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Introduction

Problem Definition: Bids, Valuations, and Click Probabilities

 $b = (b_1, \dots, b_n) = \text{Bid vector of advertisers}$ $b^{(1)}, \dots, b^{(n)} = \text{Decreasing ordering of the bids}$ $\theta_i = \text{Value derived out of a click by advertiser } i$ = Type of advertiser i $\Theta_i = \text{Set of types of advertiser } i$ $\theta = (\theta_1, \dots, \theta_n) = \text{Type vector of advertisers}$ $\alpha_{ij} = \text{Click probability of } i^{th} \text{ Ad in } j^{th} \text{ position}$ $1 \ge \alpha_{i1} \ge \alpha_{i2} \ge \dots \ge \alpha_{im} \ge 0 \ \forall i \in N \text{ (AAE Assumption)}$

Introduction

Problem Definition: Search Engine's Problem

Allocation Rule

Who should be allocated what ?

 $y_{ij}(b) = \begin{cases} 1 & \text{if advertiser } i \text{ is allocated slot } j \\ 0 & \text{o/w} \end{cases}$



Payment Rule

Which advertiser should be charged what price ?

 $p_i(b) =$ Price that is charged from advertiser *i* for per click



Introduction

Recent Literature

- B. Edelman, M. Ostrovsky, and M. Schwarz, "Internet Advertising and the Generalized Second Price Auction: Selling Billions of Dollars Worth of Keywords", *Mimeo*, September, 2005
- J. Feng, "Optimal Mechanism for selling a set of Commonly Ranked Objects", Mimeo, February 2005
- S. Lahaie, "An Analysis of Alternative Slot Auction Designs for Sponsored Search", ACM Conference on Electronic Commerce (EC'06), Ann Arbor, MI, June 11-15, 2006
- G. Aggarwal, A. Goel, and R. Motwani, "Truthful Auction for Pricing Search Keywords", ACM Conference on Electronic Commerce (EC'06), Ann Arbor, MI, June 11-15, 2006
- H. R. Varaian, "Position Auctions", Mimeo, February 2006

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- Introduction
 - Problem Definition
 - ✓ Significance
 - ✓ Recent Literature
- Three well known mechanisms
 - Generalized First Price (GFP)
 - Generalized Second Price (GSP)
 - Vickrey-Clarke-Groves (VCG)
- A new mechanism Optimal (OPT) Mechanism
- What is the best mechanism for Sponsored Search Auction?
- Comparison of OPT with GSP and VCG
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Generalized First Price (GFP)

Allocation Rule

Allocate the slots in decreasing order of bids

$$y_{ij}(b) = \begin{cases} 1 & \text{if } b_i = b^{(j)} \text{ and } j \le \min(m, n) \\ 0 & \text{o/w} \end{cases}$$

Payment Rule

For every user click, charge the advertiser his bid

$$p_i(b) = \begin{cases} b_i & \text{if advertiser } i \text{'s Ad is displayed} \\ 0 & \text{o/w} \end{cases}$$

Generalized Second Price (GSP)

Allocation Rule

Yahoo Rule

Allocate the slots in decreasing order of bids

Greedy Rule

Allocate 1st slot to advertiser $i_1 = \underset{i \in N}{\operatorname{argmax}} (\alpha_{i_1} b_i)$

Allocate 2nd slot to advertiser $i_2 = \underset{i \in N \setminus i_1}{\operatorname{argmax}} (\alpha_{i_2} b_i)$

Google Rule

Allocate the slots in decreasing order of Ranking Score

Ranking Score = $b_i \times CTR_i$

 $b^{(m)}$

 $b^{(1)}$

b⁽²⁾

2

m

Generalized Second Price (GSP)

Payment Rule

- For every click, charge next highest bid + \$0.01
- The bottom most advertiser is charged highest disqualified bid +\$0.01
- charge 0 if no such bid









Generalized Second Price (GSP)

Relationship Among Allocation Rules



Proposition

Let click probabilities satisfy AAE assumption

- Greedy allocation rule is an optimal solution of the (AE) Problem
- If click probabilities depend only on identity of the advertiser and are independent of the position of the Ad, i.e. $\alpha_{i1} = \alpha_{i2} = \cdots = \alpha_{im} = CTR_i$ then greedy rule and Google rule result in the same allocation
- If click probabilities depend only on position of the Ad and are independent of the identity of the advertiser, i.e. $\alpha_{1j} = \alpha_{2j} = \cdots = \alpha_{nj} = \alpha_j$ then greedy rule and Yahoo! rule result in the same allocation

Vickrey-Clarke-Groves (VCG)

Allocation Rule

- Solution of (AE) Problem
- Same as Yahoo! allocation under the assumption that click probability depends only on position

Payment Rule

$$t_{i}(b) = \left[\sum_{j \neq i} b_{j} v_{j}(y_{-i}^{*}(b))\right] - \left[\sum_{j \neq i} b_{j} v_{j}(y^{*}(b))\right]$$
$$p^{(j)}(b) = \frac{t^{(j)}(b)}{\alpha_{j}}$$
Google

e -Enterprises Lab, CSA, IISc

 $b^{(m)}$

 $b^{(1)}$

 $b^{(2)}$

 $b^{(m)}$

 $b^{(1)}$

 $b^{(2)}$

F

P

2

m

Vickrey-Clarke-Groves (VCG)

Payment Rule

$$\underline{Case 1} (m < n)$$

$$p^{(j)}(b) = \begin{cases} \frac{1}{\alpha_j} \left[\sum_{k=j}^{m-1} \beta_k b^{(k+1)} \right] + \frac{\alpha_m}{\alpha_j} b^{(m+1)} & \text{if } 1 \le j \le (m-1) \\ b^{(m+1)} & \text{if } j = m \\ 0 & \text{if } m < j \le n \end{cases}$$

$$\frac{Case 2}{p^{(j)}(b)} = \begin{cases} \frac{1}{\alpha_j} \left[\sum_{k=j}^{n-1} \beta_k b^{(k+1)} \right] & \text{if } 1 \le j \le (n-1) \\ 0 & \text{if } j = n \end{cases}$$
where $\beta_k = (\alpha_k - \alpha_{k+1})$



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Optimal (OPT)

Payment Rule

<u>Case 2</u> $(n \le m)$

$$\underline{Case 1}(m < n)$$

$$p_i(b_i, b_{-i}) = \begin{cases}
\frac{1}{\alpha_r} \left[\sum_{k=r}^{m-1} \beta_k z_{ik}(b_{-i}) \right] + \frac{\alpha_m}{\alpha_r} z_{im}(b_{-i}) & \text{if } 1 \le r \le (m-1) \\ z_{im}(b_{-i}) & \text{if } r = m \\ 0 & \text{o/w}
\end{cases}$$

 $p_i(b_i, b_{-i}) = \begin{cases} \frac{1}{\alpha_r} \left[\sum_{k=r}^{n-1} \beta_k z_{ik}(b_{-i}) \right] + \frac{\alpha_n}{\alpha_r} z_{in}(b_{-i}) & \text{if } 1 \le r \le (n-1) \\ z_{in}(b_{-i}) & \text{if } r = n \\ 0 & \text{o/w} \end{cases}$

 r is the position at which advertiser j is allocated

$$\beta_k = (\alpha_k - \alpha_{k+1})$$

 $z_{ij}(b_{-i})$ is the minimum bid for the advertiser *i* which can make him win j^{th} slot against the bid vector b_{-i} from other advertisers

Optimal (OPT)

Payment Rule when Advertisers are Symmetric

$$\begin{split} \Theta_{1} &= \Theta_{2} = \dots = \Theta_{n} = \Theta = [L, U] \\ \Phi_{1}(.) &= \Phi_{2}(.) = \dots = \Phi_{n}(.) \\ \underline{Case \ 1}(m < n) \\ &= \begin{cases} \frac{1}{\alpha_{r}} \left[\sum_{k=r}^{m-1} \beta_{k} b^{(k+1)} \right] + \frac{\alpha_{m}}{\alpha_{r}} b^{(m+1)} & \text{if } 1 \le j \le (m-1) \\ b^{(m+1)} & \text{if } j = m \\ 0 & \text{if } m < j \le n \end{cases} \\ \underline{Case \ 2}(n \le m) \\ \underline{Case \ 2}(n \le m) \\ p_{i}(b_{i}, b_{-i}) &= \begin{cases} \frac{1}{\alpha_{r}} \left[\sum_{k=r}^{n-1} \beta_{k} b^{(k+1)} \right] + \frac{\alpha_{n}}{\alpha_{r}} L & \text{if } 1 \le j \le (n-1) \\ L & \text{if } j = n \end{cases} \end{split}$$

Optimal (OPT)

Proposition





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Search Engine's View Points

Economic and Computational Performance measures

- The advertisers' equilibrium bidding strategy profile $(s_1^*(.), \dots, s_n^*(.))$
- Effect of $(s_1^*(.), \dots, s_n^*(.))$ on performance measures

What is the best Mechanism for Sponsored Search Auction?

Economic and Computational Performance Measures

Revenue Maximization

- Individual Rationality (IR)
- Incentive Compatibility (IC)
- Computational Complexity

What is the best Mechanism for Sponsored Search Auction?

 Sponsored Search Auction as a Mechanism Design Problem



What is the best Mechanism for Sponsored Search Auction?

Strategic Bidding Behavior of Advertisers

If all the advertisers are rational and intelligent and this fact is common knowledge then each advertiser's expected bidding behavior is given by

Dominant Strategy Equilibrium (DSE)

Strategy profile $(s_1^*(.), \dots, s_n^*(.))$ is said to be dominant Strategy equilibrium iff

 $u_i(f(\mathbf{s}_i^*(\theta_i), \mathbf{b}_{-i})), \theta_i) \ge u_i(f(\mathbf{b}_i, \mathbf{b}_{-i})), \theta_i) \forall \mathbf{b}_i \in \Theta_i, \forall \mathbf{b}_{-i} \in \Theta_{-i}$

Bayesian Nash Equilibrium (BNE)

Strategy profile $(s_1^*(.), \dots, s_n^*(.))$ is said to be Bayesian Nash equilibrium iff $E_{\theta_{-i}}[u_i(f(s_i^*(\theta_i), s_{-i}^*(\theta_{-i})), \theta_i) | \theta_i] \ge E_{\theta_{-i}}[u_i(f(b_i, s_{-i}^*(\theta_{-i})), \theta_i) | \theta_i] \forall b_i \in \Theta_i$

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- Incentive Compatibility
- VCG: Follow $s_i^*(\theta_i) = \theta_i$ irrespective of what the others are doing (DSE)
- **OPT:** Follow $\dot{s}(\theta) = \theta$ if all rivals are also doing so (BNE)
- **GSP:** Never follow strategy $s_i^*(\theta_i) = \theta_i$. Use the following BNE strategy

$$s_{i}^{*}(\theta_{i}) = \begin{cases} \theta_{i} - \frac{1}{g(\theta_{i},(m-1))} \int_{\theta_{i}}^{\theta_{i}} f(x,\theta_{i},(m-1))s'(x)dx : \text{if } n = m \\ \theta_{i} - \frac{1}{g(\theta_{i},m)} \int_{\theta_{i}}^{\theta_{i}} f(x,\theta_{i},m)s'(x)dx : \text{if } m < n \end{cases}$$

$$f(x,\theta_{i},k) = \sum_{j=1}^{k} (j-1)\alpha_{j}^{n-1}C_{j-1}(\overline{\Phi}(\theta_{i}))^{j-2}(\Phi(\theta_{i}))^{n-j}$$

$$g(\theta_{i},k) = k\alpha_{k}^{n-1}C_{k}(\overline{\Phi}(\theta_{i}))^{k-1}(\Phi(\theta_{i}))^{n-k-1} + \sum_{j=1}^{k-1} j(\alpha_{j} - \alpha_{j+1})^{n-1}C_{j}(\overline{\Phi}(\theta_{i}))^{j-1}(\Phi(\theta_{i}))^{n-j-1}$$

- Expected Revenue Earned by the Search Engine
- <u>Revenue Equivalence Theorem:</u>

Consider a sponsored search auction setting, in which

- 1. The advertisers are risk neutral
- 2. The advertisers are symmetric
- 3. For each advertiser *i*, we have $\phi_i(.) > 0$
- 4. The advertisers draw their types independently

Consider two different mechanisms, each having symmetric and increasing Bayesian Nash equilibrium such that

- 1. For each possible $(\theta_1, \dots, \theta_n)$ the final allocation is the same
- 2. Each advertiser *i* has same expected utility in two mechanisms for $\theta_i = L$

then equilibria of two mechanisms generate the same expected revenue for the search engine

- Expected Revenue Earned by the Search Engine
- Revenue Equivalence of GSP, VCG, and OPT Mechanisms

Consider a sponsored search auction setting, in which

- 1. The advertisers are risk neutral
- 2. The advertisers are symmetric
- 3. For each advertiser *i* , we have $\phi_i(.) > 0$
- 4. The advertisers draw their types independently

5. For each advertiser *i*, we have $J_i(.) > 0$ and $J_i(.)$ is non-decreasing Consider three different auction mechanisms – GSP, VCG, and OPT. Let R_{GSP} , R_{VCG} and R_{OPT} be the expected revenue earned by the search engine under these three mechanisms against every query received, then $R_{GSP} = R_{VCG} = R_{OPT}$ if m < n $R_{VCG} \le R_{GSP} \le R_{OPT}$ if $n \le m$

Expected Revenue of Search Engine

$$\frac{Case 1}{P_{OPT}} = n \left[\int_{L}^{U} \left(m \alpha_{m}^{n-1} C_{m}(\overline{\Phi}(x))^{m}(\Phi(x))^{n-m-1} + \sum_{j=1}^{m-1} j \beta_{j}^{n-1} C_{j}(\overline{\Phi}(x))^{j}(\Phi(x))^{n-j-1} \right) x \phi(x) dx \right]$$

$$\frac{Case 2}{L} \left(n \leq m \right)$$

$$R_{OPT} = n \left[\alpha_{n} L + \int_{L}^{U} \left(\sum_{j=1}^{m-1} j \beta_{j}^{n-1} C_{j}(\overline{\Phi}(x))^{j}(\Phi(x))^{n-j-1} \right) x \phi(x) dx \right]$$

$$R_{VCG} = n \left[\int_{L}^{U} \left(\sum_{j=1}^{m-1} j \beta_{j}^{n-1} C_{j}(\overline{\Phi}(x))^{j}(\Phi(x))^{n-j-1} \right) x \phi(x) dx \right]$$

Economic Performance of Auction Mechanisms

	Allocation	Payment	DSIC	BIC	IR
GSP	Decreasing order of the bids	Next Highest bid	Х	Х	
VCG	Decreasing order of the bids	Marginal Contribution			
OPT	Decreasing order of the bids	Generalized VCG	Х		



Experimental Results







Experimental Results



Experimental Results



Computational Performance of Auction Mechanisms

	Computational Complexity		
GSP	O(nlog <i>n</i>)		
VCG	$O(n\log n + (\min(m, n))^2)$		
OPT	$O(n\log n + (\min(m, n))^2)$		

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Future Directions

- Long Term Goals versus Short Term Goals
- Daily Budget
- Learning the Valuation Distribution $\Phi_i(.)$
- Assumption of Independence of Click Probability on Advertisers' Identity
- Revenue Performance under Asymmetric Advertisers
- Click Fraud
- Competing Search Engines
- Optimal Bidding Strategy of the Advertisers



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