Partial Cooperation in Multi-agent Search

(Extended Abstract)

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ABSTRACT

Multi-agent systems usually address one of two pure scenarios, completely competitive agents that act selfishly, each agent maximizing its own gain from the interaction or multiple agents that operate cooperatively in order to achieve a common goal.

The present paper proposes a paradigm for multiple agents to solve a distributed problem, acting partly cooperatively and keeping a limited form of their self-interest. The proposed framework has multiple agents solving an asymmetric distributed constraints optimization problem (ADCOP), where agents have different personal gains from any mutual assignment. Three modes of cooperation are proposed – Non-cooperative, Guaranteed personal gain, and λ-cooperation (where agents' willingness to suffer relative loss is parametrized by λ). The modes of cooperation are described, as well as their realization in search algorithms.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: [Multiagent systems]

General Terms

Algorithms, Experimentation

Keywords

Distributed Search, Cooperation, Self interest

1. INTRODUCTION

Most studies investigating multi agent systems consider either fully cooperative agents which are willing to exchange information and take different roles in the process of achieving a common global goal (cf. [1]), or self interested agents which are considered to be rational when they take actions that will increase their personal gains (cf. [3]).

When one considers the standard working environment in which employees perform tasks for the benefit of the organization they work for and get a pay check in return, it seems that this most common situation is not covered by any of the two models described above. The agents in this working environment are naturally self interested and often have the option to increase their own benefit within the organization, even when benefits are non monetary. However, the success of the organization, and ultimately of the agents themselves, requires that the agents act loyally to increase the organizational profit (e.g., optimize some global goal).

In such real world situations, agents need to collaborate in finding the best (or a good) solution to the problem in a global perspective, despite having personal goals which may be in conflict.

Combinatorial optimization problems in which agents have personal gains can naturally be represented as Asymmetric Distributed Constraint Optimization Problems (ADCOPs) [2].

Previous studies of ADCOPs considered full cooperation of the agents. In contrast, the scenarios described above have agents that are cooperative only when some conditions are satisfied. This generic situation of multi-agent complex interactions raises the need to investigate modes of collaboration for self-interested agents solving combinatorial problems.

The present paper focuses on two new and fundamental questions regarding asymmetric multi agent optimization:

- What are the basic modes of collaboration one can define for agents solving an ADCOP?
- What are the relevant search methods for exploiting such modes of collaboration?

To address these questions three degrees or categories of cooperation are proposed for agents that have different personal gains (interests) in an interaction process. The degrees are defined as a function of the personal outcomes that agents can expect of the process relatively to the expected result of a non-cooperative interaction and on their willingness to sacrifice for the common good.

In this study, the set of possible outcomes that can be reached in a search process and its dependency on the level of cooperation is investigated and a standard DCOP algorithm is adjusted in order to apply to the proposed model according to its different levels of cooperation.

2. PARTIAL COOPERATION

Three increasing degrees of cooperation are proposed for agents: Non-cooperative, Guaranteed Personal Benefit col-

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laboration (GPB) and λ-cooperation. These degrees of cooperation affect the possible outcome of an *Interaction Process* among agents in an ADCOP. An *Interaction Process* IP of n agents is a predefined sequence of events that upon termination has each agent select value assignments for its variables.

The expected outcome of an IP in the non-cooperative setting depends on the details of the interaction. For a multi-step interaction one can expect the end result to be some form of equilibrium if the problem includes such a state and the interaction process allows convergence to it. A GPB solution is defined relatively to the non-cooperative (NC) solution which serves as a baseline. In a GPB setting the outcome of a sequence of actions must be a state which is weakly superior for each agent (Pareto improves the outcome of the NC process).

λ-cooperation allows agents to consider solutions with high global quality, which are not a Pareto improvement of the baseline state. The λ-cooperation class is based on the amount of risk, in the form of personal losses, that agents are willing to undertake in order to satisfy the global objective of the organization. The following definitions are used for the definition of λ-cooperation.

If all agents in the λ-cooperation class have the possibility to approve or reject any outcome which is proposed by the interaction process, then $O^{feasible}$ defines the set of outcomes approved by all agents. However, if the interaction process requires agents to perform actions which can result in other outcomes, agents may not be willing to take any risk and perform these actions. In this case, the set of outcomes considered in the interaction process is a subset (may be empty) of $O^{feasible}$.

3. CONDITIONAL COOPERATIVE SEARCH

The simplest (and most restrictive) translation of λ-cooperation to the distributed search setting is that the set of actions that agent i is willing to perform during search includes only actions which cannot lead to an outcome whose quality is not within λ_i from the quality of the NC outcome for i.

This approach is rather conservative (risk averse). It limits to an extreme extent the outcomes that will be considered by the agents and can prevent the search process from exploring Pareto improving solutions of high quality. To overcome this shortcoming one can extend the definition of λ-cooperation search to include agents beliefs about the future actions taken by other agents. Agents exclude in their considerations states which they believe that will not be selected by other agents. This can allow agents to ignore the threat of undesirable outcomes that, according to their belief, have low probability.

Figure 1 presents the results for three versions of the Distributed Synchronous Branch and Bound algorithm when solving random minimization problems in comparison with the baseline solution and the optimal solution (which ignores the personal thresholds). The baseline non-cooperative solution was selected by using a simple greedy interaction process. The first version of the algorithm allows agents to reject any solution reached. Thus, the algorithm selects the best solution in global terms that satisfies all local λ thresholds. This version is termed *No-Commitment*. On the other hand, in the second version that is referred as *Full-Commitment* an agent must consider any outcome that may result from its action. The balanced version which is based

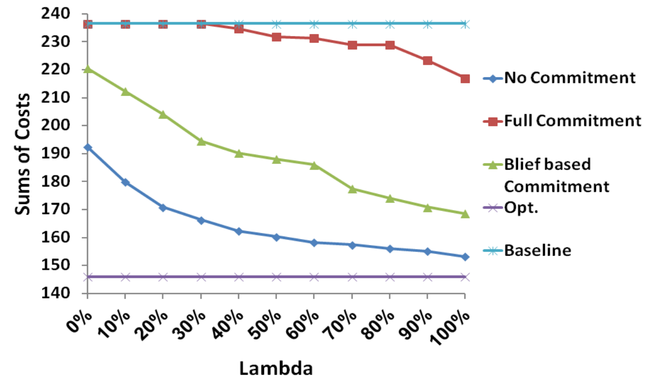

Figure 1: Solution cost of the Synch_BnB versions when solving random problems ($p_1 = 0.3$)

on the agent's belief is termed *Belief based Commitment*.

The global quality of all three versions of the algorithm improves when the λ value grows. The No-Commitment version produces solutions with lower global costs than the other two versions of the algorithm, although failing to find the globally optimal solution. Interestingly, the belief based version produces solutions whose costs are closer to the costs of the solutions found by the No-Commitment version than to the costs of solutions found by the Full-Commitment version.

4. DISCUSSION

A formalism that extends the ADCOP framework to include agents which are partially cooperative is proposed. Three modes of cooperation among agents were proposed - Non-Cooperative, Guaranteed Personal Benefits collaboration and λ-cooperation, where the willingness of agents to suffer a relative loss is parametrized by λ. The outcome of the non-cooperative mode serves as a baseline upon which the partial cooperative model is constructed. Agents seek alternatives which will satisfy their thresholds and improve the global outcome.

The set of possible solutions which are explored in the proposed partial cooperative model depends on the ability of agents to reject unsatisfying outcomes. If the search algorithm enables agents to reject unsatisfying outcomes, then the entire set of solutions which Pareto improve the non-cooperative baseline can be considered. On the other hand, if agents must commit to assignments they perform during search, they may refrain from assignments that lead to unsatisfying outcomes and thus, prevent the pursue of high quality solutions. A balanced compromise of these two extremes that is based on belief was proposed. Agents calculate the loss that they are expected to suffer and are thus able to ignore improbable outcomes with low quality.

5. REFERENCES

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