Google's AdWords Market: How Theory Influenced Practice

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Two major achievements of Google

1). Search: That is robust to spam

2). Advertising: Business model



Vioxx Online, Description, Chemistry, Ingredients - Rofecoxib ...

Revolution in advertising

- Matching merchants with customers
 How can a merchant pitch ads in a targeted way to customers who are interested in his goods.
- Difficulty: How to find out needs/desires of customers in a super-efficient manner?
- Insight: A user's search queries reveals to Google a succinct window into her mind/needs

- Solution: Auction off queried keywords to advertisers!
- This converts a giant undefined matching problem into a gigantic auction!
- Google is world's biggest auction house: billions daily!

How to allocate keywords to advertisers?

- Advertisers bid for specific keywords
- Maximize Google's revenue efficient solution!

GREEDY: Display the ad of highest bidder
 Assume: only 1 ad is shown

 Charge bid, or second highest bid (Vickery auction)

This soln. was being used!



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Problem ...



Example:



Example:



Must incorporate budgets in solution

Large fraction of advertisers are budget-constrained

Budget distribution is heavy-tailed
 Must handle small budget advertisers adequately

Solution must be real time and particularly simple!

Adwords Problem

Mehta, Saberi, Vazirani & V, 2005:

Simple framework that captures essential features.

Will add bells and whistles later!

The Adwords Problem

N advertisers.

 $\Box \text{ Daily Budgets } \mathbf{B}_1, \mathbf{B}_2, \dots, \mathbf{B}_N = \1

□ Each advertiser provides bids for keywords he is interested in.



Online competitive analysis

Compare revenue of online algorithm with that of best offline allocation.

■ E.g., GREEDY has competitive ratio of ½.

Algorithm

Will use agents'
Bid
Fraction of budget spent

"Correct" tradeoff between them given by a special function *f*



1 – 1/e competitive ratio, assuming bid << budget Simple, minipalistic solution!

Impact

- Provided a general framework for thinking about budget constrained auctions for many Ad products
- Bid scaling used widely in industry for ad auctions and for display ads:
 Very fast: one operation per bid
 Low on memory: one number per bid
 No extra communication

New algorithmic work

Numerous models:
 Queries arrive in random order
 Queries are picked from a distribution
 Submodular constraints on allocations
 Use historical data about query arrival

Solution has roots in "pure" theory, in particular, Matching Theory!













Any deterministic algorithm has competitive ratio of 1/2.

Karp, Vazirani & V., 1990:
 1 – 1/e factor randomized algorithm

Optimal!

Same as simple case of Adwords problem: All budgets \$1, all bids \$0/1.

Online *b*-matching

Kalyanasundaram & Pruhs, 1996:
 1 - 1/e factor algorithm for *b*-matching:
 Daily budgets \$b, bids \$0/1, b>>1

BALANCE: Assign query to interested bidder who has spent least so far.

Optimal!

Example: Balance

Bidder1 Bidder 2



 $B_1 = B_2 = 100

Balance Algorithm

Queries: 100 Books then 100 CDs

Revenue
\$1.50Bidder 1Bidder 2

Where did this tradeoff function come from?



New proof of BALANCE

■ N bidders, \$1 each. Each bid is $\$\epsilon$.

• OPT: optimal offline, ALG: BALANCE

• OPT = N

• Will show:
$$ALG \ge N\left(1 - \frac{1}{e}\right)$$

Idea: Upper bound no. of bidders who spent less!

Assume *k* large

S_{*i*}: Bidders who spent
$$\left[\frac{i-1}{k}, \frac{i}{k}\right)$$

• Let $|S_i| = x_i$. Will constrain $x_1, x_1 + x_2, ...$





Partition revenue of ALG

■ \$ $\varepsilon \in layer i$ if bidder had $\left[\frac{i-1}{k}, \frac{i}{k}\right)$

when this money was spent.



 S_2 S_1

Partition revenue of ALG

■ \$
$$\varepsilon \in layer i$$
 if bidder had $\left[\frac{i-1}{k}, \frac{i}{k}\right)$

when this money was spent.

BALANCE assigns next query to interested bidder who has spent least so far.

Layer $1 \le \frac{N}{k}$

•First Constraint: $|S_1| = x_1 \le layer 1 \le \frac{N}{k}$



Layer 2
$$\leq \frac{N-x_1}{k}$$

Second Constraint: $|S_1 \cup S_2| = x_1 + x_2 \le \frac{N}{k} + \frac{N - x_1}{k}$



Lower bound on ALG

LP(N): min
$$\sum_{i} \frac{i}{k} x_i$$

s.t. constraints on x_1, x_2, \dots, x_k

$$ALG \ge N\left(1 - \left(1 - \frac{1}{k}\right)^k\right) \ge N\left(1 - \frac{1}{e}\right)$$

Factor revealing LP

Jain, Mahdian, Markakis, Saberi & V., '03

- Family of LPs: LP(N) encodes problem of finding lower bound for instance of size N.
- Infimum of optimal solutions gives approximation factor

Where did this tradeoff function come from?



Larger Theme

AdWords, Amazon, eBay, Yahoo!, Alibaba, Uber, Apple (iTunes), Airbnb, Cloud Computing ...

Markets on the Internet

 Numerous new algorithmic and game-theoretic issues raised.

Much scope for creative work that can have a huge impact!