Good Afternoon, Colleagues

Are there any questions?
Logistics

- Guest lecture on Thursday
Logistics

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- Next week’s readings up
Logistics

- Guest lecture on Thursday
- Next week’s readings up
- Very fun job talk next Tuesday
# Bidding for Multiple Items

<table>
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<tr>
<th></th>
<th>Utility</th>
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<tbody>
<tr>
<td>camera alone</td>
<td>$50</td>
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  - Auctions are simultaneous
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- What’s the value of the flash?
  - Auctions are simultaneous
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- $\in [10, 50]$ — **Depends on the price of the camera**
Spectrum licenses

• Worth a lot

• But how much to whom?
Spectrum licenses

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- Used to be assigned
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So decided to auction
Goals of mechanism

- Efficient allocation (assign to whom it’s worth the most)
- Promote deployment of new technologies
- Prevent monopoly (or close)
- Get some licenses to designated companies
- No political embarrassments
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Revenue an afterthought (but important in end)
Choices

• Which basic auction format?
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- Sequential or simultaneous auctions?
Choices

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• Combinatorial bids allowed?
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- How to encourage designated companies?
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Choices

- Which basic auction format?
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- How to encourage designated companies?
- Up front payments or royalties?
- Reserve prices?
- How much information public?
Problems from New Zealand and Australia

Second price, sealed bid
Problems from New Zealand and Australia

Second price, sealed bid

- High bidder’s willingness to pay is public
- No reserve prices
- No penalties for default, so many meaningless high bids
Problems from New Zealand and Australia

Second price, sealed bid

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Any oversight in auction design can have harmful repercussions, as bidders can be counted on to seek ways to outfox the mechanism.
License interactions

- Complementarities: good to be able to offer roaming capabilities
License interactions

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• Substitutability: several licenses in the same region
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• Need to be flexible to allow bidders to create aggregations
License interactions

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- Need to be flexible to allow bidders to create aggregations

- Secondary market might allow for some corrections
  - Likely to be thin
  - High transaction costs
Limits of Theory

- Identify variables, but not relative magnitudes
Limits of Theory

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  – When there are conflicting effects, can’t tell which will dominate
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- Doesn’t scale to complexity of spectrum auctions
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Used laboratory experiments too
Open vs. Sealed Bid

- Open increases information, reducing winner’s curse
Open vs. Sealed Bid

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  - Risk aversion leads to higher bids in sealed bid auctions
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  - Circumvented!
Simultaneous vs. Sequential

- Sequential prevents backup strategies for aggregation
- Sequential also allows for budget stretching
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  - Closing one by one is effectively sequential
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Went with activity rules
Combinatorial Bids

- Nationwide bidding could decrease efficiency and revenue
Combinatorial Bids

- Nationwide bidding could decrease efficiency and revenue

- Full combinatorial bidding too complex
  - Winner determination problem
  - Active research area
Aiding Designated Bidders

- Give them a discount
Aiding Designated Bidders

- Give them a discount
- Circumvented!
Royalties vs. Up-front Payments

- Royalties decrease risk, increase bids
Royalties vs. Up-front Payments

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- But royalties discourage post-auction innovation
Royalties vs. Up-front Payments

- Royalties decrease risk, increase bids
- But royalties discourage post-auction innovation
- Decided against
Reserve Prices

- Not necessary in such a competitive market
- Did include withdrawal penalties
Results

- Big successes
  - Lots of bidders
  - Lots of revenue
Results

• Big successes
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• Also some problems
  – Strategic Demand Reduction
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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 revenue

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- 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>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>980 (±170)</td>
<td>1.00</td>
<td>.82</td>
</tr>
<tr>
<td>Knapsack</td>
<td>1</td>
<td>650 (±85)</td>
<td>1.00</td>
<td>.82</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>830 (±91)</td>
<td>1.00</td>
<td>.84</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>170 (±20)</td>
<td>1.00</td>
<td>.84</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>550 (±96)</td>
<td>1.00</td>
<td>.86</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1240 (±210)</td>
<td>1.26</td>
<td>.76</td>
</tr>
<tr>
<td>RSDR</td>
<td>1</td>
<td>820 (±83)</td>
<td>1.25</td>
<td>.77</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1300 (±290)</td>
<td>1.58</td>
<td>.74</td>
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<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>
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44% more profit; avg. ratio 1.51
Robustness

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

- Solution: Punishing RSDR (PRSDR)
  - cheater takes your licence $\Rightarrow$ 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>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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<td>PRSDR Cheater</td>
<td>1.02</td>
<td>.83</td>
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<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
## Extentions

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<tr>
<td>Multiple Cheater</td>
<td>1.03</td>
<td>1.03</td>
<td>.84</td>
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<tr>
<td>Multiple Enforcer</td>
<td>1.01</td>
<td>1.01</td>
<td>.83</td>
</tr>
<tr>
<td>50% Knapsack</td>
<td>1.70</td>
<td>1.00</td>
<td>.74</td>
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<td>50% RSDR</td>
<td>3.42</td>
<td>2.02</td>
<td>.51</td>
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<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.
  - **Agent:** simulated travel agent with 8 clients
  - **Client:** TACtown ↔ Tampa within 5-day period
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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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**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

**Preferences:** randomly generated per client
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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

\[ G \equiv \text{complete allocation of goods to clients} \]
\[ v(G) \equiv \text{utility of } G \text{ – cost of needed goods} \]
\[ G^* \equiv \text{argmax } v(G) \]
Allocation

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Given holdings and prices, find $G^*$
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  - 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
High-Level Strategy

- Learn model of expected hotel price distributions
High-Level Strategy

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• For each auction:
  – Repeatedly sample price vector from distributions
High-Level Strategy

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• Bid for all goods — not just those in \( G^* \)
High-Level Strategy

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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 $\rightarrow$ 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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  - Use BoostTexter (boosting (Schapire, 1990))
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- Can convert to estimated distribution of $Y|X$
The Learning Algorithm

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

- $Y \equiv \text{closing price} - \text{current price } \in \mathbb{R}$

- Break $Y$ into $k \approx 50$ cut points $b_1 \leq \cdots \leq b_k$

- For each $b_i$, estimate probability $Y \geq b_i$, given $X$
  - Say $X$ belongs to class $C_i$ if $Y \geq b_i$
  - $k$-class problem: each example in many classes
  - Use BoostTexter (boosting (Schapire, 1990))

- Can convert to estimated distribution of $Y|X$

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

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

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

**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

**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>
</tr>
</thead>
<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>
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</tr>
<tr>
<td>Urlaub01</td>
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<td>3909</td>
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</tr>
<tr>
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<td>3253*</td>
<td>3679</td>
<td>Southampton (UK)</td>
</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

- $ATTac$: “full-strength” agent based on boosting
- $SimpleMean$: sample from empirical distribution (previously played games)
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- **SimpleMean**: sample from empirical distribution (previously played games)
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- **CurrentPrice**: predict no change
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- \textit{EarlyBidder}: motivated by TAC-01 entry livingagents
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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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# Stability

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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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<tr>
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<td>Phase I</td>
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<tr>
<td>( \text{ATTac}_{ns} )</td>
<td>105.2 ± 49.5 (2)</td>
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<td>27.8 ± 42.1 (3)</td>
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<td>( \text{EarlyBidder} )</td>
<td>140.3 ± 38.6 (1)</td>
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<tr>
<td>( \text{SimpleMean}_{ns} )</td>
<td>−28.8 ± 45.1 (5)</td>
</tr>
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<td>( \text{SimpleMean}_{s} )</td>
<td>−72.0 ± 47.5 (7)</td>
</tr>
<tr>
<td>( \text{ConditionalMean}_{ns} )</td>
<td>8.6 ± 41.2 (4)</td>
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<td>−147.5 ± 35.6 (8)</td>
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<tr>
<td>( \text{CurrentPrice} )</td>
<td>−33.7 ± 52.4 (6)</td>
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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 $\implies$ 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.