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ABSTRACT
Creativity is typically defined as the generation of novel and useful ideas or artifacts. This generative capacity is crucial to everyday problem solving, technological innovation, scientific discovery, and the arts. A central concern of cognitive scientists is to understand the processes that underlie human creative thinking. We review evidence that one process contributing to human creativity is the ability to generate novel representations of unfamiliar situations by completing a partially specified relation or an analogy. In particular, cognitive tasks that trigger generation of relational similarities between dissimilar situations – distant analogies – foster a kind of creative mind-set. We discuss possible computational mechanisms that might enable relation-driven generation, and hence may contribute to human creativity, and conclude with suggested directions for future research.

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Creativity: product and process

General criteria for creativity

A necessary, though certainly not sufficient, criterion for a creative act is that it serves to *generate* a novel idea or artifact that proves useful. To be creative is to make something that is both novel and (by some functional or aesthetic criterion) valuable (Sternberg & Lubart, 1995; Ward, Finke, & Smith, 1995). The nature of the created product can be indefinitely varied – a deeper understanding of genetics, a poem, a cryptocurrency, a more effective way to teach math, an artistic style, an energy-efficient heating system, a good joke. But one basic quality links them all: something new has come into being.

However, an idea or other product may be new, and prove to be of value, yet still not be considered highly creative (Boden, 2004). It has often been argued that a creative act cannot, in general, be identified solely on the basis of its product. Rather, what makes something creative may be defined in part by the *process* underlying the act itself (Green, Beaty, Kenett & Kaufman, 2023; Holyoak, 2019). Besides *what* was generated, we need to consider *how* it was generated – the mode of generation. A salient example of this general claim concerns the origin of a work of art – was this painting rendered by the hand of the master, or by a meticulous forger? If the latter, the painting's value – and probably its beauty in the eye of its beholder – is diminished. Goodman (1968, chapter "Art and Authenticity") has argued that an aesthetic difference in a work of art need not require a perceptual difference: however accurate a forgery may be, its aesthetic value is less than that of the original.

Generation by direct copying constitutes a process at the low end of a continuum of creativity. As schematized in Figure 1, a system for generating novel and potentially useful products can be viewed as having three interrelated components: an *agent* who selects *inputs* to which *processes* are applied to generate products. Each of these components can vary in ways that impact the perceived creativity of the system, yielding a rough continuum of creativity (in Figure 1, the high end is shown at top and low end at bottom). The agent can be autonomous or restricted in various ways; the input can be relatively open or closed, and the process can be relatively general (with constraints that guide search in a relatively open-ended space of possibilities) or specialized to a particular type of input. A generative process operating on relatively closed input might only apply to a particular domain of thought (e.g., mathematics) or a particular sensory modality (e.g., vision), whereas a process operating on more open input might apply to multiple semantic domains or sensory modalities. By an *autonomous* agent, we mean one with a set of characteristics often associated with human creativity (Amabile, 1996; Baum & Baumann, 2019): internal motivation to create, the capacity to select one's own goals, inputs, and processes, and the ability to evaluate partial and complete products. To the extent an agent lacks any of these characteristics, the overall process is

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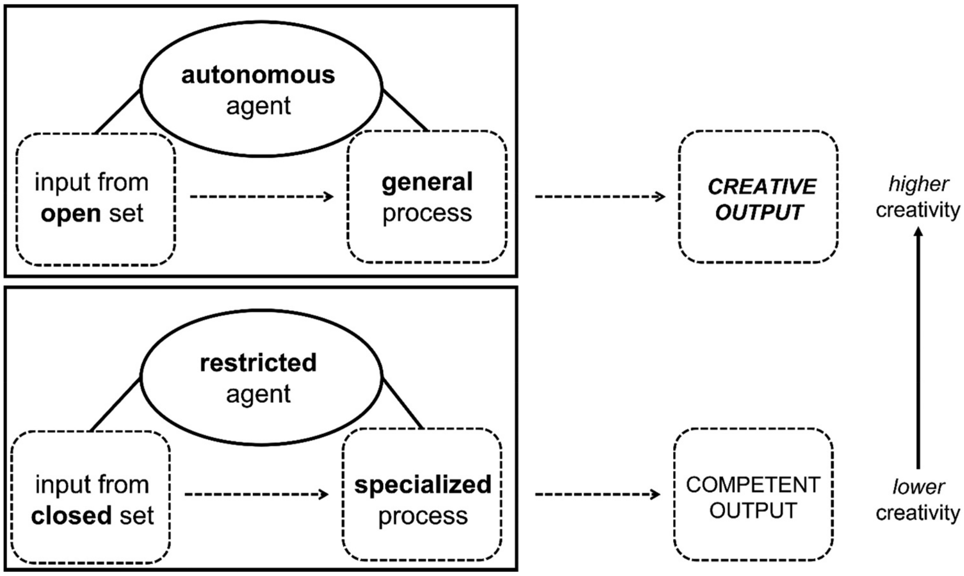

Figure 1. Schematic representation of modes of generation at high and low ends of a continuum of creativity.

less creative. A more autonomous agent is likely to have access to a more open set of inputs, making it possible to generate novel products by expanding the input set. A broader set of potential inputs in turn requires more general processes to operate on them. These general processes will be guided by inductive biases characterized by specifiable constraints (unlike, for example, simple random generation of options). These constraints serve (at least implicitly) to evaluate emerging products, thereby guiding the generation of ones likely to prove valuable (enabling the autonomous agent to act as a "self-critic").

This framework implies that creativity is best viewed as multidimensional, with multiple factors involved, rather than a strict dichotomy. But for simplicity, the extremes sketched in Figure 1 can be viewed as two modes of generation. Low versus high creativity can be related to a number of other contrasts that have been drawn in the fields of problem solving and expertise. These distinctions include well-defined versus ill-defined problems (the latter including "insight" problems; Reitman, 1964), routine versus adaptive expertise (Hatano & Inagaki, 1986), and the hypothesis that problem solving involves search in a dual space (Klahr & Dunbar, 1988), where one space operates within a fixed problem representation and the other involves a search for alternative representations. The less creative mode includes the application of specialized methods acquired by experts, such as well-defined algorithmic procedures (e.g., an established method for solving a class of mathematical problems). It has been argued that routine expertise is sometimes the enemy of creativity. As noted in a book offering advice on how to create comics, "It's hard for something original to make it past 'already knowing how.' Being good at something is its own curse . . . " (Barry, 2019).

In the remainder of this paper, we focus on one (but by no means the only) candidate process that may play a role in the more creative mode: generation of ideas based on semantically distant analogies. To investigate basic cognitive mechanisms that may support creativity, it can be useful to examine relatively simple tasks that lend themselves to both experimental and computational investigations, such as insight problems. There is evidence that solving verbal analogies in the traditional *A:B:C:D* format sometimes evokes the "aha" reaction associated with other laboratory-style insight problems (see Kounios & Beeman, 2014). We do not claim that solving such analogy problems counts as "creative" *per se*; but will review evidence that performance on some verbal analogies taps cognitive processes that are also involved in real-life creativity.

Processing semantically distant analogies

Relations and analogical reasoning

An analogy holds between two situations, termed the *source* and *target*, when systematic correspondences (a *mapping*) can be established between elements of the two, based on similarity of the entities and/or relations involved in each (Gick & Holyoak, 1980, 1983). Based on the mapping, it is possible to use knowledge about the source analog (typically better understood) to generate systematic inferences about the target. Understanding an analogy requires appreciation that the same or similar relations hold in both situations. In general, relational reasoning depends on *explicit* representations of relations that are distinct from, but bound to, the entities they relate (Holyoak & Lu, 2021). For example, thinking about a cloud above a mountain requires a representation in which the relation *above* is distinct from the objects being related (cloud and mountain), while also indicating that the cloud is the higher object and the mountain is the lower one, rather than the reverse (for a review of relevant evidence, see Doumas & Hummel, 2012). An explicit representation of the relation *above* makes it possible to identify a relational similarity between a cloud above a mountain and a table above a cat, even though the objects involved in the two situations are highly dissimilar.

Relations are often directly stated using language. However, in many cases, the reasoner will first need to retrieve or detect relations between entities, a process that in the psychometric literature is termed *eduction* of relations (Spearman, 1923). Both perception and higher cognition contribute to the eduction of relations. A wide variety of visuospatial relations appear to be picked up very quickly by early perceptual processes. These include physical relations, such as whether one object *surrounds* another or *supports* another, and whether two objects would *fit* together to form a natural whole. Certain basic events are quickly detected, such as one object *breaking* another, or *launching* another (the first object appearing to strike the second and set it in motion). Even some social events, which seem to depend on understanding goals and intentions, can be perceived rapidly: an object *chasing* another, or *helping* another, or two people *meeting* each other (for a review see Hafri & Firestone, 2021). Many other relations relevant to analogy can be derived by active reasoning processes. These include causal relations, which are central to achieving goals, and thus especially important in real-world analogies that may contribute to the generation of creative products (Holyoak, 1985).

Far analogies as a source of creative ideas

Importantly, the overall similarity of the source and target can vary. In general, analogical transfer is easier to achieve when the analogs are drawn from the same domain of knowledge (near analogies) than when they are drawn from semantically-distant domains (far analogies; e.g., Holyoak & Koh, 1987; Keane, 1987). Near analogies are likely to share causal relations, so that the source will be a useful guide to understanding the target. However, analogies drawn within a limited domain that includes the target seem less creative. In contrast, it has often been suggested that *far* analogies are especially important for human creativity. For example, one early paper on analogical problem solving began, "Where do new ideas come from? What psychological mechanisms underlie creative insight? . . . The anecdotal reports of creative scientists and mathematicians suggest that the development of a new theory depends on noticing and applying an analogy drawn from a different domain of knowledge . . . " (Gick & Holyoak, 1980, p. 306). Holyoak and Thagard (1995) surveyed many real-world examples of new ideas in science, philosophy, and other areas that were apparently triggered by far analogies (see also Hofstadter & Sander, 2013). For example, when Alexander Graham Bell was in the process of inventing the first telephone, he made explicit use of an analogy with the structure and function of the human ear. The productive power of far analogies extends well beyond science and technology. Although analogies in general vary in semantic distance between source and target, those that serve as the basis for novel *metaphors* are always drawn between entities from different semantic domains (e.g., Lakoff & Turner, 1989).

In general, analogy is a cognitive process that can be used to link a source and target drawn from any domain. Notably, individual differences in analogical reasoning tend to be correlated across broad domains (verbal, spatial, and mathematical; Snow, Kyllonen, & Marshalek, 1984) and across sensory modalities (Weinberger et al., 2022). This generality implies that the possible inputs to analogy are drawn from an open set. Moreover, analogy is guided by domain-general but systematic constraints. According to the multiconstraint theory (Holyoak & Thagard, 1989; Lu, Ichien, & Holyoak, 2022), analogy involves matching elements so as to maximize similarity of entities and their relations, with a focus on important elements (i.e., those involved in causal relations relevant to goals), and with a soft preference for one-to-one (isomorphic) mappings. When the source and target are drawn from semantically-remote domains, analogy displays characteristics associated with the open mode of idea generation.

In psychological studies of creativity, semantic distance between elements is a well-established marker of divergent thinking. Indeed, degree of divergent thinking is typically assessed using some index of semantic distance (either human ratings or measures derived from AI models; e.g., Olson, Nahas, Chmoulevitch, Webb, & Webb, 2021; Orwig, Diez, Vannini, Beaty, & Sepulcre, 2021). At the level of individuals, measures based on semantic-memory structure (He et al., 2021), including neural connectivity analyses (Ovando-Tellez et al., 2022), have been used to predict creativity for real-world tasks.

Semantic distance is also an important predictor of cortical activity during analogical reasoning tasks. For four-term verbal analogies (*A:B : C:D*), neural activity in a subregion of the left frontopolar cortex increases parametrically with semantic distance between the *A:B* and *C:D* terms (Green, Kraemer, Fugelsang, Gray, & Dunbar, 2010). For example, a near analogy such as *blindness : sight : deafness : hearing* evokes less frontopolar activity than does a far analogy such as *blindness : sight : poverty : money*. This impact of semantic distance was reliable even after statistically controlling for measures of general problem difficulty, such as response time to decide whether or not the analogy is valid. Similar findings were obtained when the task required generation of the missing *D* term (i.e., *A:B : C:?*; Green, Kraemer, Fugelsang, Gray, & Dunbar, 2012). Other studies found that interventions that increase frontopolar activity, and connectivity between that area and more posterior cortical regions, tend to enhance performance in tasks linked to creativity (Green, Cohen, Raab, Yedibalian, & Gray, 2015; Green et al., 2017; Lundy, Dasara, Beeghly, Kazmi, & Krawczyk, 2022; for reviews of the neural basis for creativity, see; Green, 2016, 2018; for analogical reasoning, see; Holyoak & Monti, 2021).

Triggering a relational set

Work on interventions that may facilitate creative thinking imply that people may vary not only in a general tendency to be creative (i.e., *trait* creativity), but also in a more transient propensity triggered by the current context (i.e., *state* creativity; Green, 2018). An intriguing possibility is that state creativity can be fostered by tasks that encourage a focus on relations—i.e., a *relational set*. There is a great deal of empirical evidence that two separable pools of semantic information–one based on entities and the other on relations – impact judgments of similarity. Relational similarity tends to be more potent when overall relational similarity across analogs is relatively high (Goldstone, Medin, & Gentner, 1991), when the objects in visual analogs are sparse rather than rich (Markman & Gentner, 1993), and for older as compared to younger children (Gentner & Rattermann, 1991). Although analogy appears to depend on both types of similarity (Lu, Ichien, & Holyoak, 2022), relational similarity is more central, especially for far analogies.

If an analogy task requires special attention to relations, then it is possible that solving some sorts of analogies may trigger a relational set for a period of time afterward, which could in turn lead to a greater relational focus in a subsequent task. To assess this possibility, Vendetti, Wu, and Holyoak (2014) administered subsets of the verbal analogies used previously by Green, Kraemer, Fugelsang, Gray, and Dunbar (2010, 2012). Two experiments used identical designs, with half of the participants receiving near analogies and half receiving far ones. Immediately afterward, all participants completed a picture-mapping task based on unrelated materials (see Figure 2a). In Experiment 1A the analogy task required verification of analogies (judging each to be valid or invalid, as in the study by Green, Kraemer,

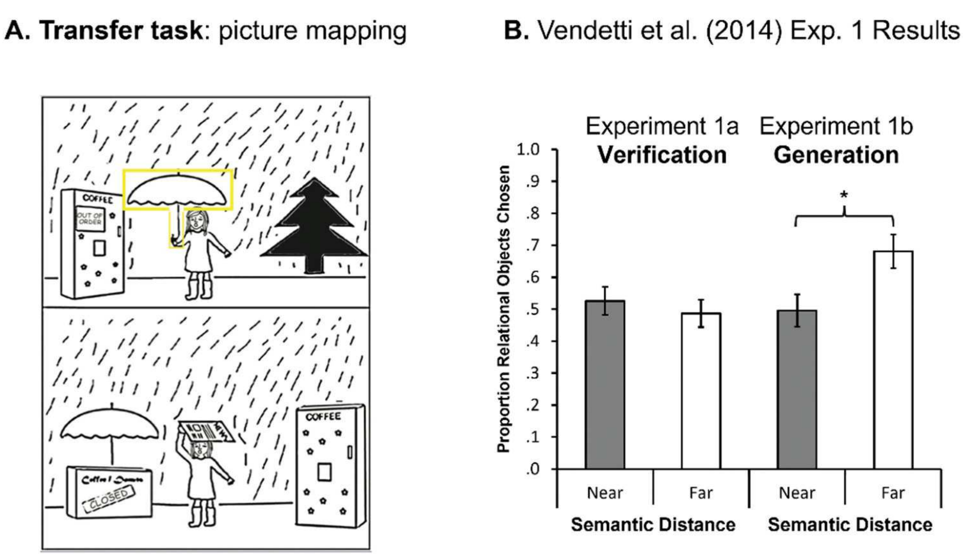

Figure 2. (a): Example of picture-mapping task (materials from Markman & Gentner, 1993; Tohill & Holyoak, 2000) used as transfer task by Vendetti, Wu, and Holyoak (2014). (b): Transfer results from Vendetti, Wu, and Holyoak (2014, Experiment 1). Prior generation of solutions to (but not verification of) far analogies (but not near analogies) led to a greater proportion of relational objects chosen on the picture-mapping transfer task. Adapted from Vendetti, Wu, and Holyoak (2014).

Fugelsang, Gray, & Dunbar, 2010). In Experiment 1B, the task instead involved generation of the missing *D* term, as in the study by Green, Kraemer, Fugelsang, Gray, and Dunbar (2012). As shown in Figure 2b, one of the resulting four conditions – generation of solutions to far analogies in Experiment 1B – was particularly likely to lead to selection of a relational (rather than featural) match in the subsequent picture-mapping task. Vendetti et al. also found that for the generation task using far analogies, a measure of fluid intelligence based on a version of Ravens Progressive Matrices (RPM; Arthur, Travis, Paul, & Sanchez-Ku, 1999) did *not* reliably predict individual differences in people's propensity to select a relational match in the transfer task, whereas the RPM did predict such individual differences for the group that generated solutions to near analogies (consistent with other evidence that the RPM test typically predicts relational responding; e.g., Gray & Holyoak, 2020).

The findings of Vendetti, Wu, and Holyoak (2014) suggest that generation of solutions to far analogies is particularly effective in evoking a relational set. This relational set enhances subsequent processing of relations other than those used to elicit the set (thus going beyond priming of specific relations; cf. Spellman, Holyoak, & Morrison, 2001). Moreover, this state manipulation of sensitivity to relations appeared to override trait differences as measured by the RPM (at least within the limited range of RPM variation among college students). Several subsequent studies provided additional evidence for a connection between generation of solutions to far analogies and subsequent relation-based responding in different tasks. Using the Green, Kraemer, Fugelsang, Gray, and Dunbar (2012) materials, Chaxel (2015) found that generating solutions to far analogies increased subsequent information distortion (for ratings of product attributes in a choice task), where the distortion was attributable to processing relations between attributes and alternative choices. Using the same materials, Andrews and Bohadana (2018; see also Du & Sun, 2022) showed that generating solutions to far analogies facilitated solution of *n*-term syllogisms (linear orderings); moreover, this manipulation eliminated the predictive impact of a fluid intelligence measure (consistent with the findings of Vendetti, Wu, & Holyoak, 2014). Goldwater and Jamrozik (2019) found that generating solutions to Green et al.'s far analogies increased relational encoding and enhanced later analogical retrieval (a potential source of creative ideas). Finally, using age-appropriate materials, Simms and Richland (2019) found that for four-year-old children, generating (rather than being told) relations increased relational responding on a subsequent analogy task involving unstudied relations.

A recent study by Chesebrough, Chrysikou, Holyoak, Zhang, and Kounios (2023) introduced a different type of relational generation task. Using materials inspired by those of Green, Kraemer, Fugelsang, Gray, and Dunbar (2010, 2012), these investigators created triplets of relation pairs. These triplets were of two types. For consistent triplets, each pair formed a near analogy such that *A:B : C:D : E:F* (e.g., *steering wheel : car*, *rudder : boat*, *handlebars : bicycle*). For expansive triplets, the first two pairs were identical to those in a consistent triplet, but the third triplet formed a far rather than near analogy with the first two (e.g., *steering wheel : car*, *rudder : boat*, *voting : government*). On each trial, participants were initially shown only the first two pairs in a triplet, and asked to generate a verbal description of "the concept the analogy represents." Then they were shown the third pair, and again asked to describe the relational concept (now linking all three pairs). Independent raters assessed the degree of conceptual change between the first and second descriptions of the concept. In addition to other measures, participants were asked to rate the extent to which they had an "aha" experience (i.e., a sense of sudden insight; Kounios & Beeman, 2014) when they processed the third triplet. Chesebrough et al. found that expansive as compared to consistent triplets triggered both greater conceptual change in relational descriptions and a greater sense of having an "aha" experience. Qualitatively, the expansive condition seemed to trigger generation of a more abstract characterization of the relational concept (e.g., for the example above, the near relation "steering a vehicle" might be generalized into "directing something" to accommodate the semantically distant third pair). The impact of generating a description based on a far analogy thus seemed to trigger a type of processing related to that associated with creative insights.

Overall, behavioral studies support the general conclusion that *generation* (rather than simply verification) of solutions to semantically *far* (rather than near) analogies is especially effective in triggering a relational set, which might plausibly support state creativity. The positive impact of generation is broadly consistent with evidence from studies of episodic memory showing that generation of responses (as compared to simply reading them) enhances subsequent memory performance (Bertsch, Pesta, Wiscott, & McDaniel, 2007), and is correlated with greater neural activity across a broad cortical network (Rosner, Elman, & Shimamura, 2013). However, the possible impact of semantic distance does not seem to have been systematically investigated in studies of the influence of generation on episodic memory; hence, these studies do not shed light on why generation of *far* analogies seems to be especially potent. In the remainder of this paper, we consider potential mechanisms that may trigger a relational set, drawing upon a framework provided by computational models of relation representation and processing.

Potential mechanisms for generation of solutions to verbal analogy problems

To verify or evaluate an analogy in *A:B : C:D* format, the obvious strategy is to educe the relation between the elements of each concept pair (i.e., the relation *A:B* and the relation *C:D*), and then assess whether these two relations are sufficiently similar to be considered a valid analogy (Lu, Wu, & Holyoak, 2019). The situation is more complex for an analogy generation task in the form *A:B : C: ?*. Without knowing the *D* term, it is impossible to immediately identify the *C:D* relation; hence, the matching strategy (compare *A:B* and *C:D* relations) is blocked. Given some candidate *D* term, the *C:D* relation might be obtained, enabling use of the matching strategy to evaluate whether or not the proposed *D* term forms a valid analogy. However, some other procedure must first be applied to generate one or more candidates for the role of *D*.

One potential mechanism for generating analogical solutions is associative in nature, involving spreading activation among semantic connections. Associative generation seems particularly plausible for near analogies. The intuitive basis for associative generation is sketched in Figure 3a, using an example of a near analogy (*blindness : sight : deafness : ?*, where a good completion would be *hearing*). Figure 3a indicates the salient preexisting semantic links that connect the *A* and *B* terms to *C* and the target *D*. In addition, the salient relation between *A* and *B* (*loss*, specifically of a physical sense) is identical to that linking *C* and the to-be-retrieved target *D*. A qualitative account of the generation of *D* given *A*, *B*, and *C* would be that some sort of spreading activation based on preexisting semantic links will tend to activate the target *D*. In contrast, as sketched in Figure 3b, prior semantic links are minimal in the case of a far analogy (*blindness : sight : poverty : ?*, where a good completion would be *money*), as the *A* and *B* terms do not have strong links to the *C* or potential *D* terms. Moreover, the salient relation between *A* and *B* (physical *loss*) is not identical to that between *C* and the target *D* (more abstract *lack* of something). Thus, an associative process seems less likely to succeed in activating the target *D* for a far analog.

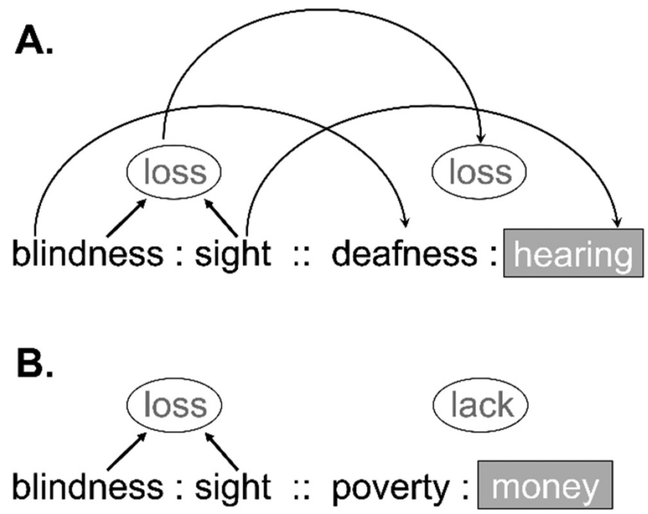

Figure 3. Completing a near analogy problem (i.e., generating *D* term) is aided by prior semantic associations from *A:B* to *C:D* and from the (unstated) relation connecting words in each pair (panel A); but prior semantic associations from *A:B* are less available for far analogy problems (panel B).

An alternative approach to generation, less dependent on spreading activation, involves making more direct use of explicit representations of relations. A natural strategy for generating the solution to a verbal analogy is to first identify the relation between *A* and *B*, and then project the same relation from *C* to estimate an “optimal” completion for *D* that would maximize the similarity of the *A:B* and *C:D* relations. A search of the lexicon would then attempt to find an actual *D* term as close as possible in meaning to the estimated optimal *D*.

Unlike associative generation, relational generation depends on the ability to form explicit representations of semantic relations between words, which can then be systematically manipulated. Our group (Ichien, Kan, Holyoak, & Lu, 2022) has developed a model of relational generation based on explicit relation representations produced by BART (*Bayesian Analogy with Relational Transformations*; Lu, Chen, & Holyoak, 2012; Lu, Wu, & Holyoak, 2019; see also Chen, Lu, & Holyoak, 2017; Holyoak, Ichien, & Lu, 2022), a model of relation learning that acquires representations of relations from unstructured vector representations of individual word meanings. BART learns explicit representations of the semantic relations between word pairs from unstructured vector representations of individual word meanings. BART’s input consists of concatenated pairs of word embeddings (300-dimensional feature vectors that approximate word meanings) created by an NLP model, Word2vec (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013). BART uses supervised learning with positive and negative examples to acquire each relation representation individually. For example, a vector formed by concatenating the individual vectors for *old* and *young* would constitute a positive example for the relation *X is the opposite of Y* and might also serve as a negative example of the relation *X is a synonym of Y*. The model was initially trained on 79 common semantic relations (Bejar, Chaffin, & Embretson, 1991) using word pairs drawn from a norming study (Jurgens, Mohammad, Turney, & Holyoak, 2012) as examples of each relation. Major classes of trained relations include contrast, similarity, class inclusion, part-whole, cause-purpose, and case relations.

BART's learning algorithm (for details see Lu, Wu, & Holyoak, 2019) identifies a subset of the feature set that most effectively predict the posterior probability that a word pair instantiates the target relation. The final basis for predicting this posterior probability is a weight distribution over the selected feature dimensions. Of particular note, BART's learned weights can be segregated into those based on features of the first word in a pair and those based on features of the second word. As we will see shortly, this characteristic proves very important in modeling relational generation, because the portion of the weight distribution associated with one word can be used to help estimate the embedding for some unknown word that would complete a word pair instantiating a target relation.

After learning, BART can compute a relation vector consisting of the posterior probability that any word pair instantiates each of its learned relations (thus accomplishing the eduction of relations). Then, to evaluate whether a four-term verbal analogy is valid, the model assesses the cosine distance between the *A:B* and *C:D* relation. If BART has been trained successfully, cosine distance tends to be smallest for near analogies, somewhat larger for far analogies, and yet larger for invalid analogies. In addition to supporting human-like analogical reasoning on simple four-term verbal problems (e.g., *artificial : natural : friend : enemy*) (Lu, Wu, & Holyoak, 2019), BART's relation representations have been used to predict human judgments of relational similarity among word pairs (Ichien, Lu, & Holyoak, 2022), and to predict patterns of similarity in neural responses to relations during analogical reasoning (Chiang, Peng, Lu, Holyoak, & Monti, 2021). BART can also support analogical mapping in problems that require finding correspondences between multiple entities across complex relational systems (e.g., mapping the solar system to atomic structure; Lu, Ichien, & Holyoak, 2022).

BART-Gen (Ichien, Kan, Holyoak, & Lu, 2022) is able to use relation representations learned by BART to generate completions of partially specified relations and of four-term analogy problems. BART-Gen exploits the fact that the weight distributions BART uses to compute posterior probabilities of relations can be decomposed into a portion based on the first word in a pair and a portion based on the second word. If BART-Gen is given a word *C* and asked to generate a completion *D* that will result in an instantiation of a specified relation, the model uses Bayesian inference to compute the features of an "optimal" *D* given the relation and the known features of *C*. This calculation includes a prior expectation that *D* will be similar to *C* (since in general, two words that are semantically related will be similar to one another in a feature space). In essence, the model estimates an optimal *D* that is a compromise between a *D* that is similar to *C*, and a *D* that makes the pair *C:D* highly likely to instantiate the target relation. The similarity prior ensures that the embedding for the optimal *D* will be fully specified, even though BART only uses a subset of feature dimensions to predict each relation. By default, each feature of the predicted *D* will have the same value as the corresponding feature of *C*, unless BART's weight distribution uses that feature to predict the *C:D* relation.

BART-Gen's procedure for generating a completion for any single relation can readily be generalized to produce a solution for a four-term verbal analogy problem. For the analogy task, the model computes the features of an optimal *D* given the relation and the known features of *C* and also the *A:B* pair. Intuitively, *A:B* serves to specify a pattern of relations, and BART-Gen seeks to maximize the probability that some optimal *D* creates the same pattern of relations for *C:D* (subject to the similarity prior that *D* will be similar to *C*). After BART-Gen calculates the feature embedding for what it predicts to be the optimal *D*, this can be compared to the Word2vec embeddings of words in a lexicon, yielding a rank of actual words by their proximity to the optimal *D* in the Word2vec feature space.

Ichien, Kan, Holyoak, and Lu (2022) performed some preliminary evaluations of BART-Gen as an account of human generation of analogy solutions. Their simulations made use of data collected by Peterson, Chen, and Griffiths (2020), who reported the frequencies of alternative human completions for the Green, Kraemer, Fugelsang, Gray, and Dunbar (2012) set discussed above, which includes both near and far analogy problems, each with a missing *D* term. Model performance was evaluated by finding the rank of the most frequent human-generated response to each problem among all human-generated responses across all problems. The most frequent human response was typically in the top half dozen completions generated by BART-Gen, suggesting that the model can produce human-like responses on a generative analogy task. Moreover, BART-Gen proved robust to variations in the semantic distance of analogies in terms of accounting for human judgments in generative analogical inference. The model's ability to generate solutions to far analogies, for which spreading activation contributes less information, suggests that explicit relation representations play an important role in human-like analogical generation.

What is special about generation of solutions to far analogies?

In light of the recent developments in computational modeling reviewed above, we can venture a possible explanation of the puzzle posed by the findings of Vendetti, Wu, and Holyoak (2014) and similar studies. Why does generation of solutions to far verbal analogies – but neither generation of solutions to near analogies, nor verification of either type – appear to trigger a relational set that increases relational responding in a subsequent task based on different relations? More speculatively, it seems generation of solutions to far analogies may be an effective intervention for increasing some form of state creativity.

We can consider this issue through the lens of computational models capable of relational generation, using BART as an example. BART learns and uses explicit relational representations to verify and also (when extended by BART-Gen) to generate solutions to verbal analogy problems. In this approach, the task of evaluating a verbal analogy problem evokes a procedure that creates a relation vector for both the *A:B* and *C:D* relations, followed by a comparison of vector similarities (based on cosine distance). Semantic distance impacts the difficulty of this comparison (in particular, the difficulty of discriminating a valid analogy from an invalid foil) because even when the dominant relation might appear to be roughly the "same" for *A:B* and *C:D*, the cosine distance between distributed vector representations of relations tends to be greater for far than near analogies. The more difficult discrimination required to evaluate far than near analogies likely leads to an increased neural response in the left frontopolar area identified by Green, Kraemer, Fugelsang, Gray, and Dunbar (2010). However, regardless of semantic distance, analogy verification involves forming relation vectors and comparing them.

The processes involved in generating solutions to analogy problems are likely to be more diverse, and in the case of far analogies more computationally intense, than the processes involved in analogy verification. As argued above, the core process in generation is not comparison of two relation vectors (because without a *D* term, the *C:D* relation is not initially specified). Rather, two general approaches seem plausible. Using an associative approach involving spreading activation, a missing *D* term can be predicted based on semantic associations among the tokens that provide its context (i.e., the words *A*, *B*, and *C*). This approach to generation (which does not involve explicit relation representations) may often suffice for near analogies. Indeed, there is evidence that generation of solutions to near analogies does not activate the left prefrontal area that is selectively associated with relational reasoning (Wendelken, Bunge, & Carter, 2008).

However, simulation results reported by Ichien, Kan, Holyoak, and Lu (2022), summarized above, indicate that generation of solutions to far analogies may require the relational approach exemplified by BART-Gen. To generate a *D* term using BART-Gen, relation vectors are not simply compared (as in verification). Rather, each component of the relation vector is fed into a further computation in order to compute a predicted optimal *D*. This computation is much more demanding than is a simple vector comparison. Moreover, the generation process also requires selection of an actual *D* term from a large lexicon of possible completions (i.e., identifying an actual word sufficiently similar to the predicted *D*). Finally, once one or more actual words have been identified as possible completions, proposed solution(s) may be further assessed by computing the cosine distance between the *A:B* relation and each (tentative) *C:D* that has been generated. That is, although generation cannot begin by comparison of two relation vectors, it may sometimes end with it.

In fact, some post-generation comparison procedure might play a role in cuing a transition from associative to relational generation modes for far analogies. A reasoner might initially adopt the computationally cheap associative approach to generate the missing *D* term in an analogy problem, and then perform a comparison to evaluate the resulting candidate completion. If this comparison indicates that the *A:B* and candidate *C:D* relations are sufficiently similar (which is more probable for near analogies), the reasoner will accept their associatively generated *D* term. However, if this comparison indicates the candidate completion is deficient, the reasoner may switch to the computationally intensive relational approach to generate an alternative *D* term. Thus, generating solutions to near analogies is insufficient to trigger a relational set because it tends to evoke an associative process. In contrast, generating solutions to far analogies tends to recruit the relational approach, thereby altering inductive biases in subsequent tasks in which different relations are relevant (cf. Kroupin & Carey, 2022).

To summarize, generation of the solution to a far verbal analogy requires not only thinking about the relations between paired words, but also using the elements of relation vectors to perform the intensive computations required to generate relational completions. In the aftermath, the reasoner's tendency to focus on relations between entities (rather than the features of the entities themselves) may be temporarily enhanced, triggering a relational set that guides processing in subsequent tasks. Such a relational set may constitute a form of state creativity, making it more likely that relation-based long-distance connections will be noticed and exploited (i.e., enhancing divergent thinking). An environment that often triggers a relational set may help to foster creativity as a long-term trait.

Directions for future research

A model such as BART-Gen demonstrates that explicit relations can be used to guide the generation of analogical completions when both entities and relations are represented as high-dimensional vectors. Unlike traditional symbolic models of analogical reasoning (e.g., Forbus, Ferguson, Lovett, & Gentner, 2017), vector-based knowledge representations are broadly compatible with neural systems (both human and artificial), and are able to exploit recent advances in machine learning that enable automated creation of semantic representations. By avoiding hand-coding of complex propositional representations, vector-based models at least begin to capture the human ability to operate as an autonomous agent capable of using its own representations to generate new knowledge.

At the same time, BART-Gen lacks the full generative ability required to solve problems by analogy. Although four-term analogies provide a useful starting point for model development, they do not require the generation of entire propositions. Thus, BART-Gen only produces the representation of a single element (the *D* term) so as to form a relation between *C* and *D* that matches that between *A* and *B*. More generally, an analogical inference, such as an idea about how to solve a target problem, depends on first finding a mapping between the source and target, and then exploiting additional knowledge about the source (ideally its solution) to fill a gap in knowledge about the target. This inference process, sometimes called "copy with substitution" (Holyoak, Novick, & Melz, 1994), involves taking an "extra" fact about the source and creating an inference about the target by swapping the corresponding elements (and sometimes postulating a new element in the target to complete the analogy). A creative product based on analogy (such as Bell's use of knowledge about human hearing in developing the first telephone) will usually depend on the generation of a complex, multi-element extension of the target representation, rather than just a single element. Future computational work will be needed to extend vector-based models to model generation of problem solutions.

Another form of generation that poses a challenge for vector-based models is the formation of more general schemas, or relational categories. It has long been known that the very process of drawing an analogy between two analogs encourages people to generalize the mapping they find, forming an abstract schema that serves as an explicit representation of commonalities between the analogs (Gick & Holyoak, 1983). Many concepts in natural language appear to be based on relations abstracted from concrete examples or metaphors (Goldwater & Schalk, 2016; Hofstadter & Sander, 2013; Turner, 1988). Such concepts are often rooted in relational roles (e.g., a *barrier* is something that obstructs something else). Objects occupying the same role in a relation (e.g., *predator*) come to be viewed as more similar to each other overall (Jones & Love, 2007). There is evidence that category labels and analogical comparisons increase general sensitivity to role-based categories (Goldwater, Markman, & Stilwell, 2011). It seems plausible that manipulations of relational set could also serve to enhance acquisition of relational categories. Moreover, abstract schemas in turn foster both retrieval of far analogs (Gick & Holyoak, 1983; for a review see Holyoak, 2012) and also the ability to detect systematic relationships between relatively far analogs (for a review see Trench & Minervino, 2020). Future work should examine the potential for using forms of analogy-based generation to create a positive feedback loop that can enhance the autonomous generation of creative products.

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