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DOPPONENT: A Socially Efficient Preference Model of Opponent in Bilateral Multi Issue Negotiations

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ABSTRACT

During the last decades, opponent modeling techniques, utilized to improve the negotiation outcome, have sparked interest in the negotiation research community. In this study, we first investigate the applicability of nearest neighbor method with different distance functions in modeling the opponent's preferences. Then, we introduce a new distance-based model to extract the opponent's preferences in a bilateral multi issue negotiation session. We devise an experiment to evaluate the efficiency of our proposed model in a real negotiation setting in terms of a number of performance measures.

1 Introduction

Automated negotiation is a process in which two or more agents collaborate to settle an agreement on one or more issues by exchanging offers and counter offers. Automated bilateral multi issue *closed* negotiation is a specific kind of negotiation in which multiple issues are being negotiated by only two agents and the preferences of the agents are considered as private information. In such negotiations in which the negotiating parties have *incomplete information* regarding the preferences of each other, estimating the opponent's preferences can improve the negotiation outcome considerably [1, 2]. In other words, an efficient opponent model not only would cause the agents to reach an early agreement, but it would also be helpful in increasing the satisfaction of the negotiating parties from the negotiation outcome by improving the utility of the agreement both from individual and social perspectives.

In spite of the variety, most of the opponent modeling techniques only use a limited set of learning methods [1]. This can be attributed to the limitations and restrictions of the negotiation problem. Firstly, all training instances (i.e., offers) are not available at the same time in a negotiation session. On the other hand, traditional learning methods often include two non-overlapping phases, which are learning phase, and prediction phase. Therefore, traditional learning methods could not be easily employed in the negotiation problem, and they should be adapted to learn incrementally. Secondly, the learning problem in automated bilateral multi issue negotiations by essence is an unsupervised problem. That is because the offers received from the opponent in a negotiation session do not include the utility values from the opponent's point of view. So the agent has to either carry out an unsupervised learning, or somehow estimate the utility values of the bids, and then use a model based on supervised learning. Thirdly, in order to be able to extract the preferences of the opponent, models

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have to make some assumptions regarding the opponent's behavior [3] such as: (1) the concession of the opponent follows a particular function, (2) the first bid made by the opponent is the most preferred bid, (3) there is a direct relationship between the preference of an issue and the number of times its value is significantly changed, and (4) there is a direct relationship between the preference of a value and the frequency it is offered. Regarding these limitations and difficulties in automated bilateral multi issue negotiations with incomplete information, in this paper we propose a new preference model of the opponent, based on the concepts underlying the *nearest neighbor learning* algorithm (DOPPONENT). This model enables the agents to make more socially and individually efficient agreements in less negotiation time than those the agents would possibly reach without using such a model. To incorporate the proposed opponent model into a complete negotiation strategy, the BOA framework [4] which is devised for decoupling the components of a negotiation strategy is used.

The remainder of this paper is organized as follows. In Section 2, the BOA framework is introduced. In Section 3, the related works in opponent modeling are briefly presented. Section 4 introduces the general negotiation setting in which the proposed opponent model is utilized. Section 5 investigates the applicability of nearest neighbor method in modeling the preferences of the opponent when the agent has access to different levels of information about the opponent. DOPPONENT, the proposed distance based algorithm, is presented in Section 6. In Section 7, the results of the experiments are presented. Section 8 concludes the paper with introducing the possible future directions of this research.

2 Negotiation Framework

Recently, with the emergence of the International Automated Negotiating Agents Competition (ANAC) [5] many new negotiation strategies have been developed. Most of the existing complicated negotiation agents are comprised of a set of separate modules which cooperatively accomplish the negotiation task. Three constituting modules can be generally distinguished in a negotiation agent [4]: (1) Bidding Strategy, (2) Acceptance Strategy, and (3) Opponent Model. These modules work together within a BOA framework and comprise the negotiation strategy. The three components are depicted in Figure 1 and briefly explained below:

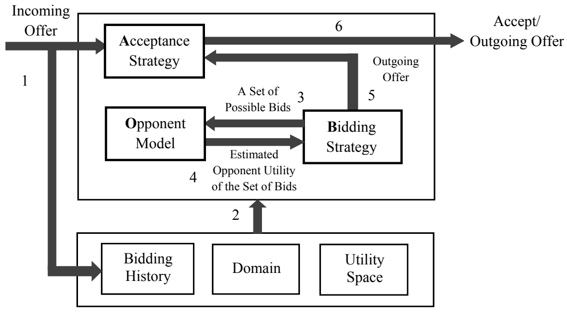

Figure 1. The BOA framework negotiation flow (adapted from Baarslag et al. [4])

- *Bidding Strategy* is a function which maps a negotiation state into a bid [1].
- *Opponent Model* (learning) is a function which maps a given bid into a utility value.
- *Acceptance strategy* is a Boolean function which maps a given bid into a Boolean value. The Boolean value determines the acceptability of the input bid.

According to the BOA framework a negotiation strategy functions as follows [4]: The agent receives a new bid from the opponent and this new bid is directly given to the acceptance strategy module, and the opponent's bidding history is updated (step 1 and step 2). The bidding strategy component then finds a set of candidate bids with equal utility values for the agent, and sends them to opponent model module. The opponent model module then estimates the utility values of those bids in the opponent's utility space and returns them to the bidding strategy component (step 3 and step 4). The bidding strategy component then selects one of the candidate bids according to an opponent model strategy (for example best bid is chosen) and sends the selected bid to the acceptance strategy module (step 5). The acceptance strategy module then decides whether the recently received bid is acceptable or not. If the new bid is acceptable, then this module forwards an accept message. Otherwise, it forwards the bid received from the bidding strategy component to the opponent (step 6).

In this paper we use the BOA framework to incorporate the proposed opponent model into a complete functioning negotiation strategy. This framework enables the evaluation of the proposed model using different bidding strategy and acceptance strategy components.

3 Related Works

Actually, opponent modeling techniques could be used to learn different aspects of the opponent [1]. For example, Jazayeriy et al. [6] proposed a model to extract the issue weight values of the opponent. This model simply assumes that all the issues are conflicting meaning that increasing the utility of an issue for one agent would decrease the utility of that issue for the opponent, and vice versa. They also simply assume that the agents are following time dependent bidding strategies. Another model proposed by Zhang et al. [7] learns the opponent's preference over negotiation issues. This model uses Bayesian learning to extract the issue weight values from the bid history of the opponent. The constructed model is then incorporated into a trade-off counter offer proposition algorithm, which proposes mutually beneficial bids for both agents in the negotiation. This model also assumes that all issues are conflicting, so the hypothesis space would only be limited to all possible orders of negotiation issue weights. Similar to the previous models, this model also assumes that opponent follows a time dependent concession strategy [8] with known parameters. There are other models which estimate the preference order of existing bids in the outcome space from the opponent's point of view (e.g. [9–11]). These models consider the hypothesis space to include all possible preference orders of the negotiation issues as well as evaluation values of each negotiation issue, and then incrementally update the probability values throughout the negotiation session. For example, the model proposed by Hindriks et al [9] estimates the utility function of the opponent using the Bayesian formula. Unlike the model proposed by Zhang et al. [7] which only includes issue weight orders, in this model the hypothesis space encompasses both evaluation functions and issue weight orders. Some other models try to learn the bidding strategy of the opponent. As an instance, the model proposed by Yu et al. [12] uses regression analysis to estimate the bidding strategy of the opponent. This model receives the bid history of the opponent and estimates the utility of the next opponent bid in the agent's own utility space.

4 Negotiation Setting

Before starting to explain DOPPONENT in detail, we first introduce the negotiation setting in which the agents negotiate and more importantly use opponent modeling to learn the preferences of the other party. The setting we use is consistent with other state of the art in the field of automated negotiations (e.g. [4, 5, 13–15]). In this setting, the agents alternately exchange bids. To regulate the interaction that takes place between negotiating parties and define the rules of how and when proposals can be exchanged, the *alternating offers protocol* is used [14, 16]. Negotiation is *bilateral*, meaning that exactly two parties are negotiating over a set of *issues*, and each issue is associated with a set of possible discrete values. The agents repeatedly exchange offers in successive rounds, until either a mutually acceptable outcome or the deadline is reached. The negotiation *deadline* is reached after a specified number of rounds N are passed. *Reservation value* is defined as the minimum acceptable utility for an agent. The agents obtain their reservation values when a break off happens. Therefore, the agents try to reach an agreement before the deadline is reached. A negotiation *session* takes place in a negotiation *scenario*, which consists of a negotiation *domain* (or alternatively referred to as an *outcome* space) and two *preference profiles* (or alternatively called *utility* spaces) one for each negotiating agent. The negotiation domain which is denoted by Ω specifies all the possible bids that the agents can send or receive. Each *bid* or possible outcome is a mapping of every issue to a value [14]. A preference profile on the other hand consists of a *utility function* $U(O)$ which maps each possible bid ($O \in \Omega$) to a value in the range [0,1]. Unlike the negotiation domain which is publicly known for both negotiating parties, preference profile is private for each agent, so the agents do not have any information regarding the *weights* and *evaluation values* associated with the preference profile of one another.

In linear multi issue negotiations, the utility of a bid can be computed as a weighted sum of the utilities associated with the values of each issue [9, 17–19]. According to this, the utility function ($U(O)$) is a *linear additive function* that is defined by a set of weights W_i, and the corresponding evaluation functions or evaluation values $U_i(O_i)$ for each of n issues. This function is calculated by Equation (1):

$$U(O) = \sum_{i=1}^{n} W_i U_i(O_i) \tag{1}$$

where, O_i is the value of i^{th} issue of the bid O, and n is the number of issues.

In this negotiation setting, the agents use Equation (1) to compute the utility of a given bid. We also assume that the agent is only allowed to use the bids exchanged during a session to learn the preferences of the opponent; that is, learning between sessions is not authorized.

5 Opponent Preferences Modeling Using Nearest Neighbor Method

Before using the nearest neighbor method to model the preferences of an opponent in bilateral multi issue negotiations, we first need to investigate the ability of this method in extracting the preferences of an opponent. The agent may have access to either the value of the issue weights (or their orders) or the evaluation values for each negotiation issue (or their orders) or both. This section investigates the applicability of different distance functions using different levels of such information about the opponent, in a number of negotiation domains.

In *nearest neighbor* (NN) method, the output label value of a new instance is determined based on the output values of its nearest neighbor instances [20, 21]. The nearest neighbor method assumes that the closer the attribute values of two training instances, the closer their output values would be. In other words, this algorithm as its basic assumption, assumes that there is a direct relationship between the distance value of two training examples and the difference of their output values. So provided that there is such a relationship between the attributes and the output label in a specific dataset, this method could be successfully used to predict the output label value of a new instance. So the best function to calculate the distance between two instances is the function which better measures the difference value between the output values of those two instances.

In order to examine the applicability of nearest neighbor method in the negotiation domains, we calculate the *Pearson Correlation* between the distance value of every two bids and the difference of their utility values in a number of negotiation domains used in ANAC competitions.

In order to calculate the distance between two bids, we consider two different states: complete and incomplete information states. In the *complete information* state, the agent has complete information about the preference profile of the opponent. In other words, the opponent's weight values, as well as the evaluation function values for all possible values of each negotiation issue are known by the agent. Although this state is unrealistic and never happens in the real world, however it is useful for analytical purposes, since it gives us insight into the best possible scenario that can happen. In the *incomplete information* state, the agent does not have complete information regarding the opponent's preference profile. There can also be multiple sub states for this state. The agent can either have information regarding the exact values for issue weights (or at least the opponent's preference order over negotiation issues), or can have information regarding the evaluation values (or at least the opponent's preference order over evaluation values for all possible values of each negotiation issue), or can even have both information. In the following sections, we consider these states in more detail.

5.1 Complete information

When the agent has complete information regarding the preference profile of the opponent, it can easily calculate the real difference between the utility values of two bids, using the utility function of the opponent. In other words, in this state we have:

$$\begin{aligned} x &= distance\left(O^1, O^2\right) \\ &\qquad = \sum\nolimits_{i=1}^{n} W_i \times \left(U_i(O_i^1) - U_i(O_i^2)\right) \\ y &= f\left(x\right) = utility\ \ diff(O^1O^2) = U\left(O^1\right) - U\left(O^2\right) \\ &f\left(x\right) = mx + b \\ &m = 1, \quad b = 0 \end{aligned} \tag{2}$$

where O^1 and O^2 are two arbitrary bids in the outcome space.

This means that when the agent have complete information about the utility function of the opponent, there is a linear relationship (with m=1 and b=0) between the independent variable x and the dependent variable y. The independent variable x contains the bid utility differences which are calculated using the distance function, and the dependent variable y on the other hand comprises real bid utility value differences. In other words, we are concerned with the linear relationship between the estimated preference profile of the opponent, and the real preference profile, while the agent is equipped with different levels of information regarding the opponent's preference profile. So when the agent has complete information about the utility function of the opponent, it can easily calculate the distance between two bids (x), and therefore estimate the real utility difference values ($f(x)$) between those two instances. So assuming that O^1 is the current bid and O^2 is the next candidate bid to be sent to the opponent, if $f(distance(O^1,O^2))$ is greater than zero, the move from the current bid to the next candidate bid will be a *conceder* [1] move, otherwise it will be an *unfortunate* [2] move. Since one of the main goals of an opponent model is preventing the agent from making unfortunate moves, knowing the function $f(x)$ for the agent is of great importance.

5.2 Incomplete information

5.2.1 Complete information regarding evaluation values order, and unknown issue weight values

When the agent doesn't have complete information about the utility function of the opponent, it could only try to estimate the real utility difference values by estimating the utility function of the opponent. So if there is a linear relationship between the two variables x and $f(x)$, the value of $f(x)$ can be easily computed using the calculated value x, and the linear

[1] Decreasing the agent's own utility and increasing opponent's utility.
[2] Decreasing both the agent's own utility and opponent's utility.

relationship between x and $f(x)$. This way, we can estimate the real bid utility value differences, and use the calculated values to prevent the unfortunate moves in a negotiation session. So an easy way to calculate the distance values in this case is as follows:

$$x = distance(O^1, O^2)$$
$$= \frac{1}{n}\sum_{i=1}^{n} sign \times \frac{\left(valueIndex(O_i^1) - valueIndex(O_i^2)\right)}{numberofvalues(i)} \quad (3)$$

in which,

$$sign = \begin{cases} +1, \text{ if } U_i(O_i^2) \geq U_i(O_i^1) \\ -1, \text{ otherwise} \end{cases} \quad (4)$$

where, $valueIndex(O_i^1)$ and $valueIndex\left(O_i^2\right)$ are the indexes of the i^{th} issue in the negotiation domain for the bid $O^1$and O^2, respectively, and *numberOfValues(i)* is the total number of possible values for the i^{th} issue.

5.2.2 Complete information regarding opponent's preference order over evaluation values, and known issue weight values

When the agent has access to the opponent's preference order over the evaluation values, as well as the exact values of the issue weights from the opponent's point of view, the following function can be used to calculate the distance value of two bids:

$$x = distance(O^1, O^2)$$
$$= \sum_{i=1}^{n} sign \times W_i \times \frac{(valueIndex(O_i^1 - valueIndex(O_i^2))}{numberOfValues(i)} \quad (5)$$

where, *sign* follows Equation (4).

5.2.3 Complete information regarding opponent's preference order over evaluation values, and the opponent's preference over negotiation issues

When the agent has information about the opponent's preference order over evaluation values, as well as the opponent's preference order over negotiation issues, the same Equation (5) can be used to estimate the distance of two bids, except that instead of the exact issue weight values, the approximate weight values are estimated using Equation (6):

$$W_i = \frac{2 \times Rank(W_i)}{n \times (n+1)} \quad (6)$$

Proposition 1. *If we use the aforementioned distance functions to estimate the distance values of two bids, there can be found a linear function y = f(x)=mx+b using linear regression, so that it yields a somewhat precise estimate of the real difference values between the utility values of two bids (y). Obviously, the closer the value m is to 1 and the value bis to 0, the more accurate the estimate of value y is.*

In the following section, we empirically show the validity of the above proposition, using a number of negotiation scenarios used in ANAC competitions.

5.3 Nearest neighbor applicability

In order to show the applicability of the nearest neighbor method in negotiation scenarios, we used 5 scenarios from ANAC competitions. These 5 scenarios included EnglandZimbabwe [5, 11, 22], ItexvsCypress [5, 23], Airport Site Selection [24], Grocery [24], and Housekeeping [24]. We then calculated the values of the pair (x,y) for all of the bid pairs for both preference profiles of these domains. Since the distance function contains error, it is obvious that there will be multiple pairs with equal values for x and different values for y and vice versa. Compared with complete information state, in this state there is a one-to-one relationship between the x values and y values, meaning that each value for x will be mapped to a unique value for y, and vice versa. In other words, in complete information state there is a linear relationship (y=$f(x)$=mx+b) between the value y and the value x with m=1 and b=0. On the other hand, in incomplete information state the y values in terms of x values will spread around the linear line y=$f(x)$=x. However, if the Pearson Correlation Coefficient value, using a specific distance function, shows strong dependence between x and y, and m and b values are close to 1 and 0 respectively, we can use that distance function to obtain the approximate values of the differences between the utility values of every pair of bids. Figures 2, 3, and 4 show the Pearson Correlation, m, and b values for the three incomplete information states introduced in the previous section.

Strong *Pearson Correlations* obtained in these figures, and the values of m and b being close to 1 and 0 respectively, show the validity of our proposition. In other words, the nearest neighbor method can be applied in the negotiation problem using the three distance functions introduced.

6 The Proposed Distance Based Opponent Model (DOPPONENT)

In order to extract the preferences of the opponent in the negotiation setting described in Section 4, we

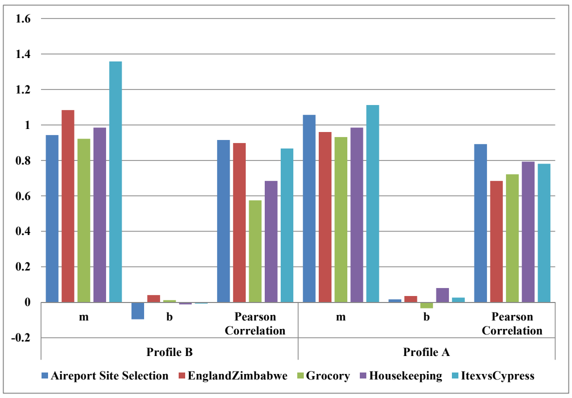

Figure 2. Applicability of NN using complete information regarding order of evaluation values

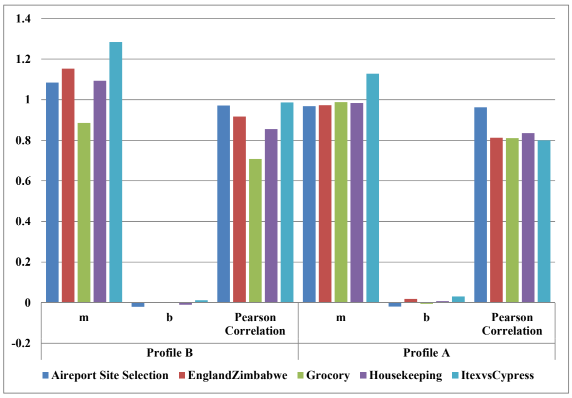

Figure 3. Applicability of NN using complete information regarding opponent's preference order over evaluation values, and known issue weight values

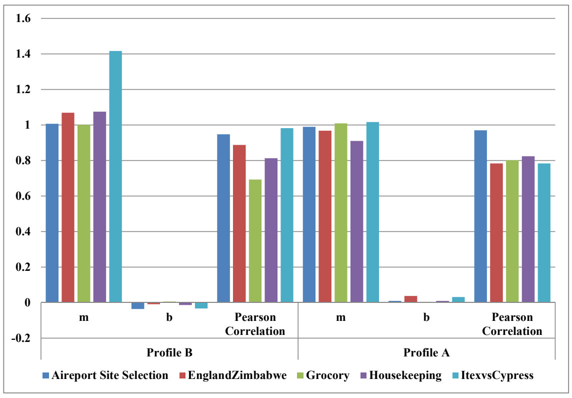

Figure 4. Applicability of NN using complete information regarding opponent's preference order over evaluation values, and the opponent's preference over negotiation issues

consider the incomplete information state with complete information regarding opponent's preference order over evaluation values, and known issue weight values. As Equation (5) shows, in order to model the preferences of the opponent using this method, we need to somehow estimate *the preference order of the opponent over evaluation values* as well as *the issue weight values*. To do so, we only consider 100 last unique bids in the opponent's bid history (the history of bids received from the opponent). To estimate the weight values, we first record the number of times each possible value for an issue is offered in the received bids. Then, for each issue we calculate the standard deviation of those values. To estimate the evaluation values, we assume that the more a possible value for an issue is offered, the greater its evaluation value will be. So, we determine the sign value in this formula, by comparing the frequency of issue values in the history of 100 last bids received from the opponent.

To estimate the utility of a candidate bid, we also calculate the distance of that bid from a randomly selected bid, using Equation (5). Notice that this randomly selected bid is chosen when this model is being initialized, and it will be used until the end of the negotiation. Obviously, obtaining the distance of every candidate bid from a constant bid is equal to adding a constant value to the estimated opponent utility value of every candidate bid. Clearly this will not affect the model, since we do not really need the exact utility values in order to prevent the agent from making unfortunate moves. The pseudo code for estimating the distance of two bids using DOPPONENT, the proposed distance-based opponent model, is presented in the algorithm below.

As it is shown in DOPPONENT pseudo code (Algorithm 1), the agent first calculates the preference order of the negotiation value associated with each negotiation issue (using sign variable) as well as its weight value (using the function IssueWeightFreqsStDev). Then it employs Equation (5) to calculate the distance value of two bids b_1 and b_2. Next, to estimate the utility of the candidate bid b_1, its distance from a randomly selected bid b_2 is calculated using getDistance function.

7 Experiments

For evaluating the performance of DOPPONENT in a realistic setting we adopted a setting from Baarslag et al. [13]. Towards this end, we used a realistic set of opponent agents which had participated in Automated Negotiating Agents Competitions (ANAC). To combine different components of the negotiating agents, we used the BOA framework [4], which had previously designed and incorporated into the Genius 4.2. Top four bidding strategies from ANAC 2011 (Agent K2 [25], HardHeaded [26], IAMHaggler2011 [27], and The Negotiator [28]) were selected. We also chose 4 time

Algorithm 1 DOPPONENT

```
b.getValue(int i): returns the value of ith issue in the bid b.
CompareFreqs(int value1, int value2, int i): returns a Boolean value depending on whether value1 is
    repeated more than value2 for an issue in the opponent's bid history.
IssueWeightFreqsStDev(int i): returns the estimated weight value of ith issue based on the standard
    deviation of the frequencies of all possible values for ith issue in opponent's bid history.
NumberOfIssueValues(int i): returns the number of possible values for ith issue.
double getDistance(Bid b1, Bid b2)
{
int i ← 1;
while i ⪯ NumberOfIssues do
    int sign ← 0;
    index1 ← IssueValueIndexes(i).get(b1.getValue(i));
    index2 ← IssueValueIndexes(i).get(b2.getValue(i));
    Boolean temp1 ← index1 ≺ index2;
    Boolean temp2 ← CompareFreqs(b1.getValue(i),b2.getValue(i), i);
    if temp1 && temp2 then
        sign ← +1;
    if temp1 && ∼ temp2 then
        sign ← -1;
    if ∼ temp1 && temp2 then
        sign ← -1;
    if ∼ temp1 && ∼ temp2 then
        sign ← +1;
    double IssueWeight ← IssueWeightFreqsStDev(i);
    double tempvar1 ← (index1 - index2) / NumberOfIssueValues(i);
    double tempvar2 ← sign * IssueWeight * tempvar1;
    distance ← distance + tempvar2;
    i ← i + 1;
return distance;
}
```

dependent bidding strategies [3] with concession rate (e) values 0.1, 0.2, 1, and 2. We executed the 8 bidding strategies equipped with DOPPONENT, against the same bidding strategies with No Model as the opponents, for 5 times, on 5 scenarios, for both preference profiles. These five scenarios were used: Grocery [14], Thompson Employment [29], Travel [5], Small Energy, and Supermarket from ANAC 2012 [24]. In order to measure the improvement made by DOPPONENT, compared with the best model, and the worst model, we also equipped those 8 bidding strategies with Perfect Model, and Worst Model. In Perfect Model, the agent has complete information regarding the utility function of the opponent. In Worst Model on the other hand, the opponent's utility function is assumed to be one minus the real utility function of the opponent. All of the sessions were executed in Genius [15] based on the round- based protocol, for an equal number of 1000 rounds.

To measure the performance of each model in the aforementioned setting, six performance measures were used [3]: (1) *Avg. Utility* [9, 14, 30] which specifies the average utility of the agents in the designed setting, (2) *Avg. Time of Agreement* [4] which specifies the average amount of time to reach an agreement, (3) *Avg. Rounds* [30, 31] which specifies the average amount of rounds before reaching an agreement, (4) *Avg. Pareto Distance of Agreement* [14, 32] which specifies the average minimal distance of agreements from the Pareto Frontier, (5) *Avg. Kalai Distance of Agreement* [32], which specifies the average distance to the Kalai Point, and (6) *Avg. Nash Distance of Agreement* [32] which specifies the average distance to the Nash Point. Among the aforementioned measures, the first measure represents *individual efficiency* of the negotiation outcome, the second and the third measures are related to the *negotiation time* elapsed before an agreement is reached, and the fourth through sixth measures correspond to the *social efficiency* of the agreements.

To better show the amount of improvement using

[3] In time dependent strategies the agent concedes according to the following formula: $u_t = 1 - t^{\frac{1}{e}}$.

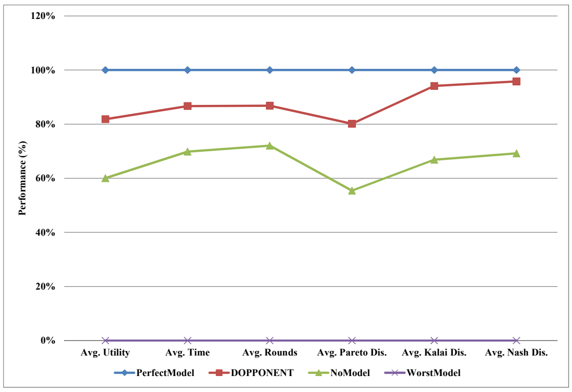

Figure 5. Normalized performance measures in the second experiment

each model in this experiment, we normalized each performance value such that the worst model's performance is 0% and the perfect models performance is 100%. So, higher percentage values show better performance for all measures. The normalized values are demonstrated in Figure 5. This figure shows that DOPPONENT results in a considerable improvement in terms of all performance measures. The results also show that DOPPONENT results in above 94 percent improvement for Kalai Distance, and Nash Distance measures. Kalai Point and Nash Point are two points to represent the social welfare in a negotiation scenario. So the results approve that the proposed model has been of great help for the agents in making socially efficient agreements in the devised negotiation setting.

8 Conclusion and Future Work

Automated negotiation is the process of resolving conflicts and settling agreements between automated intelligent negotiating agents. In this paper, we showed how the distance based algorithms can be applied to model the preferences of the opponent in bilateral multi issue negotiations. We proposed DOPPONENT, a new distance based opponent modeling technique, and demonstrated its efficiency in helping the agents making individually and socially efficient agreements in less negotiation time, using a realistic experimental setting. Finding a proper distance function is the most important factor in distance based learning methods. In Section 5, we depicted how different similarity functions using different levels of information about the opponent's preferences can be used to estimate the preferences of the opponent. We emphasized that using appropriate distance functions in distance based methods is very important in accurately estimating the utility value of a bid. We also used a method to estimate the weight values and the issue value orders. In the future, we plan to design and evaluate other and more efficient distance functions, using different levels of information and different methods to estimate the weight values and issue value orders, to be used in different negotiation domains.

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