Good Afternoon, Colleagues

Are there any questions?
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- Australia - how know when to stop defaulting?
- Why does open bidding reduce winner’s curse? (?)
- How do royalties reduce risk?
Good Afternoon, Colleagues

Are there any questions?

- Australia - how do we know when to stop defaulting?
- Why does open bidding reduce winner’s curse? (?)
- How do royalties reduce risk?
- 2 or 8 hotels in TAC? Why bidding?
- Open/close loop?
- Entertainment ticket distribution change?
Logistics

- Next week’s classes
Logistics

- Next week’s classes
- Keep working on your project!
Spectrum licenses

- Worth a lot
- But how much to whom?
- Used to be assigned
  - took too long
- Switched to lotteries
  - too random
  - clear that lots of value given away

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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• Efficient allocation (assign to whom it’s worth the most)

• Promote deployment of new technologies

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Revenue an afterthought (but important in end)
Choices

• Which basic auction format?
• Sequential or simultaneous auctions?
• Combinatorial bids allowed?
• 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

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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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License interactions

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- Substitutability: several licenses in the same region

- 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
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- Identify variables, but not relative magnitudes
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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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- May depend on unknown information
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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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  - Leads to higher bids
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  - Sealed bid auctions deter collusion
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- Decided former outweighed latter

- Went with announcing bids, but not the bidders
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- But . . .
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  - Sealed bid auctions deter colusion

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- Went with announcing bids, but not the bidders
  - 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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  - be simple and understandable
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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

- Royalties decrease risk, increase bids
- 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

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- Also some problems
  - Strategic Demand Reduction
Results

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• Incremental design changes
  – New problems always arise
  – Bidders indeed find ways to circumvent mechanisms
Results

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• Incremental design changes
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• Lessons to be learned via agent-based experiments
Class Discussion

David Barksdale on strategic demand reduction
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


- 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
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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- 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

Preferences: randomly generated per client

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

Preferences: randomly generated per client

- Ideal arrival, departure days
- Good Hotel Value
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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
  - 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
- For each auction:
  - Repeatedly sample price vector from distributions
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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
Hotel Price Prediction

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● Data:
  – Hundreds of seeding round games
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- **Data:**
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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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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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  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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- 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
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>
<td>3513</td>
<td>3931</td>
<td>Cornell</td>
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<tr>
<td>Urlaub01</td>
<td>3421</td>
<td>3909</td>
<td>Penn State</td>
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<td>Retsina</td>
<td>3352</td>
<td>3812</td>
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<tr>
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<td>3074</td>
<td>3766</td>
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</tr>
<tr>
<td>Southampton</td>
<td>3253*</td>
<td>3679</td>
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<tr>
<td>TacsMan</td>
<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

- \textit{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

- $ATTacs$: “full-strength” agent based on boosting

- $SimpleMean_s$: sample from empirical distribution (previously played games)

- $ConditionalMean_s$: condition on closing time

- $ATTacs_n, ConditionalMean_n, SimpleMean_n$: predict expected value of the distribution
Controlled Experiments

- $ATTac_s$: "full-strength" agent based on boosting
- $SimpleMean_s$: sample from empirical distribution (previously played games)
- $ConditionalMean_s$: condition on closing time
- $ATTac_{ns}, ConditionalMean_{ns}, SimpleMean_{ns}$: predict expected value of the distribution
- $CurrentPrice$: predict no change
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- \(\text{EarlyBidder}\): 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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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)
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- **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

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<td><strong>Phase I</strong></td>
<td><strong>Phase III</strong></td>
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<td><strong>ATTac</strong></td>
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<td>166.2 ± 20.8 (1)</td>
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<td>117.0 ± 18.0 (3)</td>
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<td><strong>SimpleMean</strong></td>
<td>−28.8 ± 45.1 (5)</td>
<td>−11.5 ± 21.7 (4)</td>
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<td><strong>SimpleMean</strong></td>
<td>−72.0 ± 47.5 (7)</td>
<td>−44.1 ± 18.2 (5)</td>
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<td><strong>ConditionalMean</strong></td>
<td>8.6 ± 41.2 (4)</td>
<td>−60.1 ± 19.7 (6)</td>
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<td>−147.5 ± 35.6 (8)</td>
<td>−91.1 ± 17.6 (7)</td>
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<td><strong>CurrentPrice</strong></td>
<td>−33.7 ± 52.4 (6)</td>
<td>−198.8 ± 26.0 (8)</td>
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</tr>
</tbody>
</table>
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- 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
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• Other complex rules
Strategies People Use

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It’s a poker game!
Experimental Setup

- Realistic FCC auction simulator (FAucS)
Experimental Setup

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  - follows published auction rules
  - hundreds of goods
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  - simultaneous, over 100 rounds
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Model

- Agent goals
  - desire 0, 1, or 2 licences per market
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• modeled 5 most important bidders
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- Utility is profit \( \Rightarrow \Sigma_l (value - cost) \)

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

• Considering self only: Knapsack
  – best self-only approach
Bidding Strategies

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  - Strategic Demand Reduction (SDR)
  - threats
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Randomized SDR (RSDR)

- Figure out allocations dynamically
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  - fair: own satisfaction close to average
  - convention: unlucky bidders may take licences until fair

- Small bidders take licences from owners
  - big bidders 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>Knapsack</td>
<td>1</td>
<td>980 (±170)</td>
<td>1.00</td>
<td>.82</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>650 (±85)</td>
<td>1.00</td>
<td>.82</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>830 (±91)</td>
<td>1.00</td>
<td>.84</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>170 (±20)</td>
<td>1.00</td>
<td>.84</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>550 (±96)</td>
<td>1.00</td>
<td>.86</td>
</tr>
<tr>
<td>PRSDR</td>
<td>1</td>
<td>1240 (±210)</td>
<td>1.26</td>
<td>.76</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>820 (±83)</td>
<td>1.25</td>
<td>.77</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1300 (±290)</td>
<td>1.58</td>
<td>.74</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>300 (±44)</td>
<td>1.78</td>
<td>.79</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>930 (±240)</td>
<td>1.68</td>
<td>.76</td>
</tr>
</tbody>
</table>

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)
  - cheaters may not own licences
  - recall: non-cheaters take licence from owner = fairing
  - convention: 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
## PRSDR Results

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<td>.84</td>
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<tr>
<td>(P)RSDR</td>
<td>1.51</td>
<td>.76</td>
</tr>
<tr>
<td>RSDR Cheater</td>
<td>1.63</td>
<td>.76</td>
</tr>
<tr>
<td>RSDR Victims</td>
<td>1.22</td>
<td>.79</td>
</tr>
<tr>
<td>PRSDR Cheater</td>
<td>1.02</td>
<td>.83</td>
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<tr>
<td>PRSDR Enforcers</td>
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<td>.81</td>
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- **Threats work!**
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

<table>
<thead>
<tr>
<th>Method</th>
<th>Ratio</th>
<th>Local Ratio</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple Cheater</td>
<td>1.03</td>
<td></td>
<td>.84</td>
</tr>
<tr>
<td>Multiple Enforcer</td>
<td>1.01</td>
<td></td>
<td>.83</td>
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<td>Method</td>
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<td></td>
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<td>1.01</td>
<td></td>
<td>.83</td>
</tr>
<tr>
<td>50%, Knapsack</td>
<td>1.70</td>
<td>1.00</td>
<td>.74</td>
</tr>
<tr>
<td>50%, PRSDR</td>
<td>3.42</td>
<td>2.02</td>
<td>.51</td>
</tr>
<tr>
<td>75%, Knapsack</td>
<td>1.00</td>
<td>1.00</td>
<td>.84</td>
</tr>
<tr>
<td>75%, PRSDR</td>
<td>1.51</td>
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<td>1.00</td>
<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:
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• 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
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.