CS344M
Autonomous Multiagent Systems

Todd Hester

Department of Computer Science
The University of Texas at Austin
Good Afternoon, Colleagues

Are there any questions?
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- TAC currently
- Real-world TAC
Logistics

- FAI talk on Friday
  - Dr. Karthik Dantu (Fri, 11am, PAI 3.14)
  - Challenges in Building a Swarm of Robotic Bees
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  - Hand graded version in with your final reports
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• Final projects due in 3 weeks!
Your Progress Reports

- Overall quite good! (writing and content)
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- Best ones motivate the problem before giving solutions
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- More about what worked than what didn’t
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- Clear enough for outsider to understand

Todd Hester
Your Progress Reports

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- Best ones motivate the problem before giving solutions
- Say not only what’s done, but what’s yet to do
- More about what worked than what didn’t
- Clear enough for outsider to understand
- Do not just paste in proposal text... modify/merge it in
  - Especially if your plans have changed
  - Report should not say what you plan to put in the report
Details

- Be specific - enough detail so that we could reimplement
  - Use pseudocode and/or diagrams
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- It should not be left to the reader to figure it out
- Can you say exactly how your work differs from baseline?
Style

- More about your approach, less about the process
Style

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  - Not “What I did on summer vacation”
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  – How? Why? What alternatives?
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• Slides on resources page
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• Final projects: content matters more
Trading Agent Competition

- Put forth as a **benchmark problem** for e-marketplaces (Wellman, Wurman, et al., 2000)

- Autonomous agents act as **travel agents**
Trading Agent Competition

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• Autonomous agents act as travel agents
  – **Game**: 8 agents, 12 min.
  – **Agent**: simulated travel agent with 8 clients
  – **Client**: TACtown ↔ Tampa within 5-day period
Trading Agent Competition


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- **Auctions** for flights, hotels, entertainment tickets
  - **Server** maintains markets, sends prices to agents
  - Agent sends bids to server over network
28 Simultaneous Auctions

**Flights:** Inflight days 1-4, Outflight days 2-5 (8)

- Unlimited supply; prices tend to increase; immediate clear; no resale
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**Hotels:** Tampa Towers/Shoreline Shanties days 1-4 (8)

- 16 rooms per auction; 16th-price ascending auction; quote is ask price; no resale
- Random auction closes minutes 4 – 11
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- Random auction closes minutes 4 – 11

**Entertainment:** Wrestling/Museum/Park days 1-4 (12)

- Continuous double auction; initial endowments; quote is bid-ask spread; resale allowed
Client Preferences and Utility

Preferences: randomly generated per client

- Ideal arrival, departure days
- Good Hotel Value
- Entertainment Values
Client Preferences and Utility

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Utility: 1000 (if valid) – travel penalty + hotel bonus + entertainment bonus
Client Preferences and Utility

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Utility: 1000 (if valid) – travel penalty + hotel bonus + entertainment bonus

Score: Sum of client utilities – expenditures
Allocation

\[ G \equiv \text{complete allocation of goods to clients} \]
\[ v(G) \equiv \text{utility of } G \text{ – cost of needed goods} \]
\[ G^* \equiv \text{argmax } v(G') \]
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Given holdings and prices, find \( G^* \)
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*Given holdings and prices, find \( G^* \)*

- General allocation NP-complete
  - Tractable in TAC: mixed-integer LP (ATTac-2000)
  - Estimate \( v(G^*) \) quickly with LP relaxation
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**Prices known \( \Rightarrow G^* \) known \( \Rightarrow \) optimal bids known**
High-Level Strategy

- Learn model of expected hotel price
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- Learn model of expected hotel price distributions
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• For each auction:
  – Repeatedly sample price vector from distributions
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• Bid for all goods — not just those in \( G^* \)
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Goal: analytically calculate optimal bids
Hotel Price Prediction

Features:

- Current hotel and flight prices
- Current time in game
- Hotel closing times
- Agents in the game (when known)
- Variations of the above
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  - Assumption: similar economy
  - Features $\mapsto$ actual prices
The Learning Algorithm

• $X \equiv \text{feature vector } \in \mathbb{R}^n$

• $Y \equiv \text{closing price} - \text{current price } \in \mathbb{R}$
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- $X \equiv \text{feature vector } \in \mathbb{R}^n$
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New algorithm for conditional density estimation
Hotel Expected Values

- Repeat until time bound, for each hotel:
  1. Assume this hotel closes next
Hotel Expected Values

- Repeat until time bound, for each hotel:
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Hotel Expected Values

● Repeat until time bound, for each hotel:

1. Assume this hotel closes next
2. Sample prices from predicted price distributions
3. Given these prices compute \( V_0, V_1, \ldots, V_8 \)
   - \( V_i = \nu(G^*) \) if own exactly \( i \) of the hotel
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Hotel Expected Values

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- Value of $i$th copy is $\text{avg}( V_i - V_{i-1} )$
Other Uses of Sampling

**Flights:** Cost/benefit analysis for *postponing commitment*
Other Uses of Sampling

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**Cost:** Price expected to rise over next $n$ minutes

**Benefit:** More price info becomes known
  - Compute expected marginal value of buying some different flight
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**Entertainment:** Bid more (ask less) than expected value of having one more (fewer) ticket
## Finals

<table>
<thead>
<tr>
<th>Team</th>
<th>Avg.</th>
<th>Adj.</th>
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</tr>
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<tbody>
<tr>
<td>ATTac</td>
<td>3622</td>
<td>4154</td>
<td>AT&amp;T</td>
</tr>
<tr>
<td>livingagents</td>
<td>3670</td>
<td>4094</td>
<td>Living Systems (Germ.)</td>
</tr>
<tr>
<td>whitebear</td>
<td>3513</td>
<td>3931</td>
<td>Cornell</td>
</tr>
<tr>
<td>Urlaub01</td>
<td>3421</td>
<td>3909</td>
<td>Penn State</td>
</tr>
<tr>
<td>Retsina</td>
<td>3352</td>
<td>3812</td>
<td>CMU</td>
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<td>3074</td>
<td>3766</td>
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</tr>
<tr>
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<td>2859</td>
<td>3338</td>
<td>Stanford</td>
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- **ATTac** improves over time
- **livingagents** is an open-loop strategy
Controlled Experiments

- $ATTac_s$: "full-strength" agent based on boosting
Controlled Experiments

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- $SimpleMean_s$: sample from empirical distribution (previously played games)
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- \( \text{ATTac}_{ns}, \text{ConditionalMean}_{ns}, \text{SimpleMean}_{ns} \): predict expected value of the distribution
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- $EarlyBidder$: motivated by TAC-01 entry livingagents
**Controlled Experiments**

- **ATTac**: "full-strength" agent based on boosting
- **SimpleMean**: sample from empirical distribution (previously played games)
- **ConditionalMean**: condition on closing time
- **ATTac, ConditionalMean, SimpleMean**: predict expected value of the distribution
- **CurrentPrice**: predict no change
- **EarlyBidder**: motivated by TAC-01 entry livingagents
  - Immediately bids high for $G^*$ (with SimpleMean)
  - Goes to sleep
Stability

- 7 *EarlyBidder*’s with 1 *ATTac*

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*EarlyBidder* gets more utility; *ATTac* pays less
Results

- Phase I: Training from TAC-01 (seeding round, finals)
Results

- **Phase I**: Training from TAC-01 (seeding round, finals)
- **Phase II**: Training from TAC-01, phases I, II
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- **Phase III**: Training from phases I – III
## Results

- **Phase I**: Training from TAC-01 (seeding round, finals)
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<td>$\text{ATTac}_{ns}$</td>
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<td>$105.2 \pm 49.5$ (2)</td>
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<td>$-72.0 \pm 47.5$ (7)</td>
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<td>$\text{ConditionalMean}_{ns}$</td>
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<td>$8.6 \pm 41.2$ (4)</td>
<td>$-60.1 \pm 19.7$ (6)</td>
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<td>$\text{ConditionalMean}_s$</td>
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<td>$-147.5 \pm 35.6$ (8)</td>
<td>$-91.1 \pm 17.6$ (7)</td>
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<td>CurrentPrice</td>
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<td>$-33.7 \pm 52.4$ (6)</td>
<td>$-198.8 \pm 26.0$ (8)</td>
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Other TAC competitions

• Supply Chain Management

• Ad Auctions

• Power
Discussion

- Are these agents useful for the real version of these tasks?
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• What can we learn from these competitions?
Discussion

- Are these agents useful for the real version of these tasks?
- What can we learn from these competitions?
- General strategy that works well?
Last-minute bidding (R,O, 2001)

- eBay: first-price, ascending auction
- Amazon: auction extended if bid in last 10 minutes
- eBay: bots exist to incrementally raise your bid to a maximum

• Still people *snipe*. Why?
  – There’s a risk that the bid might not make it
  – However, common-value $\rightarrow$ bid conveys info
  – Late-bidding can be seen as implicit collusion
  – Or . . . , lazy, unaware, etc. (Amazon and eBay)

• Finding: more late-bidding on eBay,
  – even more on antiques rather than computers

Small design-difference matters
Late Bidding as Best Response

- Good vs. incremental bidders
  - They start bidding low, plan to respond
  - Doesn’t give them time to respond

- Good vs. other snipers
  - Implicit collusion
  - Both bid low, chance that one bid doesn’t get in

- Good in common-value case
  - protects information

Overall, the analysis of multiple bids supports the hypothesis that last-minute bidding arises at least in part as a response by sophisticated bidders to unsophisticated incremental bidding.