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Gaming Method of Ontology Clusterization

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Abstract

In the real world an intelligent system often consists of intelligent agents, each having its own perspective and goal and executing the common task interacting with others. Those agents are often created by different developers, are based on different conceptualizations of subject area and are working with incomplete and error-riddled data. In conditions of uncertainty of ontologies, the application of the traditional methods of cluster analysis, which assume a clear breakdown of the initial set into subsets, in which each element gets into only one cluster, is not always correct. In this work is proposed the stochastic game method of ontology clustering for optimization of operations under conditions of uncertainty. The essence of game clustering is that intelligent ontology agents randomly select one of the clusters. For agents who chose the same cluster, the current measure of similarity of ontologies is calculated. This measure is used to adapt the recalculation of mixed player strategies. In the game process the probability of choosing clusters, the current composition of which led to an increase in the degree of similarity of ontologies is increased. During the repetitive game, agents will form vectors of mixed strategies that will maximize the averaged measures of similarity for clusters of ontologies. The results of the computer simulation confirm the convergence of the game method during the clustering of ontologies with the conditions and constraints of stochastic optimization.

Keywords

Stochastic game; Clustering, Ontology; Knowledge base; Intelligent agent

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Introduction

The complexity of modern information retrieval systems and the rapid development of telecommunication technologies leads to the use of automated tools for processing information with help of intellectual agents (Wooldridge, 2009; Abolhassani et al., 2006; Ahmad et al., 2007; Gozhyj el at., 2018). In the course of solving a problem in the information environment, agents interact with each other, with person and with diverse knowledge bases. The interface of interaction should provide an adequate interpretation of queries and responses to them for both agents and people. For the possibility of profound analysis of the information, agents should not operate with abstract datasets, but with a description of their structural and semantic organization in the form of metadata (data about data). It is convenient to present such metadata in the form of ontologies, which are the modern development of semantic networks. Ontology is a conceptual model of a subject area with a taxonomic structure. Ontology provides the user or agent with a generalized description of the subject area, formalizes and simplifies the perception of knowledge and may be extended with new information (Alipanah et al., 2011; Basyuk, 2015; Chyrun et al., 2018; Davydov et al., 2017; Fedushko, 2014).

The value of ontologies is augmented by the possibility of their alignment and association, which results in a new relationship between concepts and new knowledge. So, an intelligence agent often has to compare his own ontologies with others found on the network, as well as ontologies of other agents in the process of interaction. The association of ontologies is relevant due to the complexity of using unified ontologies in various fields of knowledge. Ontologies created by different developers for one subject area may differ in terms of taxonomy, vocabulary and semantics. The union of ontologies creates a resulting ontology, which contains elements of input ontologies. To do this, we should first find the interconnecting correspondence link (described by semantic match of identifier, text, concepts, hierarchical relationships, instances of classes, etc.), and then, place the elements in the new structure according to their description. Lastly, a formal verification of the correctness of the ontology association is carried out to ensure the consistency of their syntax, structure and semantics. To verify the conceptual correctness of the resulting ontology, specialists from the relevant subject areas are consulted (Kanishcheva et al., 2017; Khomytska et al., 2016; Naum et al., 2017).

In the process of subject area ontology development, the developers face the problem of uncertainty - inaccuracy, incompleteness, and lack of data or the impossibility of obtaining it at the current time. This creates difficulties in accounting for uncertainties when performing operations with ontologies (Korobchinsky et al., 2017). In most cases, the union operation is appropriate to apply to similar ontologies that have a not empty set of interconnecting links. The automated detection of such ontologies can be done by clustering - grouping of ontologies into a collection of classes based on their similarity. Methods of clustering are widely used in the tasks of intelligent data analysis and data mining (Mirkin, 2005; Chyrun et al., 2018; Davydov et al., 2017; Khomytska et al., 2017; Korzh et al., 2014). It is expected that clustering will reduce computational costs while performing operations with ontologies.

Clustering of ontologies will be necessary for:

1. reducing the number of ontology comparisons - it is easier to work with one cluster of ontologies with a limited number of elements, than with the set of all ontologies;
2. constructing of the general representational ontology of one cluster, obtained, for example, in the form of its center;
3. reducing the number of ontologies and the amount of data, that needs to be stored by combining similar ontologies into one;
4. reducing the ambiguity of the ontology merging due to their similarity within a single cluster;
5. reducing the uncertainty of ontology by combining similar ontologies in one cluster.

In conditions of uncertainty of ontologies, the application of the traditional methods of cluster analysis, which assume a clear breakdown of the initial set into subsets, in which each element gets into only one cluster, is not always correct. Most often you need to make a certain breakdown to determinate the degree of affiliation of each ontology to each set. In this case, it is advisable to use the methods of fuzzy cluster analysis, for example, the modified k-means clustering, or the Gustafson-Kessel method (Su et al., 2018; Maedche et al., 2002; Vysotska et al., 2015). However, as noted in (Lytvyn et al., 2018; Vysotska et al., 2019), these methods lack stability in situations of input data perturbations and overlapping clusters.

In this work a new model of ontology clustering is proposed, based on a repetitive stochastic game. To do this, we introduce the concept of intellectual agents that represent the corresponding ontologies. When interacting with each other, the agents can perform the necessary operations with ontologies, mainly the definition of the degree of their similarity.

The number of clean agent strategies determines the number of clusters. During the game the agents of ontologies simultaneously, independently and randomly choose one of the clusters. The probability of choosing clusters is determined by the dynamic vectors of mixed player strategies. Agents who have chosen the same cluster form its current composition. For such agents, the current degree of proximity of ontologies is calculated. The purpose of each cluster of agents is to maximize this measure in time. The proximity of ontologies is used to adapt the recalculation of mixed player strategies. The probability of choosing those clusters, whose current composition has led to an increase in the degree of proximity of ontologies, increases. Over time, agents will form such vectors of mixed strategies that will maximize the mean values of proximity of ontologies divided into clusters. A stochastic game can be used to form clusters for deterministic ontologies and for ontologies with uncertainty. The proposed adaptive gaming method has filtering properties for spikes in the input data and practically does not depend on the law of the distribution of random interference.

The purpose of this work is to develop a game model and the method of clustering ontologies according to their similarity. To achieve this goal it is necessary complete such tasks: determine the degree of similarity of ontologies; formulate the game problem of clustering ontologies; develop a method for solving a stochastic game; determine the constraints on the parameters that will determine the convergence of the game.

Ontological model in knowledge engineering

The formal model of ontology is given by a tuple:

$$O = \langle C, R, F \rangle,$$

where O is the ontology of a given domain, C is a finite set of concepts; R is a finite set of relations between concepts; F is a finite set of functions for interpreting the ontology.

Concepts are a collection of entities, terms, categories or classes (Li et al., 2010; Lytvyn et al., 2015; Vysotska et al., 2018). The relationship between concepts is a set of attributes which, when applied, result in other objects. The functions of the interpretation of ontology are axioms that define the constraints on the interpretation of concepts and relationships between them. An expanded model of ontology may also include other elements, for example:

- encapsulated data class attributes and their values;
- instances (objects) of classes containing specific data that are described by the class content;
- thematic dictionary (thesaurus) of the domain terms with semantic relations between lexical units; reasoning algorithms on ontology;
- the weights of concepts and relationships that determine the degree of their importance (for adaptive ontologies) (Lytvyn et al., 2016; Vysotska et al., 2018).

From the perspective of object-oriented programming concepts are the declared classes that contain the sets of attributes which can have different types, and methods of processing these attributes. A class describe is a set of objects that have common properties. Classes are organized into the hierarchy (taxonomy of classes). Between classes may be established relations of belonging to a certain category, among which the following are often used:

- the relation of classification "is" (is-a, member-of) - specifies that the object belongs to the set of objects;
- the generic relation of hyponymy (hyponym - hypernym), or partial - general, or "kind" (a-kind-of), or "subset-of" - each element of the first set belongs to the second set;
- the relation of metonymy (meronymy - holonymy) or part-whole (a-part-of, has-part) - describes parts or components of ontology;
- the relation "contains" specifies the class as the container for objects of other classes: exists in the form of aggregation (if container is destroyed, its content will not be destroyed), and composition (if container is destroyed, then all its contents will be destroyed);
- association relation - objects of the one class are associated with objects of another class;
- inheritance relation - one class has properties of another class and may have additional properties;
- subclass-of-a class relation;
- relation of being an instance of the class (is-an-instance-of);
- follow (is-consequent); connected to (connected);
- causal relation (is-the-cause-of);
- have similarity with (has-similarity-with);
- being the descendants from the same parent or being related on the same level (sibling-with);
- being incompatible with (disjoint-with);
- other relations - quantitative, temporal, logical, functional, attributive, linguistic, etc.

Axioms define the undeniable assertions that connect concepts and relations. They specify information that cannot be displayed in the ontology using a hierarchy of concepts and relationships between them. Also, the axioms determine the rules for replenishing the ontology with new data and allow or forbid the creation of assertions within the ontology using reasoning.

Instances are objects of the corresponding classes, filled with specific data. Ontology, along with a set of instances, forms the knowledge base. The process of ontology construction consists in splitting the subject area of knowledge into separate objects and elucidating relationships between them in a form understandable to expert with the purpose of formally processing it with currently available computers and software. Creating an ontology, on the one hand, is a creative process, since the author invests his knowledge and understanding of the subject area into its structure and semantics, and, on the other - it is an engineering process, because there is a large number of tools that automate this process. These means include (Calvaneze, 2013; Lytvyn et al., 2017; Martin et al., 2009):

1. The languages and specifications of ontologies (KIF – Knowledge Interchange Format, FrameOntology, Ontolingua, OKBC – Open Knowledge Base Connectivity, XOL – XML-based Ontology Exchange Language, FLogic – Frame Logic, KL-ONE – Knowledge Language ONE, LOOM – Lexical OWL Ontology Matcher, CLASSIC, FaCT – Fast Classification of Terminologies, OCML – Operational Conceptual Modeling Language, XML – eXtensible Markup Language, RDF – Resource Description Framework, RDF Schema, OIL – Ontology Interchange Language, DAML+OIL – DARPA Agent Markup Language+OIL, OWL – Web Ontology Language, SHOE – Simple HTML Ontology Extension, OML – Ontology Markup Language);
2. Methodologies for ontology design (METHONTOLOGY, TOVE – Toronto Virtual Enterprise, SENSUS, CommonKADs – Common Knowledge Acquisition and Documentation Structuring, KACTUS, Plinius, ONIONS – ONtologic Integration Of Naive Sources);
3. Software tools for ontology engineering (WebOnto, Protege, OntoSaurus, ODE – Ontological Design Environment, KADS22, OntoEdit, SHOE's Knowledge Annotator, i·com).

Ontologies are widely used for solving a variety of tasks:

- achieving the common understanding of the structure of heterogeneous information in the subject area by people and software agents;
- the standardization and systematization of knowledge about the subject area;
- the organization of high-level interface for access into the knowledge base about the subject area; re-use of knowledge in the subject area;
- the analysis of knowledge in the subject area;
- the organization of information search;
- in information reference systems;
- for extraction of new knowledge;
- detecting inaccuracies and logical mistakes in the organization of the knowledge base;
- eliminating duplication of information;
- creating the Semantic Web;
- the organization of dialogue between a computer and a person;
- machine translation of texts;
- in natural language processing systems for automatic creation of digests, rubricating, and other;

- the maintenance of information resources security;
- in e-commerce systems;
- the development of intellectual agents and using them in multi-agent systems;
- the construction of reasoning algorithms in descriptive logic based on knowledge of the agent;
- the organization of interactions between agents in the course of task execution.

The following types of ontologies are distinguished by the level of universality: the upper level or meta-onology, the ontology of subject areas and the ontology of tasks. Examples of ontologies are (Lytvyn et al., 2018; Keet et al., 2013; Keet et al., 2015; Zhezhnych et al., 2018): conceptual - OpenCyc (100 thousand concepts), DOLCE (4 thousand concepts), SUMO (1 thousand concepts); linguistic - WordNet (100 thousand concepts), Omega (120 thousand concepts), MikroKosmos (7 thousand concepts); mixed - Sensus (70 thousand concepts), PropBank (4 thousand concepts), FrameNet (900 frames).

In the process of practical application, a variety of operations on ontologies are used, for example (Lytvyn et al., 2018; Kushner et al., 2013; Biggs et al., 1986; Bondy et al., 2008):

- comparing or matching - finding the degree of correspondence between the semantically related entities of two ontologies;
- mapping - a way to translate the concepts and relationships of one ontology into another, finding semantic links for similar elements from different ontologies;
- alignment - the establishment of different types of mutual (in both directions) correspondences between two ontologies for the purpose of their subsequent use;
- merging - generation of one coherent ontology from the two given;
- integration - finding identical parts (correspondences) of specific ontologies with the purpose of generating a combined ontology;
- inheritance - one (specific) ontology inherits all the contents of another (generic) ontology, introducing its additional properties;
- visualization - the representation of concepts and relationships between them in a convenient graphical form;
- scaling – the increase or decrease of the ontology representation in order to consolidate or detail the connections between concepts;
- filtering – showing or hiding the elements of ontology according to specific criterion, for example, belonging to a certain class;
- the calculation of characteristics of ontology - the number of concepts and relations, the distance between concepts, the degree of similarity of ontologies, etc.

The comparison and association operations are the most costly and problematic because it is necessary to compare the large sets of structured data according to different criteria (semantic, structural or other). To do this, the following software tools are used (Keet et al., 2013; Keet et al., 2015): Chimaera, OntoMerge, Ontomorph, GLUE, OBSERVER, FCA-Merge – Formal Concept Analysis and Merging, OntEx – Ontology Exploration, ONION – ONtology compositION, Hovy, PROMPT.

Ontology construction process is affected by a number of uncertainties that exist due to the following factors:

- the initial structure of the ontology depends on the developer's understanding of subject area (the ambiguity of ontology construction);
- the contradictions are possible in the definition of concepts, relations between data, constraints and axioms;
- incomplete definition of attributes (or instances) of the ontology, taking into account the probabilistic character of data;
- the contradictions of ontologies definitions, for example, different URI (Uniform Resource Identifier) identifiers may correspond to the same elements of ontologies;
- synonymous repetition of the terms leads to ambiguity in the interpretation of queries;
- the refinement of ontology structure in time leads to changes in structure and interpretation;
- the ontology structure may vary due to operations performed on it;
- the scaling of ontology and the use of a dynamic filters results in a different (partial) interpretation of the ontology composition;
- in ontology, some components can be made readily available, while the access to others – inhibited, which are determined by the change in the weights of the links between the ontology elements, that is, the accessibility of ontology parts may vary in time depending on the history of the queries;
- the aging of the information stored in the ontology - some structural elements or facts over time cease to be relevant; the malicious distortions of ontologies could become a new kind of virus attacks.

In this regard, the result of the ontologies comparison becomes ambiguous. To work with ontologies under uncertainty it is necessary to apply adaptive methods.

Measuring the similarity of ontologies

The results of the comparison, association and clustering of ontologies are mainly determined by the applied measures of their similarity. The most effective are hybrid measures that take into account several criteria for comparing entities. Most often such hybrid measure is represented by an additive convolution of several measures:

$$S(c_1,c_2)=\sum_{i=1}^{n} w_i S^i(c_1,c_2)\,, \qquad (1)$$

S^i is the degree of proximity by a certain criterion, $w_i > 0$ is the weight of the criterion, $\sum_{i=1}^{n} w_i = 1$, n – the number of criteria, c_1, c_2 – the concepts of comparable ontologies.

There are different measures of closeness for concepts, attributes and relations. A detailed review of the measures of semantic proximity is considered in (Lytvyn et al., 2018; Peleshko, et al., 2016; Rusyn et al., 2016). The hybrid measure (1) can be calculated on the basis of taxonomic, relational and attributive measures of proximity of concepts:

$$S(c_1,c_2)=w_T\cdot S^T(c_1,c_2)+w_R\cdot S^R(c_1,c_2)+w_A\cdot S^A(c_1,c_2),(2)$$

where $w_T, w_R, w_A \in [0,1]$ – coefficients of weight, $w_T + w_R + w_A = 1$.

The value of a hybrid measure $S(c_1,c_2)\in[0,1]$, and if $S(c_1,c_2)=0$, the concepts have no common characteristics, and if $S(c_1,c_2)=1$, the concepts are identical.

In the general case, the calculation of a measure of similarity can be made for the set of concepts of ontology.

The statement of the ontologies clustering problem based on gaming approach

Let's consider a finite set of ontologies $\Omega=\{O_1,O_2,...,O_K\}$, which may be divided into N clusters Θ_n ($n=1..N$). Allocation of clusters is done by the method of stochastic game (Neyman et al., 2012; Gottlob et al., 2011), which is represented by the cortege

$$(I, U^i, \Xi^i \mid i\in I)\,,$$

where I is the set of players; $K=|I|=|\Omega|$ is number of players; $U^i=\{u^i(1),...,u^i(N)\}$ is a set of pure player's i strategies that determine the choice of one of the clusters; N is the number of player's i strategies or number of clusters; $\Xi^i : U \to R^1$ is the player's i winning function; $U = \times_{i\in I} U^i$ is a set of combined player strategies. Each gaming agent represents one of the given ontologies.

The essence of the game lies in the controlled random movement of agents from one cluster to another. To do this, at moments of time $t=1,2,...$ each gaming agent using the random events generator, independently of others, chooses a clean strategy $u^i \in U^i$, that determines its entry into one of the clusters. Taking into account (2), after the implementation of the combined version $u \in U$ agents receive random wins $\xi^i(u)$ with a priori unknown stochastic characteristics:

$$\xi_t^i = \sqrt[K_t^i]{\prod_{j \in I} \chi(u_t^i = u_t^j) S(c_i, c_j)} + \mu_t \quad \forall i \in I , \qquad (3)$$

where $K_t^i = \sum_{j \in I} \chi(u_t^i = u_t^j)$ is the current number of elements of the cluster, which includes the player's i; $\chi() \in \{0,1\}$ is function that indicates the event; $\mu \sim Normal(0, d)$ is a randomly distributed random variable that simulates the uncertainty of an ontology; d is dispersion distribution.

The proximity of ontologies is defined as the geometric mean of positive measures of the similarity of compared concepts. In addition to the multiplicative, as in (3), an additive convolution of the similarity of ontologies measure can be used in the form of arithmetic mean, for example:

$$\xi_t^i = \frac{1}{K_t^i} \sum_{j \in I} \chi\left(u_t^i = u_t^j\right) S(c_i, c_j) + \mu_t \quad \forall i \in I .$$

The effectiveness of gaming clustering is determined by the functions of average winnings:

$$\Xi_t^i = \frac{1}{t} \sum_{\tau=1}^{t} \xi_\tau^i \qquad \forall i \in I . \qquad (4)$$

The goal of the game is to maximize the values produced by the system of functions of average winnings (3) in time:

$$\underline{\lim}_{t \to \infty} \Xi_t^i \to \max \qquad \forall i \in I . \qquad (5)$$

Consequently, based on the observation of current winnings $\{\xi_n^i\}$ each player $i \in I$ must learn how to choose clean strategies $\{u_t^i\}$ in such a way as to ensure that the system of criteria (5) is implemented in the course of time $t = 1, 2, \ldots$.

The method for solution of the game problem

Let the choice of pure strategies u_t^i be made by players based on vectors of mixed strategies p_t^i, whose values change over time:

$$u_t^i = \left\{ U^i(k) \middle| k = \arg\left(\min_k \sum_{j=1}^{k} p_t^i(u_t^i(j)) > \omega \right),\ k = 1..N \right\} \quad \forall i \in I, \qquad (6)$$

where $\omega \in [0, 1]$ is a real random number with an even distribution.

The dynamics of vectors of mixed strategies should ensure the achievement of an optimal collective solution, for example, Nash or Pareto in the course of maximizing functions (5) of average player winnings (Lytvyn et al., 2018; Petrosjan et al., 2007).

We construct a method for solving a stochastic game based on a deterministic matrix game. For such a game, we define the polylinear function of average winnings:

$$V^i(p) = \sum_{u \in U} v^i(u) \prod_{j \in I; u^j \in u} p^j(u^j),$$

where $v^i(u) = E\{\xi_t^i(u)\}$ is the expected value of the current wins for player i.

In the points of equilibrium according to Nash in mixed strategies, the condition of complementary non-rigidity is true:

$$\nabla_{p^i} V^i(p) = e^{N_i} V^i(p),$$

where $\nabla_{p^i} V^i(p)$ is gradient of medium winning function; $e^N = (1_j \mid j = 1..N)$ is vector, all components of which are equal 1; $p \in S^M$ is player's combined mixed strategies are given on the convex single simplex S^M ($M = N^K$).

Let the vector $\delta = (\delta_1, ..., \delta_N)$ be the error in complementary non-rigidity condition for the simplex S^M (Neyman et al., 2012; Neogy et al., 2018; Robinson, 1965 Ramirez-Ortegon et al., 2013; Tkachenko et al., 2018):

$$\delta = \nabla_{p^i} V^i(p) - e^{N_i} V^i(p) \qquad \forall i \in D, \ (7)$$

In the points of equilibrium according to Nash in mixed strategies, the vector error equals $\delta = 0$. To account all solutions of Nash at the vertices of a single simplex, we perform the weighing of the error (7) by the elements of the vector of mixed strategies:

$$diag(p^i)\delta = 0 \quad \forall i \in D, \qquad (8)$$

where $diag(p^i)$ is square diagonal matrix of order N, constructed from elements of the vector p^i.

Taking into account , that $diag(p^i)\delta = E\{\xi_t^i[e(u_t^i) - p_t^i] \,|\, p_t^i = p^i\}$, from (8) on the basis of the stochastic approximation method (Xue et al., 2015; Lytvyn et al., 2018; Kushner et al., 2013) we obtain the following recurrent Markov chain:

$$p_{t+1}^i = \pi_{\varepsilon_{t+1}}^N \left\{ p_t^i + \gamma_t \xi_t^i (e(u_t^i) - p_t^i) \right\} \quad \forall i \in I, \quad (9)$$

where E is a symbol of expected value; $\pi_{\varepsilon_{t+1}}^N$ is projection on the unary N - dimensional simplex S^N (Euzenat et al., 2007; Poirriez et al., 2009; Precup et al., 2013; Russell e al., 2009; Solos et al, 2016); $\gamma_t > 0$, $\varepsilon_t > 0$ is the monotonically decreasing sequences of positive numbers; $e(u_t^i)$ is a single vector that indicates the choice of a clean strategy $u_t^i = u^i \in U^i$. Current wins of players ξ_t^i are determined by the degree of similarity of ontologies (3).

According to (9), the probability of the chosen option u_t^i increases in proportion to the gain obtained for this ξ_t^i, and the probability of all other options is reduced. Due to such adaptive properties during the game, the frequency of choosing the strategies that provide the highest average gain or the greatest importance of the degree of similarity of the compared ontologies will increase. As a result of the game a single cluster will get the most similar ontologies.

Deterministic functions γ_t and ε_t can be represented as follows:

$$\gamma_t = \gamma t^{-\alpha}, \ \varepsilon_t = \varepsilon t^{-\beta}, \qquad (10)$$

where $\gamma > 0$; $\alpha > 0$; $\varepsilon > 0$; $\beta > 0$.

Designing with expandable ε_t -simplex $S_{\varepsilon_{t+1}}^N$ ensures the fulfillment of the condition $p_t^i[j] \ge \varepsilon_t$ ($j = 1..N$), required for collecting complete statistical information about selected pure strategies, and the parameter $\varepsilon_t \to 0$, $t = 1,2,...$ is used for the additional control of the convergence of the recursive method. A prerequisite for convergence of strategies (9) to optimal values with probability 1 in general and in root mean square is to observe the basic conditions for stochastic approximation (Lytvyn et al., 2018; Rami et al., 2002; Rashkevych et al., 2017; Maksymiv et al., 2017; Martinez-Gil et al., 2008; Montes-y-Gómez, et. al., 2000).

Given the independence of the occasional winnings $\{\xi_n^i\}$, independence of the choice of pure strategies $\{u_n^i\}$ $\forall i \in I$ and fulfillment of conditions $\gamma_n > 0$, $\gamma_{n+1} < \gamma_n$, $\sum_{n\to\infty} \gamma_n = \infty$, $\varepsilon_n \in (0, \min_{i\in D} N_i^{-1})$, $\varepsilon_{n+1} < \varepsilon_n$ methods (9) ensures the fulfillment of the condition of complementary non-rigidity (8) in a familiar environment $v_{\min}^i > 0$ $\forall i \in I$ with probability that equals 1, if $\sum_{n=1}^{\infty}(|\varepsilon_n - \varepsilon_{n-1}| + \gamma_n^2) < \infty$, and with standard deviation, if $\lim_{n\to\infty}(|\varepsilon_n - \varepsilon_{n-1}| \gamma_n^{-1} + \gamma_n) = 0$.

The stochastic game begins with unlearned vectors of mixed strategies with values of elements $p_0^i(j) = 1/N$, where $j = 1..N$. Next, the dynamics of vectors of mixed strategies is determined by Markov's recurrent method (9).

So, at the time t each player based on a mixed strategy p_t^i chooses a clean strategy u_n^i, for which in the time $t+1$ he gets the current gain ξ_t^i, and then calculates a mixed strategy p_{t+1}^i according to (9). Due to the dynamic rebuilding of mixed strategies based on the processing of current winnings, method (9) provides an adaptive selection of pure strategies in time.

The quality of game data clustering is estimated using:

1) the function of integrated average winnings:

$$\Xi_t = \frac{1}{K}\sum_{i=1}^{K} \Xi_t^i, \tag{11}$$

where $K = |I|$ is the power of a set of players;

2) the average rate of mixed player strategies:

$$\Delta_t = \frac{1}{K \cdot t}\sum_{\tau=1}^{t}\sum_{i=1}^{L} \left\| p_\tau^i \right\| \tag{12}$$

Algorithm for solving a stochastic game

Step 1. Set the initial values of the parameters:
$t = 0$ is the initial time point;
$K = |I|$ is the number of players;
$\Omega = \{O_1, O_2, ..., O_K\}$ is set for clustering ontologies;
N is the number of clusters and the number of a pure strategies of players;
$U^i = \{u^i(1), u^i(2), ..., u^i(N)\}$, $i = 1..K$ is vectors of players' pure strategies;
$p_0^i = (1/N, ..., 1/N)$, $i = 1..K$ is initial mixed player strategies;
$\gamma > 0$ is the parameter of learning step;
$\alpha \in (0,1]$ is the order of learning step reduction;
ε is parameter of ε-simplex;
$\beta > 0$ is the order of extension of ε-simplex;
$d > 0$ is dispersion of obstacles;
$t_{\max}$ is maximum number of steps of the method.
Step 2. Select the action options $u_t^i \in U^i$, $i = 1..K$ according to (6).
Step 3. Get the value of current winnings ξ_t^i, $i = 1..K$ according to (3).
Step 4. Calculate the values of the parameters γ_t, ε_t according to (10).
Step 5. Calculate the elements of mixed strategy vectors p_t^i, $i = 1..K$ according to (9).
Step 6. Calculate the characteristics of the clustering quality Ξ_t (11), Δ_t (12).
Step 7. Set the next time period $t := t + 1$.
Step 8. If $t < t_{\max}$, then go back to step 2, or finish.

Computer simulation results

Example 1. It is necessary to perform clusterization $K = 5$ of ontologies for concept C, which can have different implementations $C = (c_1, c_2, c_3, c_4, c_5)$ in each ontology. The degrees of similarity of concepts, calculated according to (2), are given in a square matrix:

$$S = \begin{array}{c} \\ \\ \\ \\ \\ \\ \end{array}\begin{array}{c} \begin{array}{ccccc} c_1 & c_2 & c_3 & c_4 & c_5 \end{array} \\ \begin{bmatrix} 1 & 0.9 & 0.6 & 0 & 0 \\ 0.9 & 1 & 0.8 & 0 & 0 \\ 0.6 & 0.8 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0.7 \\ 0 & 0 & 0 & 0.7 & 1 \end{bmatrix} \end{array}\begin{array}{c} \\ c_1 \\ c_2 \\ c_3 \\ c_4 \\ c_5 \end{array}.$$

Based on the matrix S the average values of the winnings of agents, whose ontologies are attributed to the cluster $\Theta_{n,t}$ are calculated:

$$v_{n,t} = \sqrt[L_{n,t}]{\prod_{i,j\in\Theta_{n,t}} s_{i,j}},\ n = 1..N,$$

$\Theta_{n,t}$ is the current set of ontologies Θ_n; $L_{n,t} = \frac{(k_{n,t}-1)\cdot k_{n,t}}{2}$ is the current number of links between the compared ontology concepts of the same cluster; $k_{n,t} = |\Theta_{n,t}|$ is current number of elements (cardinality) of the set $\Theta_{n,t}$, taking into account, if $k_{n,t} = 1$, then $L_{n,t} = 1$; $s_{i,j}$ is the elements of matrix S.

All agents in the same cluster receive the same current wins: $\xi^i_{n,t} = v_{n,t} + \mu_t \quad \forall O_i \in \Theta_{n,t}$.

The value of Gaussian noise can be calculated as follows:

$$\mu_t = \sqrt{d}\left(\sum_{j=1}^{12}\omega_{j,t} - 6\right),$$

where $\omega \in [0,1]$ is a real random number with a uniform distribution law; $d > 0$ is the value of the dispersion.
The results of separating ontologies into $N = 2$ clusters and the corresponding average values of similarity of ontologies are shown in Table. 1 for $d = 0$. Other possible options are symmetric.

Table 1. The results of ontology clustering

Θ_1	$\varnothing$	{1}	{2}	{3}	{4}	{5}	{1, 2}	{1, 3}
$v_{1,t}$	0	1	1	1	1	1	0.9	0.6
Θ_2	{1, 2, 3, 4, 5}	{2, 3, 4, 5}	{1, 3, 4, 5}	{1, 2, 4, 5}	{1, 2, 3, 5}	{1, 2, 3, 4}	{3, 4, 5}	{2, 4, 5}
$v_{2,t}$	0	0	0	0	0	0	0	0
Θ_1	{1, 4}	{1, 5}	{2, 3}	{2, 4}	{2, 5}	{3, 4}	{3, 5}	{4, 5}
$v_{1,t}$	0	0	0.8	0	0	0	0	0.7
Θ_2	{2, 3, 5}	{2, 3, 4}	{1, 4, 5}	{1, 3, 5}	{1, 3, 4}	{1, 2, 5}	{1, 2, 4}	{1, 2, 3}
$v_{2,t}$	0	0	0	0	0	0	0	0.756

The results of simulation of ontologies clustering game are shown in Figure 1 with such stochastic game parameters: $K=5$, $N=2$, $U^i=(1,2)$, $\gamma=1$, $\varepsilon=0.999/N$, $\alpha=0.01$, $\beta=1$, $d=0$, $t_{\max}=10^4$.

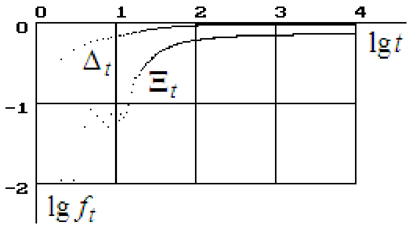

Figure 1. Characteristics of the convergence of the stochastic game

Table 2. The solution of the game in clean strategies

	p^1	p^2	p^3	p^4	p^5
u^1	1	1	1	0	0
u^2	0	0	0	1	1

Level 1 values of elements of mixed strategy vectors indicate the players' choice of specific clusters. From the obtained results it is clear that during the stochastic game two clusters of ontologies have been formed: $\Theta_1=\{O_1,O_2,O_3\}$ and $\Theta_2=\{O_4,O_5\}$.

If there is an ontology with the same degree of similarity to the ontologies in two (or more) clusters, we obtain the solution of the game in mixed strategies. The elements of the vector of mixed strategies will determine then the probability of ontology belonging to several clusters.

Example 2. Let the matrix of measures of similarity of implementations of the concept $K=5$ in ontologies look like:

$$\begin{array}{c} \\ S= \end{array}\begin{array}{c} \begin{array}{ccccc} c_1 & c_2 & c_3 & c_4 & c_5 \end{array} \\ \begin{bmatrix} 1 & 0.7 & 0 & 0 & 0.3 \\ 0.7 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0.7 & 0 \\ 0 & 0 & 0.7 & 1 & 0.3 \\ 0.3 & 0 & 0 & 0.3 & 1 \end{bmatrix} \end{array}\begin{array}{c} \\ c_1 \\ c_2 \\ c_3 \\ c_4 \\ c_5 \end{array}.$$

We will continue to split the ontologies into $N=2$ clusters. From the structure of the matrix, it is clear that the implementation of the concept in an ontology O_5 is similar to its realization in non-intersecting ontologies O_1 and O_4. From this, one should expect a solution to the game in mixed strategies. The final values of the mixed strategies obtained during the game are shown in Table. 3.

Table 3. The solution of the game in mixed strategies

	p^1	p^2	p^3	p^4	p^5
u^1	1	1	0	0	0.5
u^2	0	0	1	1	0.5

From the results, as shown in Table 3, the fuzzy ontology splitting into clusters $\Theta_1 = \{O_1, O_2, O_5\}$ and $\Theta_2 = \{O_3, O_4, O_5\}$ was created. Ontology O_5 simultaneously falls into two clusters. The degree of affiliation of ontologies to competing clusters is determined by the probabilities which are elements of vectors of mixed strategies. For clustering depicted in Figure 1, the graph of the integral norm Δ_t^i of mixed strategies will not reach the logarithmic zero.

The effect of obstacles on determining the degree of similarity of ontologies provides deterministic clustering instead of indistinct. As a result, an ontology O_5 with the probability close to 1 will belong to one of the competing clusters. This is due to the selective properties of the proposed game method. The differential shift of the same degree of similarity of ontologies, which occurs under the influence of white noise, increases the probability of choosing one of the clusters. Table 4 shows the results of a stochastic game for measures of similarity of the ontologies of Example 2, modified by the effect of white noise with the value of dispersion $d = 0.25$. Instead of solving the game in mixed strategies, the solution to pure strategies is obtained.

Table 4. The solution of the game under conditions of stochastic uncertainty

	p^1	p^2	p^3	p^4	p^5
u^1	1	1	0	0	0 (1)
u^2	0	0	1	1	1 (0)

The period of training of a stochastic game depends on the dimension of the game task, the dispersion of noise and the relations of the adjustable parameters of the game method. It should be noted that in the conditions of stochastic uncertainty, the period of learning for a stochastic game is increased, which is necessary for the clusterization of ontologies.

Conclusions

In this article a new method of adaptive clustering of ontologies is proposed, based on the stochastic game model. The method is constructed using the stochastic approximation of the condition of complementary non-rigidity, which describes the equilibrium of the solution of the game (by Nash). The developed game method provides clusterization of ontologies in conditions of stochastic uncertainty.

The results of the computer simulation confirm the convergence of the game method during the searching clustering of ontologies with the conditions and constraints of stochastic optimization. The probability of the results obtained is confirmed by the repetition of the distribution of ontologies to clusters, obtained for different sequences of random variables. The disadvantage of the proposed method is a low (with a degree of order) rate of convergence, due to the learning process of gaming agents because of uncertainty. The positive aspect is the natural possibility of parallelizing a gaming task with the use of powerful computational tools to accelerate the clustering process. Game clustering can be used to optimize operations on ontologies and as a separate example of self-organizing a stochastic game of intellectual agents.

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