Computational Aspects of Mechanism Design

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In a *preference aggregation setting*, a group of agents must jointly make a decision, based on the individual agents' privately known preferences. To do so, the agents need some protocol (or *mechanism*) that will elicit this information from them, and make the decision. Examples of such mechanisms include voting protocols, auctions, and exchanges. In most real-world settings, preference aggregation is confronted with the following three computational issues. First, there is the complexity of *executing* the mechanism. Second, when standard mechanisms do not apply to or are suboptimal for the setting at hand, there is the complexity of *designing* the mechanism. Third, the agents face the complexity of (strategically) *participating* in the mechanism.

My thesis statement is that by studying these computational aspects of the mechanism design process, we can significantly improve the generated mechanisms in a hierarchy of ways, leading to increased economic welfare.

Outcome optimization

Even when all the agents' preferences are already known, computing the optimal outcome (for example, the one that maximizes the sum of the agents' utilities) can be nontrivial. For example, in a *combinatorial auction*, bidders are allowed to place bids on any subset of the items for sale. While the expressiveness that this provides to the bidders increases economic welfare, the *winner determination problem* of deciding which bids to accept so as to maximize the total value is known to be NP-complete (Rothkopf, Pekeč, & Harstad 1998), even to approximate (Sandholm 2002).

My thesis work includes new work on the winner determination problem in combinatorial auctions (Conitzer, Derryberry, & Sandholm 2004). It also introduces an expressive bidding protocol for matching donations to charities (Conitzer & Sandholm 2004e), as well as an expressive bidding protocol for general settings in which agents' actions impose externalities on the other agents (that is, affect the other agents' utilities).

Mechanism design with strategic agents

While having a good outcome optimization algorithm is necessary for preference aggregation to be successful, it is not sufficient. The reason is that generally, the agents' preferences are not known beforehand and will have to be elicited

Copyright © 2005, American Association for Artificial Intelligence (www.aaai.org). All rights reserved. from them. Unfortunately, agents will misreport their preferences if it is in their interest to do so. This may lead to the outcome optimization algorithm choosing an outcome that is good under the reported preferences, but bad under the agents' true preferences. The solution is to choose outcomes in such a way that agents have no incentive to misreport. Economists have invented a number of general mechanisms that achieve this (under various conditions) – most notably, the Vickrey-Clarke-Groves (VCG) mechanism (Vickrey 1961; Clarke 1971; Groves 1973). However, applying these mechanisms in computationally complex settings is nontrivial. For example, using an approximate outcome optimization algorithm will destroy the strategic properties of the VCG mechanism (Nisan & Ronen 2001).

My thesis work discusses revenue and bidder collusion problems that the VCG mechanism introduces in combinatorial auctions and exchanges (Conitzer & Sandholm 2004f). It also studies the design of mechanisms for strategic agents in the expressive bidding setting for matching donations to charities described above.

Automated mechanism design

While general mechanisms such as VCG constitute some of the great successes of theoretical economics, they are not always applicable to the preference aggregation setting at hand. For example, they usually assume that there are no barriers that prevent agents from making payments to each other. Moreover, even when the general mechanisms can be applied to the setting at hand, they may not be optimal. For example, most of the general mechanisms try to maximize social welfare, but this leads to suboptimal mechanisms if the true objective is something else, such as revenue maximization. In such cases, the *automated mechanism design* approach, in which a special-purpose mechanism is computed specifically for the preference aggregation setting at hand, is required to aggregate preferences optimally.

My thesis work discusses the complexity of the general automated mechanism design problem, and introduces mixed integer/linear programming approaches for solving it (Conitzer & Sandholm 2002b; 2003a; 2004g). It also discusses special cases and structured representations of the problem which can be solved faster (sometimes with specialpurpose algorithms (Conitzer & Sandholm 2004a)). Finally, it discusses the automated design of *multistage* mechanisms.

Designing mechanisms for computationally bounded agents

The standard approach to designing mechanisms that perform well in the face of strategic agents is to assume that agents will misreport their preferences whenever this is in their best interest. This often leads to very cautious and conservative mechanisms that never give the agents incentives to misreport their preferences (that is, they are truthful), but also do not generate much value. (Occasionally, this approach even leads to an impossibility result that states that no desirable mechanism exists, such as the Gibbard-Satterthwaite theorem in the context of voting (Gibbard 1973; Satterthwaite 1975).) However, in complex preference aggregation settings, it may actually be computationally too hard for agents to find a beneficial insincere report of their preferences. An ideal mechanism design process would exploit these computational weaknesses of the agents to generate mechanisms which are better for all involved.

My thesis work shows that in some voting protocols, it can be computationally hard to find a beneficial insincere vote (Conitzer & Sandholm 2002a; Conitzer, Lang, & Sandholm 2003). It also introduces new voting protocols that are especially hard to manipulate with insincere votes (Conitzer & Sandholm 2003f). Additionally, it exhibits settings in which there are insincere mechanisms that always perform at least as well as truthful mechanisms, and perform strictly better in the face of high computational complexity (Conitzer & Sandholm 2004c). As an initial step towards the general design of mechanisms for computationally bounded agents, my thesis work studies the complexity of basic solution concepts in game theory, such as Nash equilibrium (Conitzer & Sandholm 2003e), (iterated) dominance (Conitzer & Sandholm 2005b), the core (Conitzer & Sandholm 2003d), and the Shapley value (Conitzer & Sandholm 2004d); as well as various topics on learning in games (Conitzer & Sandholm 2003b; 2003c; 2004b).

Work to be completed

There are many important unresolved questions pertaining to the individual topics discussed above. A more significant question, however, is how to combine the above approaches to mechanism design into a single unifying framework – one in which mechanisms are automatically designed for the setting at hand, for bounded agents. There are technical reasons why this is not straightforward: it would require a more sophisticated approach to automated mechanism design and/or more sophisticated models of bounded agents. Another important question that we continue to address is how to perform the actual elicitation of the agents' preferences efficiently (Conitzer & Sandholm 2002c; Santi, Conitzer, & Sandholm 2004; Conitzer & Sandholm 2005a).

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