On Possibilistic Case-based Reasoning for Selecting Partners for Multi-attribute Agent Negotiation

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ABSTRACT

We propose an enhanced mechanism for selecting partners for multi-attribute negotiation. The mechanism employs possibilistic case-based reasoning. The possibility of successful negotiation for each potential partner is predicted on the basis of its behaviour in previous multi-attribute negotiations. The qualitative expected utility for each potential partner is derived and the agents are ordered according to the values of these utilities. The order determines who is more and who is less desirable partner for negotiation. The proposed approach allows choosing the most prospective negotiation partners based on small sample of historical cases of previous interactions even if the previous situations are different from the current one. A simple example of calculations is presented to demonstrate the proposed approach.

Categories and Subject Descriptors

I.2 [**Artificial Intelligence**]: Learning, Problem Solving

General Terms

Algorithms, Theory

Keywords

possibility theory, case-based reasoning

1. INTRODUCTION

Negotiation can be considered as a distributed search through a space of potential agreements and finally coming to mutually acceptable agreement on some object [9]. The object that is the topic of negotiation can be multidimensional in the sense that it is described by a sequence of values corresponding to its different attributes. The knowledge of negotiation agents may be limited or uncertain and the preferences of agents may be conflicting. There are several applications of automated negotiation such as: task distribution, resources sharing, service composition and coalition formation. If a number of candidates for interaction partners that offer some services is small the negotiation can be carried out with all of them and the best agreement can be chosen or compound agreement may be derived to best satisfy negotiation objectives (e.g. maximal payoff)(e.g. [11], [10]). However, when a number of potential partners is large then performing negotiation with all of them may be expensive in terms of computational time and resources, or even may be impractical, especially in an open dynamic environment. An appropriate approach can be to choose from a large set of agents some subset of partners with a high chance of reaching a good agreement in subsequent negotiation. Such a selection mechanism is very important because of practicality and efficiency of multi-agent system interactions.

The most prospective partners selection resembles a problem of coalition formation widely studied in game theory and multi-agent interactions. However, the coalition formation problems focus mainly on the decision making models to determine the optimal coalition structure and the division of payoff, with a little devotion to the negotiation partner selection problem. Banerjee and Sen [1] consider a situation where an agent has to choose which partnership to join for a fixed number of interactions. It is assumed that an agent has a model of the likelihood of different outcomes in the form of a probability distribution and the corresponding utility of each partnership. The classical probabilistic decision theory is applied in that approach to calculate the probabilistic expected utility that is the basis for selecting the optimal partnership to join. This approach requires probability distribution that models the likelihood of a particular outcome. To construct such distribution a considerable history of repeated interactions is required. The authors also make a strong assumption that the payoff structure for the partnership is available. Fatima et al [5] also mention the problem of agents selection for negotiation. The authors study the influence of an amount of information about a negotiation partner on the negotiation equilibrium. Assuming specific types of strategies they consider possible outcomes of negotiation based on what information about the opposing agent is available. If there is enough information about the negotiation partner the negotiation outcome may be estimated and more predictable agent can be selected for negotiation. Also, the above approaches, do not take into account multi-attribute behaviour of the agents.

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In [2] the authors propose partners selection mechanism for single attribute negotiation. They consider a situation where the utility function is specified for the whole system of potential partners. In this paper we extend this approach to multi-attribute negotiation and consider situation were each agent is modelled separately and the utility function is also specified for each agent separately. The proposed approach is based on multidimensional possibilistic case-based reasoning. It employs the principles of possibility based decision theory [3]. The approach allows predicting the possibility of successful negotiation with a particular agent based on its past negotiation behaviour involving multiple attributes. Such possibility is determined for each potential partner and the qualitative expected utility over multi-attribute decision space is derived. The order of potential negotiation partners is constructed from best to worst based on the order of the expected utilities. This method does not assume any particular payoff structure and allows selecting agents based on small sample of historical cases of previous negotiations even if the previous situations are different from the current one. There is some similarity in deriving possibility distribution for a potential partner with construction of the distribution for choosing an appropriate bidding strategy for an agent participating in auction [6][7]. However that application is completely different because the possibility based case-based reasoning is used for determining the successful single attribute bid [6][7].

The remainder of the paper is organized as follows. Section 2 briefly presents some preliminaries including the problem outline and the principles of possibility-based decision theory. The possibilistic case-based decision model of the case-based reasoning for ordering two negotiation partners each with two attributes is detailed in Section 3. Illustrative example of calculations for the two agents with two attributes is presented in Section 4. Finally, Section 5 presents the generalization of the model to multi-attribute multi-agent ordering, and the conclusions and future work are presented in Section 6.

2. PRELIMINARIES

2.1 Problem outline and approach

The main agent (contractor) has a task to compose its service by a means of negotiation with a number of potential partner agents that offer different service characterised by multiple attributes. We consider the problem of selecting most prospective provider agents from a set of potential partners for the subsequent negotiation. The main contractor has to minimize the number of chosen agents simultaneously maximizing its utility. To be able to do this it has to predict their likelihood towards agreement during potential negotiation. The prediction can be based on the history of previous negotiations and the use of possibility theory [3]. The agent performs case-based reasoning that uses a possibilistic reasoning rule stating that: "the more similar are situations the more possible that the outcomes are similar". This approach is suitable in situations when the number of previous cases is small in opposite to the statistical approach that requires vast history. In addition it allows for selecting partners for multi-attribute negotiation. The case-based reasoning is used here because every case is a pair of situation and outcome and the situation has a big influence on the outcome. The possibility theory is also an appropriate tool because of its qualitative nature. The agent has to rely on the quality of the cases and not on the quantity as the probabilistic apporaches. In a situation of multiple identical cases they reveal the same information and therefore the quantity is not so important. The quality of a case is determined by its similarity to current situation and is therefore more informative in situations of sparse and non-indentical cases.

2.2 Possibility based Decision Theory

Let $X = \{x_1, x_2, \ldots, x_p\}$ be set of situations. We have incomplete knowledge about what is the actual situation after making decision d. This uncertainty about the actual situation may be represented by possibility distribution π_d [3]. The function π_d maps the set X to some linear valuation scale V

$$\pi_d : X \rightarrow V$$

We will assume that V is bounded: $sup(V) = 1$ and $inf(V) = 0$. The utility function u encodes preferences over a set of outcomes X by assigning to each x_i a degree of preference

$$u : X \rightarrow U$$

Similarly, $sup(U) = 1$ and $inf(U) = 0$. It is commonly assumed that $U = V$ [8]. The choice of an appropriate decision is equivalent to determining which possibility distribution value of some functional $\mathcal{U}$ is the highest. If an inequality holds: $\mathcal{U}(\pi_d) \leq \mathcal{U}(\pi_{d'})$ then decision d' is preferred over a decision d ($d \preceq d'$). The most popular definitions of the functional $\mathcal{U}$ are optimistic and pessimistic criteria defined as follows:

$$QU^+(\pi|u) = max_{x \in X} min(\pi(x), u(x))$$

$$QU^-(\pi|u) = min_{x \in X} max(1 - \pi(x), u(x))$$

$QU^-(\pi|u)$ and $QU^+(\pi|u)$ are also called the possibility and neccesity measures, respectively [8].

3. POSSIBILISTIC CASE-BASED DECISION MODEL WITH MULTIPLE ATTRIBUTES

To apply the notion of a qualitative expected utility we need to construct a possibility distribution over the multi-attribute decision space describing the possibility of successful negotiation with each of the agents providing components and to specify the utility function of the main contractor. The issues of negotiation are multiple attributes of services (objects) offered by the agents - providers. For the sake of simplicity let consider the main agent negotiates with two other agents over two attributes (the generalized case of multiple agents and multiple attributes will be considered later in this paper). For example the attributes under negotiation may be the availability and price. In the paper we consider all attributes rescaled to an interval $[0, 1]$. Let $(a_1^t, p_1^t, a_2^t, p_2^t)$ denote the negotiation outcome requirement of the main agent in a situation t where $a_j^t \in [0, 1]$ is the requirement of a value of the first attribute from an agent j and $p_j^t \in [0, 1]$ is the requirement of a value of the second attribute from an agent j. Therefore, our decision space is a cartesian product defined by a hypercube $[0, 1] \times [0, 1] \times [0, 1] \times [0, 1]$. Each stored historical case i is a pair of the situation s^i and the outcome o^i. Every situation consists of eight values: $s^i = (a_1^i, p_1^t, a_2^i, p_2^i, c_0, c_1, c_2, c_3)$ and every outcome consists of four values $o^i = (\Delta a_1^i, \Delta a_2^i, \Delta p_1^i, \Delta p_2^i)$ where:

- a_1^i, p_1^i is the initial first and second attribute requirement of the main agent in the i-th negotiation with the first agent
- a_2^i, p_2^i is the initial first and second attribute requirement of the main agent in the i-th negotiation with the second agent
- $c_0^i, c_1^i, c_2^i, c_3^i$ parameters specifying main agent's utility function during the i-th negotiation
- $\Delta a_1^i, \Delta p_1^i$ values of the first and second attribute agreements after the i-th negotiation with the first agent
- $\Delta a_2^i, \Delta p_2^i$ values of the first and second attribute agreements after the i-th negotiation with the second agent

The main contractor's utility function may for example be defined as a weighted sum of two utilities:

$$\nu(x,y) = w_1\nu_1(x) + w_2\nu_2(y)$$

The utility function ν_k specifies the preferences about the value of kth attribute obtained from the agent and may for example have a form:

$$\nu_k(x) = p(x)$$

The function p is a monotone function and its monotonicity depends on a character of the attribute. In a case of the availability it is increasing and may be defined as follows:

$$p(x) = \begin{cases} 1 & \text{if } x > c_1^t \\ \frac{x-c_0^t}{c_1^t-c_0^t} & \text{if } c_0^t \le x \le c_1^t \\ 0 & \text{if } x < c_0^t \end{cases}$$

For our calculations we assume that a history H^t of some $t-1$ negotiations is given as follows:

$$H^{t-1} = \{r^i = (s^i, o^i); i \le t-1\}$$

An example of a history is presented in Table 1.

We reason about the current behaviour of a potential partner based on its previous behaviour. Therefore the core of our model is a possibilistic principle: *"the more similar are the situation description attributes, the more possible that the outcome attributes are similar"*. We predict the possibility of successful negotiation based on the historical data in a form of the possibility distribution $\mu^t(y)$:

$$\mu^t(y) = Max_{(s^i,o^i)\in H^{t-1}} S(s^i, s^t) \otimes P(o^i, y) \qquad (1)$$

where S and P are similarity relations [4] comparing situations and outcomes, respectively. $\otimes$ is a t-norm [4] which can be defined: $a \otimes b = Min(a,b)$. In a case of such attributes like the availability or price there is an additional condition that should be satisfied. If we predict that an agent agrees on some level of availability with some degree of possibility it should also be able to agree on every smaller level of this attribute with at least the same degree of possibility. For the price it is reverse, if an agent agrees to sell a service for a price p with some degree of possibility it is assumed that it will agree on every higher price with at least the same degree of possibility. Therefore we need to perform some modification of the function obtained by formula (1). The modification will be described later. The function before modification will be called a density of possibility distribution and function after modification will be called a possibility distribution.

3.1 Case-based reasoning

We consider a situation in which there are no correlations between agents - providers. For each agent separately the possibility distribution describing the possibility of successful negotiation is calculated. For sake of simplicity we consider a case with two agents and two attributes. After applying the possibilistic principle for the first agent A_1 we obtain a density function:

$$\mu_1^t(x_1,y_1) = Max_{(s^i,o^i)\in H^{t-1}}$$
$$S((a_1^i, p_1^i, c_0^i, c_1^i, c_2^i, c_3^i), (a_1^t, p_1^i, c_0^t, c_1^t, c_2^i, c_3^i))$$
$$\otimes P(\Delta a_1^i, \Delta p_1^i, x_1, y_1)$$

Analogously for the second agent A_2:

$$\mu_2^t(x_2,y_2) = Max_{(s^i,o^i)\in H^{t-1}}$$
$$S((a_2^i, p_2^i, c_0^i, c_1^i, c_2^i, c_3^i), (a_2^t, p_2^i, c_0^t, c_1^t, c_2^i, c_3^i))$$
$$\otimes P(\Delta a_2^i, \Delta p_2^i, x_2, y_2)$$

Because of two attributes the functions are two dimensional and the decision space for each agent is a square: $[0,1] \times [0,1]$. Below we give a full description of calculations of the distributions. First we discretize the decision space for the first and second agents. We specify the number of m discrete points for the first attribute interval of the first agent and number of points q for the second attribute interval of the first agent. Analogous discretization is done for the decision space of the second agent.

- Agent A_1,
  - first attribute: $\eta_k \in \{\eta_1, \eta_2, \ldots, \eta_m\} \subset [0,1]$
  - second attribute: $\kappa_l \in \{\kappa_1, \kappa_2, \ldots, \kappa_q\} \subset [0,1]$
- Agent A_2,
  - first attribute: $\theta_k \in \{\theta_1, \theta_2, \ldots, \theta_p\} \subset [0,1]$
  - second attribute: $\lambda_l \in \{\lambda_1, \lambda_2, \ldots, \lambda_n\} \subset [0,1]$

The corresponding discrete decision spaces are defined as follows:

- Agent A_1: $(\eta_k, \kappa_l) \in \{\eta_1, \eta_2, \ldots, \eta_m\} \times \{\kappa_1, \kappa_2, \ldots, \kappa_q\} \subset [0,1]^2$
- Agent A_2: $(\theta_k, \lambda_l) \in \{\theta_1, \theta_2, \ldots, \theta_p\} \times \{\lambda_1, \lambda_2, \ldots, \lambda_n\} \subset [0,1]^2$

Now we calculate a matrix $P_1^i = P_1(\Delta a_1^i, \Delta p_1^i)$ for the outcome $(\Delta a_1^i, \Delta p_1^i)$ of every situation i in the history corresponding to the first agent as follows:

$$P_1^i = P_1(\Delta a_1^i, \Delta p_1^i) = [P(\Delta a_1^i, \Delta p_1^i, \eta_k, \kappa_l)]_{k\le m, l\le q}$$

This calculations can be done iteratively, i.e. every P_1^i can be calculated as a auxiliary vector after negotiation number i. Analogically we calculate the vector $P_2^i = P_2(\Delta a_2^i, \Delta p_2^i)$ corresponding to the second agent:

$$P_2^i = P_2(\Delta a_2^i, \Delta p_2^i) = [P(\Delta a_2^i, \Delta p_2^i, \theta_k, \lambda_l)]_{k\le p, l\le n}$$

Table 1: **Example of history with five cases and the current situation**

i	s^i								o^i			
	a_1^i	p_1^i	a_2^i	p_2^i	c_0^i	c_1^i	c_2^i	c_3^i	Δa_1^i	Δp_1^i	Δa_2^i	Δp_2^i
1	0.9	0.4	0.8	0.4	0.2	0.6	0.4	1	0.45	0.4	0.6	0.65
2	0.6	0.4	0.6	0.3	0.35	0.5	0.3	0.9	0.5	0.5	0.4	0.4
3	0.75	0.45	0.6	0.4	0.25	0.7	0.2	1	0.5	0.5	0.5	0.55
4	0.95	0.5	0.97	0.5	0.5	0.8	0.7	0.9	0.7	0.6	0.8	0.6
5	0.9	0.4	0.8	0.4	0.2	0.6	0.4	1	0.7	0.5	0.3	0.4
t	0.9	0.4	0.8	0.4	0.2	0.6	0.4	1				

where P is the similarity relation. Having the sequences of auxiliary matrices: $\{P_1^i\}_{i\le t-1}$ and $\{P_2^i\}_{i\le t-1}$ we calculate for our current situation $s^{\bar{i}} = (a_1^i, p_1^i, a_2^i, p_2^i, c_0^i, c_1^i, c_2^i, c_3^i)$ the sequences of comparisons with all situations in the history for the first agent:

$$\{S_1^i\}_{i\le t-1} =$$
$$\{S((a_1^i, p_1^i, c_0^i, c_1^i, c_2^i, c_3^i), (a_1^t, p_1^t, c_0^t, c_1^t, c_2^t, c_3^t))\}_{i\le t-1}$$

and for the second one:

$$\{S_2^i\}_{i\le t-1} =$$
$$\{S((a_2^i, p_2^i, c_0^i, c_1^i, c_2^i, c_3^i), (a_2^t, p_2^t, c_0^t, c_1^t, c_2^t, c_3^t))\}_{i\le t-1}$$

Having the sequence of vectors P_1^i and the sequence of values S_1^i we now make an aggregation $S_1^i \otimes P_1^i$ for every $i \le t-1$ as follows:

$$S_1^i \otimes P_1^i = [S^i \otimes P((\Delta a_1^i, \Delta p_1^i), (\eta_k, \kappa_l))]_{k\le m, l\le q}$$

The same for the second agent:

$$S_2^i \otimes P_2^i = [S^i \otimes P((\Delta a_2^i, \Delta p_2^i), (\theta_k, \lambda_l))]_{k\le p, l\le n}$$

The matrices are calculated for every case i in the history H^{t-1}. After obtaining all the matrices we can finaly calculate the functions μ_1^t and μ_2^t by aggregating all the vectors (for sake of notation simplicity we state only i instead of (s^i, o^i)):

$$\begin{aligned} \mu_1^t &= [\mu_1^t(\eta_k, \kappa_l)]_{k\le m, l\le q} = \\ &= [Max_i S_1^i \otimes P(\Delta a_1^i, \Delta p_1^i, \eta_k, \kappa_l)]_{k\le m, l\le q} \end{aligned}$$

The same for the function μ_2^t corresponding to the second agent:

$$\begin{aligned} \mu_2^t &= [\mu_2^t(\theta_k, \lambda_l)]_{k\le p, l\le n} = \\ &= [Max_i S_2^i \otimes P(\Delta a_2^i, \Delta p_2^i, \theta_k, \lambda_l)]_{k\le p, l\le n} \end{aligned}$$

The functions μ_1^t and μ_2^t are called densities of possibility distributions. These functions are predictions about the likelihood of the agents to agree on some levels of the attributes. The obtained functions may also be expressed in the form of a possibility measure Π as follows:

$$\Pi(\{o_j^t\}) = \Pi(\{\Delta a_j^i, \Delta p_j^i\}) = \mu_j^t(\Delta a_j^i, \Delta p_j^i)$$

The specific feature of an increasing attribute like the availability is that if an agent agrees on some value of the attribute with a level of satisfaction α it should also agree on every higher value with a level of satisfaction at least α. In case of price it is reverse because the price attribute is decreasing. Therefore, we can modify the function μ_j^t for each agent-j in order to obtain function π_j^t that is monotone in the sense of Pareto order. The new functions π_j^t are called possibility distributions and can be obtained through the following transformation for both agents:

$$\begin{aligned} \pi_1^t(o_1^t) &= \Pi([\Delta a_1^t, 1] \times [0, \Delta p_1^t]) = \\ &= sup\{\mu_2^t(\eta_k, \kappa_l) \,|\, \eta_k \ge \Delta a_1^t, \kappa_l \le \Delta p_1^t\} = \\ &= sup\{sup\{\mu_1^t(\eta_k, \kappa_l)\, \eta_k \ge \Delta a_1^t\}\, \kappa_l \le \Delta p_1^t\} \end{aligned}$$

$$\begin{aligned} \pi_2^t(o_2^t) &= \Pi([\Delta a_2^t, 1] \times [0, \Delta p_2^t]) = \\ &= sup\{\mu_2^t(\eta_k, \kappa_l) \,|\, \eta_k \ge \Delta a_2^t, \kappa_l \le \Delta p_2^t\} = \\ &= sup\{sup\{\mu_2^t(\eta_k, \kappa_l)\, \eta_k \ge \Delta a_2^t\}\, \kappa_l \le \Delta p_2^t\} \end{aligned}$$

Having the possibility distribution of each potential partner we can calculate the possibilistic expected utility for each of them. The expected utility is the predicted level of satisfaction of an agreement in potential negotiation for both sides. The expected utility is derived by aggregation of the possibility distribution π and utility function ν as follows:

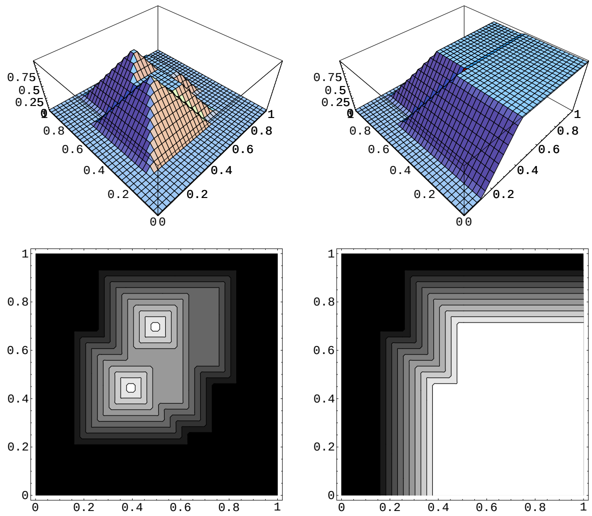
$$e_1 = Max_{(x_1,y_1)\in[0,1]^2} \pi_1^t(x_1, y_1) \otimes \nu^t(x_1, y_1)$$

$$e_2 = Max_{(x_2,y_2)\in[0,1]^2} \pi_2^t(x_2, y_2) \otimes \nu^t(x_2, y_2)$$

The higher the value of e_j the higher chance of succcesful negotiation with an agent j. Therefore, if $e_1 < e_2$ than the negotiation with the second agent is more beneficial than with the first one. Later, we will generalize this criterion to a multi-agent and multi-attribute scenario.

4. EXAMPLE OF CALCULATIONS

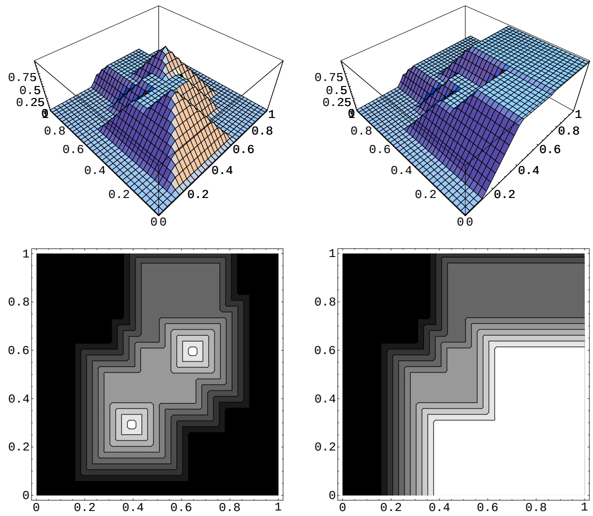
Now we present sample calculations for the data from Table 1. The Figure 1 presents results for the first agent. Our current case is $(a_1^t, p_1^t, c_0^t, c_1^t, c_2^t, c_3^t) = (0.9, 0.4, 0.2, 0.6, 0.4, 1)$. In Table 1 we can observe the full similarity between this case and two cases in the history: s^1 and s^5. The outcomes of these cases are respectively: $(\Delta a_1^1, \Delta p_1^1) = (0.45, 0.4)$ and $(\Delta a_1^5, \Delta p_1^5) = (0.7, 0.5)$. Therefore, in these points the density function reaches the maximal value 1. The similarity to other situations in the history is weaker but it is still visible in the graph and the matrix that around points $(0.5, 0.5)$ and $(0.7, 0.6)$ the values of the function are quite high reaching a value 0.6. That is because these points are outcomes of other situations in the history: s^2, s^3 and s^4 that have degrees of similarity to the current situation equal to 0.6. Figure 1 also presents the possibility distribution obtained by transformation of the density function. Figure 2 presents the results for the second agent. The current situation for this agent is $(a_2^t, p_2^t, c_0^t, c_1^t, c_2^t, c_3^t) = (0.8, 0.4, 0.2, 0.6, 0.4, 1)$. In this case we can also observe two strong maxima reaching a value 1 for points $(0.6, 0.65)$ and $(0.3, 0.4)$. That is because these points are outcomes of the situations s^1 and s^5 that are again fully similar to our current situation. The density



$$\mu_1^t = \begin{pmatrix} 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \\ 0. & 0.2 & 0.4 & 0.4 & 0.4 & 0.2 & 0.2 & 0. & 0. & 0. \\ 0. & 0.2 & 0.6 & 0.8 & 0.6 & 0.6 & 0.2 & 0. & 0. & 0. \\ 0. & 0.2 & 0.6 & 0.8 & 0.6 & 0.6 & 0.2 & 0.2 & 0. & 0. \\ 0. & 0.2 & 0.4 & 0.6 & 0.6 & 0.6 & 0.4 & 0.2 & 0. & 0. \\ 0. & 0. & 0.2 & 0.6 & 1. & 0.6 & 0.4 & 0.2 & 0. & 0. \\ 0. & 0. & 0.2 & 0.6 & 0.6 & 0.6 & 0.4 & 0.2 & 0. & 0. \\ 0. & 0. & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0. & 0. \\ 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. \end{pmatrix}$$

$$\pi_1^t = \begin{pmatrix} 0 & 0.2 & 0.6 & 0.8 & 1. & 1. & 1. & 1. & 1. & 1. \\ 0 & 0.2 & 0.6 & 0.8 & 1. & 1. & 1. & 1. & 1. & 1. \\ 0 & 0.2 & 0.6 & 0.8 & 1. & 1. & 1. & 1. & 1. & 1. \\ 0 & 0.2 & 0.6 & 0.8 & 1. & 1. & 1. & 1. & 1. & 1. \\ 0 & 0.2 & 0.6 & 0.8 & 1. & 1. & 1. & 1. & 1. & 1. \\ 0 & 0.2 & 0.4 & 0.6 & 1. & 1. & 1. & 1. & 1. & 1. \\ 0 & 0 & 0.2 & 0.6 & 1. & 1. & 1. & 1. & 1. & 1. \\ 0 & 0 & 0.2 & 0.6 & 0.6 & 0.6 & 0.6 & 0.6 & 0.6 & 0.6 \\ 0 & 0 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Figure 1: Density of possibility distribution for the first agent and its possibility distribution



$$\mu_2^t = \begin{pmatrix} 0. & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0. & 0. & 0. & 0. \\ 0. & 0.2 & 0.6 & 0.6 & 0.6 & 0.2 & 0. & 0. & 0. & 0. \\ 0. & 0.2 & 0.6 & 1. & 0.6 & 0.2 & 0.2 & 0. & 0. & 0. \\ 0. & 0.2 & 0.6 & 0.6 & 0.6 & 0.6 & 0.4 & 0.2 & 0. & 0. \\ 0. & 0.2 & 0.6 & 0.6 & 0.6 & 0.6 & 0.6 & 0.4 & 0. & 0. \\ 0. & 0.2 & 0.2 & 0.4 & 0.6 & 0.8 & 0.8 & 0.4 & 0. & 0. \\ 0. & 0. & 0. & 0.2 & 0.4 & 0.6 & 0.6 & 0.4 & 0. & 0. \\ 0. & 0. & 0. & 0.2 & 0.4 & 0.4 & 0.4 & 0.2 & 0. & 0. \\ 0. & 0. & 0. & 0.2 & 0.4 & 0.4 & 0.4 & 0.2 & 0. & 0. \\ 0. & 0. & 0. & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0. & 0. \end{pmatrix}$$

$$\pi_1^t = \begin{pmatrix} 0 & 0.2 & 0.6 & 1. & 1. & 1. & 1. & 1. & 1. & 1. \\ 0 & 0.2 & 0.6 & 1. & 1. & 1. & 1. & 1. & 1. & 1. \\ 0 & 0.2 & 0.6 & 1. & 1. & 1. & 1. & 1. & 1. & 1. \\ 0 & 0.2 & 0.6 & 0.6 & 0.6 & 0.8 & 0.8 & 0.8 & 0.8 & 0.8 \\ 0 & 0.2 & 0.6 & 0.6 & 0.6 & 0.8 & 0.8 & 0.8 & 0.8 & 0.8 \\ 0 & 0.2 & 0.2 & 0.4 & 0.6 & 0.8 & 0.8 & 0.8 & 0.8 & 0.8 \\ 0 & 0 & 0 & 0.2 & 0.4 & 0.6 & 0.6 & 0.6 & 0.6 & 0.6 \\ 0 & 0 & 0 & 0.2 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 \\ 0 & 0 & 0 & 0.2 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 \\ 0 & 0 & 0 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \end{pmatrix}$$

Figure 2: Density of possibility distribution for the second agent and its possibility distribution

function reaches value 0.6 around the point $(0.5, 0.55)$ that is the outcome of the situation s^3. The reason for that is of course similarity of the current situation and s^3 at a level 0.6. In an area of the point $(0.8, 0.6)$ the density function reaches value 0.4 that is caused by a weak but still visible similarity of the current situation and the situation s^4 that has the outcome $(0.8, 0.6)$. The possibility distributions of both agents have to be aggregated with utility function in order to calculate the expected utilities. Figure 3 present the possibility distribution of the first agent aggregated with the utility function using a T-norm: $\otimes = min$. We need to calculate the values of the expected utilities that are described by formulas:

$$e_1 = Max_{(x_1,y_1)\in[0,1]^2}\pi_1^t(x_1, y_1) \otimes \nu^t(x_1, y_1)$$

$$e_2 = Max_{(x_1,y_1)\in[0,1]^2}\pi_2^t(x_1, y_1) \otimes \nu^t(x_1, y_1)$$

We can see from Figure 3 that the highest value reached by the function $\pi \otimes \nu$ is 0.92. Therefore, $e_1 = 0.92$. From Figure 4 we can read the value of the expected utility for the second agent that is 0.8. Therefore, $e_2 = 0.8$. Because $e_1 > e_2$ the chance of a successful agreement with the first agent is higher then with the second one.

5. GENERALIZED MULTI-ATTRIBUTE CASE

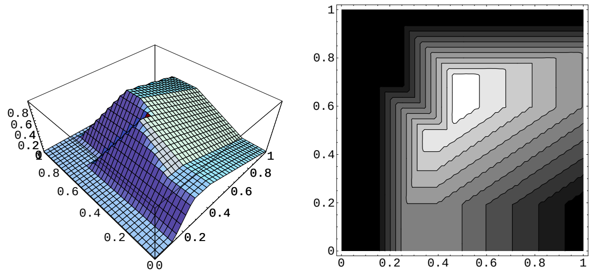
In this section we generalize the selection of most prospective agents for the multi-agent and multi-attribute system. Using the notion of qualitative expected utility we order the set of candidates for negotiation $A_1, A_2, \ldots, A_n$. In this case we have h attributes. The utility function is specified over a set of these h attributes and for example can be calculated as a weighted sum of the utilities ν_k for the particular attributes as follows:

$$\nu(z_1, z_2, \ldots, z_h) = w_1\nu_1(z_1) + w_2\nu_2(z_2) + \cdots + w_h\nu_h(z_h)$$

For each of n agents we construct a h dimensional density distribution function μ_j by case-based reasoning and transform it to a possibility distribution π_j. As previously each historical case i consists of a situation $\bar{s}^i$ and an outcome $\bar{o}^i$. In a multi-attribute scenario the situation i and the outcome i for the specific agent j have a form:

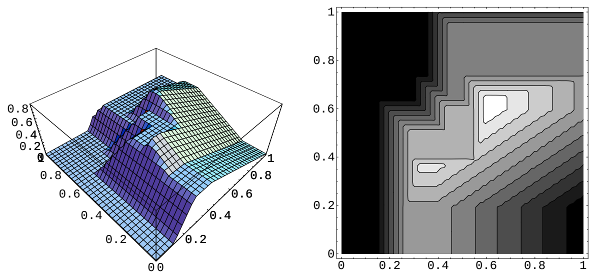
$$\bar{s}^{ij} = (a_1^{ij}, a_2^{ij}, \ldots, a_h^{ij}, c_0^{ij}, c_1^{ij}, \ldots, c_{2h-1}^{ij})$$

$$\bar{o}^{ij} = (\Delta a_1^{ij}, \Delta a_2^{ij}, \ldots, \Delta a_h^{ij})$$



$$\begin{pmatrix}
0. & 0.2 & 0.5 & 0.5 & 0.42 & 0.33 & 0.25 & 0.17 & 0.08 & 0. \\
0. & 0.2 & 0.5 & 0.5 & 0.42 & 0.33 & 0.25 & 0.17 & 0.08 & 0. \\
0. & 0.2 & 0.6 & 0.62 & 0.54 & 0.46 & 0.38 & 0.29 & 0.21 & 0.12 \\
0. & 0.2 & 0.6 & 0.75 & 0.67 & 0.58 & 0.5 & 0.42 & 0.33 & 0.25 \\
0. & 0.2 & 0.6 & 0.8 & 0.79 & 0.71 & 0.62 & 0.54 & 0.46 & 0.38 \\
0. & 0.2 & 0.4 & 0.6 & 0.92 & 0.83 & 0.75 & 0.67 & 0.58 & 0.5 \\
0. & 0. & 0.2 & 0.6 & 0.92 & 0.83 & 0.75 & 0.67 & 0.58 & 0.5 \\
0. & 0. & 0.2 & 0.6 & 0.6 & 0.6 & 0.6 & 0.6 & 0.58 & 0.5 \\
0. & 0. & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \\
0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0. & 0.
\end{pmatrix}$$

Figure 3: The function $\pi_1 \otimes \nu$



$$\begin{pmatrix}
0. & 0.2 & 0.5 & 0.5 & 0.42 & 0.33 & 0.25 & 0.17 & 0.08 & 0. \\
0. & 0.2 & 0.5 & 0.5 & 0.42 & 0.33 & 0.25 & 0.17 & 0.08 & 0. \\
0. & 0.2 & 0.6 & 0.62 & 0.54 & 0.46 & 0.38 & 0.29 & 0.21 & 0.12 \\
0. & 0.2 & 0.6 & 0.6 & 0.6 & 0.58 & 0.5 & 0.42 & 0.33 & 0.25 \\
0. & 0.2 & 0.6 & 0.6 & 0.6 & 0.71 & 0.62 & 0.54 & 0.46 & 0.38 \\
0. & 0.2 & 0.2 & 0.4 & 0.6 & 0.8 & 0.75 & 0.67 & 0.58 & 0.5 \\
0. & 0. & 0. & 0.2 & 0.4 & 0.6 & 0.6 & 0.6 & 0.58 & 0.5 \\
0. & 0. & 0. & 0.2 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 \\
0. & 0. & 0. & 0.2 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 & 0.4 \\
0. & 0. & 0. & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2
\end{pmatrix}$$

Figure 4: The function $\pi_2 \otimes \nu$

The function μ_j^t is obtained:

$$\begin{aligned}
\mu_j^t(v_1, v_2, \ldots, v_h) &= Max_{(\bar{s}^{ij}, \bar{o}^{ij}) \in H^{t-1}} S(\bar{s}^{ij}, \bar{s}^{tj}) \\
&\otimes \; P(\bar{o}^{ij}, (v_1, v_2, \ldots, v_h))
\end{aligned}$$

then it is tranformed to π_j^t

$$\begin{aligned}
\pi_j^t(z_1, z_2, \ldots, z_h) &= sup_{(z_1, z_2, \ldots, z_h) \preceq (v_1, v_2 \ldots, v_h)} \\
&\quad \mu_j^t(v_1, v_2, \ldots, v_h)
\end{aligned}$$

where $\preceq$ is the Pareto order over a decision space. For each agent we calculate the possibilistic expected utility as follows:

$$\begin{aligned}
e_j &= Max_{(z_1, z_2, \ldots, z_n) \in [0,1]^h} \pi_j^t(z_1, z_2, \ldots, z_h) \\
&\otimes \; \nu^t(z_1, z_2, \ldots, z_h)
\end{aligned}$$

We obtain a sequence of the expected utilities $(e_1, e_2, \ldots, e_n)$. The ordering of these values from the highest to the lowest gives us an appropriate ordering of the prospective agents. The further in the order the agent stands the less beneficial is the negotiation with it according to our prediction.

6. CONCLUSIONS AND FUTURE WORK

The possibility based case-based reasoning allows constructing the prediction about agent's behaviour in potential multi-attribute negotiation in a form of the possibility distribution. It can be derived from a history of previous interactions. The constructed distribution is used to calculate the chance of a successful agreement in a form of the expected utility. This approach gives us finally ordering of the potential partners. The ordering tells with whom to negotiate first and with whom later. In our future work we will consider some variations of our model allowing to model the whole system of agents with one joint possibility distribution. Such approach is useful in situations where the utility is specified for the whole system of agents and there are some dependencies among agents. Our future work will also include integration the selecting agents component with the rest of a framework currently build for discovery and negotiation of composite service executions. We will also test the component with different parameters of similarity relations. The optimization of these parameters may be required. The future work will also inlcude the problem of computational complexity.

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