Good Afternoon, Colleagues

Are there any questions?
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Are there any questions?

- SDR?
- Open-loop vs. Closed-loop
- Why only 8 agents in TAC?
- Any other TAC? Branch offs?
- Stock trading?
Logistics

- Progress reports coming back
  - Hand them in with your final reports
Logistics

- Progress reports coming back
  - Hand them in with your final reports

- Final projects due in 2 1/2 weeks!
Your Progress Reports

- Overall not bad, but not as good as proposals
Your Progress Reports

- Overall not bad, but not as good as proposals
- Best ones motivate the problem before giving solutions
Your Progress Reports

• Overall not bad, but not as good as proposals

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• Say not only what’s done, but what’s yet to do
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- Say not only what’s done, but what’s yet to do
- Clear enough for outsider to understand
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  – Exchange papers for proofreading
  – Use undergraduate writing center
Your Progress Reports

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• Say not only what’s done, but what’s yet to do

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• Enough detail so that Doran or I could reimplement
Style

• More about your approach, less about the process
Style

• More about your approach, less about the process
  – Not “What I did on summer vacation”
Style

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  - Not just “we decided.”
Style

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- Slides on resources page
Results

• Big successes
  – Lots of bidders
  – Lots of revenue
Results

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- Also some problems
  - Strategic Demand Reduction
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• Also some problems
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• Incremental design changes
  – New problems always arise
  – Bidders indeed find ways to circumvent mechanisms
Results

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  - Lots of bidders
  - Lots of revenue

- Also some problems
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- Incremental design changes
  - New problems always arise
  - Bidders indeed find ways to circumvent mechanisms

- Lessons to be learned via agent-based experiments
FCC Spectrum Auction #35

• 422 licences in 195 markets (cities)
  – 80 bidders spent $8 billion
  – ran Dec 12 - Jan 26 2001
  – licence is a 10 or 15 mhz spectrum chunk

• Run in rounds
  – bid on each licence you want each round
  – simultaneous; break ties by arrival time
  – current winner and all bids are known

• Allowable bids: 1 to 9 bid increments
  – 1 bid incr is 10% – 20% of current price

• Other complex rules
Model

- Agent goals
  - desire 0, 1, or 2 licences per market
  - desired markets have unique values
  - subject to budget constraint

Assumption: no inter-market value dependencies

- Utility is profit: $\Sigma_l (value - cost)$

- modeled 5 most important bidders
  - others served mainly to raise prices
  - modeled as several small bidders
  - lower valuations (75% → pessimistic)
Bidding Strategies

- Considering self only
  - Knapsack
  - best self-only approach

- Strategic bidding (consider others)
  - threats
  - budget stretching
  - Strategic Demand Reduction (SDR)

Explicit communication not allowed
Randomized SDR

- Figure out allocations dynamically
  - round 1: bid for everything you want
  - first big bidder winning bid owns licence
  - satisfaction = owned value / desired value

- Random ⇒ uneven allocation
  - get small share ⇒ incentive to cheat
  - fair: own satisfaction close to average
  - if unlucky, take licences until fair

- Small bidders take licences from owners
  - remember licence’s owner
  - allocate while small bidders active
## RSDR vs. Knapsack

<table>
<thead>
<tr>
<th>Method</th>
<th>Agent</th>
<th>Profit ($M)</th>
<th>Ratio</th>
<th>Cost</th>
</tr>
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<tbody>
<tr>
<td>Knapsack</td>
<td>0</td>
<td>980 (±170)</td>
<td>1.00</td>
<td>.82</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>650 (±85)</td>
<td>1.00</td>
<td>.82</td>
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<tr>
<td></td>
<td>2</td>
<td>830 (±91)</td>
<td>1.00</td>
<td>.84</td>
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<td></td>
<td>3</td>
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<td></td>
<td>4</td>
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<td>.86</td>
</tr>
<tr>
<td>RSDR</td>
<td>0</td>
<td>1240 (±210)</td>
<td>1.26</td>
<td>.76</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>820 (±83)</td>
<td>1.25</td>
<td>.77</td>
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<tr>
<td></td>
<td>2</td>
<td>1300 (±290)</td>
<td>1.58</td>
<td>.74</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>300 (±44)</td>
<td>1.78</td>
<td>.79</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>930 (±240)</td>
<td>1.68</td>
<td>.76</td>
</tr>
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</table>

44% more profit; avg. ratio 1.51
Robustness

• What if someone cheats?
  - cheat: defect back to knapsack
  - others stay out of its way ⇒ big win

• Solution: Punishing RSDR (PRSDR)
  - cheater takes your licence ⇒ take it back
  - take it back first while still have money
  - aggressively punitive: skips optimizers

Simplification: pointing out cheaters by hand
# Robustness

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<td>Knapsack</td>
<td>1.00</td>
<td>.84</td>
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<tr>
<td>RSDR</td>
<td>1.51</td>
<td>.76</td>
</tr>
<tr>
<td>RSDR Cheater</td>
<td>1.63</td>
<td>.76</td>
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<tr>
<td>RSDR Victim</td>
<td>1.22</td>
<td>.79</td>
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<tr>
<td>PRSDR Cheater</td>
<td>1.02</td>
<td>.83</td>
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<tr>
<td>PRSDR Enforcer</td>
<td>1.17</td>
<td>.81</td>
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Extensions

- **Change small bidder valuations**
  - test robustness
  - RSDR is optimal for preserving profit

- **Multiple cheaters**
  - current punishment too aggressive
  - collapse back to knapsack instead
## Extensions

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<tr>
<th>Method</th>
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<th>Local Ratio</th>
<th>Cost</th>
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<tr>
<td>Multiple Cheater</td>
<td>1.03</td>
<td>1.03</td>
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<tr>
<td>Multiple Enforcer</td>
<td>1.01</td>
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<tr>
<td>50% Knapsack</td>
<td>1.70</td>
<td>1.00</td>
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<tr>
<td>50% RSDR</td>
<td>3.42</td>
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<tr>
<td>75% Knapsack</td>
<td>1.00</td>
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<td>.89</td>
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Future Work

- Robustness enhancements
  - better punishment method

- More complex value functions
  - inter-market dependencies

- Automatic cheater detection
  - partial cheating vs. detection arms race
  - smack back into compliance

- Generalization to other auctions
  - more robust to tie-breaking procedure variations
Summary

• Communication-free coordination
• Enables much higher profits
• Works even uncertain knowledge
• Real-world functionality relies on simple assumptions:
Summary

• Communication-free coordination

• Enables much higher profits

• Works even uncertain knowledge

• Real-world functionality relies on simple assumptions:
  – bidders want more profit
  – bidders familiar with PRSDR and its benefits
  – bidders willing to try it risk-free
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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  - **Game**: 8 agents, 12 min.
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  - **Client**: TACtown ↔ Tampa within 5-day period
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  - **Client**: TACtown ↔ Tampa within 5-day period

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

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

- Unlimited supply; prices tend to increase; immediate clear; no resale
28 Simultaneous Auctions

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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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**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
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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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- General allocation NP-complete
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  - 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
High-Level Strategy

• 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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  - Features $\mapsto$ actual prices
The Learning Algorithm

- $X \equiv \text{feature vector } \in \mathbb{R}^n$
- $Y \equiv \text{closing price – current price } \in \mathbb{R}$
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Peter Stone
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  - Use BoostTexter (boosting (Schapire, 1990))
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• Can convert to estimated distribution of $Y|X$
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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:

  1. Assume this hotel closes next
  2. Sample prices from predicted price distributions
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 $V_0, V_1, \ldots V_8$
     - $V_i = v(G^*)$ if own exactly $i$ of the hotel
     - $V_0 \leq V_1 \leq \ldots \leq V_8$
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  2. Sample prices from predicted price distributions
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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

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Other Uses of Sampling

**Flights:** Cost/benefit analysis for postponing commitment

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

**Benefit:** More price info becomes known
  - Compute expected marginal value of buying some different flight
Other Uses of Sampling

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Cost: Price expected to rise over next $n$ minutes
Benefit: More price info becomes known
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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>
<th>Institution</th>
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<tr>
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<td>TacsMan</td>
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<td>3338</td>
<td>Stanford</td>
</tr>
</tbody>
</table>

- ATTac improves over time
- livingagents is an open-loop strategy
Controlled Experiments

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

- $ATTac_s$: "full-strength" agent based on boosting
- $SimpleMean_s$: sample from empirical distribution (previously played games)
Controlled Experiments

- $\text{ATTac}_s$: "full-strength" agent based on boosting
- $\text{SimpleMean}_s$: sample from empirical distribution (previously played games)
- $\text{ConditionalMean}_s$: condition on closing time
Controlled Experiments

- \( ATTac_s \): “full-strength” agent based on boosting
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- \( ATTac_{ns}, ConditionalMean_{ns}, SimpleMean_{ns} \): predict expected value of the distribution
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- **CurrentPrice**: predict no change
- **EarlyBidder**: motivated by TAC-01 entry livingagents
Controlled Experiments

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

- 7 *EarlyBidder’s* with 1 *ATTac*

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<thead>
<tr>
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<th>Utility</th>
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<tr>
<td><em>ATTac</em></td>
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<td>$8909 \pm 264$</td>
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<tr>
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<td>$-4880 \pm 337$</td>
<td>$9870 \pm 34$</td>
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Stability

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<tbody>
<tr>
<td>ATTac</td>
<td>2578 ± 25</td>
<td>9650 ± 21</td>
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<tr>
<td>EarlyBidder</td>
<td>2869 ± 69</td>
<td>10079 ± 55</td>
</tr>
</tbody>
</table>
Stability

- 7 EarlyBidder’s with 1 ATTac

<table>
<thead>
<tr>
<th>Agent</th>
<th>Score</th>
<th>Utility</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATTac</td>
<td>2431 ± 464</td>
<td>8909 ± 264</td>
</tr>
<tr>
<td>EarlyBidder</td>
<td>-4880 ± 337</td>
<td>9870 ± 34</td>
</tr>
</tbody>
</table>

- 7 ATTac’s with 1 EarlyBidder

<table>
<thead>
<tr>
<th>Agent</th>
<th>Score</th>
<th>Utility</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATTac</td>
<td>2578 ± 25</td>
<td>9650 ± 21</td>
</tr>
<tr>
<td>EarlyBidder</td>
<td>2869 ± 69</td>
<td>10079 ± 55</td>
</tr>
</tbody>
</table>

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
Results

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

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

<table>
<thead>
<tr>
<th>Agent</th>
<th>Relative Score</th>
<th>Phase I</th>
<th>Phase III</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATTac&lt;sub&gt;ns&lt;/sub&gt;</td>
<td></td>
<td>105.2 ± 49.5 (2)</td>
<td>166.2 ± 20.8 (1)</td>
</tr>
<tr>
<td>ATTac&lt;sub&gt;s&lt;/sub&gt;</td>
<td></td>
<td>27.8 ± 42.1 (3)</td>
<td>122.3 ± 19.4 (2)</td>
</tr>
<tr>
<td>EarlyBidder</td>
<td></td>
<td>140.3 ± 38.6 (1)</td>
<td>117.0 ± 18.0 (3)</td>
</tr>
<tr>
<td>SimpleMean&lt;sub&gt;ns&lt;/sub&gt;</td>
<td></td>
<td>−28.8 ± 45.1 (5)</td>
<td>−11.5 ± 21.7 (4)</td>
</tr>
<tr>
<td>SimpleMean&lt;sub&gt;s&lt;/sub&gt;</td>
<td></td>
<td>−72.0 ± 47.5 (7)</td>
<td>−44.1 ± 18.2 (5)</td>
</tr>
<tr>
<td>ConditionalMean&lt;sub&gt;ns&lt;/sub&gt;</td>
<td></td>
<td>8.6 ± 41.2 (4)</td>
<td>−60.1 ± 19.7 (6)</td>
</tr>
<tr>
<td>ConditionalMean&lt;sub&gt;s&lt;/sub&gt;</td>
<td></td>
<td>−147.5 ± 35.6 (8)</td>
<td>−91.1 ± 17.6 (7)</td>
</tr>
<tr>
<td>CurrentPrice</td>
<td></td>
<td>−33.7 ± 52.4 (6)</td>
<td>−198.8 ± 26.0 (8)</td>
</tr>
</tbody>
</table>
Later TACs

- SCM, CAT
- PLAT
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.