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Analogy

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Analogy can be defined as a kind of similarity in which the same system of relations holds across different sets of elements, regardless of whether the elements are similar. Thus analogies can capture abstract parallels across situations that have few or no concrete similarities. In addition to revealing relational commonalities, analogies also invite projection of inferences from one analog to the other. In this way, analogical processing can promote rapid transfer of information from a prior familiar domain to a new domain. Analogy is ubiquitous in cognitive science. First, in the study of problem-solving and learning, analogies are important in the transfer of knowledge across different concepts, situations, or domains. They are often used in instruction to explain new concepts, such as electricity or evaporation. Second, analogies can serve as mental models for understanding a new domain. For example, people often reason about electric current using mental models based on an analogy with water flow. Third, analogy is important in creativity. Studies in the history of science show that analogy was a frequent mode of thought for scientists like Kepler and Maxwell. Finally, analogy is often used in communication and persuasion, as in conceptual metaphors like "time is a commodity."

History

An important early work was Hesse's (1966) book on analogical models in science. In her analysis, fruitful scientific analogies involve a conceptual alignment in which corresponding parts are similar, with causal relations providing internal cohesion within each domain. For example, she analyzes the analogy between sound and light as involving similarities between loudness (sound) and brightness (light) and between pitch (sound) and color (light) and postulates that causal relations hold between the properties within each domain. Current accounts generally assume a more delineated representation of domain relations—for example, spatial and quantitative relations also enter into scientific analogies. Still, Hesse's analysis was a substantial advance in thinking about analogy. Another pioneer was Polya (1954), who argued that analogical processing is critical to mathematical induction. He made a distinction between analogy and other less precise forms of similarity: "…two systems are analogous, if they agree in clearly definable relations of their respective parts." (Polya, 1954, p. 13).

Within psychology, early work focused on four-term analogies like "horse is to donkey as wolf is to ____." Sternberg (1977) proposed a process model for solving such analogies, based on component processes of encoding, inference, mapping, application, and response. Rumelhart and Abrahamsen (1973) modeled analogy as a mapping from one mental space to another and found that respondents preserved relative position in their mappings. For example, given "horse is to donkey as wolf is to ____," respondents would choose "fox" because its position relative to wolf matches that of "donkey" relative to "horse." In the 1980s, the focus of the field shifted to more complex analogies, driven in part by research on analogical problem-solving and transfer. This work led to three generalizations: First, analogical transfer from a prior understood case to a new case can substantially increase insight into the new case. Second, people often fail to access prior analogous cases, even when such cases are demonstrably present in long-term memory (Gick & Holyoak, 1980, 1983; Novick, 1988;

Ross, 1987). Third, similarity-based retrieval from long-term memory tends to be based on common surface features, rather than on common relational structure (Gentner et al., 1993; Holyoak & Koh, 1987; Keane, 1987). These claims were later disputed.

In parallel, cognitive scientists articulated theories of the mapping process. One early theory was structure-mapping (Falkenhainer et al., 1989; Gentner, 1983), which holds that analogical mapping is a domain-general process of finding common relational structure. Another early approach was Holyoak's (1985) pragmatic account. Focusing on the use of analogy in problem solving, Holyoak defined analogy as "similarity with respect to a goal" and proposed that mapping processes are guided toward attainment of goal-states. A number of computational models were proposed, including the Structure-Mapping Engine (Falkenhainer et al., 1989; Forbus et al., 2017), Analogical Constraint Mapping Engine (Holyoak & Thagard, 1989), Copycat (Mitchell & Hofstadter, 1990), Learning and Inference with Schemas and Analogies (Hummel & Holyoak, 1997, 2003), and Discovery of Relations by Analogy (Doumas et al., 2008). Computational modeling has remained prominent in analogical research. The past few decades have seen considerable convergence on a number of core properties of analogical processing (see Table 1). Much current work is directed toward using these principles to explore the role of analogy in learning.

Core concepts

Analogical mapping

Analogical mapping is the core process that defines analogy. There is general agreement that analogical mapping entails a *structure-mapping* process, in which like relations are aligned and objects are placed in correspondence according to their roles in the common relational structure (Forbus et al., 2017; Gentner, 1983, 2010). There is empirical support for the idea that people implicitly aim for structurally consistent mappings (Krawczyk et al., 2004; Markman & Gentner, 1993). Another key assumption of structure-mapping is that there is a *systematicity* bias in selecting which commonalities to focus on: that is, people prefer to map systems of relations connected by higher-order constraining relations (such as causal or mathematical relations) rather than independent relations (Clement & Gentner, 1991; Gentner et al., 1993).

Carrying out an analogical mapping fosters learning in several ways:

1. *Schema abstraction*: The common structure that emerges from the mapping becomes more salient and available for transfer. It may be retained as an abstract schema, especially if given a label. This pattern has been found both in children (Christie & Gentner, 2010; Gentner et al., 2011) and adults (Gick & Holyoak, 1983; Loewenstein et al., 1999).
2. *Inference-projection*: If there are predicates connected to the common system, but not yet present in the target, they will be projected to the target as *candidate inferences* (Blanchette & Dunbar, 2002; Bowdle & Gentner, 1997; Clement & Gentner, 1991; Markman, 1997).

3. *Alignable differences*: Differences that play the same role in the aligned relational structures tend to pop out as a result of the mapping (Markman & Gentner, 1993; Sagi et al., 2012). Table 1 summarizes the key phenomena of analogical mapping (adapted from Gentner & Markman, 1995).

Table 1

Hallmark phenomena of analogical mapping

1	Structural consistency	Analogical mapping involves one-to-one correspondences and parallel connectivity.
2	Relational focus	Relational matches can be made regardless of whether the objects making up the relations match.
3	Object effects	Analogical mapping is easier if corresponding objects are similar, and harder if non-corresponding objects are similar.
4	Systematicity	People prefer systems of relations connected by higher-order constraining relations such as *cause* or *implies* over collections of isolated relations.
5	Candidate inferences	Analogy inferences are generated via structural completion of the aligned structure.
6	Schema abstraction	Analogical comparison renders the common structure more salient and potentiates storing it as an abstraction.
7	Alignable differences	Differences that play the same role in the two analogs tend to pop out.

Evaluation

Analogy is an inductive process; its inferences are not guaranteed to be correct. So the results of the process must be evaluated according to two (and sometimes three) criteria: First, the interpretation and inferences must be structurally consistent; second, the inferences must not contradict existing information in the target; and third, in a goal-driven context, the inferences should be relevant to the goal.

Analogical transfer

A key goal of analogical research is to characterize the process of analogical transfer. When a person is trying to solve a problem or understand a phenomenon, they are sometimes reminded of a prior analogous case from their long-term memory. This can lead to *analogical transfer*—that is, the person can then use the prior analog (the base) to understand the current case (the *target*). The stages of processing in analogical transfer are as follows:

- *Retrieval*: The base analog is retrieved from memory. (By assumption, the target is already in working memory.)
- *Mapping*: The two representations are processed to arrive at one or more interpretations. The mapping process may also include forming an abstraction or drawing candidate inferences from base to target.
- *Evaluation*: The interpretation and inferences may be judged according to structural consistency and factual correctness in the target and (sometimes) relevance to a current goal.

Analogical transfer—when it occurs—can be extremely effective. The ability to import a large connected system can lead to a rapid gain in insight as compared to incremental learning. Unfortunately, such transfer does not always occur. A series of early studies sought to capture the retrieval process by giving participants cases to remember and then probing with new target cases to see what cues led to retrieval. The answer was dismaying. People mostly failed to retrieve relationally similar cases (which would have been useful in reasoning about the target); instead, people tended to retrieve cases that were surface-similar to the target case (Gentner et al., 1993; Gick & Holyoak, 1980; Novick, 1988; Ross, 1987).

These findings were challenged on the grounds that asking people to store and retrieve materials lacks ecological validity (Blanchette & Dunbar, 2000; Hofstadter & Sander, 2013).

Supporting this challenge, studies found that people produced many more analogies when given the goal of creating a persuasive argument than when given a memory task (Blanchette & Dunbar, 2000). However, it was argued that such studies could not distinguish responses based on true memory retrieval from those in which participants simply made up an analogy to fit the task (Trench & Minervino, 2015). To settle this point required a study in which the memory items were naturally chosen by the subjects. To do this, researchers used a persuasion task with popular films such as Jurassic Park (which the subjects had seen) as the memory items. Participants were given scenarios that were analogous to scenarios depicted in the films but varied in their surface similarity to the film. Their task was to create a persuasive analogy to use in the current scenario. Seventy percent of participants in the high surface-similarity condition retrieved and used the film scenarios, as compared to 30% of participants in the low surface-similarity condition (Trench & Minervino, 2015).

These findings support the conclusion that spontaneous analogical transfer is rare without accompanying surface similarity. However, there are some mitigating factors. First, surface similarity is often correlated with relational similarity in ordinary life (Gentner, 1983), so a surface match can often bring with it a useful relational match. Second, as people gain expertise in a domain, they become better able to retrieve purely relational structures (Goldwater et al., 2021; Novick, 1988). This may be because experts develop domain-relevant schemas (Goldwater & Schalk, 2016), invited and supported by learning the domain's technical terms (Jamrozik & Gentner, 2022).

Questions, controversies, and new developments

One point of controversy concerns whether analogy is a domain-general ability, or whether different processes apply in different domains. There is evidence that the same mapping process applies across both conceptual and perceptual comparisons and across causal, mathematical, and social content (e.g., Forbus et al., 2017; Gentner, 2010; Gentner et al., 1993). On the other hand, there are arguments that causal analogies require different kinds of processes than other analogy types, such as perceptual or mathematical analogies (Lee & Holyoak, 2008). Causal relations are deemed to be critical to analogical inference since they allow one to predict the presence or absence of some outcome in the target. Proponents of the unified view counter that causal analogies show the same pattern of inferential phenomena as perceptual and mathematical analogies (Forbus et al., 2017; Gentner, 2010; Goldstone & Son, 2005).

Another controversy concerns whether large language models are capable of analogical reasoning [see Large Language Models]. A study comparing GPT-3 (a particular commercial large language model) and human subjects on a battery of analogy problems found that GPT-3 performed quite well, consistent with the claim that such models have developed an emergent analogy ability (Webb et al., 2023). This proposal has been met with controversy. A key question is whether the GPT models were simply finding the correct answer in their training data. For example, a study comparing GPT-3 and GPT-4 with humans on analogical problems (similar to those used by Webb et al., 2023) found that the GPT models were substantially worse than humans on problems not in the training data—undermining the claim that GPT can do true analogical reasoning (Lewis & Mitchell, 2024). This is an area of rapid development.

Broader connections

In the Piagetian tradition, analogical ability was thought to emerge late in development [see Cognitive Development]. Current research has shown, on the contrary, that even infants (Chen et al., 1997; Ferry et al., 2015) and young toddlers (Walker & Gopnik, 2014) can carry out analogical abstraction. However, their ability to deploy this talent is limited; young children often attend to salient objects instead of to relational patterns. This is thought to be due to lack of relational knowledge (Gentner, 2010) or to maturational factors such as low inhibitory ability (Richland et al., 2006).

There is considerable evidence that analogical processing supports children's learning. For example, in early language learning, children gain insight into verb meaning by aligning the nouns in an utterance with the participants in the referent event (Fisher, 2000; Yuan et al., 2012). Later, children align across utterances to learn verb meanings (Childers et al., 2016; Haryu et al., 2011). There is also evidence that in learning the natural number system, children carry out a structure-mapping between symbols and quantities (Sullivan & Barner, 2014). Research has also shown that analogical comparison can be an effective technique for teaching STEM and other domains (Alfieri et al., 2013; Goldwater & Schalk, 2016; Kurtz et al., 2001; Vendetti et al., 2015). For example, structural alignment between conceptual and physical models of numbers improved 4–6-year-olds' understanding of the place-value system for multidigit numbers (Yuan et al., 2021), and middle school students learned algebra better when they explicitly compared worked example problems (Rittle-Johnson & Star, 2007). In science learning, scaffolding comparisons and highlighting correspondences helped third graders understand the day/night cycle (Jee & Anggoro, 2019).

Is analogical ability unique to humans? The answer appears to be no. Although research so far indicates that humans exceed other species in the ability to carry out relational mapping, there is evidence our closest relatives, chimpanzees and bonobos, also have some relational ability (Christie et al., 2016) [see Animal Cognition]. For example, researchers compared children with other great apes on a relational task in which subjects could locate hidden rewards by mapping the relative position of containers in two distinct (but analogous) spatial arrays. They found that gorillas, orangutans, and 3-year-old children succeeded only when they had a direct causal link (such as a tube) between corresponding locations. However, chimpanzees, bonobos, and 4-year-old children succeeded with only visual links, consistent with true relational mapping (Haun & Call, 2009). Another parallel is that both chimpanzees and young children are better able to pass a challenging relational task (the Relational Match to Sample) when they have mastered symbols for *same* and *different* (Christie & Gentner, 2014; Premack, 1983).

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