Methods of calculating the strength of coalition in a dispersed decision support system with the stage of negotiations - a study of medical data

Małgorzata Przybyła-Kasperek and Alicja Wakulicz-Deja

University of Silesia, Institute of Computer Science,
Będzińska 39, 41-200 Sosnowiec, Poland
{malgorzata.przybyla-kasperek,alicja.wakulicz-deja}@us.edu.pl
http://www.us.edu.pl

Abstract. The article discusses the issues related to the decision-making system using dispersed knowledge. By dispersed knowledge we understand knowledge from one domain but stored in a set of knowledge bases. This article focuses on the use of dispersed medical data. A dispersed decision-making system with the negotiation stage was used. The impact of three different approaches to determining the strength of coalition on the effectiveness of inference in the system, have been studied.

Keywords: decision support system, dispersed decision-making system, negotiations, strength of coalition, conflict analysis

1 Introduction

In many hospitals and medical centers large volumes of medical data are collected. Mostly they are stored in a dispersed form, because each hospital has its own knowledge base. Support the decision-making process in such situations is a great challenge and a difficult task. Issues concerning the use of dispersed knowledge was considered by the authors in earlier papers [7–9]. In this paper, we develop the concepts discussed earlier. We use the system with the negotiation stage. Our main goal is to investigate the impact on the efficiency of inference of the methods for determining the strength of coalition.

The concept of distributed decision making (DDM) is widely discussed in the paper [10]. In DDM methods, it is assumed that the data are collected and stored in different decision tables representing either horizontally or vertically partitioned. In this paper, we consider an approach in which both the sets of conditional attributes and the universe are not necessarily disjoint or equal. This is more general approach than in DDM and thus we use the term dispersed knowledge rather than distributed knowledge. The concept of taking a global decision on the basis of local decisions is also used in issues concerning the multiple model approach [3]. In a multiple classifier system, an ensemble is constructed on the basis of base classifiers. The aim of this approach is to reduce the misclassification at the cost of increased computational complexity. Examples of the application of this approach can be found in the literature [1, 13]. Also in many other papers [2, 12], the problem of using distributed knowledge is considered. This paper describes a different approach to the global decision-making process. We assume that the set of local knowledge bases that contain information from one domain is pre-specified. The only condition which must be satisfied by the local knowledge bases is to have common decision attributes.

An approach to the issue of coalition formation was considered in the papers of Pawlak [4–6]. This model describes a conflict situation in which the agents have decided to analyze the conflict by using a peaceful method. The articles provide a definition of the relations - conflict, friendship and neutrality. This paper is based on the concepts that were provided by Pawlak for the analysis of conflict and coalition building.

2 The definition of dispersed decision-making system

In a dispersed decision-making system, a set of local knowledge bases that contain the knowledge from the same domain, is available. Local knowledge bases can be defined very variously, and therefore they can not be easily and without conflicts combined into a single coherent knowledge base. That's why, in order to make a global decision, a hierarchical structure of the system is created. In this structure the knowledge bases, on the basis of which similar decisions are taken, are combined into one coalition. It is realized in two steps. At first initial coalitions are created. Then the negotiation stage is implemented. Below basic notations are given and a brief overview of the process of structure creating is described. A more detailed description is given in the papers [8, 9].

We assume that each local knowledge base is managed by one agent. We use the definition of an agent introduced by Pawlak in [4]. We use two types of agents. The first is a resource agent. The resource agent has access to its local knowledge base on the basis of which it can establish the value of a local decision through the process of inference.

Definition 1. *We call ag in Ag a resource agent if he has access to resources represented by a decision table $D_{ag} := (U_{ag}, A_{ag}, d_{ag})$, where U_{ag} is a set called the universe; A_{ag} is a set of conditional attributes, and V^a_{ag} is a set of attribute a values that contain the special signs * and ?. Equation $a(x) = *$ for some $x \in U_{ag}$ means that for an object x, the value of attribute a has no influence on the value of the decision attribute, while the equation $a(x) =?$ means that the value of attribute a for object x is unknown; d_{ag} is referred to as a decision attribute and V^d_{ag} is called the value set of d_{ag}.*

Each resource agent $ag \in Ag$ can independently determine the value of the decision for a test object for which the values on the set of attributes A_{ag} are defined. In order to identify agents who make consistent decisions, for each agent a vector representing the classification of the test object made by the agents is determined. This vector will be defined on the basis of certain relevant objects. That is the objects from the decision tables of agents that carry the greatest similarity to the test object. From decision table of resource agent $D_{ag}, ag \in Ag$ and from each decision class $X_v^{ag}, v \in V^{d_{ag}}$, the smallest set containing at least m_1 objects for which the values of conditional attributes bear the greatest similarity to the test object is chosen. The value of the parameter m_1 is selected experimentally. Then for each resource agent $i \in \{1, \ldots, n\}$ and the test object x, a c-dimensional vector $[\bar{\mu}_{i,1}(x), \ldots, \bar{\mu}_{i,c}(x)]$ is generated, where the value $\bar{\mu}_{i,j}(x)$ is defined as follows: $\bar{\mu}_{i,j}(x) = \frac{\sum_{y \in U_{ag_i}^{rel} \cap X_{v_j}^{ag_i}} s(x,y)}{card\{U_{ag_i}^{rel} \cap X_{v_j}^{ag_i}\}}, i \in \{1, \ldots, n\}, j \in \{1, \ldots, c\}$, where $c = card\{V^d\}$, $U_{ag_i}^{rel}$ is the subset of relevant objects selected from the decision table D_{ag_i} of resource agent ag_i and $X_{v_j}^{ag_i}$ is the decision class of the decision table of resource agent ag_i; and $s(x, y)$ is the measure of similarity between objects x and y. In the experimental part of this paper the Gower similarity measure [9] was used. This measure enables the analysis of data sets that have qualitative, quantitative and binary attributes. The value of $\bar{\mu}_{i,j}(x)$ is equal to the average value of the similarity of the test object to the relevant objects of agent ag_i, belonging to the decision class v_j. On the basis of the vector of values defined above, a vector of the rank is specified. The vector of rank is defined as follows: rank 1 is assigned to the values of the decision attribute that are taken with the maximum level of certainty. Rank 2 is assigned to the next most certain decisions, etc. Proceeding in this way for each resource agent $ag_i, i \in \{1, \ldots, n\}$, the vector of rank $[r_{i,1}(x), \ldots, r_{i,c}(x)]$ will be defined. In order to create clusters of agents, relations between the agents are defined. The definitions of friendship, conflict and neutrality relation are given next. Relations between agents are defined by their views on the classification of the test object x to the decision class. We define the function $\phi_{v_j}^x$ for the test object x and each value of the decision attribute $v_j \in V^d$; $\phi_{v_j}^x : Ag \times Ag \to \{0, 1\}$ $\phi_{v_j}^x(ag_i, ag_k) = \begin{cases} 0 & \text{if } r_{i,j}(x) = r_{k,j}(x) \\ 1 & \text{if } r_{i,j}(x) \neq r_{k,j}(x) \end{cases}$ where $ag_i, ag_k \in Ag$. We also define the intensity of conflict between agents using a function of the distance between agents. We define the distance between agents ρ^x for the test object x: $\rho^x : Ag \times Ag \to [0, 1]$, $\rho^x(ag_i, ag_k) = \frac{\sum_{v_j \in V^d} \phi_{v_j}^x(ag_i, ag_k)}{card\{V^d\}}$, where $ag_i, ag_k \in Ag$.

Definition 2. *Let p be a real number, which belongs to the interval $[0, 0.5)$. We say that agents $ag_i, ag_k \in Ag$ are in a friendship relation due to the object x, which is written $R^+(ag_i, ag_k)$, if and only if $\rho^x(ag_i, ag_k) < 0.5 - p$. Agents $ag_i, ag_k \in Ag$ are in a conflict relation due to the object x, which is written $R^-(ag_i, ag_k)$, if and only if $\rho^x(ag_i, ag_k) > 0.5 + p$. Agents $ag_i, ag_k \in Ag$ are in a neutrality relation due to the object x, which is written $R^0(ag_i, ag_k)$, if and only if $0.5 - p \le \rho^x(ag_i, ag_k) \le 0.5 + p$.*

By using the relations defined above we can create groups of resource agents, which are not in conflict relation. The first step involves the creation of groups of agents remaining in the friendship relation.

Definition 3. *Let Ag be the set of resource agents. The initial cluster due to the classification of object x is the maximum, due to the inclusion relation, subset of resource agents $X \subseteq Ag$ such that $\forall_{ag_i, ag_k \in X} \quad R^+(ag_i, ag_k)$.*

After the first stage of clusters creating we obtain a set of initial clusters and a set of agents who are not included in any cluster. In the second group there are agents who remained undecided. By undecided agents we mean those who are in the neutrality relation with agents belonging to the initial cluster. In the second step the negotiations issues are applied, and agents who are neutral are join to an existing coalition. But now some concessions are accepted. We assume that during the negotiation, agents put the greatest emphasis on compatibility of ranks assigned to the decisions with the highest ranks. That is the decisions that are most significant for the agent. Compatibility of ranks assigned to less meaningful decision is omitted. Now we will proceed to the formal description of the second stage of cluster creating process.

We define the function ϕ_G^x for the test object x; $\phi_G^x : Ag \times Ag \to [0, \infty)$ $\phi_G^x(ag_i, ag_j) = \frac{\sum_{v_l \in Sign_{i,j}} |r_{i,l}(x) - r_{j,l}(x)|}{card\{Sign_{i,j}\}}$ where $ag_i, ag_j \in Ag$ and $Sign_{i,j} \subseteq V^d$ is the set of significant decision values for the pair of agents ag_i, ag_j. In the set $Sign_{i,j}$ there are the values of the decision, which the agent ag_i or agent ag_j gave the highest rank.

During the negotiation stage, the intensity of the conflict between the two groups of agents is determined by using the generalized distance. The generalized distance between agents ρ_G^x for the test object x is defined as follows; ρ_G^x : $2^{Ag} \times 2^{Ag} \to [0, \infty)$

$$\rho_G^x(X, Y) = \begin{cases} 0 & \text{if} \quad card\{X \cup Y\} \le 1 \\ \dfrac{\sum\limits_{ag, ag' \in X \cup Y} \phi_G^x(ag, ag')}{card\{X \cup Y\} \cdot (card\{X \cup Y\} - 1)} & \text{else} \end{cases}$$

where $X, Y \subseteq Ag$. The value of the generalized distance function for two sets of agents X and Y is equal to the average value of the function ϕ_G^x for each pair of agents ag, ag' belonging to the set $X \cup Y$. This value can be interpreted as the average difference of the ranks assigned to significant decisions within the combined group of agents consisting of the sets X and Y.

For each agent ag that has not been included to any initial clusters, the generalized distance value is determined for this agent and all initial clusters, with which the agent ag is not in a conflict relation and for this agent and other agents without coalition, with which the agent ag is not in a conflict relation.

Then the agent ag is included to all initial clusters, for which the generalized distance does not exceed a certain threshold, which is set by the system's user. Also agents without coalition, for which the value of the generalized distance function does not exceed the threshold, are combined into a new cluster. The value of the threshold is selected experimentally.

After completion of the second stage of the process of clustering we get the final form of clusters. As was mentioned above, the proposed decision-making system has a hierarchical structure. The resource agents that are connected into clusters are located at the lowest level of the hierarchy. For each cluster that contains at least two resource agents, a superordinate agent is defined, which is called a synthesis agent, as_j, where j- number of cluster.

The definition of a dispersed decision-making system is given next.

Definition 4. *By a dispersed decision-making system (multi-agent system) with dynamically generated clusters we mean* $WSD_{Ag}^{dyn} = \langle Ag, \{D_{ag} : ag \in Ag\}, \{As_x : x \textit{ is a classified object}\}, \{\delta_x : x \textit{ is a classified object}\}\rangle$ *where Ag is a finite set of resource agents; $\{D_{ag} : ag \in Ag\}$ is a set of decision tables of resource agents; As_x is a finite set of synthesis agents defined for clusters dynamically generated for the test object x, $\delta_x : As_x \to 2^{Ag}$ is a injective function that each synthesis agent assigns a cluster generated due to classification of the object x.*

3 The strength of coalition and conflict analysis

On the basis of the knowledge of agents from one cluster, local decisions are taken. An important problem that occurs when taking a global decision is to eliminate inconsistencies in the knowledge stored in different knowledge bases. This problem stems from the fact that the system has the general assumptions and we do not require that the sets of conditional attributes of decision tables are disjoint. In previous papers some methods of elimination inconsistencies in the knowledge have been proposed [9]. In this paper, one of these methods - the approximated method of the aggregation of decision tables, will be used. In this method for every cluster, a kind of combined information is determined. Each synthesis agent has access to aggregated decision table. Object of this table are constructed by combining relevant object from decision tables of the resource agents that belong to one cluster.

After the completion of the process of the elimination of any inconsistencies in the knowledge, a c-dimensional vector of values $[\mu_{j,1}(x), \ldots, \mu_{j,c}(x)]$ is generated for each cluster $j \in \{1, \ldots, card\{As\}\}$, where c is the number of all of the decision classes. The value $\mu_{j,i}(x)$ determines the level of certainty with which the decision v_i is taken by agents for a given test object x belonging to the cluster j. The vector of values assigned to the cluster is defined as follows. The value $\mu_{j,i}(x)$ is equal to the maximum value of the similarity measure of objects from the decision class v_i of the decision table of synthesis agent as_j to the test object x.

Because the synthesis agents can take contradictory decisions for a given set of conditions, conflict analysis methods must be used. The method of a density-based algorithm, which was described in the paper [9], is used. In this method the generated set of global decisions will contain not only the value of the decisions that have the greatest support of knowledge stored in local knowledge bases, but also those for which the support is relatively high. Below, three different approaches to determining the global decisions are described. These approaches are used together with the density-based method.

The approache without the strength of cluster
Each j-th synthesis agent votes for different decision values with the voting power equal to the value of the coordinate of the vector $[\mu_{j,1}(x), \ldots, \mu_{j,c}(x)]$.
The approache with the strength of cluster
In this paper, a modification of the method of calculating the vectors that assigned to clusters, is proposed. This modification consists in taking into account the strength of the cluster, which is expressed by the number of its component agents. In the proposed method of creating the system's structure, inseparable clusters are generated. Thus, one agent may be included in many clusters. This means that the partial participation of the agent in the creation of the cluster should be considered. Thus, in the first stage of the process of determining the strength of cluster, a membership of each agent in the clusters is calculated. For each resource agent $ag \in Ag$ and given test object x a coefficient of agent's membership in clusters is defined $m^x_{ag} = \frac{1}{card\{as \in As_x : ag \in \delta_x(as)\}}$. The value of the agent's membership in clusters is inversely proportional to the number of clusters to which the agent belongs. Then, for each cluster the sum of the agent's membership in clusters is calculated. Thus, for each synthesis agent $as \in As_x$ the strength of cluster subordinate to the agent as is determined $\sum_{ag \in \delta_x(as)} m^x_{ag}$. The vector assigned to j-th cluster $j \in \{1, \ldots, card\{As\}\}$ is multiplied by a scalar $\frac{\sum_{ag \in \delta_x(as_j)} m^x_{ag}}{card\{Ag\}} \cdot \Big[\mu_{j,1}(x), \ldots, \mu_{j,c}(x)\Big]$. In this way the vectors are calculated in proportion to the strength of the clusters. Thanks to such transformation, the large clusters have a greater impact on the decisions, while the impact of small clusters decreases.
The approache with the strength of cluster and the diversity of agents
In this modification of the method of calculating the vectors that assigned to clusters, in addition to the agent's membership in clusters, it is also taken into account the variability of the vector values $[\bar{\mu}_{i,1}(x), \ldots, \bar{\mu}_{i,c}(x)]$ assigned to the i-th resource agent. This is realized in the following way. For each resource agent $ag_i \in Ag$, the standard deviation of the vector values is determined as follows $SD^x_{ag_i} = \sqrt{\frac{1}{c} \cdot \sum_{j=1}^{c} \left(\frac{\sum_{k=1}^{c} \bar{\mu}_{i,k}(x)}{c} - \bar{\mu}_{i,j}(x)\right)^2}$. Then for each resource agent a coefficient is calculated $mv^x_{ag_i} = m^x_{ag_i} \cdot \frac{SD^x_{ag_i}}{\sum_{ag' \in Ag} SD^x_{ag'}}$. Analogously to the previous approach for each synthesis agent $as \in As_x$ the value $\sum_{ag \in \delta_x(as)} mv^x_{ag}$ is determined and the vector assigned to j-th cluster is multiplied by this value. In this way the vectors are recalculated in proportion not only to the strength of the clusters but also to the decisiveness of agents. Thanks to such transformation, the agents who make decisions with the same degree of certainty have less impact on the global decisions, while the impact of agents, which are sure of decisions taken, increases.

4 Results of experiments

The experiments were performed on data sets from medical domain. The following data were used: Audiology (Standardized), Lymphography, Primary Tumor.

These data are available in the UCI repository. Audiology was obtained from the Baylor College of Medicine, Houston, Texas. In this data set, on the basis of values of 69 attributes, a decision is taken what is the cause of hearing problems (one of 24 possibilities). Lymphography and Primary Tumor was obtained from the University Medical Centre, Institute of Oncology, Ljubljana, Yugoslavia (M. Zwitter and M. Soklic provided this data). Lymphography is a medical imaging technique in which a radiocontrast agent is injected, and then an X-ray picture is taken to visualize structures of the lymphatic system. This test method gives great service especially in the evaluation of cancer stage of the lymphatic system. In the Primary Tumor data set, on the basis of values of attributes such as histologic-type, supraclavicular etc. a decision is taken where (of 22 organs) the cancer cells are located. In order to determine the efficiency of inference each data set was divided into two disjoint subsets: a training set and a test set. A numerical summary of the data sets is as follows: *Audiology*: # The training set - 200; # The test set - 26; # Conditional - 69; # Decision - 24; *Lymphography*: # The training set - 104; # The test set - 44; # Conditional - 18; # Decision - 4; *Primary Tumor*: # The training set - 237; # The test set - 102; # Conditional - 17; # Decision - 22. These data can be considered as quite challenging, because on the basis of a small number of examples, the proper decision value for the test object, must be assigned, form a large set of decision values. This difficulty has been confirmed by the experimental results presented in the paper [11]. Our goal is not only to consider the case in which medical data are collected in a dispersed form but also improve the efficiency of inference obtained by other methods. The issue of the use of dispersed medical data is a very important and real problem. Each hospital or medical center collects data sets, but sets are separable, different for each hospital. The possibility to use knowledge from the sets collected separately and containing information from one domain is very important in real life area. This approach should significantly improve the efficiency of inference. At this moment, the authors do not have access to distributed real data sets. But in the future it is planned to conduct tests on real data. To test the capabilities of the dispersed decision-making system, we must provide knowledge in a dispersed form. Therefore, each of the training sets was divided into a set of decision tables. Divisions with a different number of decision tables were considered. For each of the data sets used, a dispersed decision-making system with five different versions (with 3, 5, 7, 9 and 11 resource agents) was considered. For these systems, we used the following designations: WSD_{Ag1}^{dyn} - 3 resource agents; WSD_{Ag2}^{dyn} - 5 resource agents; WSD_{Ag3}^{dyn} - 7 resource agents; WSD_{Ag4}^{dyn} - 9 resource agents; WSD_{Ag5}^{dyn} - 11 resource agents. Note that the division of the data set was not made in order to improve the quality of the decisions taken by the decision-making system, but in order to store the knowledge in a distributed form. Influence of dispersion of knowledge on the effectiveness of inference was not tested. The method of dispersing knowledge was specified by the authors in the following way. The cardinality of the set of conditional attributes in each decision table of a resource agent was determined and the number of common conditional attributes of the decision tables was defined. Then, the conditional attributes were randomly assigned to the decision tables so that the conditions that had been defined earlier were met and each conditional attribute that appears in the data set is included in at least one set of the conditional attributes of the decision tables. The measures of determining the quality of the classification are: *estimator of classification error* e in which an object is considered to be properly classified if the decision class used for the object belonged to the set of global decisions generated by the system; *estimator of classification ambiguity error* e_{ONE} in which object is considered to be properly classified if only one, correct value of the decision was generated to this object; *the average size of the global decisions sets* $\overline{d}_{WSD^{dyn}_{Ag}}$ generated for a test set. In the description of the results of experiments for clarity some designations for algorithms have been adopted: $A(m_2)$ - the approximated method of the aggregation of decision tables; W - the method of weighted voting; $G(\varepsilon, MinPts)$ - the method of a density-based algorithm. During experiments influence of the parameter p, which occurs in the definition 2 of friendship, conflict and neutrality relations, on the effectiveness of inference of a dispersed decision-making system was analyzed. Four different values of the parameter p were examined. The analyzed values are $p = 0.05$, $p = 0.1$, $p = 0.2$, $p = 0.3$. In tables presented below the best results, obtained for values of the parameter p, are given. Also the optimal parameter values of m_1, m_2, ε were selected. The parameter m_1 and m_2 determine the number of relevant objects that are selected from each decision class of the decision table of the resource agent, and then are used in the process of cluster generation or to design the decision table of the synthesis agents. In order to identify the optimum, the values form 1 to 10 were used. Then, for each system, the minimum value of the parameters m_1 and m_2 was chosen, which allowed the lowest value of estimator of classification error on a test set to be reached. The value of parameter ε of the method of a density-based algorithm was optimized by performing a series of experiments with different values of parameter ε that were increased from 0 to the threshold point. Then a graph was created on which the points with coordinates $(\overline{d}_{WSD^{dyn}_{Ag}}, e)$ are marked in an increasing order of value ε. Then, the points were marked on the graphs indicate those that had the greatest improvement in the efficiency of inference. These points satisfy the following conditions: on the left of the point you can see a significant decrease in the value of the estimator of classification error and on the right of the point there is a slight decrease in the value of this estimator with an increase in the value of parameter ε. The results of the experiments with the Audiology data set are presented in Table 1, with the Lymphography data set are presented in Table 2 and with the Primary Tumor data set are presented in Table 3. The tables show the results for three different approaches presented in this paper:

- dispersed decision-making system with the stage of negotiations and without calculating the strength of cluster,
- dispersed decision-making system with the stage of negotiations and with calculating the strength of cluster,
- dispersed decision-making system with the stage of negotiations and with calculating the strength of cluster and the diversity of agents.

The results for one approach discussed in earlier paper [7] - dynamically generated disjoint clusters, are also presented in Tables. In this approach only friendship and conflict relations are defined. In the process of generating clusters the negotiations did not occur and agents in friendship relation are connected in clusters. In tables 1, 2 and 3 the best results in terms of the measures e and $\overline{d}_{WSD_{Ag}^{dyn}}$ are bold. Summarizing the results presented in tables 1, 2 and 3: six times the best results were achieved using the approach with the stage of negotiations and without calculating the strength of cluster; nine times the best results were achieved using the approach with the stage of negotiations and calculating the strength of cluster; sixteen times the best results were achieved using the approach with the stage of negotiation, calculating the strength of cluster and the diversity of agents; and only four times the best results were achieved using the approach with dynamically generated disjoint clusters. Thus, for dispersed medical data, which were tested, the best approach was the approach with the stage of negotiation, the strength of cluster and the diversity of agents.

5 Conclusion

In this article the impact of three different approaches to determining the strength of coalition on the effectiveness of inference in the system with dispersed knowledge have been studied. In the first approach each of the coalition was equally strong, regardless of the number of agents in the coalition. In the second approach the strength of coalition was determined by the size of the coalition. In the third approach, in addition to the size of the coalition, also the diversity of the decisions made by the individual agents were taken into account. In the experiments dispersed medical data have been used. Based on the presented results of experiments it can be concluded that the best approach is the third approach.

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Table 1. Experiments results with the Audiology data set

The stage of negotiation, without the strength of cluster

System	Parameters	Algorithm	e	e_{ONE}	$\overline{d}_{WSD^{dyn}_{Ag}}$	t
WSD_{Ag1}	$m_1 = 1,\, p = 0.3$	$A(1)G(0.00069; 2)$	0.154	0.462	1.615	0.01
	$m_1 = 1,\, p = 0.3$	$A(1)G(0.000015; 2)$	**0.192**	0.423	**1.308**	0.01
WSD_{Ag2}	$m_1 = 1,\, p = 0.2$	$A(2)G(0.00099; 2)$	**0.077**	0.462	**1.808**	0.01
	$m_1 = 1,\, p = 0.2$	$A(2)G(0.00078; 2)$	0.154	0.385	1.308	0.01
WSD_{Ag3}	$m_1 = 5,\, p = 0.1$	$A(1)G(0.002844; 2)$	0.077	0.346	1.462	0.01
	$m_1 = 1,\, p = 0.05$	$A(1)G(0.00195; 2)$	0.154	0.385	1.308	0.01
WSD_{Ag4}	$m_1 = 1,\, p = 0.1$	$A(2)G(0.001248; 2)$	0.115	0.385	1.462	0.05
	$m_1 = 1,\, p = 0.05$	$A(1)G(0.000725; 2)$	0.154	0.346	1.231	0.05
WSD_{Ag5}	$m_1 = 2,\, p = 0.05$	$A(2)G(0.0036; 2)$	0.115	0.462	1.577	0.12
	$m_1 = 5,\, p = 0.2$	$A(1)G(0.00249; 2)$	0.192	0.423	1.308	0.14

The stage of negotiation, with the strength of cluster

System	Parameters	Algorithm	e	e_{ONE}	$\overline{d}_{WSD^{dyn}_{Ag}}$	t
WSD_{Ag1}	$m_1 = 2,\, p = 0.3$	$A(1)G(0.0003; 2)$	**0.154**	0.500	**1.500**	0.01
	$m_1 = 1,\, p = 0.3$	$A(1)G(0.000011; 2)$	**0.192**	0.423	**1.308**	0.01
WSD_{Ag2}	$m_1 = 1,\, p = 0.05$	$A(1)G(0.0006; 2)$	0.115	0.500	1.654	0.01
	$m_1 = 1,\, p = 0.2$	$A(2)G(0.00042; 2)$	0.154	0.423	1.346	0.01
WSD_{Ag3}	$m_1 = 8,\, p = 0.05$	$A(2)G(0.00045; 2)$	0.077	0.385	1.538	0.01
	$m_1 = 2,\, p = 0.3$	$A(2)G(0.000148; 2)$	**0.115**	0.385	**1.308**	0.01
WSD_{Ag4}	$m_1 = 2,\, p = 0.3$	$A(2)G(0.000364; 2)$	0.038	0.500	1.808	0.05
	$m_1 = 2,\, p = 0.3$	$A(2)G(0.000284; 2)$	0.077	0.346	1.385	0.05
WSD_{Ag5}	$m_1 = 3,\, p = 0.3$	$A(3)G(0.000306; 2)$	0.077	0.462	1.731	0.29
	$m_1 = 3,\, p = 0.3$	$A(3)G(0.00011; 2)$	0.154	0.346	1.239	0.29

The stage of negotiation, with the strength of cluster and the diversity of agents

System	Parameters	Algorithm	e	e_{ONE}	$\overline{d}_{WSD^{dyn}_{Ag}}$	t
WSD_{Ag1}	$m_1 = 1,\, p = 0.3$	$A(1)G(0.00018; 2)$	0.154	0.500	1.885	0.01
	$m_1 = 1,\, p = 0.3$	$A(1)G(0.000012; 2)$	**0.192**	0.423	**1.308**	0.01
WSD_{Ag2}	$m_1 = 1,\, p = 0.2$	$A(2)G(0.000456; 2)$	**0.115**	0.423	**1.385**	0.01
WSD_{Ag3}	$m_1 = 5,\, p = 0.3$	$A(1)G(0.000588; 2)$	0.077	0.500	1.808	0.01
	$m_1 = 5,\, p = 0.2$	$A(1)G(0.000339; 2)$	0.154	0.385	1.346	0.01
WSD_{Ag4}	$m_1 = 3,\, p = 0.2$	$A(2)G(0.000486; 2)$	**0.038**	0.385	**1.462**	0.02
	$m_1 = 2,\, p = 0.2$	$A(1)G(0.000276; 2)$	**0.077**	0.346	**1.308**	0.02
WSD_{Ag5}	$m_1 = 3,\, p = 0.3$	$A(3)G(0.000687; 2)$	**0.038**	0.615	**2.077**	0.28
	$m_1 = 3,\, p = 0.3$	$A(3)G(0.000195; 2)$	**0.077**	0.423	**1.385**	0.28

Dynamically generated disjoint clusters - results presented in the paper [7]

System	Algorytm	e	e_{ONE}	$\overline{d}_{WSD_{Ag}}$	t
WSD_{Ag1}	$A(1)G(0.00179; 2)$	0.154	0.538	1.808	0.01
$m_1 = 2$	$A(1)G(0.0009; 2)$	0.192	0.500	1.385	0.01
WSD_{Ag2}	$A(1)G(0.00219; 1)$	0.154	0.577	1.808	0.01
$m_1 = 1$	$A(1)G(0.00111; 2)$	0.231	0.462	1.308	0.01
WSD_{Ag3}	$A(1)G(0.00288; 2)$	**0.077**	0.346	**1.423**	0.01
$m_1 = 8$	$A(1)G(0.00207; 2)$	**0.115**	0.346	**1.308**	0.01
$WSD_{Ag4},\, m_1 = 4$	$A(1)G(0.002775; 2)$	0.154	0.385	1.346	0.01
WSD_{Ag5}	$A(3)G(0.00642; 2)$	0.115	0.538	1.885	0.01
$m_1 = 3$	$A(3)G(0.0009; 2)$	0.269	0.423	1.269	0.01

Table 2. Experiments results with the Lymphography data set

The stage of negotiation, without the strength of cluster

System	Parameters	Algorithm	e	e_{ONE}	$\bar{d}_{WSD_{Ag}^{dyn}}$	t
WSD_{Ag1}	$m_1 = 2,\ p = 0.05$	$A(1)G(0.03; 2)$	0.091	0.568	1.477	0.01
	$m_1 = 2,\ p = 0.05$	$A(1)G(0.0076; 2)$	0.114	0.227	1.114	0.01
WSD_{Ag2}	$m_1 = 2,\ p = 0.3$	$A(3)G(0.0204; 2)$	0.114	0.523	1.409	0.01
	$m_1 = 2,\ p = 0.3$	$A(3)G(0.0128; 2)$	0.136	0.318	1.182	0.01
WSD_{Ag3}	$m_1 = 1,\ p = 0.05$	$A(1)G(0.0515; 2)$	**0.114**	0.523	**1.409**	0.01
	$m_1 = 1,\ p = 0.05$	$A(1)G(0.0005; 2)$	**0.159**	0.273	**1.114**	0.01
WSD_{Ag4}	$m_1 = 1,\ p = 0.05$	$A(1)G(0.0625; 2)$	0.114	0.591	1.477	0.01
	$m_1 = 1,\ p = 0.05$	$A(1)G(0.052; 2)$	0.136	0.500	1.364	0.01
WSD_{Ag5}	$m_1 = 5,\ p = 0.3$	$A(2)G(0.058; 2)$	**0.159**	0.568	**1.409**	0.07
	$m_1 = 5,\ p = 0.3$	$A(2)G(0.0292; 2)$	0.182	0.545	1.364	0.07

The stage of negotiation, with the strength of cluster

System	Parameters	Algorithm	e	e_{ONE}	$\bar{d}_{WSD_{Ag}^{dyn}}$	t
WSD_{Ag1}	$m_1 = 2,\ p = 0.05$	$A(1)G(0.0196; 2)$	0.091	0.477	1.386	0.01
	$m_1 = 2,\ p = 0.05$	$A(1)G(0.004; 2)$	0.136	0.273	1.136	0.01
WSD_{Ag2}	$m_1 = 2,\ p = 0.3$	$A(3)G(0.014; 2)$	**0.091**	0.568	**1.477**	0.01
	$m_1 = 2,\ p = 0.3$	$A(3)G(0.0044; 2)$	**0.136**	0.227	**1.091**	0.01
WSD_{Ag3}	$m_1 = 1,\ p = 0.1$	$A(1)G(0.0144; 2)$	0.114	0.568	1.455	0.01
	$m_1 = 1,\ p = 0.1$	$A(1)G(0.0002; 2)$	**0.159**	0.273	**1.114**	0.01
WSD_{Ag4}	$m_1 = 1,\ p = 0.05$	$A(1)G(0.0148; 2)$	**0.091**	0.568	**1.477**	0.01
	$m_1 = 1,\ p = 0.05$	$A(1)G(0.0116; 2)$	0.136	0.477	1.341	0.01
WSD_{Ag5}	$m_1 = 2,\ p = 0.05$	$A(1)G(0.0126; 2)$	0.159	0.636	1.477	0.07
	$m_1 = 2,\ p = 0.05$	$A(1)G(0.0092; 2)$	**0.182**	0.500	**1.318**	0.07

The stage of negotiation, with the strength of cluster and the diversity of agents

System	Parameters	Algorithm	e	e_{ONE}	$\bar{d}_{WSD_{Ag}^{dyn}}$	t
WSD_{Ag1}	$m_1 = 2,\ p = 0.3$	$A(1)G(0.0184; 2)$	**0.045**	0.500	**1.455**	0.01
	$m_1 = 2,\ p = 0.1$	$A(1)G(0.0124; 2)$	**0.091**	0.318	**1.227**	0.01
WSD_{Ag2}	$m_1 = 2,\ p = 0.3$	$A(3)G(0.0128; 2)$	**0.091**	0.568	**1.477**	0.01
	$m_1 = 2,\ p = 0.3$	$A(3)G(0.0044; 2)$	**0.136**	0.227	**1.091**	0.01
WSD_{Ag3}	$m_1 = 3,\ p = 0.3$	$A(1)G(0.014; 2)$	0.136	0.523	1.386	0.01
	$m_1 = 3,\ p = 0.3$	$A(1)G(0.0002; 2)$	**0.159**	0.273	**1.114**	0.01
WSD_{Ag4}	$m_1 = 1,\ p = 0.05$	$A(1)G(0.0196; 2)$	0.114	0.568	1.455	0.01
	$m_1 = 1,\ p = 0.05$	$A(1)G(0.0156; 2)$	0.136	0.523	1.386	0.01
WSD_{Ag5}	$m_1 = 2,\ p = 0.05$	$A(1)G(0.0128; 2)$	0.159	0.614	1.477	0.07
	$m_1 = 2,\ p = 0.05$	$A(1)G(0.0004; 2)$	0.205	0.455	1.250	0.07

Dynamically generated disjoint clusters - results presented in the paper [7]

System	Algorithm	e	e_{ONE}	$\bar{d}_{WSD_{Ag}^{dyn}}$	t
WSD_{Ag1}	$A(1)G(0.0624; 2)$	0.091	0.591	1.545	0.01
$m_1 = 2$	$A(1)G(0.0092; 2)$	0.182	0.295	1.159	0.01
WSD_{Ag2}	$A(1)G(0.0775; 2)$	0.136	0.636	1.500	0.01
$m_1 = 2$	$A(1)G(0.029; 2)$	0.159	0.364	1.205	0.01
WSD_{Ag3}	$A(1)G(0.0858; 2)$	0.136	0.591	1.455	0.01
$m_1 = 2$	$A(1)G(0.0006; 2)$	**0.159**	0.273	**1.114**	0.01
$WSD_{Ag4},\ m_1 = 2$	$A(1)G(0.0702; 2)$	**0.136**	0.455	**1.318**	0.01
WSD_{Ag5}	$A(1)G(0.084; 2)$	0.159	0.614	1.477	0.01
$m_1 = 1$	$A(1)G(0.0672; 2)$	0.182	0.545	1.364	0.01

Table 3. Experiments results with the Primary Tumor data set

The stage of negotiation, without the strength of cluster

System	Parameters	Algorithm	e	e_{ONE}	$\overline{d}_{WSD^{dyn}_{Ag}}$	t
WSD_{Ag1}	$m_1 = 5$, $p = 0.05$	$A(1)G(0.00546; 2)$	0.373	0.814	3.020	0.01
WSD_{Ag2}	$m_1 = 3$, $p = 0.1$	$A(2)G(0.00001; 2)$	0.343	0.814	3.029	0.02
WSD_{Ag3}	$m_1 = 2$, $p = 0.05$	$A(1)G(0.00001; 2)$	0.373	0.902	3.745	0.02
WSD_{Ag4}	$m_1 = 4$, $p = 0.1$	$A(2)G(0.00001; 2)$	0.353	0.882	3.686	0.05
WSD_{Ag5}	$m_1 = 2$, $p = 0.2$	$A(3)G(0.00001; 2)$	**0.314**	0.892	**4.245**	0.36

The stage of negotiation, with the strength of cluster

System	Parameters	Algorithm	e	e_{ONE}	$\overline{d}_{WSD^{dyn}_{Ag}}$	t
WSD_{Ag1}	$m_1 = 4$, $p = 0.05$	$A(3)G(0.00273; 2)$	0.382	0.843	3.441	0.01
WSD_{Ag2}	$m_1 = 5$, $p = 0.05$	$A(2)G(0.00003; 2)$	**0.333**	0.833	**3.049**	0.02
WSD_{Ag3}	$m_1 = 2$, $p = 0.05$	$A(1)G(0.00001; 2)$	0.353	0.892	3.804	0.02
WSD_{Ag4}	$m_1 = 3$, $p = 0.05$	$A(3)G(0.00001; 2)$	0.353	0.892	3.676	0.05
WSD_{Ag5}	$m_1 = 2$, $p = 0.2$	$A(2)G(0.00001; 2)$	0.314	0.922	4.294	0.36

The stage of negotiation, with the strength of cluster and the diversity of agents

System	Parameters	Algorithm	e	e_{ONE}	$\overline{d}_{WSD^{dyn}_{Ag}}$	t
WSD_{Ag1}	$m_1 = 1$, $p = 0.3$	$A(2)G(0.00291; 2)$	**0.363**	0.882	**3.167**	0.01
WSD_{Ag2}	$m_1 = 3$, $p = 0.05$	$A(2)G(0.00003; 2)$	**0.333**	0.833	**3.049**	0.02
WSD_{Ag3}	$m_1 = 5$, $p = 0.3$	$A(1)G(0.00003; 2)$	**0.353**	0.892	**3.784**	0.02
WSD_{Ag4}	$m_1 = 3$, $p = 0.3$	$A(3)G(0.00222; 2)$	**0.333**	0.902	**3.784**	0.05
WSD_{Ag5}	$m_1 = 2$, $p = 0.2$	$A(3)G(0.00003; 2)$	**0.314**	0.912	**4.245**	0.36

Dynamically generated disjoint clusters - results presented in the paper [7]

System	Algorithm	e	e_{ONE}	$\overline{d}_{WSD^{dyn}_{Ag}}$	t
WSD_{Ag1}, $m_1 = 5$	$A(2)G(0.00549; 2)$	0.373	0.814	3.020	0.01
WSD_{Ag2}, $m_1 = 17$	$A(3)G(0.0003; 2)$	0.353	0.814	2.990	0.02
WSD_{Ag3}, $m_1 = 5$	$A(5)G(0.00573; 2)$	0.373	0.912	3.755	0.02
WSD_{Ag4}, $m_1 = 4$	$A(3)G(0.0063; 2)$	0.343	0.902	3.667	0.03
WSD_{Ag5}, $m_1 = 6$	$A(1)G(0.0003; 2)$	0.333	0.941	4.294	0.02

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