Principles for the Foundation of Integrated Higher Cognition

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Keywords: Integrated Cognition; Analogies; Ontologies.

Cognitive Diversity

Higher cognition of humans occurs in a variety of forms, contexts, and facets. For example, humans can perform deductions, inductions, and abductions, they can solve problems in domains initially completely unknown to them, and they are able to retrieve relevant information, although there is a tremendous amount of related knowledge stored in their memories. Furthermore abilities like creativity, adaptation, learning, and reasoning with inconsistencies, by analogy, or by rough estimations are remarkable capacities of humans.

In order to model such a variety of abilities computationally, researchers either develop complicated architectures with a large number of different modules (e.g. Wang, 2006; Newell, 1990), often presupposing sophisticated control mechanisms, or they try to reduce such cognitive manifolds to a few principles (e.g. Cassimatis, 2006; Forbus & Hinrichs, 2006). In the spirit of the latter approaches, we propose to reduce the enormous variety of higher cognitive abilities to analogical reasoning, dynamic updates of background knowledge, and neuro-symbolic integration.

Spanning Cognitive Manifolds

The Principles

With respect to the first principle, analogical reasoning is often assumed to be a candidate for creativity and many aspects of non-classical reasoning abilities. In Gust, Kühnberger & Schmid (2006), heuristic-driven theory projection (HDTP) is used in order to model creative analogies, to learn from a few examples, to perform non-classical inferences, or to establish non-conventional meanings of metaphors. It is therefore a framework for solving several sorts of *hard* problems in AI.

The second principle is based on the idea that background knowledge should not be considered as a fixed conceptualization of the world, but as a flexible resource that is adapted, updated, and manipulated on the fly, and constantly rewritten due to new input data. In Ovchinnikova & Kühnberger (2006), algorithms are proposed that allow an implementation of dynamic changes of ontologies for text technological and semantic web applications. Although this domain is not broad enough to explain cognitive manifolds, it is a first step towards a computational model of semantic updates.

The third principle is based on neuro-symbolic integration techniques. By learning models of reality on the neuro-symbolic level, it is possible to avoid complicated deduction mechanisms in a cognitive architecture. Good examples for such approaches are connectionist networks trained on complex data structures (cf. Brown & Sun, 2000 for an overview).

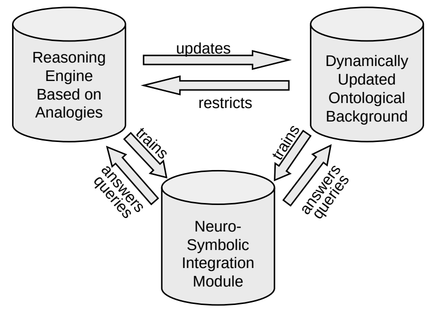

Figure 1: A simplified architecture for integrated cognition.

A rather new approach in this direction is Gust, Kühnberger & Geibel (2007): a semi-symbolic level is used to translate full first-order theories into a homogeneous data structure in order to train neural networks. The trained network represents complex models of logical theories and was tested on benchmark problems for symbolic theorem provers.

Integrated Cognition

The integration of these modules in one architecture, although still ongoing research, could be achieved as follows (cf. Figure 1): on the one hand, ontologies restrict the range of possible analogical relations computed by the analogy engine. On the other hand, generating new analogical relations can be used to update dynamically ontologies. The neuro-symbolic integration module learns models of input data, answers queries whether new analogical and ontological relations should be established or not, and shows a robust behavior, if inconsistencies occur. Every module of the architecture learns permanently from input and computed data and interacts in a non-trivial way with other modules. Integrated cognition is the result of this interaction and could be a general basis for the variety of higher cognition, such as adaptation, non-classical forms of reasoning, and creativity.

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