Adaptive Mechanism Design: A Metalearning Approach

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Auction Example

- Consider a book seller using an auction service
- Seller must choose **parameters** defining auction
- Goal is to maximize revenue
- Optimal parameters depend on bidder population
Analytical Approach

• Traditional approach
  – (e.g. Myerson 81, Milgrom and Weber 82)

• **Assumptions** are made about
  – bidder motivations (valuations, risk aversion, etc.)
  – information available to bidders
  – bidder rationality

• Derive equilibrium strategies

• What if assumptions are incorrect?
  – **revise assumptions**
  – requires time and human input
  – problem if limited time between auctions
Empirical Approach

- Possible if historical data on similar auctions
- Do **data mining** to identify optimal parameters (e.g. Shmueli 05)
  - a number of businesses provide this service

For “The Cat in the Hat”, you should run
a 3-day auction starting on Thursday
with a starting bid of $5.
Empirical Approach

- What if the item is new and no data exists?

- What if there is a sudden change in demand?
Overview

- Motivation
- Adaptive auction mechanisms
- Bidding scenario
- Adaptive mechanism implementation and results
- Incorporating predictions through metalearning
- Additional experiments
Adaptive Auction Mechanisms

- For use in situations with recurring auctions
  - repeated eBay auctions, Google keyword auctions, etc.
- Bidder behavior consistent for some period
  - possible to learn about behavior through experience
- Adapt mechanism parameters in response to auction outcomes in order to maximize some objective function (such as seller revenue)
- Seller adjusts parameters using an adaptive algorithm
  - characterizes function from parameters to results
  - essentially an active, online regression learner
Adaptive Auction Mechanisms

- Related work (e.g. Blum et al. 03)
  - apply online learning methods
  - few or no assumptions about bidders
  - worst case bounds

- What about the intermediate case?
  - between complete knowledge and no knowledge
  - can make some predictions about bidders
  - choose adaptive algorithm using this information
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Loss Averse Bidders

- Loss aversion: utility of gain = $X$, utility of loss = -$X$
- Loss averse bidders “lose” if outbid after they were the high bidder
- 2 bidder equilibrium: (Dodonova 2005)
- Reserve price important
Loss Averse Bidders
Auction Scenario

- Our seller has 1000 books to sell in auctions
  - series of English auctions with choice of reserve price
- The seller interacts with a population of bidders:
  - bidders characterized by valuation $v$, loss aversion
  - the population is characterized by distributions over $v$,
    - $0 < v < 1$; $1 < v < 2.5$
- Assume Gaussian distributions
  - mean of $v$ chosen from $[0, 1]$; mean of $x$ from $[1, 2.5]$
  - variances are $10^x$, where $x$ chosen from $[-2, 1]$
- 2 bidders per auction, following equilibrium
Individual populations:

Average:
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Adaptive Algorithm (Bandit)

- Discretize choices of reserve price ($k$ choices)
- Results in a $k$-armed bandit problem
- Tradeoff between exploration and exploitation
- Sample averaging + softmax action selection:
  - Record $avg_i$ and $count_i$ for each choice
  - Choose $i$ with probability $\frac{(e^{avg_i}/\tau)}{(\sum_{j=1}^{k} e^{avg_j}/\tau)}$
  - controls exploration vs exploitation, often decreases
Adaptive Algorithm (Bandit)
Adaptive Algorithm Parameters

- **k** (number of discrete choices)
- $$\text{start, end}$$ (decrease linearly over time)
- How to initialize values of $$\text{avg}_i$$ and $$\text{count}_i$$?
  - optimistic initialization
- We choose these **by hand**:
  - $$k = 13$$
  - $$\text{start} = 0.1, \text{end} = 0.01$$
  - $$\text{avg}_i = 0.6, \text{count}_i = 1$$
Adaptive Algorithm (Regression)

- Bandit - restricts choices, assumes independence
- Solve by using regression:
  - Locally Weighted Quadratic Regression (instance based)
  - can estimate revenue at any point
  - considers all experience, uses a Gaussian weighting kernel
- Continue to discretize choices, but at high resolution
- Parameters nearly the same
  - need to choose kernel width (0.1)
Adaptive Algorithm (Regression)
Results

• Average results over 10,000 generated bidder populations

• Significant with 99% confidence (paired t-tests)

<table>
<thead>
<tr>
<th>Adaptive algorithm</th>
<th>Avg. revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>best fixed reserve price (0.54)</td>
<td>0.367</td>
</tr>
<tr>
<td>bandit</td>
<td>0.374</td>
</tr>
<tr>
<td>regression</td>
<td>0.385</td>
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![Graph showing average revenue over auction number]
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Taking Advantage of Predictions

- Adaptive mechanism requires no assumptions
- But what if reasonable predictions are possible?
- Example: selling a brand new book
  - could make guesses about bidder valuations, strategies
  - could consider books with similar author or subject
Taking Advantage of Predictions

- Seller can predict plausible bidder populations
- Adaptive mechanism should work well if correct
Metalearning

- Suppose seller can simulate bidder populations
- Choose an adaptive algorithm that is parameterized
- Search for optimal parameters in simulation
- An instance of metalearning
Simulation of Bidders by the Seller

- Suppose seller can predict possible populations (distributions of \( v \) and \( \) )
- Essentially a distribution over bidder populations
- Choose adaptive algorithm that performs best with respect to this distribution
Adaptive Parameters

- Now chosen through metalearning
- \( \text{start} \) \( \text{end} \)
- Kernel width
- \( \text{avg}_i \) and \( \text{count}_i \)
  - optimistic initialization becomes initial experience
Parameter Search

- A stochastic optimization task
- Use Simultaneous Perturbation Stochastic Approximation (SPSA):
  - generate two estimates for slightly different parameters
  - move in direction of gradient
- Start with previously hand chosen parameters
- Time consuming, but done offline
Search Results

Bandit approach

\[
\begin{align*}
\text{start} &= .0423 \\
\text{end} &= .0077
\end{align*}
\]

Regression approach

\[
\begin{align*}
\text{start} &= .0081 \\
\text{end} &= .0013 \\
\text{kernel width} &= .138
\end{align*}
\]
Results

- Average results over 10,000 populations drawn from predicted distribution
- Significant with 99% confidence (paired t-tests)

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<tr>
<td><strong>bandit, learned parameters</strong></td>
<td><strong>0.394</strong></td>
</tr>
<tr>
<td>regression, initial parameters</td>
<td>0.385</td>
</tr>
<tr>
<td>regression, learned parameters</td>
<td>0.405</td>
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![Graph showing average revenue over auction number with lines labeled A to E representing different algorithms.]
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Questions

• Why not learn a model of the population?
• What if the population behaves unexpectedly? (different from simulated)
• What if the population changes over time?
Modeling the Population

- **Bayesian approach**
  - maintain probability distribution over possible populations (distributions of $v$ and $\theta$)
  - update after each new observation (auction result)
  - softmax action selection using expected revenues

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<td>0.407</td>
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Unexpected Behavior

- Generate populations differently
  - before: mean of $v$ in $[0, 1]$; mean of $v$ in $[1, 2.5]$  
  - now: mean of $v$ in $[.3, .7]$; mean of $v$ in $[1.5, 2]$

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<td>0.414</td>
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<tr>
<td>regression, initial parameters</td>
<td>0.575</td>
</tr>
<tr>
<td>regression, learned parameters</td>
<td>0.593</td>
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Related Work

- Evolve ZIP traders and CDA together (Cliff 01)
- Evolve buyer and seller strategies and auction mechanism with genetic programming (Phelps et al. 02)
- Identify optimal price parameter of sealed bid auction for various bidder populations (Byde 03)
Future Work

• Encountered populations with unexpected behavior
• Non-stationary populations
• Learning populations
• Multiple mechanism parameters
• More sophisticated adaptive algorithms
• Evaluate on actual auction data
Conclusion

- Described design of adaptive auction mechanisms
- Experimented with a specific bidder scenario
- Adaptive mechanism outperforms fixed one
- Introduced metalearning approach
- Improve performance when predictions available