Neurosymbolic Integration for Industrial Applications

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NEUROSYMBOLIC INTEGRATION FOR INDUSTRIAL APPLICATIONS

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Abstract:
Today, symbolic and connectionist artificial intelligence have proved their complementary efficiency for various aspects of cognitive processing. Both approaches can be seen as complementarily acting on specific parts of information, namely data and knowledge. Such a dichotomy can also be observed as one consider real world applications. A general theory is rarely available to build a complete knowledge based system. Conversely, data can generally be extracted from the problem but never cover the whole problem. Accordingly, the idea has emerged that the combination of symbolic and connectionist tools could be a way to benefit from the advantages of both approaches. Neurosymbolic integration that will be presented here is the domain whose goal is to define strategies and propose tools for the cooperation of symbolic and connectionist artificial intelligence.

Keywords: neurosymbolic integration, hybrid approach, unified approach, industrial application, cognitive aspects

1 Introduction

What is the nature of relationship between human cognition and real world applications? We will try to contribute to answering to this question through our recent experience on such typical applications and the corresponding cognitive modelization.

1.1 First example

The first experience is an industrial application in the steelmaking domain. The problem is to predict the rolling force of a roll-mill to accurately preset the machine and improve the quality of the resulting sheet of steel. Different investigations were driven. The first one was driven from an engineer point of view. The goal was to exhaustively enumerate the parameters in the process, the rolling force was depending on. Then, various engineers from such domains as physics, thermics and other steel making related domains, gathered and wrote down physical equations relating those parameters with the rolling force. A physical model resulted from this modeling step, that was able, from the expert knowledge about the process, to compute the theoretical rolling force [Roberts, 1972].

The second investigation was driven from a statistical point of view. Sensors of the process allowed engineers to build up data bases gathering thousands of examples, each corresponding to the values of the critical parameters and the corresponding rolling force.

Then, a statistical analysis, involving a multilayer perceptron, allowed to predict the rolling force, as a function of the input parameters [Pican et al., 1993]. Here, except from the selection of the pertinent parameters, no knowledge was incorporated in the model, only built with measured data.

Both models were implemented on the process and respectively yield an average error of 25% and 17%. It was then possible to conclude that a data-based approach was more efficient then a knowledge-based approach. Nevertheless, a more accurate analysis showed that large errors in both models were not committed on the same cases. It was then possible to imagine that a clever combination of both models could yield an even better result.

1.2 Second example

The second experience is concerned with the autonomous navigation of a robot. This example is more academic, though industrial applications can also be envisaged in this framework. As for the previous example, knowledge-based and data-based approaches have also been reported for this problem, where the goal is to propose at each moment the best action for the robot that will optimize its reward, as a function of its environment, perceived through sensors, and of its past history, memorized within the system.

Knowledge-based approaches are derived from classical artificial intelligence techniques, where objects and relations between them are represented by symbols. In models like [Donnart and Meyer, 1996], a rule based classifier system can control the navigation of a simulated robot with complex reasoning abilities. Nevertheless, it is much more difficult to ground the symbolic structures defined here on real numerical perceptions.

Conversely, data-based approaches like [Bühlmeier et al., 1996] are built in a bottom-up way, from the sensors. Here, the associative properties of hebbian learning are used to learn correlations between elementary numerical events. Such models are thus very efficient in tasks like obstacle avoidance, but are limited to reactive behaviors.

2 Neurosymbolic integration

We have evoked above knowledge-based and data-based approaches to real-world applications. Accordingly, Artificial Intelligence (AI) can be also divided in symbolic and numerical AI. Symbolic models offer good performances in reasoning, are able to give explanations and can manipulate complex data structures, but they have generally serious difficulties in anchoring their symbols in the perceptive world. By contrast, numerical models like neuronal models are often selected for pattern recognition and have such qualities as generalization and learning abilities, whereas they have not been reported as efficient for deduction tasks.

As a consequence, neurosymbolic integration has emerged and try to combine symbolic and neuronal AI to benefit from advantages of both approaches. Among various strategies for neurosymbolic integration, two are clearly identified.

The hybrid strategy is an opportunist approach which proposes to combine classical models from neuronal and symbolic AI. Here, the point is to wonder about possible cooperations between such models and to emulate the corresponding platforms, able to ensure parameter and data structure exchanges between the models [Hilario et al., 1994].

Another point corresponds to deciding, for a given application, which combination of symbolic and numerical models could yield a good performance. Such a general methodology and the corresponding tools were proposed during the european MIX project [Alexandre, 1997].

The unified strategy proposes that the characteristic properties of the symbolic AI can emerge from distributed local computations of a neuronal model. Among several ideas, biologically-inspired modelization of brain-like systems are of particular interest here. In this framework, complete cognitive functions, from the perceptive to the reasoning or planning level, are modelized from a neuromimetic point of view, from the neuron level up to the structural level of the nervous system [Edelman, 1987, Alexandre et al., 1991].

It is also worth noticing that neurosymbolic integration has been also justified from a cognitive point of view [Lallement et al., 1995]. Basically, the idea is to identify in human intelligence, on the one hand, low-level operations mostly concerned with perceptual tasks, best carried out by neuronal models, and on the other hand, high-level operations rather concerned with reasoning, best treated by symbolic models. It is then straightforward to state that most complex cognitive human tasks involve both types of operations, hence the need for the combination of the corresponding models.

Concerning the two types of strategies of integration evoked above, we now illustrate them to the light of the applications presented at the beginning of the paper.

3 The hybrid approach

An hybrid strategy was chosen for the steelmaking application. In addition to the two physical and neuronal modules described above, another prediction module with fuzzy logic was also built. Then, in addition to these basic modules, two kinds of higher-level modules were defined. First, a Kohonen map was used to estimate, for each basic module and each input data, a prediction of its error. Second, a case-based reasoning module was implemented, whose goal was to choose, for each input data, the best combination of modules to apply. All these modules where gathered on a multi-agent platform, in charge of their communication and parameter exchange. As a result, an average 10.5% error was obtained [Alexandre, 1997].

4 The unified approach

The autonomous navigation of a robot has been tackled with a biologically-inspired unified approach. As a connectionist model, the model developped here [Frezza-Buet and Alexandre, 1998a] has such characteristics as hebbian learning, classical neuronal activation, etc. It has also specific biologically-inspired mechanisms as feed-back control activation and lateral excitation. More interestingly, this model also includes specific knowledge, like the definition of specific maps with topology and coding derived from cortical data. This multi-map model has been proven very efficient for the learning of the behavior of an autonomous robot, from the perceptive level up to the level of the selection of action in an unknown environment [Frezza-Buet and Alexandre, 1998b].

5 Discussion

Both hybrid and unified strategies are grounded on the same idea of combining symbolic and neuronal AI principles to get their advantages. Our experience with these strategies makes us discuss now about their interest for industrial applications but also for the better understanding of human cognition.

The hybrid strategy consists in combining current classical models from both symbolic and neuronal approaches. Here, the point is to build a platform allowing for a fruitful dialogue, parameter exchange and other adaptive processes between connectionist and symbolic models. As our industrial experience illustrates and as confirmed by similar experiences made in our group, it is clear that the hybrid strategy is a rather simple and pragmatic approach, using classical AI tools. As such, it can be easily used for complex real-world tasks. Concerning its cognitive orientation, the hybrid strategy underlines the dual aspect between expert knowledge and statistical estimation obtained from data. It is thus an attempt to reconciliate to typical human processes : trying to understand, explain, formalize and giving an unconcious estimation from experience. While implementing our modules in the steelmaking plant, we have particularly observed that this dual approach was very well understood by the technical staff. We believe that this point is very important for such a new tool to be accepted and used in a plant.

The unified strategy claims that the connectionist formalism alone can perform cognitive tasks and emulate the corresponding properties. Inspiration from neurosciences domains is often used in such a framework. Here the cognitive orientation is clearly anthropomorphic. Instead of modeling its reasoning strategy like in the hybrid way, the idea here is to mimic the human substratum for perceiving and reasoning. Even if this approach is clearly potentially powerful, it is not as mature as the hybrid one. It is also not directly applicable to any industrial application, except when the topic is to modelize human behavior. Nevertheless, local properties and mechanisms of such models could be more directly exploited in an information processing point of view, without consideration of the biological framework.

As a conclusion, we think that, even if the hybrid approach is more tractable in a short term point of view and the unified approach is more generic, they tend toward the same goal and can illustrate complementary aspects of cognition.

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