Biologically Inspired Cognitive Architectures (2013) 6, 159–168

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INVITED ARTICLE

Probabilistic dynamic logic of cognition

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Received 15 March 2013; received in revised form 25 June 2013; accepted 28 June 2013

KEYWORDS
Artificial intelligence;
Probabilistic dynamic logic;
Probabilistic inference;
Neuron model;
Breast cancer

Abstract
We developed an original approach to cognition, based on the previously developed theory of neural modeling fields and dynamic logic. This approach is based on the detailed analysis and solution of the problems of artificial intelligence – combinatorial complexity and logic and probability synthesis. In this paper we interpret the theory of neural modeling fields and dynamic logic in terms of logic and probability, and obtain a Probabilistic Dynamic Logic of Cognition (PDLC). We interpret the PDLC at the neural level. As application we considered the task of the expert decision-making model approximation for the breast cancer diagnosis. First we extracted this model from the expert, using original procedure, based on monotone Boolean functions. Then we applied PDLC for learning this model from data. Because of this model may be interpreted at the neural level, it may be considered as a result of the expert brain learning. In the last section we demonstrate, that the model extracted from the expert and the model obtained by the expert learning are in good correspondence. This demonstrate that PDLC may be considered as a model of learning cognitive process.

1. Introduction

Previously, an original approach was developed to the cognition simulation based on the theory of neural modeling fields and dynamic logic (Kovalerchuk & Perlovsky, 2008; Perlovsky, 1998; Perlovsky, 2006; Perlovsky, 2007). On the one hand, this approach is based on the detailed analysis of the cognition problem for artificial intelligence – combinatorial complexity and logic and probability synthesis. On the other hand, it is based on the psychological, philosophical or cognitive science data for the basic mechanisms of cognition. The main idea behind success of NMF is matching the levels of uncertainty of the problem/model and the levels of uncertainty of the evaluation criterion used to identify the model. When a model becomes more certain then

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2212-683X/$ - see front matter
http://dx.doi.org/10.1016/j.bica.2013.06.006

the evaluation criterion is also adjusted dynamically to match the adjusted model. This process is called dynamic logic of model construction, which mimics processes of the mind and natural evolution.

Analysis of the cognition problems has, in fact, a broader meaning and overcoming these problems can lead to the other formal characterizations of the cognition process. With this purpose, in Kovalerchuk and Perlovsky (2008) a generalization of the theory of neural modeling fields and dynamic logic was obtained in the form of dynamic logic of cognition and cognitive dynamic logic. These logics are formulated in rather general terms: *relations of generality, uncertainty, simplicity; maximization the similarity with empirical content; training method*.

In this paper, we interpret these concepts in terms of logic and probability: the uncertainty we interpret as a probability, and the process of training as a semantic probabilistic inference (Smerdov & Vityaev, 2009; Vityaev, 2006a; Vityaev, 2006b; Vityaev & Smerdov, 2009). Obtained Probabilistic Dynamic Logic of Cognition (PDLC) belongs to the field of probabilistic models of cognition (Probabilistic Inductive Logic Programming, 2008; Probabilistic models of cognition, 2006; The Probabilistic Mind, 2008). We show that this logic also solves the cognition problems (combinatorial complexity and logic and probability synthesis). Thus, by the generalization obtained in Kovalerchuk and Perlovsky (2008), we extend the interpretation of the theory of neural modeling fields and dynamic logic on the probabilistic models of cognition. Probabilistic dynamic logic had been used for simulation of brain activity and cognitive processes in Demin and Vityaev (2008).

2. Cognition problem from the probabilistic point of view

Now we repeat and extend the description of cognition problem for artificial intelligence stated in Perlovsky (1998) and Kovalerchuk and Perlovsky (2008). The founders of artificial intelligence in the 1950s and 1960s believed that by reference to the rules of logic, they would soon create a computer which intelligence would be far superior to the human brain. But the application of logic to artificial intelligence didn't lead to the results expected. We need to clearly distinguish the theoretical and empirical attitudes. In theory using the idealized knowledge, for example, in physics, geometry, chemistry and other sciences, logic and logical inference are justified and work perfectly. But the intelligent systems are based on the empirical learning process, with the knowledge, obtained as a result, being inductive. For the inductively derived knowledge logical inference does not work well.

The brain is not a logical but a predictive one. However, a suitable definition of prediction for the inductively derived knowledge is a problem.

A generally accepted definition of prediction belongs to Karl Popper and is based on the fact that for the prediction of some fact it is necessary to infer it from the available facts and laws. But this definition does not work for the inductively derived knowledge with estimations of probability, confirmation, etc. At the same time, in the logical inference of predictions it is necessary to deduce the estimations of probability, confirmation, etc. for the obtained prediction. For probability estimations there is a probabilistic logic (Gabbay, Johnson, Ohlbach, & Woods, 2002) and probabilistic inductive logic programming (Raedt et al., 2008) to deal with it. But it is well known that prediction estimations may fall during the logical inference and leading to zero prediction estimations. Predictions with zero estimation can not be regarded as predictions. This problem is now regarded as a problem of logic and probability synthesis (Cozman et al., 2009). There have already been five symposia between 2002 and 2011 under the common title Progic (Probability + Logic).

We have introduced a new concept of prediction (Smerdov & Vityaev, 2009; Vityaev, 2006b; Vityaev & Smerdov, 2009) which is not use a logical inference and replace the ''true'' and ''false'' values by probability. Instead of logical inference we introduced semantic probabilistic inference. The new definition of the prediction is fundamentally different from the Karl Popper's one — the prediction of some fact occurs not as a logical inference of the particular fact from the existing ones but as a direct inductive inference of the rule that predicts the fact we are interested in. Estimates of probability strictly increase in the process of semantic probabilistic inference.

Another problem of cognition in artificial intelligence is the combinatorial complexity problem (CC), (Kovalerchuk & Perlovsky, 2008; Perlovsky, 1998). Perception associates a subset of signals corresponding to the external objects with representations of these objects. The process of association-recognition-understanding turned out to be not at all easy, and is connected with the notion of combinatorial complexity. Subsequent studies found a connection between CC and logic in a variety of algorithms. Logic considers a very small change in data or models as a new proposition. Attribution of truth values ''true'' and ''false'' does not allow comparing statements and this leads to CC. In (Hyafil & Rivest, 1976) it is proved that even the simplest task of finding the set of propositions describing the decision trees is NP-hard.

Follow the work (Kovalerchuk & Perlovsky, 2008) we introduced two order relations on propositions: relations of generality and comparison that are used in semantic probabilistic inference. This essentially reduces the search and, along with the use of statistical estimates, makes it acceptable and solves CC problem.

Now we recall and extend the basic definitions related to cognition (Kovalerchuk & Perlovsky, 2008; Perlovsky, 2006). We assume that the basic mechanisms of cognition include: instincts, concepts, emotions and behavior. Further we explain how semantic probabilistic inference may be used in formalization of these concepts.

Ray Jackendoff (2002) believes that the most appropriate term for mechanism of concepts is a model, or an internal model of cognition. Concepts are models in a literal sense. Within our cognitive process, they construct world objects and situations. Cognition involves the multi-leveled hierarchy of concept models: from the simplest elements of perception (line, point) to the concept models of objects, relations between objects and complex situations.