Autonomous Bidding Agents:
Strategies and Lessons from TAC Travel

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Autonomous Trading Agents

- **Trade** is a quintessential human activity
- Compared to other interactive decision-making domains, trade is particularly amenable to automation
- **Autonomous agents** (a.k.a. agents) are software programs that make decisions without direct human intervention
  - a program that carries out the direction “bid $99 for eBay item 123” is not autonomous
  - a program that carries out the direction “buy a digital camera at a good price” is autonomous
Trading Agent Research

Aim

- develop techniques for the effective design and analysis of trading agents
  - specific solutions to particular trading problems, as well as
  - general principles to guide the development of trading agents

Challenge

- markets are multiagent environments, in which the performance of a particular agent’s strategy depends on the other agents’ behavior
- natural approach is for separate institutions/researchers to develop agents to participate in a common market environment
Trading Agent Competition

Divisions

- Travel
  - bid in simultaneous auctions for flights, hotels, entertainment

- Supply Chain Management
  - procure raw materials, manufacture, deliver finished goods

- CAT Market Design
  - specialist: attract traders, match buyers and sellers

Coming Soon: Ad Auctions

Entrants

- US, England, Sweden, Australia, Hong Kong, Greece, Croatia, Iran, etc.
Sequential and Simultaneous Combinatorial Valuations

- **Complementary Goods**
  - $v(A) + v(B) \leq v(A \cup B)$
  - camera, flash, and tripod

- **Substitutable Goods**
  - $v(A) + v(B) \geq v(A \cup B)$
  - Canon AE-1 and Canon A-1
The Bidding Problem

Key Question
Trading Agent: “How do I bid in separate markets for goods whose values are highly interdependent?”

Our Solution
Agent Architecture: Prediction & Optimization, applied in the context of TAC Travel.
Overview

I. TAC Travel Market Game
   – Rules
   – Anecdotes

II. Agent Architecture
   – Prediction
   – Optimization
Rules

Complementary and Substitutable Goods

- **Flights**: Inbound and Outbound
- **Hotels**: Grand Hotel and Le FleaBag Inn
- **Entertainment**: Red Sox, Symphony, Theatre
Rules

Simultaneous and Sequential Auctions

- **Flights**: infinite supply, prices follow random walk, clear continuously, no resale permitted
- **Hotels**: ascending, multi-unit, 16th price auctions, random auction closes each minute, no resale permitted
- **Entertainment**: continuous double auctions, initial endowment, resale is permitted
## Rules

### Client Preferences

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<th>IAD</th>
<th>IDD</th>
<th>HV</th>
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</table>
Rules

Utility = 1000 - travelPenalty + hotelBonus + funBonus

\[
\text{travelPenalty} = 100(|IAD - AD| + |IDD - DD|)
\]

\[
\text{hotelBonus} = \begin{cases} 
    Hv & \text{if } H = G \\
    0 & \text{otherwise}
\end{cases}
\]

funBonus = entertainment values
Anecdotes

- 2000: eBay sniping
- 2001: LivingAgents
- 2002: WhiteBear
- 2003: TAC SCM
- 2004: WhiteBear
- 2005: Mertacor
- 2006: RoxyBot
Agent Architecture

LOOP

0. **Download** current prices and winnings from server

1. **PREDICT** build a model of the auctions’ clearing prices

2. **OPTIMIZE** solve for an approximately optimal set of bids

3. **Upload** current bids to server
Price Prediction

Competitive Equilibrium Prices

- prices at which supply = demand
  - all producers are profit-maximizing
  - all consumers are utility-maximizing

Notation

$\mathbf{p}$: price vector
$\mathbf{z}$: excess demand

Tâtonnement: $\mathbf{p}_{t+1} = \mathbf{p}_t + \alpha_t \mathbf{z}$

SimAA: $\mathbf{p}_{t+1} = \mathbf{p}_t + \alpha_t \max\{\mathbf{z}, 0\}$
Price Prediction
2002 Finals

Expected Value of Perfect Prediction vs. Euclidean Distance

- tattonnement, expected
- SimAA, expected
- tattonnement, random
- SimAA, random

$t_{tatonnement}$, $E_{expected}$, $E_{random}$, $E_{exact}$
Price Prediction
2002 Finals [Wellman, et al. 04]
Price Prediction with Distribution

**Algorithm 1** Distribute

1: **for all** hotel auctions $h$ **do**
2:     initialize price to 0
3:     initialize supply to 16
4: **end for**
5: compute competitive equilibrium prices \{$\hat{T}\text{-attonnement or SimAA}$\}
6: **for all** closed hotel auctions $h$ **do**
7:     distribute units of $h$ to those who demand them at the
8:         computed competitive equilibrium prices
9:     distribute any leftover units of $h$ uniformly at random
10: **end for**
Price Prediction with Distribution
2006 Finals

![Graph showing expected value of perfect prediction per hotel over time]

- tatonnement, expected clients
- SimAA, expected clients
- tatonnement, random clients
- SimAA, random clients
- tatonnement, random clients, with distribution
- SimAA, random clients, with distribution
Price Prediction with Distribution

2006 Finals

Euclidean Distance per Hotel

Minute

tatonnement, expected clients
SimAA, expected clients
tatonnement, random clients
SimAA, random clients
tatonnement, random clients, with distribution
SimAA, random clients, with distribution
Bidding in Simultaneous Auctions
Sealed-Bid & Second-Price

Given
a finite set of goods $X$
a valuation function $v : 2^X \to \mathbb{R}$
an additive pricing function $p : X \to \mathbb{R}$
a distribution $f$ over additive pricing functions
utility $u(Y) = v(Y) - p(Y)$, for all $Y \subseteq X$

Winner Determination Rule

\[
x \in \text{Winnings}(X, p, b) \text{ if and only if } b(x) \geq p(x)
\]  

(1)

Bidding Problem

\[
\text{SIM}(X, v, f) = \max_{b \in \mathbb{R}^X} \mathbb{E}_{p \sim f}[u(\text{Winnings}(X, p, b))]
\]  

(2)
Optimization

Bidding Problem

\[ \text{SIM}(X, v, f) = \max_{b \in \mathbb{R}^X} E_{p \sim f}[u(\text{Winnings}(X, p, b))] \]  

Sample Average Approximation

- sample \( S \) scenarios \( p_1, \ldots, p_S \sim f \)
- \( \text{SAA}(X, v, p_1, \ldots, p_S) = \max_{b \in \mathbb{R}^X} \sum_{i=1}^{S} u(\text{Winnings}(X, p_i, b)) \)

Theorem [e.g., Ahmed and Shapiro 2002]

The probability that an optimal solution to \( \text{SAA}(X, v, p_1, \ldots, p_S) \) is an optimal solution to \( \text{SIM}(X, v, f) \) converges to 1 exponentially fast as \( S \to \infty \).
“Collapsing” Heuristics

Example

\[ v(\text{camera + flash}) = 750 \]
\[ v(\text{camera}) = v(\text{flash}) = 0 \]

\[ p(\text{camera}) = 500, \ \text{with probability} \ \frac{1}{2} \]
\[ p(\text{camera}) = 1000, \ \text{with probability} \ \frac{1}{2} \]
\[ p(\text{flash}) = 50, \ \text{with probability} \ 1 \]

Predictions

\[ p(\text{camera}) = 750, \ \text{with probability} \ 1 \]
\[ p(\text{flash}) = 50, \ \text{with probability} \ 1 \]

Optimal Bid Vector

Bid Vector \( A \): \((0, 0)\)

Value\((A) = 0\)
“Exploiting” Heuristics

Example
\[ v(\text{camera + flash}) = 750 \]
\[ v(\text{camera}) = v(\text{flash}) = 0 \]

\[ p(\text{camera}) = 500, \text{ with probability } \frac{1}{2} \]
\[ p(\text{camera}) = 1000, \text{ with probability } \frac{1}{2} \]
\[ p(\text{flash}) = 50, \text{ with probability } 1 \]

Bid Vectors
Bid Vector \( A \): \( (0, 0) \) is optimal, with probability \( \frac{1}{2} \)
Bid Vector \( B \): \( (500, 50) \) is optimal, with probability \( \frac{1}{2} \)

Value of Stochastic Information = 75
\[ \text{Value}(B) = \frac{1}{2}(200) + \frac{1}{2}(-50) = 75 \]
\[ \text{Value}(A) = 0 \]
Bidding Heuristics

“Collapsing” Heuristics

- RoxyBot–2000 and RoxyBot–2000*
- Straight Marginal Utility
- FirstBot

“Exploiting” Heuristics

- RoxyBot–2002 and RoxyBot–2002*
- Average Marginal Utility
- SAA and SAA*
Marginal Utility

**Straight Marginal Utility**

\[
\left( \max_{Y \subseteq X \setminus \{x\}} \left[ v(Y \cup \{x\}) - \frac{1}{S} \sum_{i=1}^{S} p_i(Y) \right] \right) - \left( \max_{Y \subseteq X \setminus \{x\}} \left[ v(Y) - \frac{1}{S} \sum_{i=1}^{S} p_i(Y) \right] \right)
\]  

(5)

**Average Marginal Utility**

\[
\frac{1}{S} \sum_{i=1}^{S} \left( \max_{Y \subseteq X \setminus \{x\}} \left[ v(Y \cup \{x\}) - p_i(Y) \right] - \max_{Y \subseteq X \setminus \{x\}} \left[ v(Y) - p_i(Y) \right] \right)
\]

(6)

[Stone, et al. 01]
## Experiments

### Scores, Utilities, and Costs

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<th>Rank</th>
<th>Agent</th>
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TAC Travel Online Experiments
Scores, Utilities, and Costs

8 Agent Experiment

Score (thousands)

8 Agent Experiment

Trip Utility (thousands)

8 Agent Experiment

Cost (thousands)
**TAC Travel Online Experiments**

**Parameter Settings and Runtimes**

<table>
<thead>
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*Machines were not dedicated.*
Summary and Future Directions

Summary

◦ develop techniques for the effective design and analysis of trading agents
  – specific solutions to particular trading problems, as well as
  – general principles to guide the development of trading agents

Future Directions

◦ Humans make hundreds of routine decisions, fewer and fewer of which can be made in isolation, in our increasingly networked world.

◦ Soon our interactive decision-making will be carried out by agents that “understand” our preferences and negotiate with one another accordingly.
  – Proxy bidders in online auctions are early evidence of this coming generation of agents, in the trading domain.

◦ Research in agent technology is helping to lay the foundations for a future where agents figure prominently in our daily lives.
Thank You!

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