A Top-down Process for Human-like Everyday Analogical Reasoning

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1 The Problem: Transfer of concepts to similar things

Artificial Intelligence (AI) seems to struggle to transfer concepts with the same ease that humans do. Let us consider three examples illustrating this deficiency in three different domains that are important to AI applications. (i) In vision a robot in a kitchen could see and recognise a spatula, but it would not know that a cleaver with a broad flat blade might be equally effective for sliding under a pancake and lifting it from a surface; a large serving fork with flat prongs might also be equally effective for the task. These tools are similar to the spatula in the way that matters for the task at hand, but a robot based on current vision systems would fail to see this; if a spatula is absent it would not recognise a viable alternative. The concept of spatula should be more flexible and transferable. (ii) In robot manipulation planning a robot may be trained to apply pressure to scrape dirt from a worktop surface while wiping it clean. If the same robot is later scooping cake mix from a bowl with a silicone spatula, and encounters a stubborn sticky portion of cake mix, the spatula will skip over it. The robot would not immediately see the similarity to scraping dirt from a surface, and the necessity to apply more pressure perpendicular to the surface. The task is different. The material to be scraped is different. The tool is different. The surface is not flat like a worktop. (iii) In language understanding commonsense knowledge can be added to systems to give deep understanding, but the knowledge applies rigidly to precise situations that were envisaged. It does not naturally generalise as human knowledge does. For example a sophisticated restaurant narrative understanding system by Mueller [4] handles the roles of waiter and cook, but will not cope with assistant waiter or manager or greeter, even if these may be related in function to the roles it already handles. Also it will not deal with variants such as buffet dining or sharing tables.

The recognition of similarity in each of the three domains above is easy for humans. Across the different domains there is a common theme of being flexible about how a concept can be mapped to real world data. In classical AI entities in the world are crisply classified into definite categories in a strict one-to-one fashion; in contrast, in human-like reasoning pressures from the current situation can influence categorisation/recognition such that an entity in the real world can be seen as one concept at one time, and some different concept at another time. In the next section we outline a theory of a mechanism to achieve this.

This is at the root of the commonsense knowledge problem. Commonsense knowledge efforts such as Cyc require many years of human effort to code huge sets of facts, and still they fall far short of the knowledge of a human child in everyday reasoning; whereas human children learn fewer facts in less time, but easily transfer them to a much wider variety of situations. This suggests that something is fundamentally wrong with the knowledge representation and reasoning used in the artificial system; it does not lend itself to transfer to varied situations. The commonsense knowledge problem problem may be the 'Elephant in the Room' for human-like computing; i.e. such a big problem that nobody wants to talk about it. AI applications such as conversational assistants (e.g. Siri) fail to give a human-like satisfactory experience largely because they lack common sense. A complete solution to the commonsense knowledge problem may be many years away, but in the shorter term we can make a significant advance by endowing computers with the ability to see similarities between concepts and situations in a human-like way. i.e. we do not address the vastness of human common sense in the first instance, but focus on a human-like (analogical) reasoning ability with a limited set of concepts.

2 The Solution: A non-classical knowledge representation and reasoning, based on a theory of analogy

Here we want to introduce analogy, but we also want to point out that this is not exclusively an advanced intellectual activity such as appearing in typical IQ tests, or poetic writing, or scientific discovery. We are interested in analogy as it occurs in everyday mundane activities, even in infants and toddlers. 'Everyday' analogical reasoning means the kind of reasoning a human does in the examples given in the previous section above. In conversation 'everyday' analogy refers to many examples given by Hofstadter such as when people hear of an event and say 'the same thing happened to me'; it is not the same in a strict sense, but there is some similarity where a mapping can be made. In everyday human language, analogy or metaphor is very common, for example people may say 'that extended abstract was meandering' or 'the economy is stumbling'. Everyday analogy has much relevance to AI applications that will help humans with everyday tasks in vision, language, and robotics. Analogical reasoning is reckoned to be involved in many core cognitive tasks in humans, for example decision making, memory, perception, creativity, communication, etc. It seems essential to capture this aspect of human-like reasoning for machines that are to behave in a human-like way, or to understand humans.

One process in analogical reasoning is the rendering of situations as similar; a second process is creating a mapping between the corresponding components of the two similar situations. Most computational work on analogy focuses on the latter process, and very little on the former (although Hofstadter's work [2] is a notable exception). The former process of rendering situations as similar goes against classical Artificial Intelligence (AI) ways of thinking in that the representation is not fixed in advance; rather representations need to be made up on the fly, as dictated by task demands. The work of Indurkhya [3] gives a conceptual framework for approaching this problem, and we are implementing this computationally. Indurkhya's framework proposes a top down 'projection' mechanism, by which a 'source' situation imposes a representation on a 'target' situation in order to facilitate an analogical mapping. Thus far we have a working implementation of this idea in the domain of vision for robot tool-using tasks [1]. We believe that there may be a common 'projection' mechanism which crosses several domains of human-like reasoning, with application in AI tasks in vision, language and robotics.

Our implementation of analogical reasoning via a 'projection' mechanism uses three core components. (i) A set of ideal models that serve as 'sources' to be used to create a suitable representation of some 'target' situation. These ideal models can be considered as the pre-existing 'concepts' in the system. (ii) A 'fitness function' which gives a measure of how good a particular analogical match is. This component generally requires experience in some domain and can be learnt with machine learning. (iii) An algorithm that creates multiple candidate representations of a particular target. This last component is where top-down pressures from the task meet with bottom-up realities of the real-world situation. Although we have focused only on robot vision tasks thus far we can extrapolate how the same mechanism could be applied in other domains. What we propose is a new approach to knowledge representation and reasoning, where representations are not decided in advance of approaching a particular task or situation, rather they are composed according to task demands. There are multiple possible representations of any situation. The approach is designed to facilitate analogical reasoning.

References

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