Facets of Artificial General Intelligence

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We argue that time has come for a serious endeavor to work towards artificial general intelligence (AGI). This positive assessment of the very possibility of AGI has partially its roots in the development of new methodological achievements in the AI area, like new learning paradigms and new integration techniques for different methodologies. The article sketches some of these methods as prototypical examples for approaches towards AGI.

1 Aims of AGI

Artificial intelligence has been showing impressive results in solving many domain-specific problems, for example, in game playing, search tasks, or information retrieval from vast amounts of information. Nevertheless, we believe that this success is one of several reasons why mainstream AI research often does not focus on its original goal, namely finding models, methodologies, and applications for general intelligence.

Starting with a new research paradigm (or, in our case, continuing an old research paradigm) is necessarily coupled with the challenge to clarify the content of this endeavor. In other words: what is AGI? In [1], Ben Goertzel has given a nice characterization: *"What is meant by AGI is [. . .], AI systems that possess a reasonable degree of self-understanding and autonomous self-control, and have the ability to solve a variety of complex problems in a variety of contexts, and to learn to solve new problems that they did not know about at the time of their creation."*

The germ of Goertzel's characterization of AGI seems to be the *generalizability* property of frameworks used, i.e. applicability to various scenarios, learnability of new capacities, adaptivity to new circumstances (in time-critical settings and with limited resources). As a consequence of the given characterization a model for AGI needs to integrate various cognitive abilities, for example, problem solving, learning, interaction with the environment (i.e. perceiving and acting), and autonomy. Clearly, classical AI is also concerned with developing and implementing models for such abilities and taking these abilities into account in isolation, AI research is a documentation of (sometimes) impressive results towards solutions. Nevertheless, neither the generalizability property of frameworks nor the integration of different specialized frameworks are realized in a way, such that general intelligence emerges. We believe that newer developments of modeling techniques that have been developed during the last decades and have launched a growing interest in the research community are steps into the direction of AGI. We focus in this contribution on two aspects, namely learning and integration.

2 Learning

2.1 Neurally-Inspired Processing

An artificial neural network (ANN) is an abstract formalization of the essence of neural activity in the brain. During the last two decades there has been a growing interest in neural processing for AI applications. It is the adaptation potential of ANNs (in form of learning) that highlights the strength of this approach and makes it interesting for modeling aspects of general intelligence. Nevertheless, there are weaknesses of ANNs like the lack of memory, the problem to represent complex data structures, and the difficulty to use a uniform network topology for multiple computations, just to mention some of them. The reason for these deficiencies is simple: instead of recursively defining complex expressions based on atomic entities, ANNs are processing flat real-valued input vectors and are outputting again flat real-valued vectors.

Recently, there has been a substantial advance in overcoming some of these problems. Neural techniques have been pushed further by new topologies and learning algorithms of the network: not only learning by backpropagation of errors in feedforward networks, but also network topologies with recurrent connections were proposed. For example, Elman networks re-connect neurons of the hidden layer with the input layer allowing the learning of auxiliary inversion in natural language [6], recurrent neural networks were proposed for modeling complex data structures [3], and liquid state machines were proposed to naturally explain how a fixed network structure can be used for multiple computations and for the induction of spatio-temporal activation patterns of the network by time varying inputs [7]. In summary, classical boundaries of neural techniques are expanded for modeling higher cognitive abilities directing towards an AGI relevant generalization potential.

2.2 Markov and Bayesian Techniques

A boost of arousing interest can be traced back to new developments in understanding the behavior of Markov decision processes (MDP) and Bayesian techniques for learning and reasoning. MDPs have been applied to reinforcement learning in the area of finite state spaces, continuous state spaces, for deterministic state transitions, and stochastic state transitions, for totally and partially observable environments, as well as for model-based learning (value iteration) and model-free learning (Q-learning) [4]. The importance of these learning techniques for AGI applications is mainly based on the fact that they provide a testbed for acting in a wide range of (complex) environments. For example, if history lists of observations are taken as approximations of the current state of an agent, it is possible to model many different environments, such as games, motor actions, or planning problems with a uniform learning mechanism. Although the generalization potential of this framework seems to be very promising, there are also challenges: besides some theoretical questions with respect to certain types of MDPs, main problems for practical applications of MDPs to AGI tasks are complexity issues of appropriate (versions of) learning algorithms.

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3 Integration Methods

3.1 Reasoning Paradigms

It is quite obvious that natural agents can choose from a rather large repertoire of different reasoning paradigms in order to solve problems, generate plans, or to understand an ordinary text. In particular, the different reasoning abilities range from deductive, abductive, and inductive inferences to statistical, vague, uncertain, non-monotonic, and analogical inferences. A challenge for a model of general intelligence is not so much to find a representation of these types of inferences – for example, first-order logic is a strong representation format which can be used for coding many different forms of inferences – but to integrate these different forms of reasoning into one uniform framework.

A proposal to achieve this integration is the usage of analogical reasoning to cover different types of inferences. An example for such an approach is heuristic-driven theory projection, an analogy engine that comprises several different reasoning paradigms [8]. Although such an integration approach using analogy is confronted with many non-trivial problems (e.g. scalability, embedding of the system in large knowledge bases, modeling of the learning process), the endeavor includes steps towards an integrative perspective on reasoning tasks, a perspective that seems to be crucial for AGI.

3.2 Neural-Symbolic Integration

The gap between neural and symbolic representations is usually considered to be a hard problem. We find it hard to believe that significant progress in AGI can be realized if the unification of neural and symbolic approaches in terms of theories and computational models cannot be achieved. A reason for this belief is the fact that symbolic and subsymbolic approaches have rather complementary strengths and weaknesses, whereas an AGI model needs to realize the strengths of both approaches.

In Subsection 2.1, we mentioned already some steps towards an integration of neural ideas and symbolic theories, like the representation of complex data structures with neural means. A natural idea is to extend this also to logic: the task is to develop theories for learning logic with neural networks. Whereas learning of propositional logic with neural networks is rather well-established, the current state of the art of neural-symbolic integration attempts to expand these ideas to non-classical extensions of propositional logic and to first-order logic. Although conceptually a lot is gained by this research, there are several practical problems connected with this research tradition [2].

3.3 Cognitive Architectures

For a certain time the cognitive architecture SOAR, based on production rules and chunking as learning mechanism, was considered to be the only relevant architecture in AI [5]. Currently, this situation has dramatically changed due to an inflationary increase of new proposals for cognitive architectures in the field.[1] The rapid increase of new available methodologies is mirrored in the underlying principles of these architectures: symbolic, subsymbolic, and hybrid representations are used and there are modules for emotions, different types of reasoning and learning, and various types of memory. Furthermore, new tasks are chosen for testing such architectures, like priming effects, analogical associations, or learning skill knowledge. The strive to model intelligence as a whole including perception, action, and generalization abilities, seems to be common in all architectures.

[1] A few examples are Micro-Psi, Lida, OSCAR, I-Cog, BICA [9].

4 Conclusions

There are many new computing paradigms used in AI research. It has been argued that these new research traditions fit perfectly into the overall goals of AGI. Nevertheless, a certain tension remains: similar to the case of classical AI, these computing paradigms cover only single aspects of general intelligence and not the whole range of cognitive abilities on a human scale. In a certain sense, the AGI endeavor shifts the problem of developing integrated frameworks for general intelligence to another level. This makes the need for integrative cognitive architectures even more important. The future will tell whether there will be light at the end of the tunnel.

References

[1] B. Goertzel and C. Pennachin, editors. *Artificial General Intelligence*. Springer, 2007.

[2] B. Hammer and P. Hitzler, editors. *Perspectives of Neural-Symbolic Integration*. Springer, 2007.

[3] B. Hammer and B. Jain. Neural Methods for Non-Standard Data. In *ESANN'2004 Proceedings*, pages 281–292, 2004.

[4] M. Hutter. Feature Markov Decision Processes. In B. Goertzel, P. Hitzler, and M. Hutter, editors, *Artificial General Intelligence. Proceedings of the Second Conference on Artificial General Intelligence, AGI 2009*, pages 61–66. Atlantis Press, 2009.

[5] J. Laird, A. Newell, and P. Rosenbloom. Soar: An Architecture for General Intelligence. *Artificial Intelligence*, 33(1):1–64, 1987.

[6] J. Lewis and J. Elman. Learnability and the Statistical Structure of Language: Poverty of Stimulus Arguments Revisited. In *Procedeedings of the 26th Annual Boston University Conference on Language Development*. Cascadilla Press, 2001.

[7] W. Maass. Liquid Computing. In *Procedeedings of the Conference CiE'07*, pages 507–516. Springer, 2007.

[8] A. Schwering, U. Krumnack, K.-U. Kühnberger, and H. Gust. Syntactic Principles of Heuristic-Driven Theory Projection. *Cognitive System Research*, in press, 2009.

[9] P. Wang, B. Goertzel, and S. Franklin, editors. *Artificial General Intelligence 2008. Proceedings of the First AGI Conference*. IOS Press, 2008.

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