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Analogy

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Analogies are partial similarities between different situations that support further inferences. Specifically, analogy is a kind of similarity in which the same system of relations holds across different objects. Analogies thus capture parallels across different situations.

Analogy is ubiquitous in cognitive science. First, in the study of learning, analogies are important in the transfer of knowledge and inferences across different concepts, situations, or domains. They are often used in instruction to explain new concepts, such as electricity or evaporation (see Article 54, EDUCATION). Second, analogies are often used in PROBLEM SOLVING and REASONING. Third, analogies can serve as mental models for understanding a new domain. For example, novices in electricity often reason about electric current using mental models based on analogies with water flow or with crowds of moving entities. These analogical mental models can be misleading as well as helpful. The cognitive anthropologist Willet Kempton interviewed home-owners about how their furnaces worked and found that many of them applied incorrect analogies, such as a gas pedal model whereby the higher the thermostat is set, the faster the furnace heats up the house. Fourth, analogy is important in creativity. Studies in history of science show that analogy was a frequent mode of thought for such great scientists as Faraday, Maxwell, and Kepler. More direct evidence comes from studies by Kevin Dunbar, who traced scientists' day-to-day activities and discussions in four different microbiology laboratories. He found that frequent use of analogy was one of the chief predictors of research productivity. Fifth, analogy is used in communication and persuasion. For example, environmentalists may compare the Earth to Easter Island, where overpopulation and exploitation of the island's bountiful ecology led to massive loss of species, famine, and societal collapse. The invited inference is that the point of no return may pass unnoticed. A final reason to study analogy is that analogy and its cousin, similarity, underlie many other cognitive processes. For example, most theories of conceptual structure assume that items are categorized in part on the basis of similarity between the current situation and the prior exemplars or prototype (see Article 25, WORD MEANING). Much of human categorization and reasoning may be based on implicit or explicit analogies between the current situation and prior situations. As another example, analogical processes are involved in using conceptual metaphors, such as "Love is a journey" or "Time is a commodity." Such metaphors have been claimed to perform a structuring role across different domains (see Article 37, COGNITIVE LINGUISTICS).

History

The study of analogy has been characterized by fruitful interdisciplinary convergence between psychology and artificial intelligence, with significant influences from history of science, philosophy, and linguistics. Important early work came out of philosophy, notably Mary Hesse's (1966) analysis of analogical models in science. However, early psychological research on analogy mostly focused on simple four-term analogies of the kind used in intelligence testing. David Rumelhart and Adele Abrahamsen modeled analogy as a mapping from one mental space to another and found that respondents given analogies like "Horse is to zebra as dog is to——?" would choose the answer (e.g., *fox)* whose position relative to *dog* was the same as that of *zebra* relative to *horse*. Robert Sternberg measured solution times to solve such analogies as a way of studying component processes - *encoding, inference, mapping, application,* and *response* - and individual differences in their use.

In the early 1980s, a new breed of analogical models appeared that assumed complex representations and processes. Artificial intelligence researchers like Patrick Winston and Jaime Carbonell suggested computational principles applicable to human processing and inspired psychologists to create explicit models of representation and process. In cognitive science, a multidisciplinary approach grew up in which analogy was viewed as a mapping between structured representations, such as propositional representations or schemata.

Processes of analogical use

To model the use of analogy in learning and reasoning, current accounts distinguish the following subprocesses: (1) *retrieval:* given some current situation in working memory, the person accesses a prior similar or analogous example from long-term memory; (2) *mapping:* given two cases in working memory, *mapping* consists of *aligning* their representational structures to derive the commonalities and *projecting inferences* from one to the other. Mapping is followed by (3) *evaluation* of the analogy and its inferences and often by (4) *abstraction* of the structure common to both analogs. A further process that may occur is (5) *re-representation: adaptation* of one or both representations to improve the match. We begin with the processes of mapping through evaluation, reserving retrieval for later.

Analogical mapping

The core process in analogy is *mapping:* the process by which one case is used to explain and predict another. In mapping, a familiar situation - the *base* or source analog - provides a kind of model for making inferences about an unfamiliar situation - the *target* analog. One of the first theories to focus on this process was structure-mapping theory (Gentner, 1983). According to this theory, an analogy conveys that a system of relations that holds in the base domain also holds in the target domain, whether or not the actual objects in the two domains are similar. The alignment must be *structurally consistent:* there is *one-to-one correspondence* between elements in the base and elements in the target, and the arguments of corresponding predicates must also correspond (*parallel connectivity).* A further assumption is the *systematicity principle:* systems of relations connected by higher-order constraining relations such as cause contribute more to analogy than do isolated matches or an equal number of independent matches, The information highlighted by the comparison forms a connected relational system, and commonalities connected to the matching system gain in importance. For example, Clement and I found that people given analogous stories judged that corresponding assertions were more important to the analogy when they were connected to other matching information than when they were not. A parallel result was found for inference projection: people were more likely to import a fact from the base to the target when it was connected to other predicates shared with the target. Thus there is a kind of "no match is an island" phenomenon. In analogical matching, people are not interested in isolated coincidental matches; rather, they seek causal and logical connections that give the analogy its inferential force.

Another important approach to analogy that grew up in the 1980s was Holyoak's pragmatic account. Focusing on the use of analogy in problem solving, this approach emphasized the role of pragmatics in analogy - how current goals and context guide the interpretation of an analogy. Holyoak defined analogy as similarity with respect to a goal and suggested that mapping processes are oriented towards attainment of goal states. Holyoak and Paul Thagard (1989) combined this pragmatic focus with the assumption of structural consistency and developed a multi-constraint approach to analogy in which similarity, structural parallelism, and pragmatic factors interact to produce an interpretation.

Evaluation

Evaluating an analogy involves at least three kinds of judgment. One criterion is structural soundness: whether the alignment and the projected inferences are structurally consistent. Another is the factual validity of the projected inferences in the target. Because analogy is not a deductive mechanism, these candidate inferences are only hypotheses; their factual correctness is not guaranteed by their structural consistency and must be checked separately. Brian Falkenhainer's Phineas program operationalized this by first attempting to prove the inferences true or false in the target domain. If this failed, an empirical test was derived. A third criterion, which applies in a problem-solving situation, is whether the analogical inferences are relevant to the current goals. An analogy may be structurally sound and yield true inferences, but still fail the relevance criterion if it does not bear on the problem at hand. A related issue discussed by Mark Keane is the *adaptability* of the inferences to the target problem.

Schema abstraction

In *schema abstraction*, the common system that represents the interpretation of an analogy is retained for later use. For example. Mary Gick and Holyoak's (1983) research on problem solving provided evidence that people can abstract the relational correspondences between examples into a schema. Comparing structurally similar problems leads to improved performance on further parallel problems and promotes transfer from concrete comparisons to abstract analogies.

Computational models of analogical mapping

Computing an analogy typically involves both matching the representations and projecting new inferences. Computational models can be classified into *projection-first* and *alignment-first* models, according to which process occurs first. In *projection-first* models, the analogical abstraction is derived initially from the base alone and projected onto the target, after which it is aligned (or matched) with the target's representation. In this kind of model, the first step in processing an analogy is to find a projectable schema or derive an abstraction in the base and project it onto the target. Then the system attempts to verify the projected structure in the target: to discover for each assertion either (a) that it can be proved correct in the target on the basis of existing knowledge (or is already present), or (b) that it can be proved false in the target (in which case the analogy must be rejected), or (c) that it can neither be proved nor disproved, in which case it stands as a possible new inference. Two recent simulations that fit loosely into the projection-first mode are Keane's IAM (Incremental Analogy Machine) and Hummel and Holyoak's LISA model.

In *alignment-first* models, the common system arises interactively, via processes of alignment, with the projection of inferences as a second step. For example, the Structure-Mapping Engine (SME) of Falkenhainer, Kenneth Forbus, and myself begins by aligning two representations and then carries over further predicates from the base to the target. When given two potential analogs, it first finds all possible local matches between elements of the base and the target. Then it combines these into kernels - little clusters of connected correspondences - and finally it merges the kernels into the two or three maximal structurally consistent systems of matches, which represent possible interpretations of the analogy. It performs a structural evaluation of the analogy, which reflects the size and depth of the matching system, and draws spontaneous *candidate inferences* using a process of structural completion from base to target. (See Forbus, Gentner, and Law, 1995, for a description.)

Another alignment-first model is Holyoak and Thagard's (1989) Analogical Constraint Mapping Engine (ACME), which uses a local-to-global algorithm similar to SME's. However, ACME differs from SME in some important ways. First, it is a multi-constraint connectionist system. In ACME, structural consistency is only a soft constraint, along with semantic similarity and pragmatic bindings. This allows more flexibility in the mapping process, but with the cost that structurally inconsistent mappings can easily occur. Second, whereas SME typically produces two or more winning interpretations, ACME uses a winner-take-all algorithm, producing one interpretation that is the best compromise among the three constraints. Third, candidate inferences are requested by the user rather than being generated automatically as in SME.

Projection-first models are particularly apt when there is one main schema associated with the base that can be projected onto the target. However, they encounter difficulties when more than one schema is associated with the base. A further drawback is that they do not readily capture emergent processing, in which the juxtaposition of two cases leads to insights not initially obvious in either representation. Alignment-first models seem apt for processing new comparisons, in which the common abstraction is not already a salient schema. However, in cases where the base domain possesses a conventionalized abstract schema, it seems likely that the learner will simply project this schema rather than deriving a new match from scratch. Thus a complete account of analogical processing will probably involve both kinds of algorithms, at different stages of knowledge. For example, given the analogy "The atom is like a solar system," an advanced learner might process it in projection-first mode, by projecting the abstraction *central force system* from the base (the solar system). However, a novice learner who has not yet explicitly stored the central-force abstraction will need to derive the common *central force* abstraction via an alignment process. As discussed above, one result of such an alignment is that the common system becomes more salient, thus promoting the development of a relational abstraction. Thus, with increasing domain expertise, projection-first processes may supplant alignment-first processes.

Retrieval

A striking and robust finding is that people often fail to retrieve potentially useful analogs, even when it is clear that they have retained the material in memory. For example, Gick and Holyoak (1983) gave subjects a classic thought-problem: How can a surgeon cure an inoperable tumor without using so much radiation that the surrounding flesh will be killed? Only about 10 percent of the participants came up with the ideal solution, which is to converge on the tumor with several weak beams of radiation. If given a prior analogous story in which soldiers converged on a fort, three times as many people (about 30 percent) produced convergence solutions. Surprisingly, the majority of participants still failed to think of the convergence solution. Yet when these people were simply given a hint to think about the story they had heard, the percentage of correct convergence solutions again nearly tripled, to about 80 percent. We can infer that the fortress story was stored in memory and was potentially useful, but it was not retrieved by the analogous tumor problem. This failure to access potentially useful analogs is a major cause of the *inert knowledge* problem in EDUCATION.

FA'idence further suggests that memory not only fails to produce analogous items, but often produces superficially similar items instead. Gentner, Rattermann, and Forbus gave subjects a set of stories to remember and later showed them probe stories that were either surface-similar to their memory item (e.g., similar objects and characters) or structurally similar (i.e., analogous, with similar higher-order causal structure). Subjects were told to write out any of the prior stories that they were reminded of. Surface commonalities were the best predictor of memory access: Recall rates were two to five times higher when the probes had surface commonalities than when the probes had structural commonalities. However, in a separate rating task, structurally similar pairs were rated much higher in inferential soundness and even in rated similarity than surface-similar pairs. Participants rated their own surface-similar remindings as low in inferential value and in similarity. The good news here is that although surface similarity has a large say in initial memory retrieval, people often reject purely superficial matches quickly, retaining matches with structural commonalities for further processing. (See Forbus, Gentner, and Law, 1995, for further details.)

Similar results have been found in problem-solving tasks. (See Reeves and Weisberg, 1994, for a comprehensive review.) Research by Brian Ross, Miriam Bassok, Laura Novick, and others bears out the finding that remindings of prior problems are strongly influenced by surface similarity, although structural similarity better predicts success in solving current problems. This gap between access and use may be less pronounced for experts in a domain. For example, Novick found that people with mathematics training retrieved fewer surface-similar lures in a problem-solving task and rejected them more quickly than did novice mathematicians. This may stem in part from experts' encoding patterns. There is evidence that relational remindings increase when the same relational terminology is used in the memory item and the probe item, suggesting that uniform encoding of the items is important in promoting retrieval.

Computational models of similarity-based retrieval

There are two main approaches to similarity-based retrieval. The CASE-BASED REASONING approach is founded on the view that much human reasoning is based on retrieval and on use of specific episodes in memory. This research focuses on how memory can be organized such that relevant cases are retrieved when needed. The second approach, more prevalent among psychologists, aims to capture the phenomena of human memory retrieval, including errors based on surface similarity. Two models in this spirit are Analog Retrieval by Constraint Satisfaction (ARCS), by Thagard, Holyoak, Nelson, and Gochfeld, and Many Are Called/but Few Are Chosen (MAC/FAC), by Forbus, Gentner, and Law. For example, MAC/FAC utilizes a two-stage process. An initial content-similarity stage is followed by a structural alignment process (that of SME) that filters the initial pool of potential retrievals. ARCS uses a competitive retrieval algorithm combination of content similarity, structural similarity, and pragmatic relevance. (See Holyoak and Thagard, 1995, for a discussion of ARCS, and Forbus, Gentner, and Law, 1995, for a comparison of the two models.)

Development of analogy

Even preschool children appear to engage in metaphor and analogy, as Ann Brown, Usha Goswami, and others have shown. However, there are marked developmental changes. Young children are likely to interpret analogies and metaphors in terms of thematic connections or common object properties rather than common relational systems. For example, when I asked children "Why is a cloud like a sponge?", five-year-olds respond that both are round and fluffy, rather than responding that both can hold and release water (the adult response). Some theorists explain this relational shift as due to children's increasing domain knowledge, with mapping processes remaining roughly constant across age. Others suggest that the shift is due to a change in processing capacity. (See Goswami, 1992; Halford, 1993; and Gentner and Rattermann, 1991, for further discussion.)

Extensions of analogy theory

Theories of analogy have been extended to ordinary (literal or overall) similarity. The basic idea is that overall similarity can be thought of as an especially rich analogy - one that shares both structural and surface commonalities. (See Gentner and Markman, 1997, and Medin, Goldstone, and Gentner, 1993, for reviews.) This perspective suggests a continuum of similarity types. At one end lies abstract analogy, in which the two terms share only a common relational system, as in the match between *[hen and chick]* and *[mare and colt]*. As more commonalities are added, the comparison becomes one of overall literal similarity, as in the match between *[hen and chick]* and *[duck and duckling]*. There is evidence that many of the same processes of structural alignment and mapping described for analogy also apply to overall similarity comparisons. As in analogy, common systems of connected information become more salient in literal comparison, and inferences are projected using a kind of structural-completion process. Analogical alignment processes have also been extended to metaphor, decision making, and categorization.

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