Modeling of Cognitive Agents

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Abstract. Agent-based Modeling (ABM), a novel computational modeling paradigm, is the modeling of phenomena as dynamical systems of interacting agents. Here, we apply this methodology for designing cognitive agents that are allowed to perform categorization process of input training items. The internal agent structure, as in presented previously brainstorming algorithm, and it is equipped with the set of basic machine learning, or clustering algorithms, which allow it for constructing prototypes of categories. Agent links prototypical categories with the subsets of training objects (so called prototypes for a category) during the simulation time. The equilibration process is described here using the mean-field theory, and fully connected cellular automata network of different categories. The individual outcomes of clustering, or machine learning algorithms are combined in order to determine the most effective partitioning of a given training data into the set of distinct categories. The dynamics of cellular automata network simulates the higher level of information integration acquired from repetitive learning trials. The final categorization of training objects is therefore consistent with equilibrium state of the complex system of linked and interacting machine learning methods, each representing different category. The proposed cognitive agent is the first autonomous cognitive system that is able to build the classification system for given perceptual information using ensemble of machine learning algorithms.

1 Introduction

The one of main challenges in cognitive sciences is the symbol-grounding problem. It is originating in long term discussions how to build the cognitive representation of the environment (so called world) using some internal states of intelligent individual. The relation between a symbol, a real-world object, and a concept applicable to the object is typically implemented using semiotic triad, which links a subset of objects, the concept for a category, and a symbol that represents this category. The underlying mapping between the concept and the object is performed using a method, i.e. a procedure to decide whether the concept applies to an object or not. The idea of semiotic triad was first introduced by Peirce (1839-1914) as a method for linking things and symbols used to describe them. Further work by Searle [1] supported idea that semiotics is not only theory of language, but also a theory of production of meaning. The main driving force behind the development of semiotics is a practical purpose. We use things or events as signs that facilitate the navigation in complexity of life.

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We apply similar approach to study the categorization process within Agent-Based Modeling (ABM). The ABM method extends the cellular automata-like models [2], to more complex computational setups, for example by introducing the asynchronous interactions between agents. Agent is defined here as a subsystem distinguished from its environment by some functional characteristics. Moreover, it has some ability to perform an autonomic action, i.e. dynamical interaction with surrounding world without external control. The presently used agent models are ranging from simple ones (simulations of a disease spreadout, predator-prey systems), to complex ones (insects colonies, immune responses modeling, financial markets etc.). Typically ABM simulations require an explicit representation of the space, on which agents are located. The most important step in the definition of an ABM is to introduce a set of rules in order to describe the changes of system's state.

Here, we use specific type of an agent, namely cognitive agents (CA) that are equipped with brainstorming algorithm, i.e. several clustering, or machine learning algorithms, which are running in parallel. The complex internal structure allows to perform classification tasks on training objects, and storing learned knowledge in terms of predictive models that can be further applied to unknown cases. This mimics the ability of natural cognitive systems (for example neuronal system, living cell, or human brain) to deal with incoming information. We need such advanced logic build into the agent model in order to construct the symbolic representation of external world objects in terms of symbols that represent grounded categories of training data.

Agent models the grounding process by training its internal learning method to map a subset of observed objects into single category. The "name" of this category (i.e. the sign denoting it in internal language of an agent) is a symbol representing it. The learned predictive model is the proposed concept that describes the category, and it is applicable to objects in order to assign them with a proper symbol. The semiotic triad first proposed by Peirce is therefore modeled on the level of single agent within Agent Based Modelling paradigm. The set of semiotic triads representing several categories (or symbols) builds up the semiotic network. In the case of simple cognitive tasks, i.e. when either a set of objects is not large, or a number of categories distinguishing those objects is small.

Summarizing, cognitive agents can be used as a model complex system for studying the details of categorization process, the emergent phenomena, patterns learning, selection of rules, or in general knowledge discovery. We provide here the foundations of proposed cognitive ABM framework, and initial computational results. The simulations are performed for given training information randomly selected from available training data, agent during the course of simulation is building its semiotic network of input training data, linking proposed categories with selection of training objects. The results are compared with categorization studies performed within last decade, especially in the field of psycholinguistics. Perspective applications of this approach are also sketched. They could include modeling of perceptual grounding of symbols using text mining techniques, context information, and visual or auditory sensor data categorization in robotics.

2 Design of Cognitive Agent

Our model of categorization process is based on *agent based modeling* (ABM) paradigm known from many applications in informatics [3], life [4-11]and social sciences [12]. Our present model extends previous results, where probabilistic cellular automata (CA) model of opinion formation in groups of individuals was simulated by Lewenstein et al. [13] using social impact theory introduced by Latane [14, 15]. The intermittent behavior was observed with a variety of stationary states with a well-localized and dynamically stable clusters (domains) of individuals, who share minority opinions [13]. In the social impact theory a group of *N* agents influence of a given agent opinion, where the level of influence depends on three factors. First, the social strengths of all members of the whole group; secondly, their social distance from the selected individual; and finally their total number *N*. Kohring [16, 17] extended Latane's theory to include learning. Plewczynski [18, 19] solved analytically the model in the continuous limit and the Cartesian space with learning rules. Hołyst et al. performed numerical simulations in simplified geometries, also provided the mean-field approximation of the social impact theory [20-23].

Here, I present an application of agent based modeling in simulating the process of categories formation. Each agent (so called **"cognitive agent"**) is equipped with a machine learning, or clustering algorithm. The mathematical method allow them to classify training examples based on their features, find differences between them and categorize them into separate, or overlapping categories. Moreover, the **"cognitive interaction"** between two agents is proposed by introducing guessing games, which allow for coupling of categories not only by sharing the same training data, but also by exchanging proposed models outcomes. The topology of a network of interactions between agents is defining their "**cognitive space**" (for example the Cartesian space, fully connected, nearest neighbors coupling, or hierarchical geometries). The final stable semiotic landscape is defined here as the stationary state for such population of agents.

The agent based model of category formation is based on several assumptions:

2.1 Discrete Categories

We assume that training data can be described in the form of several distinct or overlapping categories. In the first case, the crisp clustering can be applied and training examples can be divided into separate groups of objects using their features. In the second case, the full separation cannot be performed, and fuzzy clustering techniques have to be applied in order to assign objects to the proposed categories. Both clustering techniques are optimized using some internal parameters, or validity indices. In some cases, the multiobjective optimization can be used, which simultaneously optimizes two internal fuzzy cluster validity indices to yield a set of Pareto-optimal clustering solutions. In the case of machine learning algorithms we deal with binary class prediction (only two categories are described), or a set of distinct categories, each described by different machine learning model. Here, internal parameters of ML algorithms may seriously impact the performance of each method, therefore the diversity between agents is achieved. Our population of agents consists from *N* cognitive agents. When a given training or testing object is presented to each agent, its internal state is described holds one of several distinct categories (from *1* up to *k*, where k is the number of categories constructed by an agent). These states are binary $\sigma_i = 1,..,k$, similarly to Ising model of ferromagnet. In most cases the machine learning algorithms that can model those agents, such as support vector machines, decision trees, trend vectors, artificial neural networks, random forest, predict two classes for incoming data, based on previous experience in the form of trained models. The prediction of an agent answers single question: is a query data contained in class A ("YES"), or it is different from items gathered in this class ("NO").

2.2 Disorder and Random Strength Parameter

Each learner is characterized by two random parameters: persuasiveness p_i and supportiveness s_i that describe how individual agent interact with others. Persuasiveness describes how effectively the individual state of agent is propagated to neighboring agents, whereas supportiveness represent self-supportiveness of single agent. In present work I assume that influential agents has high self-esteem, what is supported by the fact that highly effective learners should have high impact on others in meta-learning procedure. For example, we can select $p_i = f\left(precision, i\right)$ and $s_i = f\left(recall, i\right)$ in the case where agents are modeled as single machine learning procedures. In general the individual differences between agents are described as random variables with a probability density $\hat{p} = \left(p_i, s_i\right)$, with mean values $p = \sum \frac{p_i}{N}$ and $s = \sum \frac{s_i}{N}$. Similarly to the social influence theory, the quality of predictor in some way affect its influence strength, when the final optimization of meta-learning consensus is done.

In the case of meta-learning procedure the persuasiveness p_j represents here the ability of learning agent *j* to persuade agents who hold the opposite state to switch to having the same state as *j*. The supportiveness s_j represents the ability of learning agent *j* to support agents who hold the same state, so not only the self-support of an individual agent (to itself), but the support that an agent gives to other agents who share the same state as it has.

We use here cognitive agents that are allowed to perform categorization process of training objects, therefore trying to autonomously build the classification system for given perceptual information. Each agent during the simulation time is building its semiotic network of input data, linking proposed categories with subsets of objects (so called prototypes for a category).

2.3 Learning Space and Learning Metric

Each agent is characterized by a location in the learning space, therefore one can calculate the abstract learning distance $d\left(i, j\right)$ of two learners *i* and *j*. The strength of coupling between two agents tend to decrease with the learning distance between them. Determination of the learning metric is a separate problem, and the particular form of the metric and the learning distance function should be empirically determined, and in principle can be a very peculiar geometry. In present manuscript, I select the fully connected learning space, where all distances between agents are equal $d\left(i,j\right)=1$. This particular geometry is useful for example in the case of simple consensus between different yet not organized machine learning algorithms, where no group of learners perform significantly better than others.

The interaction between agents dynamically shape their semiotic networks, adjust the categories in order to match them between different individuals, and finally lead to equilibrium, stable shared semiotic landscape of training data. The equilibration process is described here using the mean-field theory, and fully connected cellular automata network of agents.

2.4 Learning Coupling

Agents exchange their opinions by biasing others toward their own classification outcome. This influence can be described by the total learning impact I_i that ith agent is experiencing from all other learners. Within the cellular automata approach this impact is the difference between positive coupling of those agents that hold identical classification outcome, relative to negative influence of those who share opposite state, and can be formalized as

$$I_i = I_p\left(\sum_j \frac{p_j}{N}\left(1-\sigma_i\sigma_j\right)\right) - I_s\left(\sum_j \frac{s_j}{N}\left(1+\sigma_i\sigma_j\right)\right), \tag{1}$$

where $I_p\left(.\right)$ and $I_s\left(.\right)$ are the functions of persuasiveness and supportiveness impact of the other agents on the *i*-th agent. It should be noted here that the persuasiveness p_j represents here the ability of agent *j* to persuade agents who hold the opposite state to switch to having the same state as *j*. On the contrary the supportiveness s_j represents the ability of agent *j* to support agents who hold the same state, i.e. preventing them from switching to the opposite state. That is, persuasiveness represents the propensity of *j* to cause other agents to switch to her state, and supportiveness represents her propensity to keep them there.

The social interaction between agents are modeled as guessing games between a pair of agents, where the first agent presents to the second one a samples randomly selected from different classes of its prototype categorization.

2.5 Meta-learning

The equation of dynamics of the learning model defines the state $\sigma_i^{'}$ of ith individual at the next time step as follows:

$$\sigma_i^{'} = \left(-sign\left(\sigma_i I_i\right)\right), \tag{2}$$

with rescaled learning influence:

$$I_i = \sum_j \frac{p_j}{N\left(s+p\right)}\left(1-\sigma_i\sigma_j\right) - \sum_j \frac{s_j}{N\left(s+p\right)}\left(1+\sigma_i\sigma_j\right). \tag{3}$$

I assume a synchronous dynamics, i.e. states of all agents are updated in parallel. In comparison to standard Monte Carlo methods the synchronous dynamics takes shorter time to equilibrate than serial methods, yet it can be trapped into periodic asymptotic states with oscillations between neighboring agents.

The dynamics of cellular automata network simulates the higher level of information integration acquired from repetitive learning trials, so called the dynamics of semiotic landscape for the whole population. The final categorization of training objects is therefore consistent with equilibrium state of the complex system of interacting agents. The individual outcomes of clustering, or machine learning algorithms are combined in order to determine the most effective partitioning of a given training data into the set of overlapping categories.

2.6 Noise

The randomness of state change (phenomenological modeling of various random elements in the learning system, and training data) is given by introducing noise into dynamics:

$$\sigma_i^{'} = \left(-sign\left(\sigma_i I_i + h_i\right)\right), \tag{4}$$

where h_i is the site-dependent white noise, or one can select a uniform white noise, where for all agents $h_i = h$. In the first case h_i are random variables independent for different agents and time instants, whereas in the second case h are independent for different time instants. I assume here, that the probability distribution of h_i is both site and time independent, i.e. it has uniform statistical properties. The uniform white noise simulates the global bias affecting all agents, whereas site-dependent white noise describes local effects, such as prediction quality of individual learner etc.

Each category consists of several prototypes; therefore it is grounded in classified data objects. The population of autonomous agents establishes via communication a repertoire of perceptually grounded categories that is shared among them.

3 Concluding Remarks

Intelligent agents theory is a fascinating topic in modern science [24-28]. Decision making transitions depend to high degree on global factors influencing an ensemble of independent learners. On the other hand, those changes are dependent to a high degree on individual decisions (predictions) that are based on agents' attititudes. During consensus, i.e. the final decision making, the reciprocal influence is critical as each learner exchange its opinion with others. In my approach, I assume that external factors acting on each learner are present during only the first phase of meta-learning, where initial states for a population of learners are setting up. Yet, both processes even if acting on different time scales, are important for understanding the computational intelligence process.

In this manuscript I have presented the statistical theory of meta-learning. In my approach I select long-range coupling between agents, as opposite for example to the Euclidean two dimensional learning space, where only nearest-neighbors are coupled. This assumption is well supported by the fact that we are typically focused on only equilibrium, stationary states. The fully connected learning space lets agents evolve faster in comparison to other types of cellular automata. In addition, all agents influence each other, therefore we avoid local minima traps for the global system.

Each learner is characterized by two random parameters: persuasiveness p_i and supportiveness s_i that describe how individual agent interact with others. The random strength parameters simulate different individual features of learning agents. In principle one can define both parameters in various different ways. In the case of a set of machine learning algorithms, each of them can be described by its intrinsic parameters affecting precision of single classification model of training data. In general case, several different types of machine learning algorithms can be used as individual learners. There, the distribution of quality of local prediction can be described as random providing that algorithms differ significantly between each other in terms both of the quality of prediction (classification accuracy), recall values (the ability to memorize the positive items in the training dataset), or precision (the ability to precisely predict the classification of training items).

The other definition of those parameters (persuasiveness and supportiveness) can enhance the method persuasiveness (the value of p_i), if the method has the state $\sigma_i = +1$, and make its p_i value lower when the opposite state is taken. In this way, it allows to speed up the consensus process by forcing system to reach equilibrium state more rapidly, yet pushing it to the +1 decision based on the selected training dataset. This can cause several problems with overtraining, therefore some limitations of this approach should be taken into account. The actual solutions presented in this paper, yet do not depend strongly on the selected form of those parameters. Anyway we assume that they are some random variables describing the variety of individual decisions in the ensemble of learners.

There two time scales in the system. The first time scale is related to the fast evolution of individual learners. When input testing data is presented to the system, each learner respond by its own single prediction. This local prediction of each agent is done very rapidly, almost instantly. Then those individual predictions are processed by cellular automata algorithm in order to find the stationary state of the system. This part is denoted as integration of information. As it was shown above, such stationary state has the form of minority clusters surrounded by the sea of majority prediction. Therefore, the final consensus prediction given by the majority rule, still preserves non-orthodox solutions, allowing for fast adaptivity of the system when training data pattern is changed. The time scale for this integrative process is relatively long in comparison to individual predictions, therefore very fast (preferably optimized for parallel processing) cellular automata software implementations have to be prepared in order to apply described above formalism in real life problems. In the statistical model presented here, I assume that there is no coupling between those two time scales. Therefore I neglect all details of individual evolution of learners, focusing our attention for integration phase of incoming local information into single, consensus answer.

The population of cognitive agents performs classification tasks on training objects, in order to build the shared complex system of signs and meanings. for given perceptual information. Charles Peirce introduced semiotics as a theory of human experience mediated by our ability to reflect upon it and create explainations (representations). According to Peirce, the major research endeavour of semiotics is to find out what are the conditions for meaning to occur in human experience. Thus semiotcs directly addresses the issue of meaning: "What is wanted, is a method of ascertaining the real meaning of any concept, doctrine, proposition, word, or other sign. The object of a sign is one thing; its meaning is another. Its object is the thing or occasion, however indefinite, to which it is applied. Its meaning is the idea which it attaches to that object, whether by way of mere supposition, or as a command, or as an assertion" (Peirce, C. 1931-58 Collected Papers of Charles Peirce in Eight Volumes. Eds: A. Burke, C. Hartshorne and P. Weiss. Cambridge: Harvard University Press, 5.5).

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