Analogy as Integrating Framework for Human-Level Reasoning

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Abstract. Human-level reasoning is manifold and comprises a wide variety of different reasoning mechanisms. So far, artificial intelligence has focused mainly on using the classical approaches deduction, induction, and abduction to enable machines with reasoning capabilities. However, the approaches are limited and do not reflect the mental, cognitive process of human reasoning very well.

We contend that analogical reasoning is the driving force behind human thinking and therefore propose analogy as an integrating framework for the variety of human-level reasoning mechanisms.

Keywords. analogy, analogical reasoning, integrated cognitive abilities, cognitive model

1. Motivation

In most current approaches to model reasoning capabilities on machines, researches have examined certain reasoning mechanisms isolated from the overall context of human reasoning and learning. These reasoning mechanisms cover deduction [1], induction [2] and abduction [3]. Although such research-endeavors clearly are successful in various aspects and applications, they model just a fraction of the overall complexity of human-level reasoning. The problem of integrating such approaches to reach a cognitive system for human-level reasoning is non-trivial. We propose analogical reasoning as an integrating framework for various human-level reasoning mechanisms. This paper describes the role of analogies in performing different reasoning mechanisms in one integrated cognitive model and proposes a concrete approach for human-level reasoning based on Heuristic-Driven Theory Projection (HDTP).

The remainder of the paper is structured as follows: Section 2 explains the integrating role of analogy in various examples for cognitive reasoning or learning processes. Section 3 proposes a cognitive model for human-level reasoning, which is elaborated further in section 4 by specifying an implementation based on HDTP. We explain how knowledge is organized and represented in the knowledge base, how the reasoning unit utilizes this knowledge to perform different types of reasoning and how new knowledge is stored in the knowledge base.

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2. The Role of Analogies in Human-Level Reasoning and Learning

Learning means inferring new or revising old knowledge and adapting the knowledge base. By the kind of knowledge learned, we can distinguish various cognitive tasks:

Learning new domain knowledge. Analogical comparison is a central mechanism for problem solving: new problematic situations (target domain) are compared to similar problems experienced in the past (source domain). Analogy is used to analyze the source and the target problem for common structures. The solution strategy applied in the source problem is transferred to the target domain to solve the problem in the new domain.

Creative learning of new conceptual knowledge. Analogical transfer is not limited to domain knowledge, but can also hypothesize new concepts. For instance, in physics, "heat" is energy that can be transferred from one body to another due to a difference in temperature. Heat in contrast to temperature is not observable and can be conceptualized only via analogy to a perceivable domain, e.g. water flowing between two vessels with different water levels. The height of the water is aligned to the temperature. From the observation that water keeps flowing until it has the same height in both vessels (source domain) and that temperature balances after some time (target domain), it can be inferred via analogy, that there exists an analogous "flowing thing" on the target side: the concept $heat$. Creative generation of knowledge of this type is classically modeled via abduction. Using analogy in this abductive process guides and motivates why certain things are hypothesized and others not.

Creating ad-hoc concepts. Establishing an analogy between two domains leads also to the construction of new ad-hoc concepts: e.g. in the Rutherford analogy between the solar system and the Rutherford atom, the sun and the nucleus, respectively the planet an the electron are aligned. For the purpose of the analogy they form the ad-hoc concept $central\ body$ and $orbiting\ object$ respectively. These ad-hoc concepts can emerge as permanent concepts after several learning cycles.

Learning general principles via abstraction. Analogy also plays an important role in learning general principles. Induction, the predominant mechanism of generalization in AI, is rather restricted and is usually considered to require a large set of samples incorporating identical patterns. Combining analogical and inductive reasoning mechanisms enables a reasoning system to generalize over analogical patterns which increases the flexibility and makes it similarly powerful as human generalization [4].

3. Cognitive Model for Human-Level Reasoning

Figure 1 illustrates a cognitive model for human-level reasoning. We now explain the role of the knowledge base, the reasoning unit and the interaction of both.

The knowledge base stores all information about the world. It represents the human memory. Domain knowledge constitutes the main part of the knowledge and contains information such as "Planets revolve around the sun." or specific rules for solving problems. As part of the knowledge base we explicitly distinguish conceptual knowledge, describing all concepts by their taxonomic relationships to each other in a hierarchy. This hierarchy contains top-level concepts as well as domain concepts.

The reasoning unit comprises four different reasoning mechanism: the classical approaches deduction, induction and abduction, but also analogical reasoning. Analogical reasoning performs as the core of this framework.

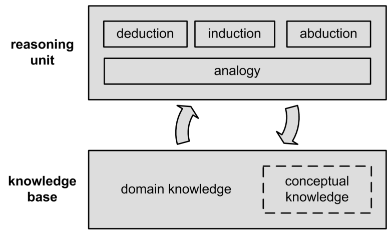

Figure 1. Cognitive model of human-level reasoning.

Deduction infers knowledge given implicitly by facts or rules: if the premises evaluate true, deduction infers that the conclusion is true as well. From a cognitive science perspective, researchers often claim that deduction plays no or a minor role in human reasoning [5,6]. Deduction is nevertheless a component of the reasoning unit, because it can support analogical reasoning in different ways: Deduction enables a machine to make implicit knowledge explicit and therefore knowledge becomes independent of the chosen representation. Moreover, the ability to establish an analogy highly depends on an adequate representation of the domains. Deduction is used to re-represent knowledge to make analogous structures in the domains obvious.

Induction creates knowledge via generalization over a set of cases which share common properties or relations and deduces some general law or principle. The "classical induction" in artificial intelligence and machine learning requires a very large set of data samples to draw sound conclusions. Humans apply inductive strategies for reasoning already with a limited number of examples (e.g. four or five cases). Moreover, they are able to compare samples which share the common pattern only at an abstract level, while "classical induction" works only when the patterns across the data samples are identical. Combining induction with analogy, this reasoning mechanism gains the flexibility it needs to reflect human generalization techniques (c.f. section 4 or [4]).

Abduction is reasoning from an effect to its cause: from a known general rule and a true conclusion it is hypothesized that the premise is true as well. Analogical reasoning can motivate abduction-like inferences [7]: Assume p and $p \to q$ are true in the source domain and therefore q can be inferred. If an analogous counterpart q' of q is known in the target domain, we can transfer via analogy the rule $p' \to q'$ and abductively conclude that p' also holds in the target domain. There could be other causes for q', but since p is the cause in the analogous domain, it is likely that p' is also the cause in the target domain.

Analogies aim to identify structural commonalities, analogous relations or objects playing the same roles in two different domains - the source and the target domain. Analogical learning is typically applied across two different domains. The purpose of analogies is to adapt knowledge available about the source such that it can be applied to the target in a way that new analogous inferences can be drawn. This way it is possible to gain completely new hypotheses about the target domain which still have to be proven. Analogical transfer leading to inconsistencies in the target domain is considered as an indicator for a bad (wrong) analogy. Analogical reasoning can also be used to extract commonalities between source and target which are captured in an abstract generalization. However, this generalization is not assumed to be generally true (as it is the case for induction), but only for the specific source and target domain. Good analogies can be analogously applied and tested in other domains.

4. Implementation of the Cognitive Model

Figure 2 illustrates our approach to the cognitive model for human-level reasoning.

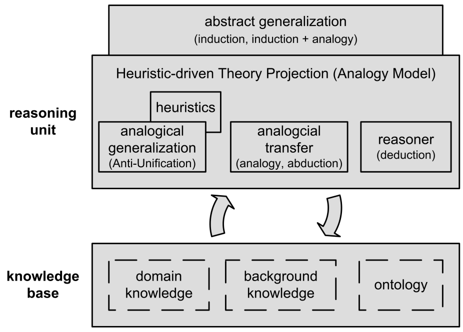

Figure 2. An HDTP-based implementation of the cognitive model for human-level reasoning.

The knowledge base consists of domain knowledge, background knowledge and an ontology. The domain and the background knowledge constitute all knowledge about the world and are specified by formulas represented in many-sorted first-order logic. The domain knowledge contains domain-dependent knowledge, such as knowledge about thermodynamics and fluid dynamics (e.g. water and its flowing characteristics). The background knowledge contains domain-independent knowledge such as the formula $distance_{eucl}(X,Y)$=$distance_{eucl}(Y,X)$ stating that the Euclidian distance is symmetric. The ontology contains conceptual knowledge specified via taxonomic relations to other concepts [8]. It describes the relation of top-level concepts like $massterm$, $time$ or $object$ to (usually domain-specific) concepts such as $vessel$ or $water$.

The heart of the **reasoning unit** is the HDTP [9], a symbolic approach developed at the University of Osnabrück to model analogies. Since HDTP is based on first-order logic, it can naturally interact and easily integrate the formal reasoning mechanisms deduction, induction and abduction. The reasoning unit contains different modules. The interaction of these modules enables the modeling of human reasoning strategies. We explain the reasoning unit by describing the different steps of the reasoning process. Of course, the process differs depending on what kind of knowledge is inferred or learned.

All reasoning processes start with some knowledge as input - in analogical reasoning two domain theories Th_S and Th_T modeling source and target. The theory of anti-unification [10] is used to generalize the structural commonalities between two formal theories. The module *analogical generalization* computes an analogy by successively selecting a suitable formula from Th_T and Th_S and constructing a generalization (Th_G) together with the corresponding substitutions. Heuristics to minimize the complexity of substitutions [9] have been developed to guide this anti-unification process. The output is the generalized theory Th_G, which covers explicitly the commonalities and establishes an analogous relation between source and target. Usually, the source domain is well known and modeled richer than the target domain (about which you want to learn something). Based on the analogical relation between source and target, the module *analogical transfer* identifies knowledge in the source which could be transferred to the target domain. The knowledge gained by the analogical transfer can be facts or rules, but also conceptual knowledge such as new concepts or a revised concept hierarchy. The *reasoner* module must check the hypotheses suggested by the analogy for consistency, i. e. it must prove whether the new facts or rules hold or conflict in the target domain. The reasoner module can also be used during the analogical generalization for restructuring domain knowledge, e.g. restructure the target domain by inferring implicit formulas from the given facts and rules such that the resulting representation is suitable for a structural comparison and can be anti-unified (e.g. [11]). On top of HDTP, the module *abstract generalization* applies inductive reasoning mechanisms based on the analogical comparison to enable inferring general principles [4].

All inferred knowledge is stored in the knowledge base and leads either to extended or revised theories (in case new facts or laws are learned for the domain or background knowledge or new general principles are hypothesized via the abstract generalization module) or an extended or revised ontology (if concept knowledge is learned).

5. Summary

This paper proposes to model human-level reasoning based on analogy. Combining analogy with classical reasoning mechanisms leads to a cognitive model in which various human reasoning and learning strategies can be explained. We outline our approach using HDTP as integrating framework and describe the role of analogy in various inferences.

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