Machine Learning, Market Design, and Advertising

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Paid Search

Harry Potter and the Order of the Phoenix showtimes for IL 60614 - Change location
2hr 18min - Rated PG-13 - Action/Adventure/Drama/SciFi/Fantasy
AMC Loews Streets of Woodfield 20 - 601 N. Martingale Road, Schaumburg, IL, USA - Map
1:35 7:05pm
More theaters »

News results for harry potter
Harry Potter exhibit coming to Museum of Science and Industry - 14 hours ago
By William Mullen | Tribune reporter Harry Potter fans will roam the Great Hall of The Hogwarts School of Witchcraft and Wizardry next spring and summer as ...
Chicago Tribune - 59 related articles »
‘Harry Potter’ Star Emma Watson ‘Intrigued’ For ‘Deathly Hallows’ - MTV.com - 158 related articles »
Harry Potter: The Tales of Beedle the Bard becomes fastest-selling - Telegraph.co.uk - 95 related articles »

Sponsored Links
The Tales of Beedle the Bard
J.K. Rowling Top Seller Books 2009
The Tales of Beedle the Bard Books-247.com/Harry+Potter
Is Harry Potter Like You?
Take This Personality Test & See If You’re The Same As Harry Potter!
www.DaVinciMethod.com/Harry-Potter

Harry Potter
Harry Potter & the Deathly Hallows
FREE Super Saver Shipping!
www.Amazon.com

Harry potter
Fantastic prices on harry potter
Deal with Canadians and save
www.ebay.ca
Definition: Generalized Second Price (GSP) auction

- Advertisers bid for keywords in advance.
- On query,
  - Find all bids that match query.
  - Rank by bid.
  - If ad clicked, charge next highest bid.

(can also scale bids by “quality” or click-through rate)
Overview

Part I: Beyond GSP.

- Advertising market overview.
- Short-comings of GSP.
- Proposal: add pre-sale market.
- Many connections to ML.

Part II: Machine learning and market design.
Part I: Beyond GSP.
Market Participants:
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- search engine
- users
- advertisers
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- *search engine* (e.g., wants to maximize \( \text{profit} = \text{payments} - \text{costs} \))
- *users*
- *advertisers*
Market Participants:

- **search engine** (e.g., wants to maximize profit = payments − costs)
- **users** (e.g., want to max search/ad relevance, min search time)
- **advertisers**
Online/Search Advertising Markets

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- *maximize welfare* = user welfare + advertiser welfare − search engine costs.

- *maximize profit* = payments − costs.
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Market Design Objectives:

- **maximize welfare** = user welfare + advertiser welfare − search engine costs.

- **maximize profit** = payments − costs.
  (short-term profit maximization is probably short-sighted)
Recall Definition: Generalized Second Price (GSP) auction

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Properties:

- *low-level bidding language*: bids for keywords.
- *decentralized*: advertisers are optimizers.
- *local*: advertisers adapt bids to market conditions.
- *diffuse info*: advertisers know demand, engine knows supply.
- *online greedy*: allocation ignores future supply and past allocation.
Evidence of GSP Non-optimality:

- *search engine marketers* are necessary (i.e., significant bid cost).
- Pervasive use of *broadmatch*.
- Many advertisers do not actively change bids.
- Budgets often *binding* (advertisers could bid less and get more).
Example: broadmatch

*Broadmatch* allows a single advertiser bid to match many search queries.
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**Note:** better to have expressive bids and low bid-maintenance cost.
Example: “Harry Potter”
Example: “Deathly Hallows”

Harry Potter and the Deathly Hallows - Wikipedia, the free encyclopedia
Harry Potter and the Deathly Hallows is the seventh and final of the Harry Potter novels written by British author J. K. Rowling. The book was released on ...

Magical objects in Harry Potter - Wikipedia, the free encyclopedia
30 Jul 2007 ... The coins are also used in Harry Potter and the Deathly Hallows to .... The Deathly Hallows are three magical objects that appear in Harry ...

Harry Potter and the Deathly Hallows: Part I (2010)
Directed by David Yates. With Daniel Radcliffe, Emma Watson, Helena Bonham Carter. Visit IMDb for Photos, Showtimes, Cast, Crew, Reviews, Plot Summary, ...

Video results for deathly hallows
Broadmatch Discussion

Discussion:

- Compare Amazon’s value-per-click: Probably “Harry Potter” < “Deathly Hallows”
- Compare advertiser competition: Probably “Harry Potter” > “Deathly Hallows”
- Compare keyword supply: Probably “Harry Potter” > “Deathly Hallows”
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Suggestion:

- Use “conversion tracking” to learn conversion rates. (compatible with GSP)
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Conclusion: Amazon should bid differently for “H.P.” vs “D.H.”

Suggestion:

- Use “conversion tracking” to learn conversion rates.
  (compatible with GSP)

- Use auction where advertisers bid true value-per-click.
  (incompatible with GSP)
Challenges and Tasks

Challenges:

1. complex advertiser and user preferences.
2. online supply.
3. large tail.
4. incentives (esp. with budgets)
# Challenges and Tasks

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What would be a better mechanism?
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Combine pre-sale (offline) mechanism with spot (online) mech.
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- **timber**: 20% spot auction, 80% pre-sale (prices from spot)

- **pollution allowance**: short and medium-term markets.

- **electricity markets**: short (≤ 1 day), medium (1–3 years), long-term (4–20 years) markets.
Beyond GSP

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How should we design the advertising pre-sale market?
Part II: Machine learning and market design.
Setting:

- can estimate supply.
- can estimate preferences. (if advertisers provide automated reports)
- can cluster tail.

Market Design Goal:

- incentivize advertisers to provide automated reports.
- optimize objective.
Pricing-based mechanisms

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**Claim:** many justifications for pricing-based approach.
Limited Supply

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**Natural Objective:** for class of offers $G$, find offer that maximizes objective payoff. (e.g., social welfare, profit, etc.)
Optimization Challenge: given preferences and supplies, compute offer with highest performance.
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Incentive Challenge: advertisers can manipulate this optimal offer.

Can we design mech. where it is optimal to report true preferences?
Approach 1: Random Sampling Auction

**Random Sampling Optimal Offer Auction, RSOO_{G}**

1. Randomly partition bidders into two sets, \( S_1 \) and \( S_2 \).
2. Compute optimal offers, \( g_1 \) and \( g_2 \), for each set.
3. Offer \( g_1 \) to \( S_2 \) and \( g_2 \) to \( S_1 \).
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\[
\begin{array}{c}
S \\
S_1 \\
S_2
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Note: close connection to sample complexity and machine learning.
Theorem: (Approximately) For any linear objective (e.g., welfare or profit), class of offers \( \mathcal{G} \), and \( \epsilon \);

\[
E[\text{RSOO}_\mathcal{G}] \geq (1 - \epsilon) \text{OPT}_\mathcal{G}
\]

as long as

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\text{OPT}_\mathcal{G} \geq \frac{h}{\epsilon^2} \log \frac{|\mathcal{G}|}{\epsilon}
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and \( h \) is upper bound on payoff from any agent.
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and $h$ is upper bound on payoff from any agent.

Interpretation: convergence rate is $O(h \log |\mathcal{G}|)$. 
Example: Selling tee shirts.

- Bidders with valuations in $[1, h]$ for a tee shirt.
- Reasonable offers: $\mathcal{G} = \{\text{price } 2^i \text{ for } i \in \{1, \ldots, \log h\}\}$.
- Convergence Rate: $O(h \log |\mathcal{G}|) = O(h \log \log h)$
Recall Interpretation: convergence rate is $O(h \log |G|)$.

Extensions:

- use *covering* arguments to improve bounds.
- use *structural-risk-minimization* to penalize for “complex” offers.

Selected References:

- Pricing Algorithms: E.g., [Gurusuami et al., 2005]
- Unlimited Supply: [Balcan et al., 2005]
- Limited Supply: [Balcan et al., unpublished]
Definition: A function $f$ satisfies $\epsilon$-differential privacy if for $S$ and $S'$ differing in one coordinate and set $R$ in range of $f$,

$$\Pr[f(S) \in R] \leq e^\epsilon \times \Pr[f(S') \in R]$$
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**Selected References:**

- Differential Privacy: [Dwork, 2006]
- Differential Privacy Auction: [McSherry and Talwar, 2007]
Approach 2: Differential Privacy Auction

Privacy Preserving Optimal Offer Auction, DPOO$_G$

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$S \rightarrow g = \hat{\text{opt}}(S)$
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Claim: $\text{DPOO}_G$ has near optimal performance.

Claim: With high probability in $\text{DPOO}_G$, reporting true preferences is optimal.

Note: “high probability” is as $\text{OPT} \gg h \log |G|$. 
Conclusions

1. GSP unlikely to optimize desired objectives.

2. ML can significantly help advertising market design.
   - predict supply.
   - learn preferences.
   - cluster tail.
   - pricing-based mechanisms.

3. advertising markets need pre-sale market.

4. pricing-based mechanisms may be right way to go.