Multi-Agent Contracting for Tasks with Temporal and Precedence Constraints

Maria Gini

University of Minnesota

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Overview

- Agents, markets, and auctions
- Introduction to MAGNET
- I. Winner determination problem
- II. RFQ formulation problem
- III. Evaluation of agents strategies
- Conclusions and future work
Agents, Markets, and Auctions

Our long term goal is to enable programs ("agents") to buy and sell on electronic markets on behalf of a user.

Why electronic markets and auctions?

- Electronic markets have the potential for reduced costs and increased access to world-wide markets.
- Auctions are a general and proven way to negotiate among rational entities.
Auction Terminology

- Bid-taker is the organizer of the auction. If the bid-taker is the seller it is a forward auction, if it is the buyer it is a reverse auction.
- Goods can be sold as single items or in bundles in a combinatorial auction.
- The auction is sealed-bid when bids are not public.
- The auction is first-price when the price paid is that of the highest bid.
Adding the time dimension

- For many domains, it is not enough to bid on an item or a bundle. The time dimension needs to be specified (i.e. shipping, construction, manufacturing tasks).
- This requires bids to specify items, prices, time windows, and durations.
- Time and precedence constraints make the selection of winning bids more complex for the bid-taker.
Introduction to MAGNET (1)

- MAGNET ≡ Multi-AGent NEgotiation Testbed
- Current MAGNET design supports
  - multiple agents (customers and suppliers)
  - negotiating contracts with temporal and precedence constraints
  - in automated first-price sealed-bid combinatorial auction environment.

Introduction to MAGNET (2)

Customer agent formulates and sends to the market a request for quotes: task descriptions, precedence relations and time windows.
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Supplier agent decides whether to participate in the auction, formulates and sends a bid.
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Supplier agent decides whether to participate in the auction, formulates and sends a bid.

Customer agent executes winner determination procedure to decide on which bundle of bids to accept, sends award and reject messages to participating suppliers.
I. Winner Determination Problem

For \( m \) items and \( n \) bids

\[
\text{minimize} \quad \sum_{i=1}^{n} c_i x_i \\
\text{subject to} \quad x_i \in \{0, 1\} \\
\text{and} \quad \sum_{i : s_j \in S_i} x_i = 1, \text{ for } j = 1, \ldots, m.
\]

where \( c_i \) is the bid price for bid \( b_i \), \( S_i \) is the set of items in bid \( b_i \). This ensures that at most one bid is accepted for each item. \( i : s_j \in S_i \) is the set of all \( i \) such that task \( s_j \) is in the set of tasks \( S_i \) in bid \( b_i \).
I. Algorithms

We extended winner determination algorithms to deal with time windows:

**Integer Programming (IP)**: preprocess precedence constraints to reduce number of constraints;

**A***: classical search algorithm from AI;

**Iterative Deepening A*** (IDA***): extended Sandholm’s bidtree-based IDA***.

**Simulated Annealing (SA)**: stochastic method.
I. Why runtime predictions?

We need to estimate runtime performance to allocate time for negotiation.
I. Comparison of algorithms

Runtime performance of A*, IDA*, and IP search (35 tasks, 111 bids) with bid tree sorted by increasing or decreasing bid count.
I. Performance criteria

Need the *probability* that a solution can be found in a given amount of time, based on:

- Task count – number of tasks in task network;
- Bid count – number of bids submitted.
- Bid size – mean number of tasks specified in each bid.
- Plan complexity – mean size of the precedence set of a task in the task network.
I. IP vs Task Count

Observed and inferred runtime distributions for IP across task count values, with nearly constant ratio of bids to tasks.
I. IP vs Bid Count

Observed and inferred runtime distributions for IP search for a range of bid count values, with task count = 20, bid size $\approx 7.3$ tasks/bid.
I. IP vs Bid Size

Observed and inferred runtime distributions for IP search for a range of bid size values, with task count = 20, and bid count \( \approx 87 \).
I. Estimating IP time

Estimating IP search time for the task count experiment.

\[ 13.30 \times 2^{(-25.8 \text{ bs/tc} + 0.045 \text{ bc} + 0.00384 \text{ tc})} \]
I. Conclusions on performance prediction

- In aggregate terms, IDA* outperforms IP, which outperforms SA.
- On a problem-by-problem basis, we observed little correlation between the performance of IP and SA, or between IP and IDA*.
- We developed predictive models of IP and IDA* using linear regression.

II. Formulation of RFQs

Issues with the current approach:

- solicitation of mutually incompatible bids;
- high computational complexity of winner determination;
- reputation loss due to rejection of bids.

Proposed solution:

- formulate RFQ based on market information and customer’s preferences over risk-profit expectations.
II. Expected Utility (1)

Gamble/lottery: a set of events and corresponding probabilities, e.g., “get $100 or nothing with equal probabilities.”

Utility: an increasing function $u$ of a monetary value.

Expected utility: $Eu[G] = \sum_{(x_i, p_i) \in G} p_i u(x_i)$, where $x_i$ are the possible payoffs, $p_i$ the probabilities, and $u$ the utility function.

Certainty equivalent: the equivalent of a gamble in certain money. $CE[G] = u^{-1} Eu[G]$
Risk neutral person or agent values “$100 or nothing” gamble at $50, risk loving — more than $50, and risk averse — less than $50.
II. Assumptions

- Customer’s preferences can be described by expected utility.
- Customer can collect information on the cost of tasks and on their success rate as a function of time:
EU maximizing (i.e. ideal) time allocations for the 6-task plan shown before. Left schedule is for risk-loving agent, right schedule is for risk-averse agent.
II. Summary of Results

Task network

Masonry → Plumbing → Exterior → Interior

RFQ
II. Summary of Results

[Diagram with various colored lines and markers across a timeline from 0 to 10 on the x-axis and values from -0.03 to 0.07 on the y-axis.]

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II. Benefits of EU Approach

- Allows for *a-priori* bid filtering based on customer’s preferences and market information.
- Suggests intuitive relation between customer’s willingness to take risk and expected profit.
- After some modifications can also be used for winner determination.
II. Open Issues in EU Approach

- Need to convert ideal schedules to RFQs that balance number of incoming bids and profit expectations.
- Non-linear global maximization problem.
- Require market information to test related algorithms.

III. Assessing the performance of a multi-agent system

- Real market data analysis? Requires real data, which is often private or inadequate.
- Analytical analysis? Requires simplifications.
- Competition? Requires strict rules, disregards non-transitivity, requires fixed market structure on competitors’ side.
- Evolutionary approach? Allows to find out which agent strategies are good for which market conditions.
III. Evolutionary Approach

Generalized setup: a *dynamic society* of agents who *enter the market* with one of available strategies and initial parameters as determined by a reproduction rule and *survive* in the market according to their accumulated wealth.

III. Example: Citysim Model (1)

Citysim — a discrete event simulation of the evolving society of service suppliers and their customers living in one city:

- Customers come to the market with a fixed frequency with a higher density close to the center of a city.
- Customers seek for the cheapest provider of the service where cost is a linear function of a price, distance to supplier and wait time.
III. Results (1)

Snapshot of a city after 2 years of simulation. Suppliers of all sizes are distributed evenly.
III. Results (2)

Snapshot of a city after more time.

Suppliers of size 1 and 3 have divided “zones of control.”
Snapshot of a city after yet more time.
Suppliers of size 2 are in the market again after they had been washed away from the market.
III. Results (4)
Conclusions

- extended winner-determination algorithms for combinatorial auctions to include time constraints;
- characterized the performance of the winner-determination algorithms;
- showed how EU approach can be used to improve winner determination through \textit{a-priori} bid selection;
- proposed an evolutionary framework for assessing strategies in multi-agent systems.
Future Work

- finalize theory of EU-based RFQ generation;
- create simulation environment and use it to assess and improve the theory;
- develop evolutionary framework on top of MAGNET.
Contacts

email: magnet@cs.umn.edu
URL: www.cs.umn.edu/magnet