Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence (IJCAI 2015)

A Cognitively Inspired Approach for Knowledge Representation and Reasoning in Knowledge-Based Systems*

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Abstract

In this thesis, I investigate a hybrid knowledge representation approach that combines classic knowledge representations, such as rules and ontologies, with other cognitively plausible representations, such as prototypes and exemplars. The resulting framework can combine the strengths of each approach of knowledge representation, avoiding their weaknesses. It can be used for developing knowledge-based systems that combine logic-based reasoning and similarity-based reasoning in problem-solving processes.

1 Introduction

Knowledge-based systems are characterized by a *top-down* approach, where the relevant knowledge is explicitly represented in a computer-processable way and supports the problem-solving process performed by the system. These systems can be applied when there is no data available for applying *bottom-up* (data-driven) approaches. However, for developing these systems, it is necessary to elicit the relevant knowledge from reliable knowledge sources (domain experts, domain literature, etc). This is one of the weak points of adopting this approach, since the knowledge acquisition is a notoriously difficult task, involving costly and error-prone processes. Besides that, sometimes, the elicited knowledge is not enough to cover all the situations with which the application should deal.

In my thesis, I assume that these weaknesses of the knowledge-based systems can be mitigated by providing to the system the capability of extracting useful knowledge from the available data (previously solved instances available to the system). The resulting approach allows to combine knowledge-driven (top-down) and data-driven (bottom-up) approaches. Hybrid approaches like this were already proposed in the literature. However, in this work, we go a step further, by proposing a *cognitively inspired* hybrid knowledge representation approach for supporting this kind of system.

According to [Murphy, 2002], within the cognitive sciences there are three main theories about how the knowledge is represented in the human mind. The *classical theory* assumes that each concept is represented by a *set of features* that are *shared* by *all* the instances that are abstracted by the concept. In this way, concepts can be viewed as *rules* for classifying objects based on features. The *prototype theory*, on the other hand, states that concepts are represented through a *typical instance*, which has the typical features of the instances of the concept. Finally, the *exemplar theory* assumes that each concept is represented by a set of *exemplars* of it. These exemplars are real entities that were previously experienced by the agent. In theories based on prototypes or exemplars, the categorization of a given entity is performed according to its *similarity* with prototypes or exemplars.

Our main proposal is to investigate how to combine *classic representations*, such as *ontologies* and *rules*, with non-classic representations, such as *prototypes* and *exemplars*, in a *knowledge representation* framework for supporting the problem solving process in knowledge-based systems. We hypothesize that the resulting framework can combine the strengths of the *knowledge-driven* and *data-driven* approaches, overcoming the weaknesses of both.

2 The proposed approach

In our framework, part of the knowledge is represented classically, through *ontologies* and *rules*, and part of the knowledge is represented as *prototypes* and *exemplars*, which can be extracted from the data that is processed by the system. Thus, our approach can provide the reliance of the expert knowledge when it can be applied, however, it also is able to provide solutions for cases that cannot be covered by this knowledge, but that can be estimated from the available data. In this approach, the resulting system can perform problem-solving processes by combining *rule-based reasoning* with *similarity-based reasoning*. The rule-based reasoning can be used first for reducing the search space and; if a suitable solution is not found, a similarity-based reasoning can be triggered for refining the solution already found (and finding a better solution), by comparing the observation that is being analyzed with the available *prototypes* and *exemplars* of previously interpreted observations.

Currently, we are focusing on knowledge representation approaches for supporting the development of knowledge-based systems for interpretation, where the tasks can be characterized by the application of *rules* in the form of

*We thank the PRH PB-217 program for the financial support to this work, and Sandro Fiorini for comments and ideas.

observation $\Rightarrow$ *interpretation*, where *observation* is a set of statements that describe the features that should be perceived in some *observable entities* for supporting the *interpretation*, and *interpretation* is a set of statements about *interpretable entities*. We consider as an observable entity every kind of entity specified in the domain ontology that is inspected for supporting some interpretation. For example, the human body is an observable entity in a task of diagnosis. On the other hand, we consider as an interpretable entity, every kind of entity specified in the domain ontology that is mentioned in interpretations. For example, different kinds of diseases can be considered as interpretable entities in a diagnosis task.

For some interpretation tasks, the system should be able to provide interpretations in several levels of generalization/specificity, since sometimes there is not enough information in the observations for supporting more specific interpretations. In general, this can be achieved by including a taxonomy (with several levels of generalization) of *interpretable entities* in the domain ontology and by including the necessary rules for interpreting each different interpretable entity specified by this taxonomy. In an application for medical diagnosis, for example, it would be necessary a taxonomy of diseases, describing types of diseases in several levels of generality, and rules, associating features in the human body (symptoms) to each specific type of disease in the taxonomy.

The *ontology*, the *rule base* and the *rule-based reasoning engine* constitute the *knowledge-driven* component of our approach. In general, it can be very effective in reducing the set of alternative possible interpretations of a given observation. It can prune entire branches of alternatives in the taxonomy of interpretable entities. It can even reach specific interpretations (some leaf of the taxonomy), if the description of observation is detailed enough. However, this is not always the case. It is common the absence of important information in the observation's description. Also, the set of rules can be incomplete, in a way that it cannot cover all the possible cases that arise in real scenarios. In these cases, the knowledge-driven component can only provide a more general interpretation (interpreting *Breast disease* instead of *Malignant neoplasm of breast*, for example).

For overcoming these weaknesses, we propose a *data-driven component* that acts in conjunction with the knowledge-driven component. This component relies on a knowledge representation approach that is inspired by the *prototype theory* and *exemplar theory* of knowledge representation in the human mind. Following this idea, we assume that for each possible relevant *interpretable entity ie*, the system should have a *prototype* and a *set of exemplars* of the *observations* that can support the interpretation of *ie*. In this component, the interpretation is carried out through *similarity-based reasoning*, where the observation that should be interpreted is compared with the prototypes and exemplars for determining the suitable interpretation. Besides that, within the *data-driven component*, our approach also includes a component for extracting prototypes and exemplars from the observations that were previously interpreted by the system: the *knowledge extractor*.

Thus, a system adopting our approach would have a set $IE = \{ie_1, ie_2, ...ie_m\}$ of *m interpretable entities*, where each ie_i is a concept provided by the domain ontology. The elements of IE are organized in a taxonomy, related by a subsumption relation. This system should have a database $DB = \{r_1, r_2, ..., r_n\}$, which can be abstractly considered as a set of *n records*. Each r_i can be viewed as a 2-tuple $(observation, interpretation)$; where *interpretations* are articulated using concepts in the domain ontology that are generically called *Interpretable entities*, and *observations* are articulated using concepts in the domain ontology that are called *observable entities*. Also, $O_{DB} = \{o_1, o_2, ..., o_n\}$ is the set of the *observations* of the records in DB, in a way that $o_i \in O_{DB}$ is the observation of the record $r_i \in DB$. Moreover, $obs\colon IE \rightarrow 2^{O_{DB}}$ is a function that maps a given *interpretable entity* $ie_i \in IE$ to a set $O_{ei} \subseteq O_{DB}$, which represents the set of observations related to the records in DB whose interpretation is specified by the interpretable entity $ie_i \in IE$. In this context, considering a given interpretable entity $ie_i \in IE$, the function $prototype(ie_i)$ maps ie_i to the prototype of the observations in $obs(ie_i)$, while the function $exemplars(ie_i)$ maps ie_i to a subset of the observations in $obs(ie_i)$.

In a task of medical diagnosis, a system adopting our approach would have a set IE of diseases. The database DB would store records where the observation would be a description of symptoms and the interpretation would be a specific disease. The function $prototype(ie_i)$ would map a specific disease ie_i to the typical set of symptoms associated to ie_i, while the function $exemplars(ie_i)$ would map ie_i to a set of specific descriptions of symptoms associated to ie_i.

The interpretation process carried out by the *interpretation component*, combines rule-based reasoning (supported by the ontology and rules) and similarity-based reasoning (supported by the prototypes and exemplars).

3 Conclusions and future works

We propose a cognition-inspired approach for *knowledge representation and reasoning* for supporting knowledge-based systems. In future works, we will provide a detailed account of the process of extracting prototypes and exemplars, and of the interpretation process. We also will discuss how the system can update its representations (prototypes and exemplars) when new data is included in its database. This approach will be applied for developing a knowledge-based system for automating the task of interpretation of depositional processes, in the domain of Petroleum Geology. Our approach will be validated by comparing the developed system with the approach presented in [Carbonera *et al.*, 2015; Carbonera *et al.*, 2013], using real cases.

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