Self-supervised Learning in Symbolic Classification

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Abstract: A new approach to modelling self-supervised learning for automated constructing and improving algorithms of inferring logical rules from examples is advanced. As a concrete model, we consider the process of inferring good maximally redundant classification tests or minimal formal concepts. The concepts of external and internal learning contexts are introduced. A model of an intelligent agent capable of improving its learning process is considered. It is shown that the same learning algorithm can be used in both external and internal learning contexts.

1 INTRODUCTION

Self-learning embodies one of the essential properties of the human intelligence related to an internal evaluation of the quality of mental processes. Vukman and Demetriou (2011, p. 37) suggest that the mind has a three-level hierarchical structure. The first level interfaces directly with the environment and it includes several specialized capacity systems addressed to representing and processing different domains of the environment. The remaining two levels cover goal elaborating mechanisms, assessments of the proximity to the goal, algorithms defining the ability to present and process information on the first level, and (third level) the hypercognitive processes related to self-consciousness and self- regulation.

Empirical research of Vukman and Demetriou (2011, p. 38) has revealed that the first level covers 6 specific domains of thought: (1) the categorical system (deals with similarity-difference relations and classifications); (2) the quantitative system (deals with quantitative variations and relations in the environment); (3) the causal system for revealing cause-effect relations; (4) the system for evaluating spatial orientation and representation of the environment in images; (5) the system of formal logic (deals with the truth/falsity and the validity/invalidity of the flow of information); (6) the system for evaluating the social relations.

The second level is responsible for the complexity and efficiency of information processing at the first level at any given time. Operations of this level set the speed of information processing, realize the control of thinking processes, and direct the attention to important stimulus and prohibit irrelevant ones. This level also includes working memory.

The hypercognition includes self-awareness and self-regulation of knowledge and strategies operating as the interface between (a) mind and reality, and (b) any of the various systems and processes of mind. The hypercognitive level has two components: the working hypercognition and the long term hypercognition. The first component is responsible for setting goals, planning, and monitoring the achievement of goals, including responsibility for updating goals and sub-goals. The self-consciousness is an integral part of the hypercognitive system. The component of long-term hypercognition involves the internal representation of past cognitive experience.

Our analysis of modern research has been implemented in the following directions: modeling of self-learning (self-supervised learning) and learning in robots and robotic systems. In artificial intelligence, the theory of self-learning is still in the formation, the practical results are obtained mainly in the modeling of robot management. In the second direction, it is particularly interesting the principles and technologies of creating a robot that can move in

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the environment, manipulate objects and avoid obstacles (Pillai, 2017). The self-learning robot should be aware of its own localization and have an internal reflection of spatial situation. It is declared by the author (Pillai & Leonard, 2017) that the robot should be self-esteemed and self-managed on the basis of previous experience. It must constantly adapt its spatial and semantic models, improving the performance of its tasks. Some concepts and algorithms are proposed to evaluate the robot's own movement (Self-Supervised Visual Ego Motion Learning) (Sofman, Line et al., 2017). Note that such a robot has not yet been implemented but the concept of self-learning proposed by the author coincides with the concept of self-learning offered by us.

In (Pathak, Agraval, et al., 2017), the role of curiosity in self-learning is analyzed and the concept of self-learning with the phenomenon of curiosity is developed.

In (Shaukat, Burroughe & Gao, 2015), a robot's internal evaluation of its future path cost is proposed on the basis of the probabilistic Bayesian method.

In some works, the authors propose the use of robot's manipulation reflection in learning algorithms for improving and accelerating robot's training. For example, industrial Robot of Japanese Company Fanuc uses a method known as "training with reinforcement" to grab objects by a manipulator. In this process, a robot fixes its work on video and uses this video for correcting own activity. Domestic development of robots is based on the use of artificial neural networks (Pavlovsky & Savitsky, 2016; Pavlovsky V.E. & Pavlovsky V.V., 2016; Pavlovsky et al., 2016).

In paper (Bretan et al., 2019), the authors introduce "Collaborative Network Training" – a self-supervised method for training neural networks for learning robots. This method covers task objective functions, generates continuous-space actions, and performs an optimization for achieving a desired task. Also, the method allows learning parameters when a process for measuring performance is available, but labelled data is unavailable. The method involves three randomly initialized independent networks that use ranking to train one another on a single task.

Major improvements in time and data efficiency to learn robot are achieved in (Berscheid, Rühr & Kröger, 2019). Using a relatively small, fully-convolutional neural network, it is possible predict grasp and gripper parameters with great advantages in training as well as inference performance. Motivated by the small random grasp success rate of around 3%, the grasp space was explored in a systematic manner. The final system was learned with 23000 grasp attempts in around 60h, improving current solutions by an order of magnitude. The authors measured a grasp success rate of (96.6±1.0) %.

To model a self-learning process, we focus on the logical or symbolic supervised methods of machine learning. This mode of learning covers mining logical rules and dependencies from data: "if-then" rules, decision trees, functional, and associative dependencies. This learning is also used for extracting concept from data sets, constructing rough sets, hierarchical classification of objects, mining ontology from data, generating hypotheses, and some others (Kotsiantis, 2007; Naidenova, 2012). It has been proven in (Naidenova, 1996) that the tasks of mining all logical dependencies from data sets are reduced to approximating a given classification (partitioning) on a given set of object descriptions. The search for the best approximation of a given object classification leads to the definition of a concept of good classification (diagnostic) test firstly introduced in (Naidenova & Polegaeva, 1986). A good classification test has a dual nature. On the one hand, it makes up a logical expression in the form of implication, associative or functional dependency. On the other hand, it generates the partition of a training set of objects equivalent to a given classification (partitioning) of this set or the partition that is the nearest one to the given classification with respect to the inclusion relation between partitions (Cosmadakis, Kanellakis & Spiratos, 1986, Naidenova, 2012). It means that inferring good classification tests gives the least possible number of functional or implicative dependencies.

Table 1: Example of dataset (adopted, (Ganascia, 1989)).

ndex of object	Height	Color of hair	Color of eyes	Class
1	Low	Blond	Blue	1
2	Low	Brown	Blue	2
3	Tall	Brown	Hazel	2
4	Tall	Blond	Hazel	2
5	Tall	Brown	Blue	2
6	Low	Blond	Hazel	2
7	Tall	Red	Blue	1
8	Tall	Blond	Blue	1

It means also that good classification tests have the most possible generalization properties with respect to object class descriptions. We consider two ways for giving classifications: (1) by a target attribute KL or (2) by value v of a target attribute. In Table 1, an example of object classification is given.

The target attribute partitions a given set of objects into disjoint classes the number of which is equal to the number of values of this attribute. The target value of attribute partitions a given set of objects into two disjoint classes: the objects in description of which the target value appears (positive objects); all the other objects (negative objects). The problem of machine learning to approximate a given classification consists in solving the following tasks:

Given attribute KL, to infer logical rules of the form:

A B C → KL or D S → KL or …or A S Q V → KL,

where A, B, C, D, Q, S, V – the names of attributes.

Given value *v* of attribute KL, to infer logical rules of the form:

if ((value of attribute A = "*a*") & (value of attribute B = "b") & …, then (value of attribute KL= "*v*").

Rules of the first form are functional dependencies as they are determined in the relational data base theory. Rules of the second form are implicative dependencies. The left parts of rules can be considered as the descriptions of given classifications or classes of objects. In our approach to logical rules mining, the left parts of these rules constitute classification tests. Implicative assertions describe regular relationships connecting objects, properties, and classes of objects. Knowing the implication enables one to mine a whole class of implicative assertions including not only simple implication (*a*, *b*, *c* → *d*), but also forbidden assertion (*a*, *b*, *c* → *false* (*never*)), diagnostic assertion (*x*, *d* → *a*; *x*, *b* → not *a*; *d*, *b* → *false*), assertion of alternatives (*a* or *b* → *true* (*always*); *a*, *b* → *false*), compatibility (*a*, *b*, *c* → VA, where VA is the occurrence's frequency of rule).

We propose, in this paper, an idea of a deeper level of self-learning allowing to manage the process of inferring good tests in terms of its effectiveness through an internal monitoring and evaluation of this process and the development of rules for choosing the best strategies (algorithms), and learning characteristics.

Let's call a set of given objects with a class-partitioning an external or application context. The internal or reconfiguration level implements the analysis and evaluation of the process of inferring classification rules in the external context allowing to identify the relationships between the external contexts (sub-contexts) and the parameters of learning process.

2 SOFTWARE AGENT CAPABLE OF SELF-LEARNING

In the tasks of logical rule inference, the objects in the external context (training samples) are described in terms of their properties (features, attributes) and they are specified by splitting into classes. The task of learning is to find rules in each given context in order to repeat the classification of objects represented by splitting objects into disjoint classes. The learning algorithms have a number of convenient properties for self-monitoring the process of inferring tests (Naidenova & Parkhomenko, 2020): a) external context is decomposed into sub-contexts in which good tests are inferred independently; b) sub-contexts are chosen based on analysing their characteristics; c) the choice of sub-context determines the speed and efficiency of classification task. The strategies to select sub-contexts and learning algorithms are easy to describe with the use of special multi-valued attributes.

Decomposition of context into sub-contexts allows to reduce the problem of large dimension to ones of smaller dimension and thereby to decrease the computational complexity of the classification problem.

Let us now introduce an intellectual agent implementing the following functions.

First, the agent needs to memorize the situations of learning and the activity associated with them (at the application (external) level). Then the agent has to evaluate the learning process in terms of its effectiveness, temporal parameters, the number of sub-contexts to be considered, the consistency between the parameters of external contexts (sub-contexts) and the parameters of the learning process. Generalizing and simplifying the above, let's assume that the internal context necessarily contains:

1. Description of selected sub-context in terms of its properties.
2. Description of selected learning steps.
3. Internal estimation of learning process with the use of some given criteria of its efficiency.

3 THE STRUCTURE OF INTERNAL CONTEXT

Let K be the descriptions of external sub-context via its properties, A = {A1, A2, ….An} be the descriptions of algorithms of good tests inferring via their properties in this sub-context, R = {R1, R2, ….Rm} be the rules for selecting sub-contexts, and

V= {V1, V2, …, Vq) be the set of rule for evaluating the process of good test inferring.

Then the internal context is described by the direct product of sets K, A, R and its mapping on V: $K \times A \times R \rightarrow V$. A and R describe the learning process, V is an internal evaluation of the learning process.

In order this assessment to be feasible as an internal evaluation, the self-learning agent must have some special functions of analysing the processes taking place in it. One of these functions can be a counter of the number of sub-contexts processed during good test inferring, a counter of time requested for processing sub-context, the calculator of the relationship between the number of received good tests in sub-context and some of its quantitative characteristics (number of objects, number of attributes, number of different attribute values), etc.

There are more simple variants of the internal context:
$K \times A \rightarrow V$ and $K \times R \rightarrow V$.

Now, to infer the logical rules for distinguishing the variants of learning in the external context evaluated as good ones from the variants evaluated as not good ones, we can use any algorithms of inferring good classification tests in the internal context.

A few algorithms for good test inferring have been elaborated: ASTRA, DIAGARA, NIAGARA, and INGOMAR (Naidenova, 2006; Naidenova & Parkhomenko, 2020).

On the basis of internal learning, the agent can select rules for more successful learning in solving the main problem in the application context.

The internal context is a memory of the agent, the rules extracted from the internal context represent the agent's knowledge about the effectiveness of its actions in the external context.

The practical implementation of self-learning in this work is not developed. In the simplest case, we can separate two processes in time: accumulating data and forming an internal context (with an assessment of the quality of learning) and building rules for choosing sub-contexts by their characteristics. Once these rules are received, they can be used to learn in an external context and form a new internal one.

The internal context for choosing sub-contexts can contain the following information:

1. The number of objects in sub-context.
2. The number of values of attributes in sub-context.
3. The number of essential values of attributes (Naidenova & Parkhomenko, 2020) in sub-context.
4. The number of essential objects in sub- context (1Naidenova & Parkhomenko, 2020).
5. The number of already obtained good tests covered by sub-context.
6. The number of values of attributes (objects) uncovered by already obtained good tests in sub-context.
7. Some relationships between the characteristics of sub-contexts listed above.
8. The strategies (rules) to select sub- contexts.
9. The evaluation of the process of external learning (it gives the partition of accumulated data).

As a result of learning in this internal context we obtain the rules revealing the connection between the characteristics of sub-contexts and the strategies of selecting them. Strategy can be: selecting sub-context with the smallest number of essential values of some attributes; selecting sub-context with the smallest number of essential objects and some others.

Actions in the internal and external contexts can be represented as actions of two agents functioning in turn or in parallel and exchange data (Figure 1).

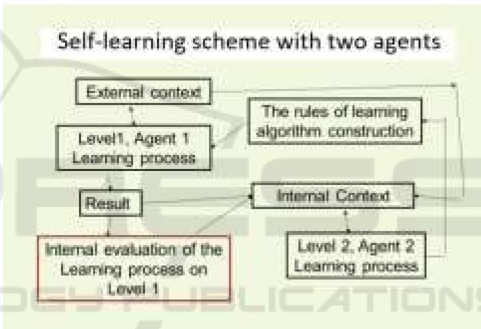

Figure 1. The interaction of two agents

Agent A1 transmits the data (the descriptions of contexts, algorithms, rules for selecting sub-contexts) to Agent A2. Agent A2 acts in the internal context (obtained from agent A1) and passes to agent A1 the rules, the latter applies these rules to select the best variant of learning with each new external sub-context.

For Agent A2, the internal context (memory) should not be empty, but this agent (as well as Agent A1) can work in an incremental mode of learning. A few incremental algorithms for good test inferring in symbolic contexts are proposed in (Naidenova, 2006; Naidenova & Parkhomenko, 2020).

4 CONCLUSIONS

The results of this article are the following. A model of self-learning was proposed allowing to manage the process of inferring good tests in terms of its

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effectiveness through an internal evaluation of the learning process and the development of rules for choosing the best strategies, algorithms, and learning characteristics. The concepts of internal and external learning contexts were formulated. The structure of the internal context was proposed. A model of intelligent agent, capable of improving own learning process of inferring good classification tests in the external context was advanced.

It was shown that the same learning algorithm can be used for supervised learning in the external and internal contexts. The model of self-learning proposed in this article is closely related to the especially important research in artificial intelligence: forming internal criteria of the learning process efficiency, modelling on-line plausible deductive-inductive reasoning on the level of self- learning.

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