ratings into one sample, allowing us to capitalize on the large diversity among samples. Across all participants (*N* = 1397), forward flow was positively associated with creativity, *r*(1395) = .19, *p* < .001, even when controlling for cognitive capacity in the studies that measured it (Studies 1, 2, and 3), β = .20, t(958) = 6.49, *p* < .001. See Figure 2 for a bar graph comparing the average forward flow and creativity ratings of all samples and Figure 3 for a scatterplot of all forward flow and creativity ratings.

As a robustness check, we replicated our analysis using multilevel techniques, regressing creativity on forward flow while controlling for cognitive capacity and between-study variation (i.e., for the fact that participants are nested within studies). We used a linear mixed effects model where study sample was considered a random effect. Specifically, each sample contributes to the predicted value of a random intercept, assumed to be independently and identically drawn from a normal distribution with a mean of zero and unknown variance. As expected, the effect of forward flow on creativity remained positive and significant, $b = 1.89$, $SE = .30$; $p < .001$.

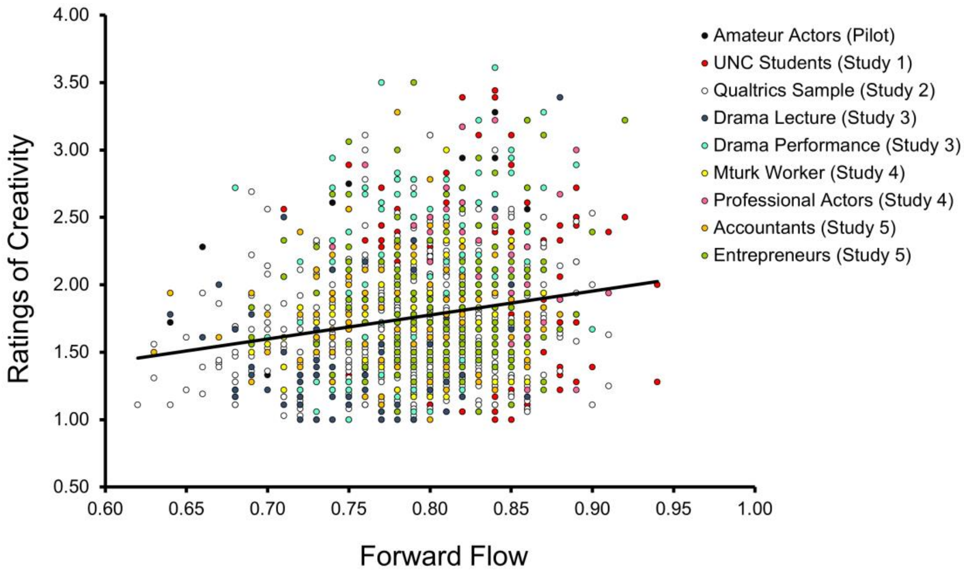

Figure 3: Forward flow and ratings of creativity in divergent thinking tasks across all participants in Studies 1-5 (N = 1395)

Study 6: Predicting Creative Achievement from Twitter Posts

To examine the predictive power of forward flow in a more naturalistic, real-world context, Study 6 tested whether the forward flow of celebrities' Twitter streams predicted the scope of their creative achievements. We suggest this study is especially useful for two reasons. First, it extends the predictive ability of forward flow to big data. Second, it addresses the (unlikely) possibility that participants may have been trying to generate outlandish associations to seem creative (i.e., "cheat" the measure of forward flow), even though they were not instructed to do so. Users on Twitter are not instructed to free associate nor are their tweets (often spanning across years) likely to be generated by concerns of maximizing semantic distance.

We developed an online Twitter application using Python code to analyze the forward flow of up to 3200 tweets (the maximum allowed for download) from each of the 100 most-followed Twitter users, including Jimmy Fallon, former President Barack Obama, and Kim Kardashian (see supplementary materials for complete list).[4] Our LSA engine was adapted to calculate the forward flow from a sequence of tweets, creating a composite score for each tweeter. There were 5 exclusions based on outliers of forward flow or unprocessable words.

To assess creativity, three coders (α = .77) blind to hypotheses completed the Creative Achievements Questionnaire (CAQ; Carson, Peterson, & Higgins, 2005) for each Twitter user. Although the CAQ is typically a self-report measure, here we used third-person ratings.

Results. As predicted, forward flow predicted Twitter users' CAQ score, $r(95) = .22$, $p = .035$. See Figure 4 for example thought plots comparing Ariana Grande and the Dalai Lama. These results suggest further promise for the predictive power of forward flow.

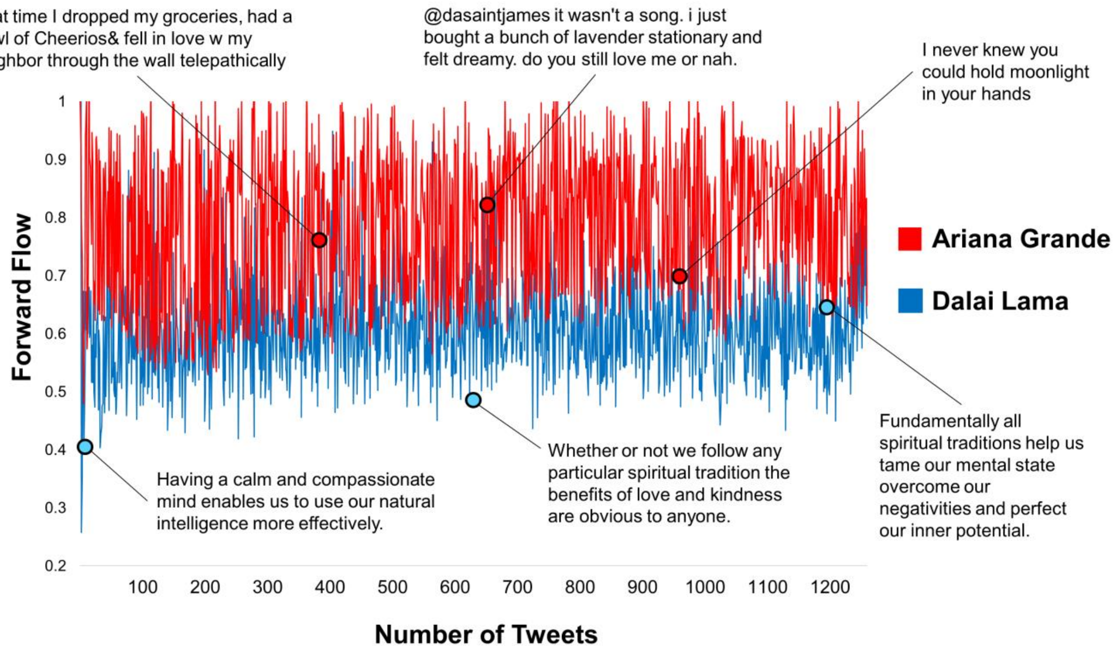

Figure 4: Forward flow across a sample of tweets from Ariana Grande (red) and the Dalai Lama (blue). The higher flow of Grande reflects greater semantic evolution across posts.

General Discussion

Our everyday subjective experience can be likened to a stream of thoughts, flowing freely over time (James, 1890); however, modern psychological studies frequently measure task-bound thoughts at a single point time. While focused measures of thoughts are undoubtedly useful, it

[4] We note that these data were collected in the summer of 2016, before Twitter restricted the available tweets for download to include only the last 6 days (and also before the election of Donald Trump).

may also be worth studying the dynamic unfolding of unconstrained thought. In this paper, we provide a metric that captures the semantic evolution of relatively free thought as represented by free association—a metric called "forward flow." Consistent with links between creativity and free thought (as captured by default network activity; Beaty et al., 2016), we suggest that forward flow also predicts creativity.

Across multiple studies, forward flow was associated with creativity as assessed by both well-validated tasks and real-world career trajectories. Studies 1-2 revealed that forward flow was positively associated with people's ability to provide creative answers on divergent thinking tasks, even controlling for cognitive ability. Studies 3-5 revealed that forward flow predicts more creative college major and careers, even controlling for creativity in divergent thinking tasks. A super-analysis examined forward flow metrics across all participants and samples and revealed a robust relationship between forward flow and ratings of creativity. Study 6 revealed the predictive power of forward flow within a truly naturalistic context: Twitter. The semantic evolution of tweets predicted assessments of celebrities' creative achievements. The utility of forward flow is further advanced by a suite of open-access web resources, which can be used for both demonstrative purposes and large-scale data analyses.

Caveats

We recognize creativity is multifaceted and its breadth cannot be reduced to a single metric. Indeed, the point of these studies is not to argue that forward flowing thought is the best predictor of creativity, but instead to provide a proof of concept for an important addition to researchers' toolboxes. Combined with other metrics of unconstrained thought—such as mind-wandering (Smallwood & Schooler, 2015), speed of thought (Pronin & Jacobs, 2008), or vividness of imagery (McKelvie, 1995)—forward flow may help scientists quantify the various dimensions of subjective experience.

We also recognize potential issues with forward flow. First, forward flow captures only one aspect of free thought, and there may be other ways to quantify the richness of naturalistic thought. Second, as with any individual difference measure (Paulhus, 1984), people can "cheat" on forward flow. For example, it is possible to increase forward flow by deliberately trying to generate random words. Because forward flow is a measure designed to capture unconstrained thought, it will likely not be diagnostic if thoughts are deliberately bent on generating randomness. Forward flow may also be less predictive if contaminated by task-bound thoughts, and so should generally be assessed via free-association at the very beginning of a study session.

Beyond Creativity

Forward flow may predict creativity, but it should not be thought of as merely a creativity measure. Instead, we suggest the semantic dynamics of thought may predict other phenomena across scales of human behavior. At the level of the brain, forward flow may predict neural dynamics such as connectivity between intrinsic neural networks related to memory and emotion, because semantic associations help to trigger (and are triggered by) episodic memories

(Baddeley, 2007) and affective content (e.g., being positive or negative; Lindquist et al., 2012).

The affective content of naturalistic thoughts may also allow forward flow to predict emotional trajectories, such as mania (high forward flow) and depressive rumination (low forward flow), consistent with work that links mood with both "mental progression" (Mason & Bar, 2012) and free association breadth (Brunyé, Gagnon, Paczynski, Shenhav, Mahoney, & Taylor, 2013). Forward flow may predict other individual-level variables: In therapeutic writing, it could predict post-traumatic growth (Pennebaker, 1997; Woodward & Joseph, 2003), and in life narratives, it could predict flourishing (McAdams, 1997). Forward flow could predict the quality of gut decisions in complex situations (Hayashi, 2001), someone's adaptability to new situations (Pulakos, Arad, Donovan, & Plamondon, 2000), and leadership ability—as all require dynamic adjustment over time. Indeed, James (1880) believed that "great men" have high forward flow.

At the level of groups, the forward flow of meetings may predict their productiveness, as discussions that keep spiralling around the same topic are likely to be less than useful. Relatedly—but at a larger scale—forward flow in congressional sessions could predict their level of accomplishments and the resultant appproval ratings. Across large scales of time, forward flow in fiction books may predict the vitality of the arts and forward flow in scientific abstracts may predict the vitality of science. Even within single creative products, forward flow could predict whether a book's plot seems compelling or whether a play's characters seem dynamic. More generally, forward flow provides a new metric for scholars who use naturalistic language processing to predict behavior (e.g., Pennebaker, 2011; Packard & Berger, 2016). By examining the evolution of semantics, forward flow may explain additional variance.

Linear or Non-Linear? Forward Flow and Mental Illness

One important remaining question is whether the relationship between forward flow and creativity is linear. Some psychological disorders are characterized by disorganized thoughts (e.g., schizophrenia; Moritz, Woodward, Küppers, Lausen, & Schickel, 2003); and while such disorganization likely yields high forward flow, it may not yield high creativity—especially insofar as creativity requires usefulness in addition to originality (Runco & Jaeger, 2012). While there are robust correlations between mental illness and creativity (Kyaga et al., 2013), even our most creative samples—acting students and creative professionals—had a mean forward flow of ~.83, which is some distance from the theoretical maximum of 1.00. It may be that a completely disorganized stream of consciousness represented by extreme forward flow is tied to detriments in creative performance. If true, this suggests forward flow—at its upper bounds—might also be a useful indicator of some kinds of mental illness, consistent with recent work on atypicality in semantic memory structure (Faust & Kenett, 2014). Moreover, although we have suggested high forward flow helps creativity, it may hinder task performance when focus is required—e.g., for air traffic controllers or pilots (Kanfer & Ackerman, 1989).

Conclusion

More than a century ago, William James suggested that our mental lives may be best understood as a stream of thoughts. The idea of "forward flow" both formalizes this insight and quantifies the classic technique of free association so that free thought can be easily assessed in modern psychology. As a demonstration of the utility of free thought, our studies revealed that forward flow predicts creativity across diverse domains. Beyond creativity, there are likely many ways in which the dynamics of free thought are predictive; perhaps the drifting thoughts of an idle mind can be put to work.

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