Optimal Preference Clustering Technique for Scalable Multiagent Negotiation(Short Paper)

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Abstract. We propose protocol for automated negotiations between multiple agents over multiple and interdependent issues. We consider the situation in which the agents have to agree upon one option (contract) among many possible ones (contract space). Interdependency between issues prevents us from applying negotiation protocols that have linear time complexity cost like Hill Climbing implementing mediated text negotiation protocol(HC). As a result most previous works propose methods in which the agents use non linear optimizers like simulated annealing to generate proposals. Then a central mediator can be used to match the proposals in order to find an intersection. But this matching process usually has exponential time cost complexity. We propose multi round HC(MR-HC) for negotiations with multiple and interdependent issues. In each round the normal HC is used to determine a negotiation deal region to be used by the next round. We propose that the agents should cluster their constraints by the cardinality of the constraints in order to get socially optimal contracts before applying MR-HC. To showcase that our proposed clustering technique is an essential one, we evaluate the optimality of our proposed protocol by running simulations at different cluster sizes.

Keywords: Artificial Intelligence, Distributed Artificial Intelligence, Coherence and Coordination, Automated Negotiation.

1 Introduction

We propose protocol for automated negotiations between multiple agents over multiple and interdependent issues. We consider the situation in which the agents have to agree upon one option (contract) among many possible ones (contract space). Each issue of the negotiation has finite number of possible values. A contract is identified by the value it has for each issue of the negotiation.

The issues are interdependent means that for example it is generally not possible for an agent to decide about each issue independently and finally reach at an optimal contract. And more over negotiation protocols that are designed for independent issue negotiations may not result in an optimal deal when the issues are interdependent. We define the optimal deal to be the one that maximizes social welfare that is the total utility.

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Interdependency between issues prevents us from applying negotiation protocols that have linear time complexity cost like Hill Climbing implementing mediated text negotiation protocol(HC 2.1). As a result, most previous works propose methods in which the agents use non-linear optimizers like simulated annealing to generate proposals. Then a central mediator can be used to match the proposals in order to find an intersection. But this matching process usually has exponential time cost complexity. Therefore the number of agents that can be supported by such negotiation mechanisms is very limited.

We propose multi round HC for negotiations with multiple and interdependent issues. In each round the normal HC is used to determine a negotiation deal region to be used by the next round. We propose that the agents cluster their constraints by the cardinality of the constraints. . In the first round of multi round HC the cluster which contains the largest constraints should be used by the agents to evaluate the contracts proposed by the mediator, and in the second round the second largest cluster and so on. To showcase that our proposed clustering technique is an essential one, we evaluate the optimality of our proposed protocol by running simulations at different cluster sizes.

In a non linear utility space it is not also possible to locate the optimal contracts of even one agent using HC. Instead non linear optimization technique like simulated annealing(L-SA) is much better(Figure 1). As a result the previous approach for such negotiation was to make agents submit bids (identified by L-SA) to a central mediator which tries to find a match. But such protocols only support a few number of agents due to the computational time complexity of exhaustive matching [1]. Here we want to revisit HC in order to modify it to support non linear negotiations.

We adopt the constraints based utility space model in [1] to represent agents utility spaces. An agent's utility for a contract is the sum of the weights of the constraints the contract satisfies. An optimal contract for an agent is the one that maximizes its utility.

2 Cardinality Based Clustering

Our solution concept is based on the observation that constraints that make up an agent's utility space can be divided into those representing very broad and general criteria , those that represent very specific ones and the rest some where between the two. And we expect that contracts that satisfy the specific constraints also satisfy the general ones. Therefore an agent can iteratively narrow down the search region for optimal the contract(See Algorithm 2.3).

Before running the MR-HC agents cluster their constraints by their cardinality. In cardinality based grouping the criterion for a set of constraints to belong to the same cluster is the similarity of the size of the constraints. Therefore while general constraints that are easily met by many contracts are grouped together, specific constraints that are satisfied by only a few of contracts will be grouped together in another group. Therefore before the beginning of MR-HC each agent is expected to have created $\mid C \mid$ number of clusters. Each cluster

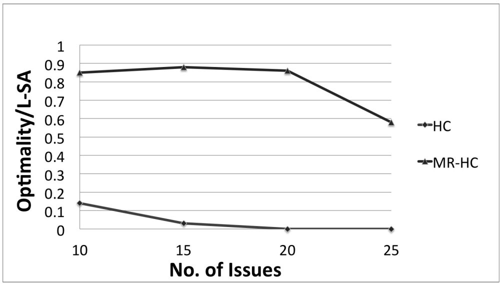

Fig. 1. Optimality for one Agent

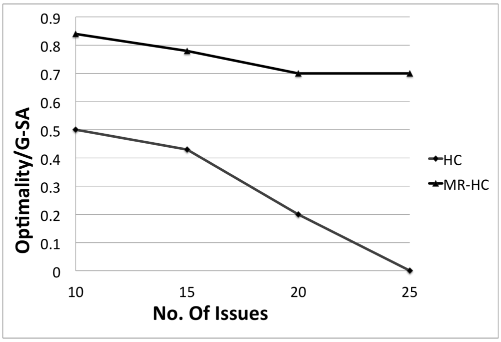

Fig. 2. Optimality for multiple Agents

contains some number of constraints. For each agent the cluster C_1 contains the largest constraints and $C_{|C|}$ the smallest constraints.

Other researchers ([4])have presented a similar generic idea, but here we have implemented a concrete algorithm which has the additional advantage of being efficient. Also [2] have considered iterative narrowing, but while they group constraints based on their positions we cluster them by their cardinality. Author [5] has considered reducing non linearity of utility spaces by analyzing the issue interdependencies. We think methods that reduce non linearity can be used as a pre process for our protocol. Our protocol should be used when there is no way to avoid non linearity.

The symbols in the algorithms are as follows: I : The issues of the negotiation. A : A set of agents. V : A set of values for each issue, V_n is for issue n. C : A set of constraint clusters $C = C_1, C_2 ... C_c$. Each C_i is characterized by the maximum cardinality of the constraint it can contain. C_c^a : Set of constraints in Agent a's cth cluster.DR: DealRegion is a set of set of values for each issues. DR_i:A set of values for Issue i in DR. Initially DR_i contains all of the V_i, hence the cross product of the initial DR_is represents the entire contract space.

Algorithm 2.1. HC(I, V)

$$
\begin{array}{l}
S \leftarrow initialsolution(setrandomly) \\
\textbf{for each } i \in I \\
\quad \textbf{do} \begin{cases} \textbf{for each } j \in V_i \\ DO \begin{cases} SS \leftarrow S \textit{ with issue i value set to j} \\ \textbf{if } \forall A, U(SS) > U(S) \textbf{ then } S \leftarrow SS \end{cases} \end{cases} \\
\textbf{return } (S)
\end{array}
$$

Algorithm 2.2. HC(I, V, c, DR, S)

$$
\begin{array}{l}
\forall A, DR^a \leftarrow DR \\
\textbf{for each } i \in I \\
\quad \textbf{do} \begin{cases} \textbf{for each } j \in DR_i \\ DO \begin{cases} SS \leftarrow S \textit{ with issue i value set to j} \\ if\ \forall A\ , U(SS, C_c^a, DR^a) > U(S, C_c^a, DR^a) \\ then\ S \leftarrow SS \end{cases} \\ //Each\ agent\ updates\ DR^a \\ DR^a \leftarrow DR^a \cap satisfied\ cons. \in C_c^a \\ DR \leftarrow DR^{a1} \cap DR^{a2} \cap DR^{a3}.... \\ S \leftarrow random\ contract \in DR \end{cases} \\
\textbf{return } (S).
\end{array}
$$

Algorithm 2.3. MR-HC$(I, V, \mid C \mid, DR)$

$$
\begin{array}{l}
S \leftarrow initialsolution(setrandomly) \\
\textbf{for } c \leftarrow 1 \textbf{ to } \mid C \mid \\
\quad \textbf{do } \{ S \leftarrow HC(I, V, c, DR, S) \\
\textbf{return } (S)
\end{array}
$$

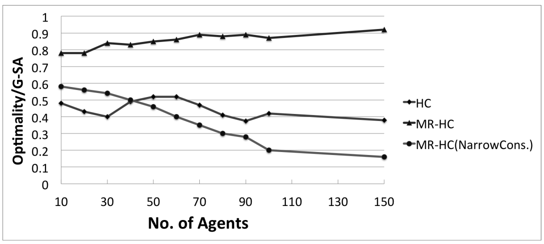

Fig. 3. Optimality at Various Number of Agents(No. of issues 10)

3 Experimentation and Analysis

3.1 Simulation Setup

For a negotiation over I issues we create $4 \times I$ constraints. Each issues has 10 possible values represented by the numbers $1 - 10$.Each agent clusters its constraints into I number of groups. Each group contains 4 constraints that share a common center. This center is randomly chosen contract. Width of each of the constraints in the group is selected from a uniform distribution of the width values 2 to 8. However based on the location of the center point of a group, a constraint's width might be truncated if it exceeds the issue values range. First, each of the constraints in a group are assigned the same of $Ran(1, I) * 100$. Additionally each constraint will have an additional weight of $100/Ran(1, 10)$. It is possible that two or more groups of constraints to overlap.

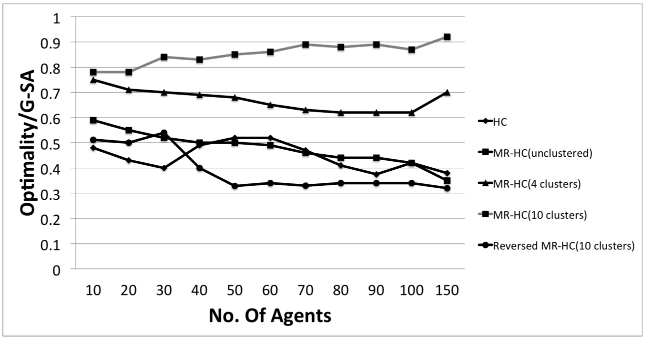

Fig. 4. Optimality at Various Number of Clusters(No. of Issues 10)

3.2 Analysis

Figure 1 shows that MR-HC has better optimality than HC for an agent. The number of issues is varied from 10 to 25 number of issues. This shows that the proposed algorithm MR-HC indeed has better optimality than HC. Moreover from the definition of the algorithm we can see that for fixed number of clusters (C), MR-HC execution time cost increases only linearly with the number of issues.

Figure 2 and Figure 3 show that mediation protocol based on MR-HC has better optimality than HC protocol. G-SA is simulated annealing run on the sum of the utility of the agents. However, MR-HC optimality is affected by the average width of constraints and by the grouping level(See Fig. 3 OP. MR-HC for narrow constraints). That is when most of the constraints have small cardinality and can not be effectively grouped into various size levels, MR-HC can not give optimal results.

Figure 4 shows some experimental result used to prove the essentiality of cardinality based clustering before applying MR-HC. As shown MR-HC with each agent defining ten clusters has the highest optimality followed by MR-HC with 4 clusters per agents. Applying MR-HC without any clustering produces sub optimal results like HC. It is conceptually flawed but we experiment with the reverse MR-HC. That means in the first round the agents use the cluster which contains their smallest constraints, and the second round the cluster containing second smallest constraint sizes and so on. As expected reversed MR-HC has also poor optimality.

4 Conclusions

We note that when MR-HC is run for one agent, it is basically a greedy optimizer. In the first round an agent's task is to select a constraint from cluster 1. It simply greedily chooses the one with the highest weight. This is repeated for each cluster but with the condition that the newly selected constraint should have intersection with the previously chosen constraints.

At these stage we can only say that there is an incentive for both the agents and the mediators to use this protocol. A Mediator that has been using HC has an incentive to start using MR-HC because MR-HC gives more optimal results. Moreover a mediator has incentive to switch from using non linear protocols like bidding based deal identification because it can support more number of agents with MR-HC. The agents as a society have incentive to use MR-HC because they get a chance to collaborate with many other agents while producing optimal social outcomes.

However, we have to investigate at least on average whether agents are better off using MR-HC or not in terms of their final individual utility for the selected deal. Especially we expect that agents to ignore the clustering step in order to manipulate the protocol to end with deal which is most beneficial to them.

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