What cognitive research can do for AI: A case study

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Abstract

This paper presents a practical case study showing how, despite the nowadays limited collaboration between AI and Cognitive Science (CogSci), cognitive research can still have an important role in the development of novel AI technologies. After a brief historical introduction about the reasons of the divorce between AI and CogSci research agendas (happened in the mid'80s of the last century), we try to provide evidence of a renewed collaboration by showing a recent case study on a commonsense reasoning system, built by using insights from cognitive semantics.

1. Introduction

The research in Artificial Intelligence has been based, from a historical standpoint, on a strong collaboration between computer scientists, psychologists, engineers, philosophers and biologists working in the Cognitive Science field. This collaboration, fostered by the influence of the cybernetic approach to the study of natural and artificial systems, has produced – along the years – the development of fruitful research lines in bionics, robotics, biologically and neurally inspired systems and, more in general, in the area of cognitive artificial systems and systems science [1][2].

After decades of mutual and pioneering collaborations, however, Artificial Intelligence and Cognitive Science have produced several sub-disciplines, each one with its own goals, methods and criteria for evaluation. This fragmentation, on the one hand, has facilitated the development of some AI systems able to produce super-human competences, in restricted domains (such as in computer vision, or in games such as chess, Jeopardy, Go, etc.). On the other hand, however, it has been based on a *divide et impera* approach that has significantly inhibited the cross-field collaborations and the scientific efforts aimed at investigating a more general picture of what natural and artificial intelligence are, and how intelligent artefacts can be designed by taking into account the insights coming from the natural world. In more recent years, however, the area of cognitively inspired artificial systems has attracted a renewed attention both from academia and industry and the awareness about the need for additional research in this interdisciplinary field has gained widespread acceptance. To use the words by Aaron Sloman, in fact, "the gap between

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natural and artificial intelligence is still enormous” [3] and the research in this area seems now crucial for the development of better artificial systems.

In particular, cognitive research can provide useful insights about a wide range of tasks that seem to be particularly easy to do for humans (due to the automatic adoption of evolutionarily shaped heuristics[1]) and are, on the other hand, still particularly hard to solve for artificial systems [2]. In the following pages we detail a recent case study in the field of commonsense reasoning, a notorious problem in AI still in search of a suitable solution. In particular, the case study addresses a specific instance of such a problem: namely, the problem of commonsense concept combination.

2. A case study in commonsense reasoning: the $\mathbf{T}^{\mathrm{CL}}$ logic

The generative capability of inventing novel concepts by combining the typical knowledge of pre-existing ones is an important phenomenon in human cognition. Such ability, in fact, concerns high-level capacities associated to creative thinking and problem solving. Still, it represents an open challenge in the field of artificial intelligence [5]. Dealing with this problem requires, from an AI and cognitive modelling perspective, the harmonization of two conflicting requirements that are hardly accommodated in artificial systems: the need of a syntactic and semantic compositionality (typical of logical systems) and that one concerning the exhibition of typicality effects [6]. According to a well-known argument [7], in fact, prototypes (i.e. commonsense conceptual representations based on typical properties) are not compositional. The argument runs as follows: consider a concept like PET FISH. It results from the composition of the concept pet and of the concept fish. However, the prototype of pet fish cannot result from the composition of the prototypes of a pet and a fish: e.g. a typical pet is furry and warm, a typical fish is grayish, but a typical pet fish is neither furry and warm nor grayish (typically, it is red). The PET FISH problem is a paradigmatic case for what concerns the difficulty of modelling the phenomenon of human-like concept combination. Recently, a logical framework able to account for the PET FISH problem has been proposed in the field of nonmonotonic Description Logics of typicality: $\mathbf{T}^{\mathrm{CL}}$ (Typicality-based Compositional Logic, for the details see [8]). This logic combines three main ingredients. The first one relies on the DL of typicality $\mathcal{ALC} + \mathbf{T_R}$ introduced in [9] 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”. As a difference with standard DLs, in the logic $\mathcal{ALC} + \mathbf{T_R}$ one can consistently express exceptions and reason about defeasible inheritance as well. For instance, a knowledge base can consistently express that “normally, athletes are fit”, whereas “sumo wrestlers usually are not fit” by $\mathbf{T}(\mathit{Athlete}) \sqsubseteq \mathit{Fit}$ and $\mathbf{T}(\mathit{SumoWrestler}) \sqsubseteq \neg \mathit{Fit}$, given that $\mathit{SumoWreslter} \sqsubseteq \mathit{Athlete}$. 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 $\mathbf{T}^{\mathrm{CL}}$ 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

[1] Heuristics (or judgements heuristics) are, according to the definition from Gigerenzer [4] , shortcuts of thought that take a minimum amount of time, knowledge and calculation (computation) to process adaptive choices in concrete environments. This kind of shortcuts guides, on the basis of empirical rules (emerging from previous experience and knowledge), our daily actions that must be carried out immediately orin a short time and relying on limited knowledge.

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 $0.9 :: \mathbf{T}(\mathit{Athlete}) \sqsubseteq \mathit{Fit}$ and $0.75 :: \mathbf{T}(\mathit{Athlete}) \sqsubseteq \mathit{Young}$, 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 heuristics inspired by cognitive semantics [11] 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 $C \sqsubseteq C_H \sqcap C_M$.

In $\mathbf{T}^{\mathsf{CL}}$, given a hybrid KB $\mathscr{K} = \langle \mathscr{R}, \mathscr{T}, \mathscr{A} \rangle$ (composed by typical and standard or rigid assertions, i.e. assertion with and without exceptions, as derived from [12]) and given two concepts C_H and C_M occurring in $\mathscr{K}$, the logic 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. Here all the inconsistent scenarios are discarded, 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 $\mathbf{T}(C) \sqsubseteq D$ that are entailed from w in the logic $\mathbf{T}^{\mathsf{CL}}$.

An important element emerging from this framework, and relevant with respect to the overall overview proposed in this paper, lies in the fact that it would have been not possible to model all such phenomena without considering all the three ingredients of such logic (including the HEAD-MODIFIER heuristics). In other words, all such elements are individually necessary but only jointly sufficient to tackle a complex problem like the one described above. This is a symptom of the fact that, the application (and integration) of cognitive heuristics in artificial systems and formalisms, can still play an important role in AI.

3. $\mathbf{T}^{\mathsf{CL}}$ applied to creative problem solving

A first application developed from $\mathbf{T}^{\mathsf{CL}}$ is a system 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. We tested our system in the task of object invention via conceptual composition. This task is considered an important proxy of natural intelligence [13] since such ability is found, in nature, only in primates (humans and great apes) and in ravens [14]. 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 [15] 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 performance match with human responses [16]. This result was reinforced by the showed compliance of such a mechanisms with different cognitive architectures like SOAR and the Common Model of Cognition, by extending, de facto, their knowledge level capabilities [17].

4. $\mathbf{T}^{\mathsf{CL}}$ applied to content generation and suggestion

A completely different application of $\mathbf{T}^{\mathsf{CL}}$ has been exploited in DENOTER [18]: a content generator and suggestion system exploiting the logic $\mathbf{T}^{\mathsf{CL}}$ in order to generate and suggest novel editorial genres for RaiPlay (https://www.raiplay.it), the online platform of on-demand contents of RAI (RAdio televisione Italiana, http://www.rai.it. An overview of the DENOTER pipeline is reported in the figure 1). DENOTER is implemented in Python and it makes use of the library `owlready2` (https://pythonhosted.org/Owlready2/) for relying on the services of efficient DL reasoners (like HermiT). DENOTER first builds a prototypical description of basic genres available in RaiPlay, namely: action/adventure, kids, comedy, drama, science fiction, horror, musical, religious, sentimental, and thriller.

To this aim, a web crawler extracts metadata from multimedia contents available on the platform. More in detail, for each item (program, episode, etc.) the crawler extracts (i) the genre to which it belongs and (ii) the set of "significant" words (i.e., excluding prepositions, proper names, articles, etc.) occurring in the description of each item, as well as their frequency. These information are used in order to provide a description of each basic genre in terms of its typical properties in the logic $\mathbf{T}^{\mathsf{CL}}$, where the frequency of a concept/word for a genre is obtained from the number of occurrences of such a concept/word in the items belonging to that genre. The five properties with the highest frequency over 0.5 are included in the prototypical description of each basic genre.

DENOTER combines the two basic genres by implementing a variant of CoCoS [19], a Python implementation of reasoning services for the logic $\mathbf{T}^{\mathsf{CL}}$ in order to exploit efficient DLs reasoners for checking both the consistency of each generated scenario and the existence of conflicts among properties. More in detail, DENOTER considers both the available choices for the HEAD and the MODIFIER, and it allows to restrict its concern to a given and fixed number of inherited properties. As an example, the new, derived genre combining kids and drama with the limit fixed to four properties has the following $\mathbf{T}^{\mathsf{CL}}$ description (concept $Kids \sqcap Drama$):

$$0.83 :: \mathbf{T}(Kids \sqcap Drama) \sqsubseteq Life$$
$$0.72 :: \mathbf{T}(Kids \sqcap Drama) \sqsubseteq Queen$$
$$0.7 :: \mathbf{T}(Kids \sqcap Drama) \sqsubseteq DeadPerson$$
$$0.64 :: \mathbf{T}(Kids \sqcap Drama) \sqsubseteq World$$

Obviously, rigid properties (i.e. properties that do not exhibit any exception) of both basic concepts *Kids* and *Drama* are inherited by the derived concept, and this avoids the system to consider the property *Homicide*, even if it has the highest probability/degree of belief associated to the prototypical description of *Drama*. DENOTER is also able to involve *derived* genres in the concept combination, for instance we can combine derived genres $Action \sqcap Sentimental$ and the above $Kids \sqcap Drama$.

Apart from the process of automatic knowledge generation, DENOTER is also able to reclassify the multimedia items/episodes of RaiPlay within the novel derived genres (generated as described in the previous section). As mentioned, indeed, each multimedia item/episode is equipped by some information available in RaiPlay, namely: title, name of the program/episode, description of the program/serie, description of the episode. DENOTER extracts such information and then computes the frequencies of concepts in order to compare them with the properties of a derived genre. If the item contains all the rigid properties and at least the 30~ of the typical properties of the genre under consideration, then the multimedia content is classified as belonging to it.

The system has been tested in threefold evaluations showing promising results for both the percentage of the automatically reclassified content in the novel generated classes for the user

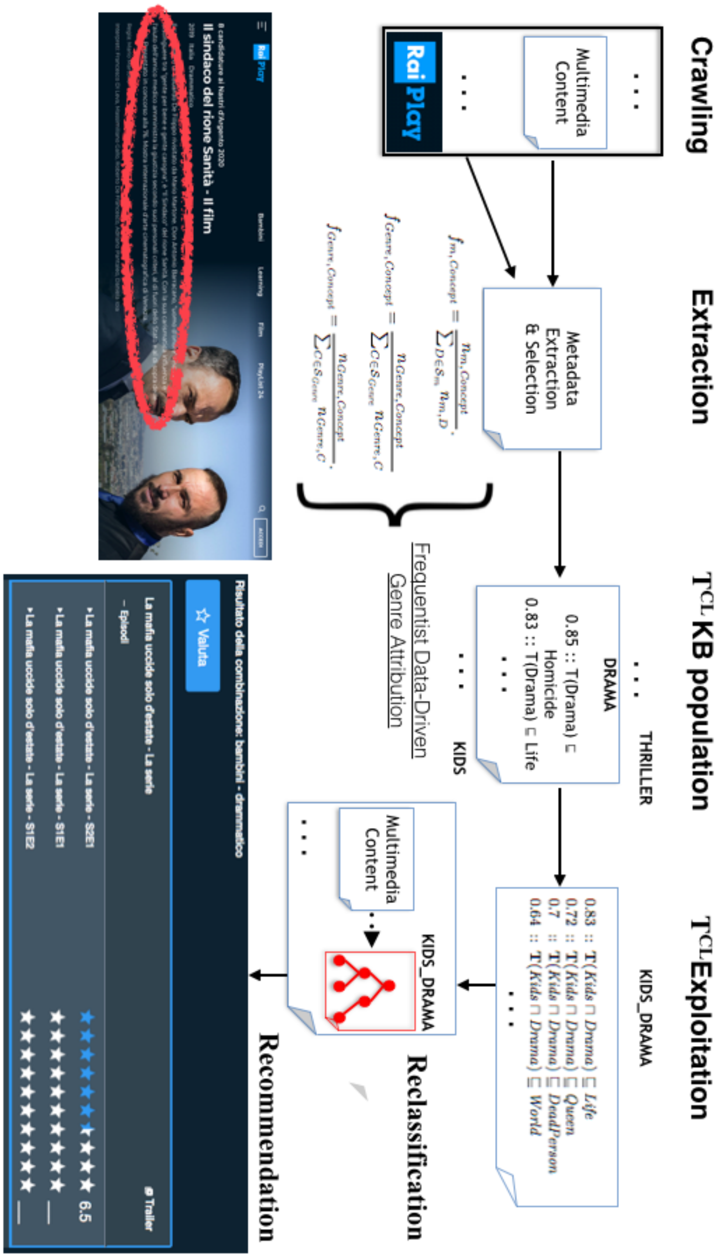

Figure 1: An overview of the pipeline of DENOTER applied in the context of the RaiPlay platform.

acceptability of the recommended items. The evaluations is described in detail in [18].

5. Conclusion

In this paper, we have showed a double application, in the fields of creative goal-oriented reasoning and content recommendations, of a logic framework explicitly built to model, in human-like fashion, the concept combination phenomenon and explicitly grounded on heuristics coming from the field of cognitive semantics. In the first application, the proposed approach has been tested in the task of object composition and compared with the available results of the system OROC [15] that is, to the best of our knowledge, the first system proposing a proof-of-concept procedure for the evaluation of such tasks. In particular, we have shown how our framework is able to generate the same results provide by the OROC system by adopting different representational and reasoning assumptions. In addition, we have also compared the obtained results with a preliminary evaluation involving human subjects in the task of object composition. As a further element, we have also shown that the proposed framework is compliant with all the major mechanisms available in the SOAR cognitive architecture and, as such, it can be effectively used to extend its subgoaling procedures (and therefore the reasoning capabilities of the agents equipped with such architecture).

In the second application we have used the $\mathbf{T}^{\mathrm{CL}}$ framework in DENOTER. Such system can be used to address the very well known filter bubble effect [20], by introducing seeds of serendipity in content discovery by users. From a the technical point of view, the system differs from the current mainstream approaches in recommender systems that are mostly based on the comparison and matching of visual and aural features of the content [21, 22] by adding a logic framework capable of mapping and representing genuinely new intuitive principles influencing user preferences and usage attitudes which cannot be derived from the pure analysis of content and/or the comparison of similar users. Furthermore, it has a native adaptability to industrial contexts in which the editorial input has to be merged with automatic recommendation, since both kinds of input can be effectively processed by the same framework. In other words: it can be considered yet another (recent) example of how the inclusion of a cognitive design perspective in the realization of artificial systems can advance the development of current and future AI technologies.

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