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Free Association Ability Distinguishes Highly Creative Artists From Scientists: Findings From the Big-C Project

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The associative theory posits that creativity relates to people's ability to connect remote associations to form new ideas, based on the structure of their semantic memory. This theory has spurred several recent studies connecting semantic memory structure and associative thinking to creativity, capitalizing on advances in computational methods. To date, however, this research has almost exclusively focused on assessing creativity in the general population (e.g., assessed via divergent thinking tests), with far less work examining the role of associative thinking in eminently-creative individuals across the arts and sciences. Leveraging data collected as part of the Big-C Project—a sample of world-renowned visual artists (VIS) and scientists, and an intelligence-matched comparison group—we tested whether the ability to generate remote word associations differs as a function of creative expertise. Specifically, we used distributional semantic models to calculate the semantic distance of word associations across three conditions: a free association condition and two goal-directed conditions (common association and uncommon association). We found an interaction between domain expertise and association condition: while artists generated more distant associations overall, this effect was driven by substantially more distant responses in the free association condition. Our findings indicate that VIS spontaneously produce more remote associations—potentially due to a more interconnected semantic memory network structure—but that creative expertise is less relevant for producing associations that require goal-directed cognitive search. The findings are interpreted in the context of the ongoing debate on the domain-generality and domain-specificity of creativity.

Keywords: expertise, domain-specific creativity, semantic memory, free association

An ongoing question in creativity research concerns how existing knowledge is retrieved from memory and combined to form novel ideas (Abraham & Bubic, 2015; Benedek & Fink, 2019; Benedek, Franz, et al., 2012; Kenett, 2018a). The associative theory of creativity, proposed by S. Mednick (1962), postulates that creativity relies on the structural characteristics of semantic memory—mental storage for knowledge and concepts—which constrains the processes governing mental navigation (i.e., search) when connecting remote concepts to generate ideas (He et al., 2020; Kenett & Faust, 2019; Ovando-Tellez, 2022; R. Beaty & Kenett, 2020; Volle, 2018). The associative theory of creativity has since been expanded upon, now being understood to inform a larger dual-process framework of creative cognition, one which acknowledges the roles of both bottom-up/structural and top-down/executive processes (Sowden et al., 2015; Zhang et al., 2020). In particular, the relevance of bottom-up, structural memory processes has been informed by several recent studies showing that individual differences in creative thinking ability, across the general population, are related to variations in the structure of semantic memory (Benedek, Franz, et al., 2012; Benedek, Könen, et al., 2012; Kenett et al., 2014, 2018; Li et al., 2021; Ovando-Tellez, Kenett, et al., 2022; Beaty et al., 2014, 2021).

Associative abilities—individual differences in concept retrieval and combination—were the original focus of Mednick's work, who suggested that variation in associative strength between concepts is a primary source of individual creative ability (S. Mednick, 1962). Yet measuring associative abilities has been challenging, and direct evidence for Mednick's theory has been limited (see Benedek & Neubauer, 2013). Recently, advances in the computational modeling of semantic memory, that is, via network science and distributional semantic modeling, have enabled researchers to quantify associative abilities and link them to individual differences in creativity (e.g., He et al., 2020; Beaty & Johnson, 2021). So far, such work has focused exclusively on "domain-general" creativity (e.g., Gray et al., 2019; Beaty et al., 2021). However, little is known about whether such associative abilities extend to real-world creativity in the arts and sciences, in part due to the difficulty of accessing eminent creators and quantifying word associations. In the present research, we leverage data collected as part of the Big-C Project (Knudsen et al., 2019)—a sample of world-renowned VIS and prolific scientists—and use distributional semantic models

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to objectively quantify the semantic distance of word associations (Kenett, 2019; Beaty & Johnson, 2021).

According to the associative theory of creativity, the recombination of distant or weakly connected semantic concepts is central to creative thinking, and this process is largely dependent on the underlying structure of the semantic system (Abraham & Bubic, 2015; Kenett, 2018b; S. Mednick, 1962). The classic network model of semantic memory, proposed by Collins and Loftus (1975), suggests that the strength of a semantic association between two concepts is determined by the overlap of shared features: the higher the similarity between two semantic concepts, the stronger the link connecting their respective mental representations (see also Klimesch, 1987; Kroll & Klimesch, 1992). Further, distributed semantic memory frameworks have stressed the importance of featural overlap over shared semantic categories as the driver for semantic similarity (Masson, 1995). Semantic similarity has since been understood to be comprised of several possible associative relations of meaning, such as perceptual, functional, or contextual (Allport, 1976; McRae & Boisvert, 1998), or as grounded in either taxonomic or thematic relations (Mirman et al., 2017). Measuring semantic similarity enables researchers to capture associative processes unfolding over a segment of a semantic memory network. In this context, creative ideation is thought to arise from the recombination of stored semantic items into novel and useful products or ideas, an ability that would be facilitated by a rich and flexible semantic memory network structure (i.e., stronger and more connections between distantly related concepts).

Word association tasks (WATs) have long been employed to study the mechanisms of creative thought, particularly when evaluating an individual's ability to formulate remote associations between existing knowledge (S. Mednick, 1962). For example, Mednick and colleagues found that highly creative individuals—having scored highly on the Remote Associates Task—generated more (and faster) word associations than low-creative individuals (M. T. Mednick et al., 1964). These findings were corroborated in later works demonstrating the critical role of associative abilities in divergent thinking ability, with one study finding that associative abilities explained roughly half of the variance in divergent thinking performance (Benedek, Könen, et al., 2012). Other recent work has focused on free association, where no explicit creativity instruction or goal-directed strategy is required, such as forward flow, that is, continuously producing the first word that comes to mind in response to a cue word (Gray et al., 2019; Beaty et al., 2021). Although free association has a long tradition in creativity research (Gough, 1976), only recently has it been objectively quantifiable by computational tools, allowing researchers to ask more nuanced questions regarding the role of associative processes in creativity.

To quantify performance on WATs, researchers are increasingly employing computational tools based on distributional models of *semantic distance*. Distributional semantic models calculate word-pair similarity via the distributional probabilities in large text corpora of natural language (e.g., textbooks) based on co-occurrences: words that tend to co-occur (e.g., *pen-paper*) have a higher semantic similarity value (and thus lower distance value) than words that do not (Günther et al., 2019). The earliest application of distributional semantic models in creativity research is through latent semantic analysis (LSA). LSA leverages natural language corpora and calculates pairwise co-occurrence probabilities between words, as exemplified by one of its earliest applications in modeling vocabulary learning in children (Landauer & Dumais, 1997). More recently, Beaty and Johnson (2021; cf. Dumas, 2021) introduced additional semantic models in the computation of semantic distance for creativity assessment—including neural network models that use prediction and text corpora based on a diverse range of texts (e.g., movie subtitles)—yielding composite semantic distance values that are more generalizable (and less idiosyncratic) than a single model alone (Kenett, 2019). Semantic distance values correlate strongly with human evaluations of creativity, novelty, and appropriateness (Dumas & Dunbar, 2014; Dumas, 2021; Heinen & Johnson, 2018; Beaty & Johnson, 2021), thus providing an automated and objective tool for creativity research (Kenett, 2019).

Semantic distance has also yielded important insights into the cognitive processes involved in creative thinking. For example, cuing participants to "think creatively" on a verb generation task —thinking of verbs that can be creatively associated with nouns— resulted in higher semantic distance values, compared with when participants were not cued to think creatively (Prabhakaran et al., 2014). Cueing participants to think creatively has been shown to drive the engagement of top-down search processes associated with executive control, with one study showing that "be creative" instructions led to higher creativity scores in individuals with higher fluid intelligence on both verbal (Nusbaum et al., 2014) and figural (Wilken et al., 2020) divergent thinking tasks.

Cognitive research on creativity has focused extensively on studying cognitive processes relevant for creative thinking in the general population (i.e., domain-general or "little-c" creativity). In contrast, less work has examined cognitive processes as they relate to specific creative domains, such as the arts and sciences (i.e., domain-specific creativity), and even less work has directly studied creative cognition at the highest level of creative achievement (i.e., "Big-C" creativity) —likely due to the challenge of recruiting renowned artists and scientists to complete psychological tests.

However, decades of research and theory have been dedicated to understanding the role of knowledge in creativity, via case studies and experimental studies in students with modest levels of domain expertise (Finke et al., 1992; Weisberg, 1999; Wiley, 1998). According to the creative cognition perspective (e.g., Finke et al., 1992; Ward & Finke, 1995), creative thinking requires the extraordinary operation of ordinary cognitive processes, including the ability to flexibly build upon prior knowledge (at different levels of abstraction) to generate new ideas. Many other researchers have suggested that knowledge has a linear relationship with creativity: the more domain content (or expertise) that is acquired, the more likely that knowledge will be combined in creative ways (Hayes, 1989; Kulkarni & Simon, 1988; Weisberg, 1998). Moreover, according to the "tension" view of knowledge and creativity, too much knowledge can impede creativity by inducing fixation on what is known and thus not original (Frensch & Sternberg, 1989; Beaty et al., 2022; Simonton, 1984). Knowledge can induce fixation and rigidity, as studied extensively in the field of design (Jansson & Smith, 1991), although fixation may vary depending on domain and training (Purcell & Gero, 1996). Notably, these theories, and their supporting evidence, tend to focus on the quantity of knowledge—whether acquiring more knowledge benefits creativity—and less on the quality (and organization) of such knowledge. The present study extends past work by examining how the organization of knowledge relates to creative achievement in the arts and sciences (cf. Groussard et al., 2010; Merseal et al., 2023).

Another enduring question in the literature concerns the extent to which domain-general cognitive systems (e.g., semantic memory) contribute to domain-specific creative performance (e.g., literary, or visual arts). Although some studies have reported differences between artists, scientists, and less-creative individuals on measures of creativity and general cognitive abilities (e.g., intelligence; J. C. Kaufman et al., 2009; S. B. Kaufman et al., 2016; see also Dumas et al., 2021; Meyer et al., 2019), other studies have either found no differences between these groups (J. C. Kaufman & Baer, 2004; van Broekhoven et al., 2020) or differences that are common to exceptionally creative artists and scientists compared with less creative people (Feist, 1998; Gable et al., 2019). Similarly unclear is the extent to which creative thinking operates over domain-general or domain-specific knowledge structures. That is, when thinking creatively, how much do experts draw upon their general knowledge of the world versus their expert knowledge of a domain? It is therefore unclear whether and how exceptionally creative artists and scientists differ at the level of fundamental cognitive systems (e.g., semantic memory).

The Present Study

Recent developments in distributional semantics are uncovering associative processes that underlie creative thinking. Distributional models of semantic distance, for example, can now quantify "how far" people mentally travel when searching for creative ideas (Kenett, 2019), and they are also sensitive to subtle variations in memory retrieval strategies, such as free association versus goal-directed search (e.g., instructions to "be creative"; Heinen & Johnson, 2018). However, these insights have been mostly limited to non-specific, domain-general creativity, and much less is known about cognitive processes associated with domain-specific creativity, likely due to the challenge of gathering a sufficiently large sample of highly successful creatives (Sternberg & Lubart, 1996).

Here, we leverage data collected as part of the Big-C Project—a sample of eminent, world-renowned artists and scientists, and an intelligence-matched comparison group—who completed a range of personality and cognitive assessments, including a WAT (Knudsen et al., 2019). The WAT required participants to produce a single-word association in response to a series of cue words. Importantly, the WAT included three instructional conditions—one free association condition (say the first word that comes to mind) and two goal-directed search conditions (think of a common or uncommon word)—allowing us to test whether different instructions (and corresponding cognitive strategies) yield different responses in artists, scientists, and the comparison group, based on computational models of semantic distance.

We hypothesized that, consistent with past work (Heinen & Johnson, 2018; Rastelli et al., 2022), the three instructional conditions would result in increasingly distant responses, from common to free to uncommon, respectively, as measured with distributional semantic models. More importantly, we hypothesized that the three groups would not differ on semantic distance for the goal-directed conditions (common and uncommon) because the groups were matched on intelligence. That is, the common and uncommon conditions should more strongly rely on controlled memory retrieval, and thus intelligence (Gerwig et al., 2021), consistent with past work on instructions and intelligence on verbal creativity (Nusbaum et al., 2014).

Critically, we expected artists to show higher semantic distance scores in the free association condition. This rationale was based in part on previous reports of artists showing higher openness to experience (Feist, 1998) and associative abilities (Dumas, Doherty, & Organisciak, 2020; Gray et al., 2019) when compared with less creative control groups. Higher openness to experience has also been linked to a more flexible semantic memory network structure (Christensen et al., 2018), and since artists tend to show higher levels of Openness compared with scientists (S. B. Kaufman et al., 2016), artists should more easily combine distant concepts when freely associating.

Method

Participants

The Big-C Project examined personality, cognitive ability, and brain functioning in eminently creative artists and scientists (Japardi et al., 2018; Knudsen et al., 2019). After identifying a list of candidates from lists of prestigious award recipients (e.g., Guggenheim Fellowships, Macarthur Awards), recommendations by an advisory panel of internationally acclaimed VIS and scientists, and bibliometric statistics (for scientists), 398 Big-C participants were invited, and 227 comparison group participants. The comparison group participants were, in part, invited based on educational achievement and/or performance on IQ subtests in prior research. Doctoral-level comparison group candidates were also recruited through electronic flyers posted on local university listservs. Following informed consent ($N = 107$), participants completed a large test battery of creativity, cognitive ability, personality, and psychopathology measures. Initial reports of these data can be found in Knudsen et al. (2019); the present analysis is a secondary analysis from previously unreported data collected during the Big-C Project.

Knudsen et al. (2019) reported results of some of these measures for the same sample that is reported here: Big-C VIS ($n = 35$, 49% women, M age = 43 years, $SD = 7$), Big-C scientists (SCI, $n = 41$, 46% women, M age = 45 years, $SD = 8$), and a "smart comparison group" (SCG; $n = 31$, 52% women, M age = 42 years, $SD = 9$). The group classification was confirmed by the Creative Achievement Questionnaire (CAQ; Carson et al., 2005). The VIS group had full CAQ scores on average about 100 times higher than SCG, and the SCI group had CAQ scores about 50 times higher than SCG, in the domains of Visual Arts and Science/Invention, respectively. The SCG was matched to the wider Big-C sample in terms of age, sex, race/ethnicity, parental education, and estimated IQ. Individuals within the SCG had no prior history of psychiatric illness or brain injury, as well as no current drug or alcohol abuse. Additional demographic information about the overall sample, as well as tasks completed as part of this battery, can be found in Knudsen et al. (2019).

Due to the length of the test battery, all participants did not complete all tasks: 2 from the VIS group, 4 from the SCI group, and 4 from SCG. Here, we include only participants who completed the WAT ($N = 98$, 48 women, M age = 44.26, $SD = 1.5$). These participants did not differ from the overall group on demographic characteristics or estimated IQ (for the 95 participants who completed the WAIS-Vocabulary and Matrix Reasoning tasks). A chi-square test of homogeneity revealed that the proportions of sex between these three groups of VIS (15 female, 45.5%), SCI (19 female, 51.4%), and SCG (14 female, 49.0%) were not statistically significantly different, $p = .879$. A one-way ANOVA showed that there were no statistically significant group differences in age between VIS ($M = 44.30$, $SD = 7.96$), SCI ($M = 46.39$, $SD = 7.91$), and SCG ($M = 42.25$, $SD = 9.29$), $F(2, 95) = 1.98$, $p = .143$. A one-way ANOVA also showed no statistically significant group differences in estimated IQ between VIS ($M = 111.74$, $SD = 10.83$), SCI ($M = 113.97$, $SD = 9.92$), and SCG ($M = 113.25$, $SD = 10.31$), $F(2, 92) = 0.405$, $p = .668$.

To highlight how well the groups matched, we used Hedge's g as a measure of between-subject equivalence between the SCG and Big C groups. Regarding the estimated IQ between SCI and SCG, Hedge's $g = 0.14$. For estimated IQ between VIS and SCG, Hedge's $g = -0.07$. Regarding age between SCI and SCG, Hedge's $g = -0.24$. For age between VIS and SCG, Hedge's $g = -0.48$.

Materials

Word Association Task

A total of 24 noun words (see item 1 in the Appendix) were extracted from an inventory published in Palermo and Jenkins (1964). Participants were asked to verbalize single-word responses that they thought would be associated with each item, across three consecutive task phases. Task phases were defined by the specific instructions that were given to participants (see item 2 in the Appendix for specific instruction wording) and the same items were presented in each phase. Phase 1 (*free*) required participants to respond with the first solution that came to mind (i.e., free association). Participants were specifically instructed to respond as quickly as possible. In contrast to Phase 1, Phases 2 and 3 assessed goal-directed word association. Phase 2 (*common*) required participants to provide a word that most people would think of. Phase 3 (*uncommon*) required participants to provide idiosyncratic responses, namely words that were uncommon and relevant to the presented item. Participants were provided more time to generate responses for Phases 2 and 3, being encouraged to respond only after 10–15 s.

Importantly, we did not counterbalance the order of conditions to avoid priming effects on the free association and uncommon conditions. For example, instructing participants to think of uncommon responses first can bias their responses on subsequent free association tasks by priming a specific cognitive search strategy before a condition that is intended to promote unconstrained thinking (cf. Heinen & Johnson, 2018). Responses were recorded in handwriting by the administering experimenter.

Semantic Distance

Semantic distance scores were calculated using the method described in Beaty and Johnson (2021). Specifically, we computed the semantic distance between each cue word and its responses using *SemDis*, an open-access web application developed to automate scoring of novelty and creativity (semdis.wlu.psu.edu). Semantic distance is increasingly used in creativity research to objectively quantify conceptual distance on verbal tasks (including WATs) by computing the inverse of the cosine similarity (i.e., 1-similarity) between word vectors in high-dimensional semantic space (Hass, 2017a, 2017b; Kenett, 2019). Several studies have found that semantic distance values correlate positively with human judgments of novelty (Dumas & Dunbar, 2014; Heinen & Johnson, 2018) and creativity (Orwig et al., 2021; Beaty & Johnson, 2021), as well as established measures of creativity (e.g., creative achievement)—providing evidence for the validity of this automated approach (Gray et al., 2019; Beaty et al., 2021).

SemDis generates a composite semantic distance score from the average scores calculated from five different semantic spaces, reducing the idiosyncratic effects of a single model/text corpus (e.g., textbooks vs. movie subtitles; Kenett, 2019; Beaty & Johnson, 2021). Three of these spaces are built upon continuous bag of words (CBOW) prediction models (cbowukwacsubtitle, cbowsubtitle, and cbowBNCwikiukwac) and two are built upon count models (GloVe and Touchstone Applied Science Associates [TASA]). The CBOW models use a neural network architecture (Mandera et al., 2017) that predicts a given word from surrounding context words within a given text corpus. In this instance, the three CBOW models used (a) a concatenation of the ukwac web crawling corpus (~2 billion words) and the English subtitle corpus (~385 million words; cbowukwacsubtitle); (b) only the English subtitle corpus (cbowsubtitle); and (c) a concatenation of the British National Corpus (~2 billion words), ukwac corpus, and the 2009 Wikipedia dump (~800 million words; cbowBNCwikiukwac). The two count models, which count the co-occurrence of words within text corpora, include (a) the global vectors (GloVe; Pennington et al., 2014) model, which is trained on ~6 billion tokens across a concatenation of the 2014 Wikipedia dump and the Gigaword corpus (news publications from 2009–2010); and (b) the TASA model, which uses LSA to compute co-occurrences across a text corpus of documents, textbooks, and literary words.

Analytic Goals and Statistical Approach

The present study had two main goals: (a) to test whether semantic distance differed across the three WATs (free, common, and uncommon) and (b) more importantly, to test whether Big-C artists, Big-C scientists, and comparison group participants produced more (or less) distant responses on the three association tasks. Data analyses were conducted using *R* v4.1.0 (R Core Team, 2020), with figures generated using ggplot2 (Wickham, 2016). All analysis code is publicly available on GitHub (https://github.com/hannah-merseal/big-c-semantic-fluency).

Results

WAT Responses

Each participant produced 24 associations per condition (free, common, uncommon), for a total of 7,056 responses. Responses were curated and transformed for semantic distance analysis (e.g., correcting spelling errors, transforming plural nouns into singular, removing proper nouns and non-words not recognized by the semantic models) by two independent raters. This preprocessing resulted in a total of 244 changed responses and 7 removed responses. The remaining 7,049 responses were uploaded to the SemDis platform to calculate a mean semantic distance score for each item-response pair.

Semantic Distance

Normality of the data was checked and confirmed, with a slight left skew. Levene's test for equality of variances between groups/

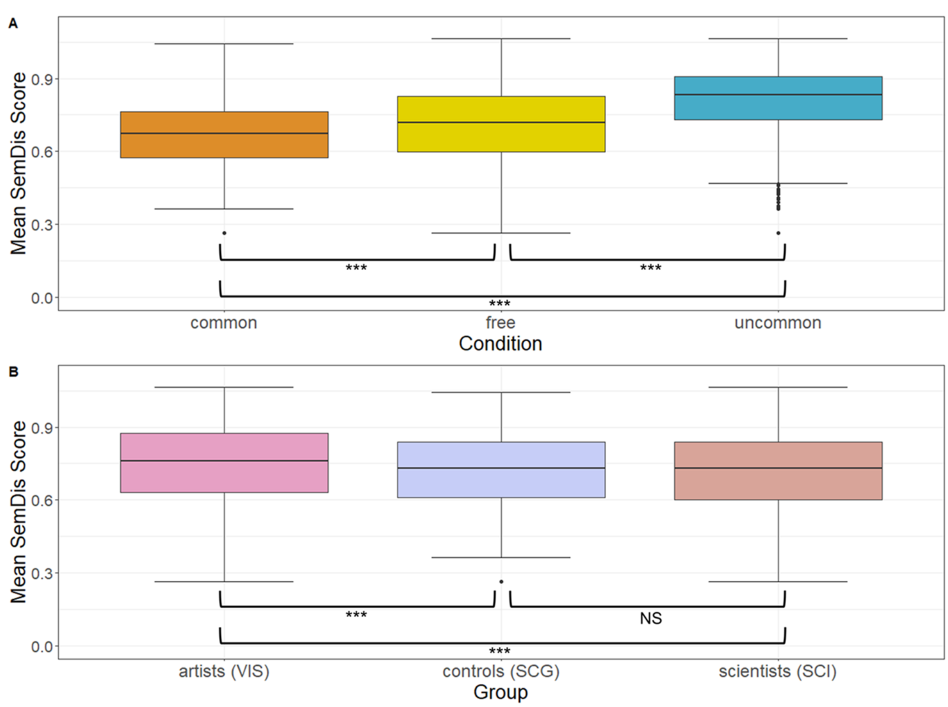
conditions revealed that semantic distance scores violated the homogeneity of variances assumption. We therefore interpreted differences between groups and conditions, and the interaction between the two, using a robust two-way factorial ANOVA with trimmed means (*t2way* function in *WRS2* package, trim = 0.1; Mair & Wilcox, 2020). Robust statistical methods use trimmed means to increase statistical power and remain robust in situations of heteroskedasticity and mild departures from normality (Wilcox & Rousselet, 2018). Simple main effects, including an explanatory measure of effect size, were calculated using robust t-test analyses via the *t1way* (analogous to a 1-way ANOVA) and *lincon* (for multiple comparisons) functions, trim = 0.2. Effect sizes (ξ is analogous to partial eta-squared in ANOVA, $\hat{\Psi}$ is analogous to Cohen's d in t-test simple comparisons) of 0.10, 0.30, and 0.50 correspond to small, medium, and large effect sizes, respectively (Wilcox & Tian, 2011). False discovery rate (FDR) Bonferroni correction was applied to control for multiple comparisons during robust t-tests (Wilcox, 2011). For further information on robust methods, we refer readers to Wilcox (2011).

Our analysis began by testing whether semantic distance differed across the three conditions (free, common, and uncommon). A robust two-way factorial ANOVA revealed a significant effect of condition, $F(2, 2{,}789) = 661.30$, $p < .001$, $\xi = 0.46$, p-FDR $< .001$ (Figure 1a) such that responses generated in the uncommon condition ($M = 0.81$, $SE = 0.003$) had higher *SemDis* scores than responses generated in the free ($M = 0.70$, $SE = 0.004$). $\hat{\Psi} = -0.11$, 95% CI [−0.12, −0.10], $p < .001$, or common ($M = 0.66$, $SD = .003$). $\hat{\Psi} = -0.16$, [−0.17, −0.15], $p < .001$, conditions. Free association responses had higher scores than common association responses, $\hat{\Psi} = -0.05$, [−0.06, −0.03], $p < .001$. There was also a significant main effect of group, $F(2, 2{,}728) = 28.10$, $p < .001$, $\xi = 0.11$, p-FDR $< .001$ (Figure 1b), such that VIS responses overall ($M = 0.74$, $SE = 0.003$) had significantly higher *SemDis* scores than both SCI responses ($M = 0.71$, $SE = 0.003$), $\hat{\Psi} = 0.04$, [0.02, 0.05], $p < .001$, and SCG responses ($M = 0.71$, $SE = 0.004$), $\hat{\Psi} = 0.03$, [0.02, 0.04], $p < .001$. SCG did not have significantly higher *SemDis* scores than SCI, $p = .30$.

Next, we conducted the critical test of whether semantic distance differed as a function of group (VIS, SCI, SCG) and condition (free, common, uncommon). The interaction between group and condition on semantic distance scores was significant, $F(4, 7{,}038) = 33.83$, $p < .001$, p-FDR $< .001$ (Figure 2). For responses generated in the free association condition, VIS responses ($M = 0.74$, $SE = 0.006$) were significantly higher than SCI responses ($M = 0.67$, $SE = 0.006$), $\hat{\Psi} = 0.08$, 95% CI [0.06, 0.10], $p < .001$, and SCG responses ($M = 0.69$, $SE = 0.007$), $\hat{\Psi} = 0.06$, [0.04, 0.08], $p < .001$. For responses generated in the uncommon association condition, VIS responses ($M = 0.82$, $SE = 0.005$) were higher than SCI responses ($M = 0.80$, $SE = 0.004$), $\hat{\Psi} = 0.02$, [0.01, 0.04], $p = .002$, and SCG responses ($M = 0.80$,

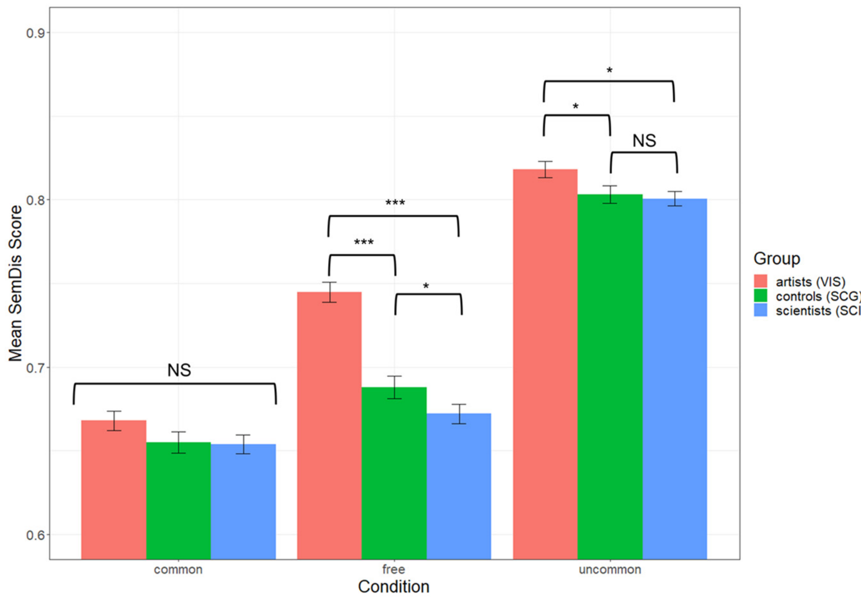
Figure 1

Mean Semantic Distance Scores Generated From the SemDis Application, for Overall Group (a) and Overall Condition (b)



Note. Overall group scores were calculated separately for the smart control group (SCG), scientists (SCI) and visual artists (VIS). Overall condition scores were calculated separately for the three instruction types of common, free, and uncommon association. X-axis label denotes group or condition; annotation denotes significance for main effects of group and condition. See the online article for the color version of this figure.
***$p < .001$, NS = not significant.

Figure 2
Mean Semantic Distance Scores Generated from the SemDis Application by Condition and Group



Note. Error bars represent standard error. Y-axis label denotes group; annotation denotes significance for within-condition effects. See the online article for the color version of this figure.
***$p < .001$. **$p < .01$. *$p < .05$, NS = not significant.

$SE = 0.005$), $\hat{\Psi} = 0.02$, [0.01, 0.04], $p = .02$. There were no significant differences between SCI and SCG, $\hat{\Psi} = 0.01$, [−0.01, 0.02], $p = .62$, in the uncommon association condition. No significant group differences were found for the common association condition.

Discussion

Mounting evidence supports the role of associative abilities in creativity (Benedek, Könen, et al., 2012; Kenett & Faust, 2019; R. E. Beaty et al., 2014, 2021), yet much less is known about whether such general cognitive abilities support domain-specific creative expertise. In the present research, we analyzed word association data collected as part of the Big-C Project (Knudsen et al., 2019) of eminently creative artists and prolific scientists. This allowed us to examine whether these creative experts (and an intelligence-matched comparison group) show differences in their ability to generate semantically distant associations across three conditions: a free association condition and two goal-directed conditions (common and uncommon association). As expected due to instructional differences, when collapsing across groups, uncommon associations were more semantically distant than free and common associations, and when collapsing across conditions, artists produced more distant associations overall. Critically, artists produced substantially more distant responses in the free association condition, compared with both scientists and comparison group participants, and compared with the goal-directed conditions. Our findings indicate that although artists, scientists, and intelligence-matched individuals (not selected for their creativity) produce similarly distant associations when prompted to do so (i.e., common and uncommon word associations), Big-C artists spontaneously produce far more distant free associations. Interestingly, artists scored slightly higher than both scientists and the control group in the uncommon condition—contrary to hypotheses—indicating a possible superiority of artists for producing uncommon associations across conditions.

The current study extends recent work on the role of associative abilities and semantic memory structure in creativity (He et al., 2020). Several recent studies indicate that general, non-specific, creative ability is characterized by a more "flexible" semantic memory structure, that is, high connectivity and short distances between concepts (Kenett et al., 2014; Li et al., 2021). This more flexible semantic memory structure is thought to be conducive to connecting remotely associated concepts to form new ideas (Kenett, 2018a). Here, using word association data from the Big-C Project (Knudsen et al., 2019), we show that highly creative artists produce more distant word associations when instructed to think of the first word that comes to mind. Although we did not explicitly model participants' semantic memory structure in this sample, one possibility is that artists exhibit a more flexible semantic memory structure that allows them to efficiently connect concepts. Notably, the sample was comprised of VIS, who do not typically have special linguistic training (e.g., like writers). It is thus remarkable that VIS would exhibit such pronounced word association ability, especially when compared with intelligence-matched scientists and comparison group participants (who possess comparable verbal abilities). Future research should explore whether superior free association ability is intrinsically domain-general within artistic domains, and whether the findings reported here relate to the underlying architecture of semantic networks.

Another finding from this study is that the groups performed comparably on the "goal-directed" conditions (i.e., common and uncommon), with the exception of modestly higher distances for artists in the uncommon condition. We interpret this observation in the context of cognitive control and goal-directed memory search processes. That is, the common and uncommon tasks gave participants an explicit goal, that is, find an association that is typical or unusual, respectively, which required generating retrieval cues that needed to be maintained in mind (e.g., "find a common associate") to strategically search memory. Because the three groups were matched on intelligence—a proxy measure for executive control that supports goal-directed memory search (Gottfredson, 1997; Jensen, 1998)—this likely indicates that artists, scientists, and comparison group participants were equally able to follow task instructions, strategically searching memory for appropriate responses. This finding is consistent with research on the contribution of cognitive control to creative thought (Benedek & Fink, 2019). For example, instructing participants to "be creative" during a divergent thinking task improves the creative quality of their responses (Acar et al., 2020; Harrington, 1975; Said-Metwaly et al., 2020). Notably, the same instructions have also been shown to engage cognitive control processes, as evidenced by a strengthening of the correlation between idea quality and fluid intelligence under such "be creative" instructions (Nusbaum et al., 2014).

On the other hand, it is possible that artists exhibited a less cognitively controlled approach (Chrysikou et al., 2014; Maysless & Shamay-Tsoory, 2015) to the free association task than scientists and comparison group participants. In other words, the control-related processes that supported the goal-directed conditions (common and uncommon) could have been suppressed in artists during the free association condition, allowing more distant associations to come to mind. This is consistent with the matched filter hypothesis, namely that task-dependent demands dictate the optimal levels of cognitive control required for its execution (Chrysikou et al., 2014). According to this hypothesis, tasks that require spontaneity and automaticity, such as those potentially engaging creative thinking, should benefit from lower levels of cognitive control. In this view, semantic memory structure would be less relevant (compared with "hypofrontal" states) for explaining performance differences across the groups. In this context, artists may benefit from a tendency to engage in combinatorial processes between more distant associations when freely associating, as suggested by their higher levels of Openness to Experience (Kaufman et al., 2016), a personality trait linked to flexible semantic network structure (Christensen et al., 2018).

The present research uncovers group-level (correlational) differences in semantic distance scores between artists and scientists. Future investigations are required to determine whether any causal relationship is driving the observed effects. Subsequent studies could examine whether the memory structure of artists dynamically shifts more than scientists over time. The findings should also be replicated and extended to other creative domains to warrant stronger generalizations beyond this sample of VIS and research scientists. Future research is also needed to disentangle the relative contributions of associative and controlled processes to both domain-general and domain-specific creativity, and to further examine the extent to which domain-general cognitive systems (e.g., semantic memory) support specific aspects of creative performance in the arts. Studies could also more directly link expertise and semantic memory structure. To do so, computational network science methods could be employed to model how artists and scientists organize concepts in long-term memory, allowing stronger claims to be made regarding the role of knowledge structure in associative cognition.

In sum, the present findings provide new insight into the cognitive profile of experts from separate creative domains. However, our study was limited in terms of sample size, given the challenge of recruiting a large sample of award-winning creatives. Moreover, given the relatively small sample size, we simply averaged the SemDis values across the five semantic spaces to derive person-level composite scores on the WAT. Future studies, with larger samples, should consider factor-analytic methods (R. E. Beaty & Johnson, 2021), which can model the relative weight of individual semantic spaces in composite/factor scores, unlike averaging, which assumes equal effective weights (Forthmann et al., 2022). Our findings are also correlational, so causal claims cannot be made. Moreover, it remains unclear the extent to which the observed differences in domain-general cognitive ability actually contribute to the creative outputs of artists and scientists, or whether they more narrowly characterize their general cognitive profile, without contributing to their creative practice. Future efforts should further characterize the cognitive profiles of domain-specific creative experts, for example, via longitudinal studies tracking the development of cognitive abilities at different stages of their careers. Such work could advance our understanding of the extent to which domain-general cognitive systems contribute to domain-specific creative achievement in the arts and sciences.

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Appendix

1. *Prompts for the Word Association Task.*

Fork	Pineapple	Lip
Skirt	Bus	Cake
Mustard	Salmon	Flute
Butterfly	Uncle	Thumb
Celery	Rabbit	Wrench
Lily	Hairdresser	Fir tree
Stomach	Table	Juice
Silver	Zebra	Raven

2. *Instructions for the Word Association Task.*

Free Association: (Participants should respond as fast as they can) “I am going to read you a list of words. Please respond to each of these words with the first suitable word that comes to your mind. Do not reflect too much, and please answer quickly. Ready?”

Common Association: (Participants can take some time, prompted after 10–15 s) “You may imagine that other people would not answer exactly the way you did. Nevertheless, there are some similarities in the way people reply to single words. Thus, most people would say for SHEEP, WOOL, or for WASP, BITE. On the other hand, scarcely anybody would reply to SHEEP, RABBIT, or to WASP, WING, although these are possible responses. I am going to read you the same words again. Now, please respond to each of these words with a word you think most or many people would give as a response. You may, of course, use words answered in the first round, if you believe many people would give them. Ready?”

Uncommon/Individual Association: (Participants can take some time, prompted after 10–15 s) “Now I am going to read you the list one more time. This time, please respond with a word that you think scarcely anybody else would use, *although it has some connection with the word read to you*. Thus, for instance, SHEEP and RABBIT, or WASP and WING are some words that have a relationship to each other, and yet almost nobody would answer that way. Ready?”

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