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A Goal-Oriented Framework for Knowledge Invention and Creative Problem Solving in Cognitive Architectures

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Abstract. In this paper we describe a reasoning framework for knowledge invention and creative problem solving that can integrate and extend the knowledge level mechanism of diverse cognitive architectures (CAs). This framework exploits an extension of a Description Logic (DL) of typicality able to combine prototypical (commonsense) descriptions of concepts. It works as follows: given a goal expressed as a set of properties, in case an intelligent agent cannot find a concept in its knowledge base (KB) able to fulfill these properties, our framework is able to dynamically recombine, in a goal-oriented perspective, the concepts in the KB in order to find a suitable creative combination able to satisfy the goal. The KB of the agent is then extended via a mechanism of commonsense concept combination where the resulting combined concept represents the solution for the initial goal. Here we discuss how such framework is compliant with the general tenets of the Standard Model of Mind and can extend the knowledge level capabilities of diverse CAs.

1 INTRODUCTION

A challenging problem in AI concerns the capability of an intelligent agent to achieve its goals when its knowledge base does not contain enough information to do that. Currently, existing goal-directed systems usually implement a re-planning strategy in order to tackle such problem. Such strategy is usually performed via either an external injection of novel knowledge or as the result of a communication with another intelligent agent. Here, we describe an alternative approach introduced in [6]: namely a framework for the dynamic and automatic generation of novel knowledge obtained through a process of commonsense reasoning based on typicality-based concept combination. We exploit a recently introduced extension of a Description Logic of typicality able to combine prototypical descriptions of concepts in order to generate new prototypical concepts. Intuitively, in the context of our application of this logic, given a goal expressed as a set of properties, if the knowledge base does not contain a concept able to fulfill all these properties, then our system looks for at least two concepts to recombine in order to extend the original knowledge base and satisfy the goal.

2 A DL FOR CONCEPT COMBINATION

We adopt a nonmonotonic extension of DLs called $\mathbf{T}^{\mathsf{CL}}$ (typicality-based compositional logic) able to reason about typicality [7, 8]. This logic combines three main ingredients. The first one relies on the DL of typicality $\mathcal{ALC} + \mathbf{T_R}$ [1], which allows to describe the *prototype* of a concept. In this logic, "typical" properties can be directly specified by means of a "typicality" operator $\mathbf{T}$ enriching the underlying DL, and a TBox can contain inclusions of the form $\mathbf{T}(C) \sqsubseteq D$ to represent that "typical Cs are also Ds". The semantics of $\mathbf{T}$ is characterized by the properties of *rational logic*, recognized as the core properties of nonmonotonic reasoning.

As a second ingredient, the logic $\mathbf{T}^{\mathsf{CL}}$ exploits a distributed semantics similar to the one of probabilistic DLs known as DISPONTE [10], allowing to label inclusions $\mathbf{T}(C) \sqsubseteq D$ with a real number between 0.5 and 1, representing its degree of belief/probability, assuming that each axiom is independent from each others. As an example, we can formalize that we believe that a typical athlete is fit with degree 0.9, whereas we believe that, normally, athletes are young, but with degree 0.75, with the inclusions $0.9 \ :: \ \mathbf{T}(Athlete) \sqsubseteq Fit$ and $0.75 \ :: \ \mathbf{T}(Athlete) \sqsubseteq Young$, respectively. Degrees of belief in typicality inclusions allow to define a probability distribution over *scenarios*: roughly speaking, a scenario is obtained by choosing, for each typicality inclusion, whether it is considered as true or false.

Finally, $\mathbf{T}^{\mathsf{CL}}$ employs a method inspired by cognitive semantics [3] for the identification of a dominance effect between the concepts to be combined: for every combination, we distinguish a HEAD, representing the stronger element of the combination, and a MODIFIER. The basic idea is: given a KB and two concepts C_H (HEAD) and C_M (MODIFIER) occurring in it, we consider only *some* scenarios in order to define a revised knowledge base, enriched by typical properties of the combined concept $C \sqsubseteq C_H \sqcap C_M$.

Given a KB $\mathcal{K} = \langle \mathcal{R}, \mathcal{T}, \mathcal{A} \rangle$ and given two concepts C_H and C_M occurring in $\mathcal{K}$, the logic $\mathbf{T}^{\mathsf{CL}}$ allows defining a prototype of the compound concept C as the combination of the HEAD C_H and the MODIFIER C_M, where the typical properties of the form $\mathbf{T}(C) \sqsubseteq D$ (or, equivalently, $\mathbf{T}(C_H \sqcap C_M) \sqsubseteq D$) to ascribe to the concept C are obtained by considering blocks of scenarios with the same probability, in decreasing order starting from the highest one. We first discard all the inconsistent scenarios, then: (1) we discard those scenarios considered as *trivial*, consistently inheriting all the properties from the HEAD from the starting concepts to be combined; (2) among the remaining ones, we discard those inheriting properties from the MODIFIER in conflict with properties that could be consistently inherited from the HEAD; (3) if the set of scenarios of the current block is empty, i.e. all the scenarios have been discarded either because trivial or because preferring the MODIFIER, we repeat the procedure by considering the block of scenarios, having the immediately lower probability. Remaining scenarios are those selected by $\mathbf{T}^{\mathsf{CL}}$. The ultimate output is a KB in $\mathbf{T}^{\mathsf{CL}}$ whose set of typicality properties is enriched by those of the combined concept C. Given a scenario w satisfying the above properties, the prototype of C is defined as the set of inclusions $p \ :: \ \mathbf{T}(C) \sqsubseteq D$, for all

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$\mathbf{T}(C) \sqsubseteq D$ that are entailed from w in the logic $\mathbf{T}^{\mathsf{CL}}$.

3 DYNAMIC KNOWLEDGE GENERATION

We developed a system implementing $\mathbf{T}^{\mathsf{CL}}$ able to dynamically generate novel knowledge in the cases in which the original goal cannot be directly satisfied. The overall pipeline of the system can be described as follows: the system receives in input a certain goal to achieve. The goal is expressed in terms of tuples representing the desired final state. For example: a goal can be expressed as $\{Object, Cutting, Graspable\}$ to identify the scope of retrieving, from the inventory of the available knowledge in the agent declarative memory, an element that is a graspable object able to cut some surfaces. Once processed the input, the system verifies, via a searching process in the hybrid, probabilistic, knowledge base assumed in $\mathbf{T}^{\mathsf{CL}}$, whether there is some element that can directly satisfy the desired conditions. If so, the element(s) (if any) satisfying the request are returned and ranked in descending order of probability. If not, the system tries to perform, via WordNet (`https://wordnet.princeton.edu/`), a task of semantic-driven goal-reformulation by looking for synonyms and hyperonyms of the terms specified in input (in order to find at least a minimal set of candidate concepts sharing, if considered jointly, all the required goal desiderata). Once this process is executed, and the minimal set of candidate concepts is reached, the system adopts the typicality-based reasoning procedure of concept combination of $\mathbf{T}^{\mathsf{CL}}$. As an example, suppose to have: $\mathcal{G} = \{Object, Cutting, Graspable\}$, and suppose that the knowledge base contains $Spoon \sqsubseteq Graspable$, $0.85 :: \mathbf{T}(Spoon) \sqsubseteq \neg Cutting$, $0.9 :: \mathbf{T}(Vase) \sqsubseteq Graspable$, $Vase \sqsubseteq Object$. Both $Vase$ and $Spoon$ are included in the list of candidate concepts to be combined (along with other concepts satisfying, for example other properties of the goal such as, for example, being able to cut some surface). As a second step, for each item in the list of candidate concepts to be combined, the system computes a rank of the concept as the sum of the probabilities of the properties also belonging to the goal, assuming a score of 1 in case of a rigid property. In the example, $Vase$ is ranked as $0.9 + 1 = 1.9$, since both $Graspable$ and $Object$ are properties belonging to the goal: for the former we take the probability 0.9 of the typicality inclusion $\mathbf{T}(Vase) \sqsubseteq Graspable$, for the latter we provide a score of 1 since the property $Vase \sqsubseteq Object$ is rigid. Concerning the concept $Spoon$, the system computes a rank of 1: indeed, the only inclusion matching the goal is $Spoon \sqsubseteq Graspable$. Finally, the system checks whether the concept obtained by combining the candidate concepts with the highest ranks, (e.g. C_1 and C_2 in case of only 2 concepts), is able to satisfy the initial goal. The system computes a double attempt, by considering first C_1 as the HEAD and C_2 as the MODIFIER and, in case of failure, C_2 as the HEAD and C_1 as the MODIFIER.

4 EVALUATION AND CONCLUSIONS

We tested our system in the task of object invention via conceptual composition. This task is considered an important proxy of natural intelligence [6] since such ability is found, in nature, only in primates (humans and great apes) and in ravens. As an example of the obtained results: given the above mentioned goal of looking for a graspable object able to cut, the system proposed the combination $Stone \sqcap Shelf$ as a solution, thus suggesting a combined concept having the characteristics resembling a rudimentary $KnifeWithAWoodHandle$. The obtained results reached state of the art when compared with OROC [9] the only available system able to perform the same task and, in addition, we also extended our evaluation to human subjects showing a good level of compliance with human responses [6]. An additional element of interest concerns the possibility of integrating the proposed framework in different cognitive architectures due to its compliance, shown in Fig. 1, with the mechanisms of knowledge retrieval of the Standard Model of Mind (SMM) [4]. In particular, our system can easily communicate with any of the Declarative Memory formats proposed in the SMM (i.e. symbolic chunks or probabilistic based symbolic expressions) since the process of bi-directional translation between a chunk-like representation and the language of $\mathbf{T}^{\mathsf{CL}}$ can be provided as presented in [2]. This compliance represents an important aspect to point out since it enables the adoption of such a dynamic management of the memory systems to a variety of cognitive architectures, by extending, de facto, their knowledge level capabilities [5].

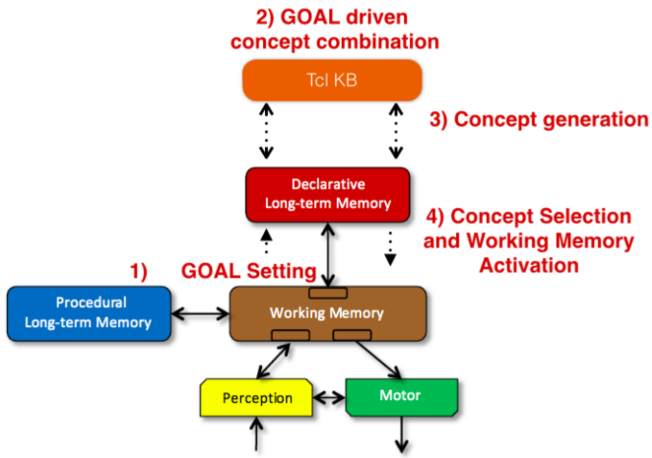

Figure 1. System Integration with the Standard Model of Mind.

REFERENCES

[1] L. Giordano, V. Gliozzi, N. Olivetti, and G.L. Pozzato, ' Semantic characterization of Rational Closure: from Propositional Logic to Description Logics', *Artif. Int.*, **226**, 1–33, (2015).

[2] L. Giordano, V. Gliozzi, G. Pozzato, and R. Renzulli, 'An efficient reasoner for description logics of typicality and rational closure', in *Proc of DL 2017*, (2017).

[3] J. Hampton, 'Inheritance of attributes in natural concept conjunctions', *Memory & Cognition*, **15**(1), 55–71, (1987).

[4] J. Laird, C. Lebiere, and P. Rosenbloom, 'A standard model of the mind: Toward a common computational framework across artificial intelligence, cognitive science, neuroscience, and robotics.', *Ai Magazine*, **38**(4), (2017).

[5] A. Lieto, C. Lebiere, and A. Oltramari, 'The knowledge level in cognitive architectures: Current limitations and possible developments', *Cognitive Systems Research*, **48**, 39–55, (2018).

[6] A. Lieto, F. Perrone, GL Pozzato, and E. Chiodino, 'Beyond subgoaling: A dynamic knowledge generation framework for creative problem solving in cognitive architectures', *Cognitive Systems Research*, **58**, 305–316, (2019).

[7] A. Lieto and G.L. Pozzato, 'A description logic of typicality for conceptual combination', in *Proceedings of ISMIS, LNAI 11177*, pp. 189–199. Springer, (2018).

[8] A. Lieto and GL Pozzato, 'A description logic framework for commonsense conceptual combination integrating typicality, probabilities and cognitive heuristics', *J. Exp. & Theor. Artif. Intell.*, (2020).

[9] A. Olteţeanu and Z. Falomir, 'Object replacement and object composition in a creative cognitive system. towards a computational solver of the alternative uses test', *Cognitive Systems Research*, **39**, 15–32, (2016).

[10] F. Riguzzi, E. Bellodi, E. Lamma, and R. Zese, 'Reasoning with probabilistic ontologies', in *Proc. of IJCAI 2015*, pp. 4310–4316, (2015).