The Integration of Connectionist Models with Knowledge-based Systems: Hybrid Systems

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ABSTRACT

The main difference between Connectionist Models and technologies of symbolic Artificial Intelligence is the form, in which knowledge is represented i.e. subsymbolic vs. subsymbolic. to represent symbolic knowledge. This paper clarifies and emphasizes this paradigmatic difference, in particular with respect to the so called hybrid systems. The terms symbolic and subsymbolic knowledge representation will be precised. Furthermore, the central constituents of a subsymbolic represenation will be named. Necessary requirements for Connectionist Models are clarified. As hybrid systems in a strict sense those systems are identified that realize the conversion between subsymbolic and symbolic knowledge

1. INTRODUCTION

The notion "hybrid" stands for the formation of hermaphrodites constructed by an amalgamation or crossing. The main motivation for the hybridization of Connectionist Models and Artificial Intelligence (AI) technologies is derived from the assumption that both technologies are different but complementary [4]. AI technologies are said to be easy interpreted, easy controlled and contain a high level of knowledge abstraction. Connectionist Models, in contrast, show advantages with regard to learning capabilities and robustness. Furthermore, they claim to be more error tolerant than AI technologies [3].
Beside the above mentioned pragmatical differences a principal, i.e. paradigmatical, difference between Connectionist Models and AI technologies is claimed [6 8]. One of these differences should concern the computational power, i.e. what is possible to be computed by computer systems in principal. Furthermore, it is assumed that by renunciating to understand the derivation of the solution, a broader class of problems can be solved. The difference mainly should lie in the difference between subsymbolic knowledge representation in Connectionist Models vs. the symbolic knowledge representation in AI technologies [5].
In this paper we focus on the difference in knowledge representation in both technologies. We want to stress the point, however, that a symbolic representation may also be used in Connectionist Models. Such models are characterized by assigning an explicit meaning to each unit or neuron. Moreover, the omission of a few units does dramatically change the represented knowledge.

Symbolic representation in Connectionist Models from [9]

Numerical representation is no guarnetee for a subsymbolic representation. As an example, consider patients state of health coded in number ranging from 0 to 100, where the value 100 means "completely healthy". This is a symbolic representation of a fact that is coded numerically.

In contrast to this, consider the following numbers.
128 128 128 128 130 127 128 134 125 121 136 133 112 126 139 121 132 137 122 131 136 115 140 140 106 118 139 114 124 153 111 111 159 134 103 142 139 97 124 148 108 111 153 118 106 150 139 106 193 193 14 64 188 96 164 138 74 171 175 27 160 148 75 128 199 96 108 142 132 132 103 138 145 108 103 159 122 114 132 134 114 124 118 138 117 134 134 103 96 164 100 117 148 128 128 132 122 108 177 132 117 70 175 139 31 134 156 100 156 124 128 139 81 106 159 114 117 170 124 103 132 118 100 132 134 114 148 118 134 124 118 128 138 111 128 134 114 138 132 111 100 139 122 117 134 148 153 111 111 159 134 103 142 139 97 124 148 108 111 153 118 106 150 139 106 134 142 103 124 145 114 114 148 128 111 142 138 108 134 150 108 103 148 132 111 142 124 114 145 134 114 138 128 111 124132 134 114 124 118 138 117 134 134 103 96 164 100 117 148 128 128 132 122 64 128 118 128 134 192 111 124 128 118 90 118 188 148 86 145 170 92 79 148 171 142 118 128 159 122 68 114 166 159118 134 124 118 128 138 111...
Subsymbolic representaion of data

They are extracted from a CD with an interpretation from Georges Bizet's opera Carmen. A single number can only be understood in the context of the music. The number by itself possesses no meaning at all. As a matter of fact we could change or omit a single number and presumably no changes of the original sound will be heard. Moreover, the CD player will be able to correct the changed number.
The numbers above can be understood as a subsymbolic representation of the music. A symbolic representation of the same content would be the writing of notes of the same music. Each note is hereby a symbol.
Andante moderato

Symbolic Representation of Georges Bizet's Oper Carmen

2. Basic Notions

Symbol
The word "symbol" as defined in a dictionary is an "object or a process that serves as a place-holder for a psychic entity which cannot be perceived directly" [2]. In computer science "object or process" is usually defined as an element of an alphabet i.e. a singe. This sign, for example a letter, is regarded atomic and cannot be divided into subelements without loss of the meaning of the sign. As "psychic entity which cannot be perceived directly" the semantics of the sign or words build out of signs can be regarded.

Letter A as a symbol
Knowledge Representation
Much more difficult is it to find a definition of the word "knowledge" (for example see [1]). Represented knowledge implies an "interpreter with symbol processing competence" [10], respectively a "semantic engine" [1]. In order to differentiate "knowledge" from similar notions like "skills", it is necessary to demand of a representation of knowledge, that a transfer of this knowledge can be performed using language alone. In this sense, for example, the ability to "ride a bicycle" would not considered to be knowledge. Strategies to get a solution of a mathematical equation, however, would be knowledge.
Symbolic Knowledge Representation
As a consequence from the definition of symbol as an "object or a process that serves as a place-holder for a psychic entity which cannot be perceived directly", we demand for the

symbolic knowledge representation that it should be in a linguistic form using signs understandable for humans. The signs are considered to be atomic in a given context. Examples for such symbols are words, function names, variable names, predicate names, notes, etc. Examples for linguistic representation forms are: German, English, predicate logic, mathematical calculus, notes of music's, etc. All representation forms used in AI as, for example, frames, scripts, semantic nets, etc., can be derived from and implemented with predicate calculus. One of the main parts of a Knowledge-Based System is therefore an inference engine that is able to conduct formal proofs in the calculus of predicate logic.

Subsymbolic Knowledge Representation

For a subsymbolic knowledge representation numerous elements (units, neurons, weights) cooperate in a shared representation of a symbol. This is done in such a way, that

-the symbol emerges by means of a collective (synergetic) cooperation of all elements,

-no element possesses a meaning for itself (in the context of the represented symbol),

-no element for itself allows an identification of the represented, item

-the omission of single elements will not c hange the identity of the symbol, which is represented collectively (redundancy/ error tolerance).

Parts of the representation of an element of a symbol are often called microfeatures.

Microfeatures of the Symbol "A"

Often it is assumed that each unit takes part in the representation of many or even all symbols. I.e. in a single unit exists an overlap or mixture of the representation of different symbols. As an example for this consider a hologram.

A subsymbolic representation gives rise to some expectations in Connectionist Models. A subsymbolic representation is presumably error tolerant since the modification of one microfeature will in general have no sensible consequences on the represented symbol. In symbolic AI techniques for the acquisition of "new" knowledge exist. These techniques are known for example as machine learning (ML) algorithms [7]. Assuming a symbolic representation of knowledge one could object that by machine learning techniques only known symbols are agglomerated to form linear combinations of known entities. Something really new in the sense of new entities or the detection of new relationships is not to be expected from these technologies. The superposition of representations in the units implies for connectionistic systems that they can detect really new entities or new relations.

3. COOPERATIVE VS. HYBRID SYSTEMS

Regarding the integration of Connectionist Models with symbolic AI techniques two different approaches can be distinguished: cooperative and true hybrids.

Cooperative Systems

The main feature of such systems is that no transition between subsymbolic and symbolic knowledge representation takes place. A cooperative system may be divided into several modules and different tasks that are implemented in different technologies. For example, a set of observations that are subsymbolically described, for example, "normal blood parameters ", may be represented in a connectionist component. Inferences that may be derived from this, however, are performed by a symbolic Knowledge-based System.

True Hybrid Systems

The main characteristic of such systems is that a conversion of the different knowledge representations (subsymbolic vs. symbolic) takes place. As seen above, symbolic knowledge representation may be realized via proofs in the calculus of predicate logic. For the conversion of knowledge representation it is therefore very important how the constituents of predicate logic can be represented in a subsymbolic form. Going the other way it is essential how inference mechanisms will be performed by Connectionist Models. Another central question is how the entities that a Connectonist Model has learned can be converted into a symbolic representation.

4. CENTRAL ISSUES IN THE REPRESENTATION OF SYMBOLIC KNOWLEDGE

The following issues are important for a symbolic representation form of the predicate logic and have to be treated by a subsymbolic form of the representation of symbolic Knowledge. [13].

The Representation of Atomic Symbols and Agglomerated Structures

The main problem here is that not only single symbols have to be represented but also structures which are derived from single symbols in a syntactically well-defined way. An example of this is the formation of structures using well-balanced parenthesis. As an example, the fact that Anna is the mother of Peter could be represented as follows:

(anna, is_mother_of, peter).

Such structures can be arbitrarily big and complex. It must be possible to access single parts of a structure and the structure by itself must be able to be subject of a syntactic analysis. For example, the permutation of "anna" and "peter" in the example above would result in a senseless fact.

Representation of Variables and Instances

In predicate logic a variable stands for an arbitrary, atomic or complex symbol that could eventually be specified furthermore. Variables need to have the properties of being equal, unifiable or unequal. Furthermore, a variable could be identified with a symbol or a structure (instantiation). Calculi which operate on vague knowledge have in addition the requirement for a notion of "approximately equal".

Inference

Inference is the derivation of conclusions from given facts via rules (inference rules). The best known example for this is the modus ponens [1]. A principal difference hereby are purely logical inference methods (e.g. resolution) and inference methods which admit estimations (vage knowledge). Common examples of the later are probability theory with the theorem of Bayes, Dempster Shafer Theory and Fuzzy Logic.

One problem with inference is strategy of the derivation of conclusions. Since Gödels proofs we know that all non trivial inference methods are only semi-decidable. Even very restricted inference methods, however, result in a combinatorical complexity in the set rules that may be applied. For this heuristic search methods are applied in symbolic AI. Humans as problemsolvers seem to be developing rather a "look" or a "feeling" for the solution. For this aesthetic factors ("this equation is elegant") seem to be important .

Connectionist Models that use a subsymbolic knowledge representation have to be able to realize the parts of reasoning systems mentioned above in a subsymbolic way in order to be equivalent to symbolic AI technology.

5. CONCLUSION

In this paper the central differences between symbolic and subsymbolic knowledge representation are pointed out. The central issues of symbolic representation that need to be solved by subsymbolic Connectionist Models are presented. We want to insist, that not all

Connectionist Models use a subsymbolic knowledge representation. The main criteria of a subsymbolic knowledge representation is that no single elements like neurons or weights have a meaning by themselves. Additionally, the omission of one unit modifies the performance of the system gradually and would not lead to a breakdown of the whole system.
From the point of view of the theoretical computer science, it seems improbable that renouncing explanations using subsymbolic Connectionst Models leads to the handling of a broader class of algorithms, as some Connectionist Models researchers postulate. It can be observed, however, that certain abilities of biological systems, like pattern recognition, abstract thinking, the ability to assign semantics and flexible learning are hardly, if at all, realized with symbolic AI systems. On the other hand, systems with AI technologies have clear advantages if calculations take place in a known calculus [14]. It is not understandable why a system that solves algebraic equations efficiently and probably correct should be realized in a connectionist technology.
Both technologies, Connectionist Models and AI systems, have their advantages and disadvantages. As a consequence, we propose an integration of both methods. The main condition for an integration remains, however, the conversion of knowledge from subsymblic to symbolic, and vice versa. A possibility for the realization of such a knowledge conversion, for example, is the extraction of symbolic rules from subsymbolic Connectionist Models [11].

6. REFERENCES

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