Cognitive Artificial Intelligence: Learning and reasoning by analogy

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Abstract. Analogies are an important part of how we process information. New information is abstracted and matched to information we acquired previously, generating insight and allowing the transfer of skills and expectations through abductive reasoning. This paper sums up research by Patrick H. Winston described in his papers "Learning structural descriptions from examples" and "Learning and reasoning by analogy: The details", wherein he presents theories of analogical reasoning and explores how a machine might also learn those capabilities, and gives a quick overview of related research into analogy of the time.

Keywords: Computing methodologies→Knowledge representation and reasoning; analogical reasoning, information retrieval

1 Introduction

We use Analogies in our daily lives: When we look at a clock, recite a proverb, or try to pass on information with the help of a 'rhetoric analogy'. Analogies allow us to make assumptions, and decisions, in the face of new and unknown situations that are similar to situations we already have solutions for. When we learn something new, we fit the new information into a framework of existing knowledge, based on how we can abstract it. According to Winston, reasoning happens when conclusions drawn from abstracted information are successfully applied to a different set of information that we abstracted similarly(Winston, 1980, p. 1), allowing us to make sense of the world without infinite trail and error – we can infer from an apple falling off a tree that oranges would also do so, given similar circumstances.

As shown in definition 1, analogies are "typically used for the purpose of explanation or clarification". In his papers "Learning structural descriptions from examples" and "Learning and reasoning by analogy: The details", Patrick H. Winston presented theories on how analogies work and systems that build on these theories to allow a machine to learn by means of examples (cf. Winston, 1970, 1980, p. 7,p. 1-3).[1]

[1] References to Winston's work are based on PDFs available at `https://dspace.mit.edu/handle/1721.1/5732` and `https://dspace.mit.edu/handle/1721.1/6884`, and as such use the page numbers in those PDFs. These digital page numbers by differ by up to 2 from the page numbers printed in the referenced papers.

Definition 1. *Analogy: a comparison between one thing and another, typically for the purpose of explanation or clarification. (*Oxford Dictionary*, n.d.)*

2 Background

Analogy, as a means of human reasoning, is integral to our way of thinking and problem solving. Early research on creating computer programs to solve analogy problems was done by Evans, who described a program written in LISP to solve "geometric analogy problems" found in intelligence-tests (Evans, 1962).

S ternberg states that analogical reasoning must begin with "*encoding*" — translating analogy terms into an internal mental representation—, and the analogy solution is only completed "by indicating a response"(Sternberg, 1977, p. 354). He also lists "three intermediate comparison operations" :

1. *inference*: Inferring the relation between a given object and its known meaning.
2. *mapping*: Map the relation between objects.
3. *application*: Apply "a relation analogous to the inferred one" to other objects and their potential meanings(Sternberg, 1977, p. 354).

Sternberg lists three theories that differ in which intermediate comparison operations they include:

1. "Inference, mapping, and application."
2. "Inference and application, but not mapping"
3. "Inference and mapping, but not application"(Sternberg, 1977, p. 354-355).

He states that the third theory "is a distillation and simplification of theories presented by Evans and Winston"(Sternberg, 1977, p. 355),(cf. Winston, 1970).

3 Learning and reasoning with analogies

In both "Learning with Analogies" and the preceding work "Learning structural descriptions from examples", Patrick H. Winston describes research aimed at enabling a machine to learn rules from a series of examples and apply them to new situations.

3.1 Learning structural descriptions from examples

In "Learning structural descriptions from examples", Winston describes research "on how a machine can recognize concepts and learn concepts to be recognized"(Winston, 1970, p. 4). He postulates that learning by examples, teaching, and imitation all all necessitate the "ability to generate and manipulate abstract descriptions"(Winston, 1970, p. 7). He illustrates and explains his approach with simple geometric shapes, as seen in Figure 1, which shows a relation between two boxes, A and B.

[2]. He elaborates that the system starts with an input image, then builds a "very coarse description", and then adds detail to the description(Winston, 1970, p.8). He states that the generated description allows the comparison of different situations on an abstract level, and that a program that does this would have to be capable of deducing "that there is a supported-by relation in one case, while there is an in-front-of relation in the other"(Winston, 1970, p. 10-11).

W inston says that an important part of generating concepts from examples is what he calls a "near miss": Only by recognizing what is *not* important can the program properly assess a given situation. He exemplifies this with Pictures in Figure 1, showing two archs made from simple geometric shapes, as well as two "near miss"-pictures, here shown in Figure 3. The misses teach the program that the lower two blocks must not touch, and that the top block lying atop the others is a requirement for a scene showing an arch. He states that the learned concepts can help the program generate more complex abstraction with the help of the previously understood ones, and the results suggest that the shown methods "may lead to increasingly powerful performance" (Winston, 1970, p. 11-13).

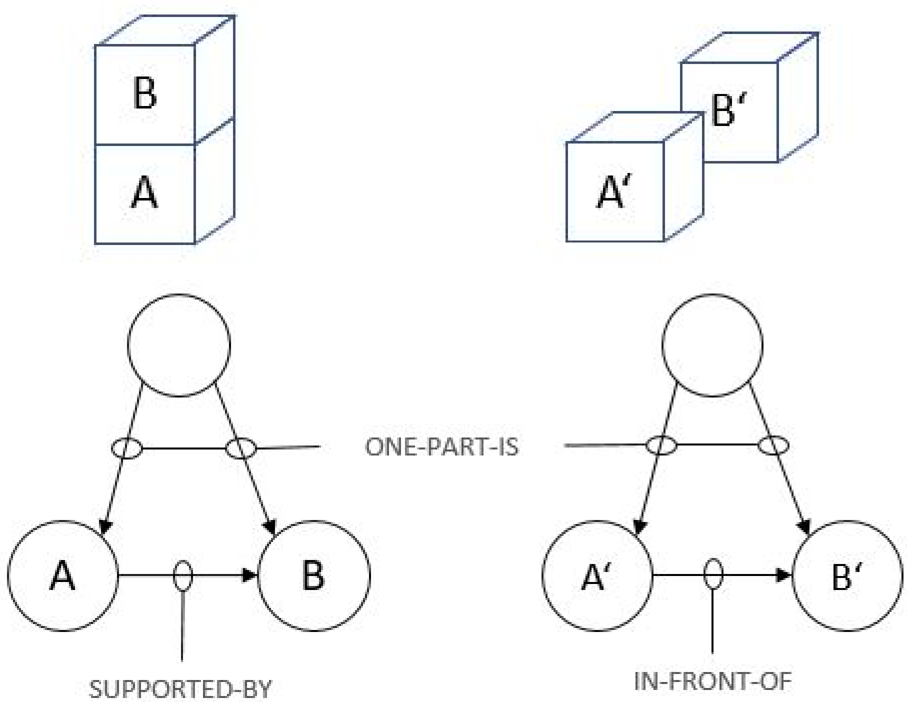

Fig. 1. Relation between boxes

[2] Figures shown in this chapter are reinterpretations of figures used in (Winston, 1970, p. 7-11)

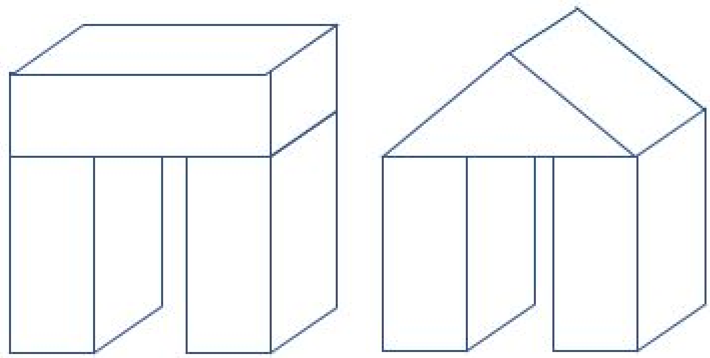

Fig. 2. Two Examples of arches

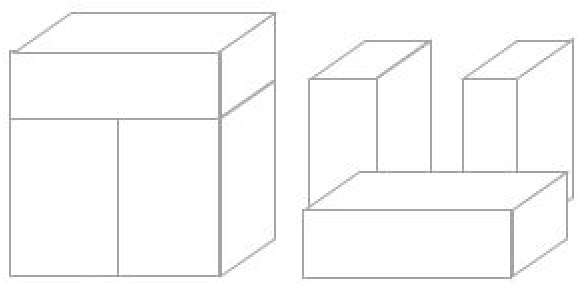

Fig. 3. Two Examples of a "near miss"

3.2 Learning sand reasoning by analogy: the details

In "Learning sand reasoning by analogy: the details", Winston "presents a theory of analogy and describes an implemented system that embodies this theory"(Winston, 1980, p. 1). He lists five "key ingredients" for his system :

1. *"Extensible-relations representation"*: "Situations are represented using relations between *pairs* of parts". Descriptions can be added to relations to elaborate.
2. *"Importance-dominated matching"*: Similarity between situations is measured "according to what is important in the situations", e.g. cause and effect.
3. *"Analogy-driven constraint learning"*: Constraints are learned when mapping "parts of a situation in a well understood domain into the parts of another situation in an ill-understood domain", e.g. learning Ohm's law

4. *"Analogy-driven reasoning"*: In questions about whether a relation holds in a situation, "causes found in a remembered situation" may serve as precedents.
5. *"Classification-exploiting hypothesizing"*: It is assumed that remembered situations "similar to a new, given situation will involve the same sorts of things" found in the new situation(Winston, 1980, p. 3) .

1. *"Symbolic sufficiency"*: A situation can be sufficiently described with a limited set of relation types.
2. *"Description-determined similarity"*: Two situations are similar if their important relations are similar.
3. *"Constraint-determined importance"*: The *important* relations are defined as such.
4. *"Historical continuity"*: "A situation that is similar to a past situation generally leads to similar results"(Winston, 1980, p. 4) .

He also lists several examples for reasoning by analogy, e.g. comparing Shakespear's plays with each other, or hypothetical legal cases where an analogous situation from a past case would be used as a precedent.

W inston describes a representation as a "vocabulary of symbols together with some conventions for arranging them". As this representation would favor matching situations by correspondence, he chooses an "object-oriented representation", where the relations in a given situation form a "semantic net"(Winston, 1980, p. 6-7).

Winston concludes that simple situations can be analyzed through the analogy process using previously stored situations and subsequently added to the pool with which to analyze "newer, perhaps bigger situations", closing with the finding that "experience makes an analogy-making system smarter"(Winston, 1980, p. 35). An example of such a semantic net is shown in Figure 4: The shown relations are :

1. Prince finds Cinderella [instrument shoe]
2. The prince loves Cinderella
3. (The prince loves Cinderella) causes (the prince kisses Cinderella) "(Winston, 1980, p. 4) .

Relations can have different types. The various types of relations can be ordered by importance, e.g. *cause* could be more important than *instrument* when describing a story plot. Winston also mentions "demons" to automatize simple deductions, e.g. "when one person kills another, it is clear that the killed person is dead", and states that demons are essentially miniature analogies(Winston, 1980, p. 10).

4 Conclusion

Both of the papers summed up here conclude with an iterative process wherein a system requires previous input to learn new relations, using the learned situations

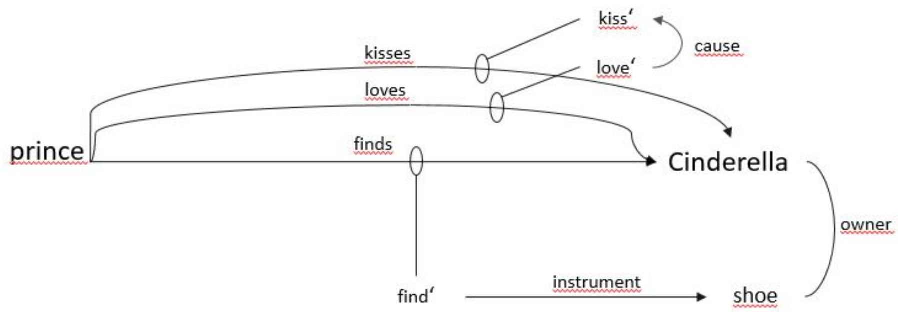

Fig. 4. Two Examples of a "near miss"

to generate descriptions and relations that can be used to better assess and analyze new input. (cf. Winston, 1970, 1980, p. 250-251,p. 34-35). This is not unlike the learning process of a child, which, with years of life experience, will be able to understand ever more complex relations by comparing them with experiences it already made. As Winston hints at in his closing remarks, to make a computer understand something the way we do, one must first understand what *understanding* actually means(Winston, 1970, p. 249-250). As such, research into creating human-like intelligence also teaches us something about ourselves, and his works have possibly influenced research into psychology just as much as research in the field of computer science.

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