The computational modeling of analogy-making

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Our ability to see a particular object or situation in one context as being 'the same as' another object or situation in another context is the essence of analogy-making. It encompasses our ability to explain new concepts in terms of already-familiar ones, to emphasize particular aspects of situations, to generalize, to characterize, to explain or describe new phenomena, to serve as a basis for how to act in unfamiliar surroundings, and to understand many types of humor. Within this framework, the importance of analogy-making in modeling cognition becomes clear.

Analogy-making, whether human or computational, is typically conceived of as involving a 'mapping' between two domains, called the source (or 'base') and the target. Hall [1] lists four abstract processes that are widely considered to be necessary for analogical reasoning:

(1) recognition of a source, given a target description;
(2) elaboration and evaluation of the mapping between the two;
(3) transfer of information from the source to the target;
(4) consolidation (i.e. learning) of the outcome.

Chalmers, French and Hofstadter suggested that this basic framework should also include dynamic representation-building mechanisms and parallel sub-process interaction [2].

The following (true) example anecdotally illustrates not only these processes, but also the ubiquity of analogical processing, even in completely ordinary situations. In 1973 I was, for the first time ever, in a European bathroom [target]. This obviously brought to mind [recognition] an American bathroom [source] because [elaboration and evaluation] the European bathroom sink clearly mapped to an American bathroom sink, the European bathtub approximately mapped to an American bathtub (although having a significantly different shape), the European towel-rack to an American towel-rack, the European mirror to an American mirror, and so on. However, one object in the European bathroom puzzled me. It was made of porcelain, had a drain, and could be rinsed out with water from two faucets. I concluded [transfer] that this object must be a European toilet and acted on my conclusion…

(I only later discovered what a 'bidet' was and realized that European toilets are frequently not in the bathroom.)

Classes of computational models of analogy-making

Although there are many ways of classifying analogy-making programs, I have chosen to classify them into three broad groups based on their underlying architectures. (For another classification scheme, see, for example, Ref. [3]). These are:

- 'symbolic' models, so called because they are largely part of the symbolic paradigm in AI, in which symbols, logic, planning, search, and means–ends analysis, play a predominant role. (See Ref. [1] for an extensive review of these early models.)
- 'connectionist' models that adopt, broadly speaking, the framework of the connectionist networks, including nodes, weights, spreading activation, and so on.
- hybrid models that lie somewhere in between connectionist and symbolic models.

Symbolic models

The distinction of being the first computer model of analogy-making probably goes to Reitman's Argus [4]. The program solved proportional analogies that, by today's standards, seem trivial. For example, the program was given: *bear*:*pig*::*chair*:? and had to pick an answer from one of four choices: *foot*, *table*, *coffee*, *strawberry*. Although the program was simple in the extreme, its architecture nevertheless included many far-sighted principles, including the use of a conceptual network, interactions between the concept network and the problem to be solved, the realization of the necessity of automatic representation-building for the source and target, and so on.

The best known model from the 1960s was Evans' ANALOGY [5]. Like Argus, this program was designed to do proportional analogies of the form A:B::C:? taken from standardized high-school IQ tests (see Box 1). All of the objects in the analogies were simple geometric figures. One important feature of ANALOGY was that its input was a low-level description of each figure and, based on this, the program built a high-level description of the figure. All of the problems solved by ANALOGY are from the same domain, that is, both source and target consist of geometric figures.

Also about that time, JCM attempted to put the computational modeling of analogy-making into a more cognitively plausible, real-world framework [6]. It did this by incorporating incipient notions of learning, working memory (WM) and a long-term memory (LTM), in which were stored representations of a set of primitive objects, importance-ranked relations between them, events and causal mappings.

A number of models from this early period drew heavily on formal logic. For example, ZORBA-1 was an automated theorem prover that solved (target) problems by finding an analogous (source) problem, taking its proof and applying it to the target problem [7]. Munyer (PhD thesis, University College of Santa Cruz, 1981) and Greiner [8] also developed

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Box 1. Constructing rules

ANALOGY, one of the earliest analogy-making programs [a] attempts to 'construct a rule which transforms figure A into figure B, and figure C into exactly one of the five answer figures' (see Fig. I). The representation module first analyzes the input (written as a low-level description, rather than being the actual figures) and describes figure A, for example, as [(inside P2 P3) (above P1 P3) (above P1 P2)]. Similar representations are made for figures B and C and for the five test figures. Based on these representations, the program matches the most similar descriptions in order to discover the correct analogy. Notice that the program has no semantic knowledge about the figures it manipulates. For example, it does not know that squares and rectangles are generally closer in people's minds than, say, squares and letters.
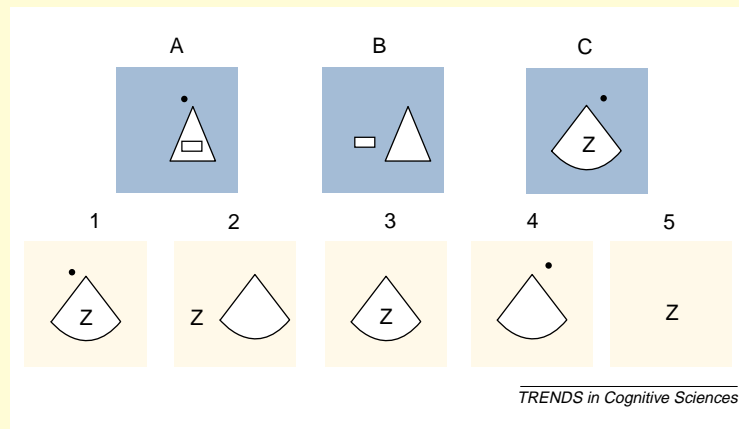

TRENDS in Cognitive Sciences

Fig. I. (see text for details)

Reference
a Evans, T. (1968) A program for the solution of a class of geometric analogy intelligence test questions. In *Semantic Information Processing*, pp. 271–353, MIT Press

analogy-making systems based on formal logic. Munyer's system, in particular, combined planning, problem-solving and deductive logic and implemented a process of gradual 'convergence' to a correct mapping via an interaction between top-down (logic) and bottom-up, competitive processes.

The first attempt to apply production systems to computational analogy-making was McDermott's ANA [9] a program that did problem-solving in a micro-world. This program had an LTM knowledge base (stored as production rules) and a working memory. ANA progressively built the appropriate productions needed to solve the target task, analogous to a source task stored in LTM that it already knows how to do. It learned by saving the new productions in LTM.

Carbonell applied means–ends analysis to analogical retrieval [10]. One key difference with previous work was that his transformational-analogy method used weak search methods and sub-goaling to find 'solution paths' to a solution to a particular target problem. The program had a stored set of second-order representations of solution paths for previously solved problems. Means–ends analysis was then used to discover the source problem that best corresponded to the target problem. This transformational-analogy method was later extended to a more powerful derivational-analogy method [11,12], which operated on automatically derived representations and included a peripheral knowledge base to improve the evaluation of various parts of the solution path.

Simpson's MEDIATOR was the earliest application of case-based reasoning (CBR) to analogy-making [13]. Prodigy/Analogy combined CBR and Carbonell's derivational approach to analogy-making [14]. This architecture was explicitly designed to be scaled up to larger domains and several empirical results have shown that, as the number of stored episodes increased, the integrated learning system was able to keep search requirements under control.

In the late 1970s, Winston developed the notion of 'transfer frames' [15]. Two objects (one source, one target) were presented to the program as being similes. Mappings were then made by the program between the source and target based on the most salient properties of the source, the prototypicality of the information in the target, and the instructional context provided by a tutor. After checking for inconsistencies with respect to these criteria, properties were transferred from the source to the target. This work was extended to a model of analogical reasoning in which, in order to respond to a particular query, a rule was extracted from the source situation based on attributional and relational information in the source situation [16,17]. This rule, based on consistent relational structure, was used to answer the target query.

Winston's work anticipated, in some sense, Gentner's Structure Mapping Theory (SMT) [18] (and see Box 2). SMT is unquestionably the most influential work to date on the modeling of analogy-making and has been applied in a wide range of contexts, from child development to folk physics. SMT explicitly shifts the emphasis in analogy-making to the *structural* similarity between the source and target domains. Two major principles underlie SMT:
(1) the relation-matching principle: good analogies are determined by mappings of relations and not attributes (originally only identical predicates were mapped).
(2) the systematicity principle: mappings of 'coherent systems' of relations are preferred over mappings of individual relations.

Box 2. Structure mapping

SME, the Structure Mapping Engine [a], a computational implementation of the Structure Mapping Theory [b], has been the most influential computational model of analogy-making to date. It receives predicate-calculus representations of the base and source and searches both representations to determine where there are structural similarities between them. It builds a mapping between the two situations based on these structures and their overall coherence. Discovering two matching systematic structures (Fig. I, heavy lines) in the source (Solar system) and in the target (Rutherford atom) allows the program to transfer structure found in the source to the target (in this case, to conclude that the cause of the electron revolving around the nucleus is the charge). It is hard to know what conclusions SME might have drawn if the representation of the Rutherford atom had also included the fact that, in addition to electrical forces, there are gravitational forces between the nucleus and the electron (for a discussion of this point, see Ref. [c]).

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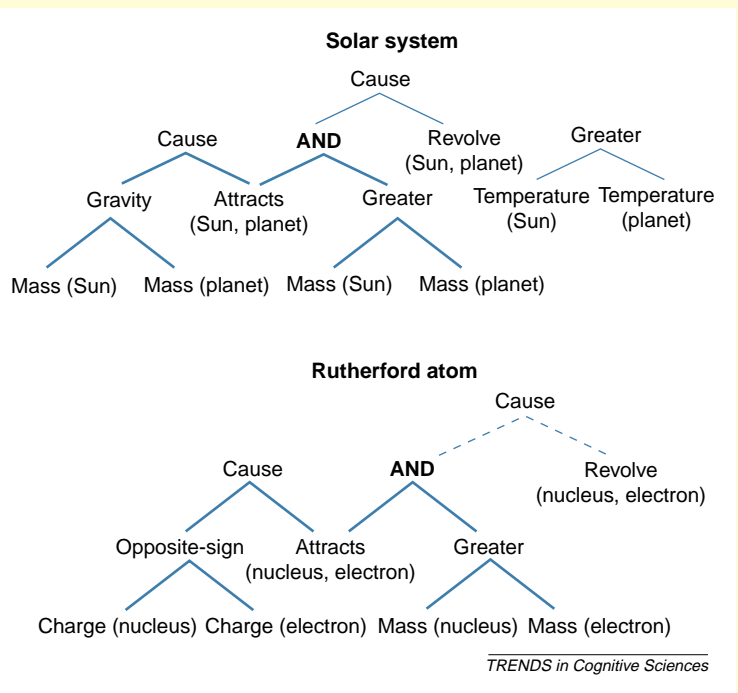
b Gentner, D. (1983) Structure-mapping: a theoretical framework for analogy. *Cogn. Sci.* 7, 155–170

c French, R. (1995) *The Subtlety of Sameness: A Theory and Computer Model of Analogy-Making*, MIT Press

Fig. I. (see text for details)

This structural approach was intended to produce a domain-independent mapping process.

The Structure Mapping Engine (SME) was the computational implementation of SMT [19]. More recent versions of SME have explored the use of pragmatics, as well as re-representation techniques that allow related, but not identical, predicates to match [20]. MAC/FAC, a two-stage analogical retrieval engine, was later developed as a front-end to SME [21,22]. The first stage of its retrieval process consists of a sweep through LTM, retrieving many potential source episodes based on a superficial search; the second stage is a detailed, best-match process designed to select the best matches to the target. Only then does the structure-mapping phase begin. MAGI, another SME-based model, detects regularity within a given situation or scene by seeking maximally consistent mappings among its parts [23]. Depending on the nature of the mappings found, elements of the scene can be categorized as being repetitions, or symmetrical. This structural notion of regularity applies to conceptual, as well as perceptual, materials.

IAM incrementally maps portions of a base domain to the source, thereby gradually building up a single interpretation based on selected portions of the domain rather than on many alternative interpretations [24,25]. If the mapping produced is not optimal then this mapping will be abandoned and another constructed. The completely serial nature of IAM processing, however, has produced doubts about its ability to scale up [26]. I-SME is an incremental version of SME based, in part, on the IAM architecture [26]. The most significant difference with the latter program is that, instead of the strictly serial approach adopted by IAM, I-SME mixes serial and parallel processing.

In recent work, another SME-based program, SEQL, has been applied to infant categorization [27]. The authors suggest that categories are represented via structured descriptions and formed by a process of progressive abstraction, through successive comparison with incoming exemplars.

Burstein's CARL extends the ideas of Gentner in a multi-stage analogy-making program that constructs analogies based on several others presented by a teacher in a somewhat context-dependent manner [28]. Kedar-Cabelli's model of purpose-driven analogy attempts to derive relevant structural and functional features automatically in order to make mappings [29].

Recently, a 'path-mapping' model [30] of how humans integrate analogical mapping and problem-solving has been developed based on ACT-R [31]. ACT-R has also been used in the context of analogy-making to attempt to develop a unified theory of metaphor

understanding, semantic illusions and text memory [32] and to model invention by analogy [33].

A final pair of symbolic models, BORIS [34] and MORRIS [35], deserve mention. These programs attempt to understand narrative through the use of abstract 'thematic abstraction units', which closely resemble Schank's 'Thematic Organization Points' (TOPS) [36] implemented in a dynamically organized memory. Analogies in these models are recognized largely through structural relations, rather than with simple attribute information.

Connectionist models

Symbolic systems are generally well equipped to model relational structures involving situations represented as objects and relations between objects. For this reason, these models held the high ground for many years in the computational modeling of analogy-making. However, connectionist models have taken their place alongside symbolic models of analogy-making, largely owing to recent advances in their representation techniques. Most importantly, distributed connectionist representations provide a natural internal measure of similarity, thereby allowing the system to handle with relative ease the problem of similar, but not identical, relations, a problem that has proved difficult for symbolic models.

> ### '...connectionist models have taken their place alongside symbolic models of analogy-making...'

ACME was the first attempt to develop an architecture in which analogy-making was an emergent result of constrained, parallel activation of states of in a neural network-like structure [37]. In this model, structural similarity, semantic similarity, and pragmatic importance determine a set of constraints to be simultaneously satisfied. The model is supplied with representations of the target and source and proceeds to build a localist constraint-satisfaction network in which hypothesis nodes correspond to all possible hypotheses pairing the elements of the source with those of the target. Excitatory and inhibitory links between these nodes implement the constraints. In this way, contradictory hypothesis nodes compete with one another and (usually) do not become simultaneously active, whereas consistent nodes tend to mutually support each other. The relaxation of the network provides a parallel evaluation of all possible mappings and finds the best one, represented by the set of most active hypothesis nodes. ARCS is a model of retrieval that is coupled with ACME in which mapping is dominated by structural similarity and retrieval is dominated by semantic similarity [38].

One of the most ambitious connectionist models of analogy-making is LISA [39]. Whereas ACME required all objects in the source to be pairwise connected to all elements in the target, LISA relies on more plausible mechanisms, such as partially distributed representations of concepts, selective activation and dynamic binding as the means of associating the relevant structures. Only node structures that oscillate in synchrony are bound together [40,41]. Crucially, the synchronous binding mechanism means that both WM and LTM can interact during both retrieval and mapping. Even though, for the moment, LISA cannot make inferences, it does successfully integrate the process of retrieval of a base and the mapping of the base and target.

STAR-1, designed to solve proportional analogies, was the first distributed connectionist model of analogy-making [42] and is based on the tensor product connectionist models developed by Smolensky [43]. STAR-2 is a recent and more complex version of STAR-1, developed in an attempt to achieve a better understanding of the development of analogy-making capabilities in children [44].

DRAMA [45] is a recent connectionist model of analogy-making that implements holographic reduced representations [46], a type of convolution-correlation memory [47]. This program, using fully distributed representations of concepts, attempts to integrate the semantics and structure of the base and target during the mapping process.

Jani and Levine [48] have developed a neural-network approach to analogy-making based on Adaptive Resonance Theory [49]. This system has a concept-association mechanism based on synaptic triads, and explicitly appeals to neurobiological plausibility. Analogator is a connectionist model that learns to make analogies by seeing numerous analogies (Blank, PhD thesis, Indiana University, 1996).

Hybrid models

Hybrid models share features of both connectionist and symbolic models. (The term 'connectionist' here is meant to be broadly construed, encompassing architectures that rely on connectionist-like mechanisms, such as spreading activation among node structures, excitation and inhibition between nodes, and so forth.) The first two models discussed here rely on agent-based approaches to analogy-making.

COPYCAT ([50]; see Box 3), TABLETOP [51], LETTER-SPIRIT [52], and METACAT [53] form a family of models whose basic architectural principles were described by Hofstadter [54,55]. Three of the most important features of these models of analogy-making are: (1) their ability to build up their own representations of the source and target as well as the mapping between them via an agent-driven interaction between top-down (LTM) and bottom-up (WM) processing; (2) their

Box 3. Using non-deterministic agents

COPYCAT [a,b] solves letter-string analogies of the form: ABC:ABD::KJI:? and gives probabilistically possible answers, such as LJK, KJJ, KJD (see Fig. I). The architecture of

COPYCAT involves a working memory, a semantic network (simulating LTM) defining the concepts used in the system and their relationships, a procedural memory storing small, nondeterministic computational agents ('codelets') that build, examine and, possibly, destroy the structures in the working memory and continually interact with the semantic network. The system gradually settles towards a set of consistent set of structures that will determine the mapping between the base and the target.

Fig. I. (see text for details)

References
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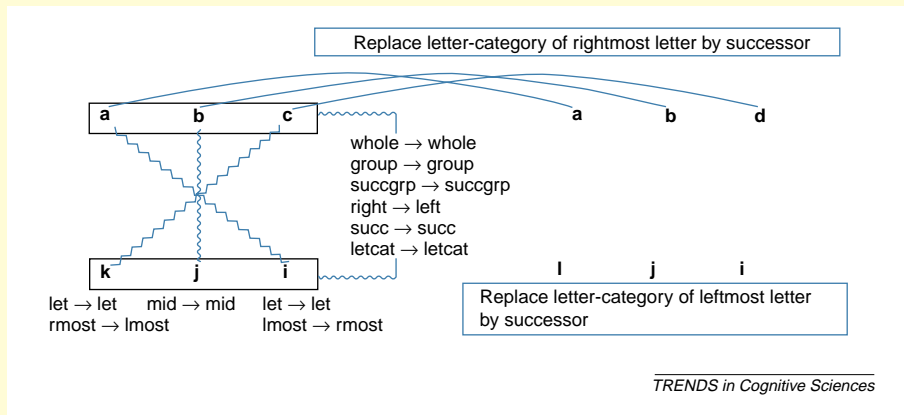b Mitchell, M. (1993) *Analogy-Making as Perception: A Computer Model*, MIT Press

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use of (simulated) parallelism; and (3) their stochastic nature. These models abandon traditional sequential processing and allow representation-building and mapping to run in parallel and continually to influence each other. In this way, partial mappings can have an impact on further representation-building (and vice-versa), thus allowing the gradual construction of context-sensitive representations.

> **'...almost 40 years of research in the (...) modeling of analogy-making have (...) shown us just how hard the problem is.'**

AMBR [56], an analogical problem-solver, is based on the principles of the DUAL model [57], a general, context-sensitive cognitive architecture consisting of many micro-agents each of which represents a small piece of knowledge. Each micro-agent has a symbolic part that encodes the declarative and/or procedural knowledge it is representing, and a connectionist part that computes the agent's activation level, which represents the relevance of this knowledge to the current context. The AMBR model, and its later extension, AMBR-2 [58], implement the interactive parallel processes of recollection, mapping and transfer that emerge from the collective behavior of the agents. The result is an analogy, but also a re-representation of the old episode which might turn out to be illusory memory.

Other hybrid models that combine symbolic and connectionist mechanisms use spreading activation mechanisms, node structures implementing knowledge bases, and other mechanisms, and include ASTRA [59] and ABR-conposit [60]. ASTRA implements 'continuous analogical reasoning', which recognizes the importance of integrating the various stages of analogy-making rather than treating them independently. ABR-conposit is an implementation of Analogy-Based Reasoning that implements WM–WM matching, creates and modifies WM representations, and manipulates complex data structures in an explicit attempt to bridge the symbolic–connectionist gap.

Conclusion
I have presented a brief, and necessarily incomplete, survey of computational models of analogy-making over the past 35 years. These models are divided into three broad classes: those whose architectures are based largely on the principles of the symbolic tradition of artificial intelligence, those that draw on connectionist principles, and, finally, hybrid models that depend on a combination of these and other principles. Even though the field has come a long way since Walter Reitman's and Thomas Evans' first analogy-making programs of the mid-1960s, great challenges still lie ahead. These include: (1) the development of context-sensitive ways for analogy programs to settle on the appropriate representations of the base and target situations; (2) the development of a better understanding of the long-term memory retrieval mechanisms that allow 'analogous' situations to be activated in working memory; (3) the systematic exploration of experimenter-independent representation-building and learning mechanisms; and (4) the incorporation of these mechanisms into analogy-making programs – and all of this, with a keen eye, as always, to the all-important issue of scaling-up. The lessons of almost 40 years of research in the computational modeling of analogy-making have, more than anything else, shown us just how hard the problem is. Analogy-making is so intimately and so deeply part of human cognition that it is probably safe to say that any program capable of doing analogy-making in a manner truly comparable to human beings would stand a very good chance of passing the Turing Test.

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