HYBRID KEYWORD AUCTIONS

Kamesh Munagala Duke University

Joint work with Ashish Goel, Stanford University

ONLINE ADVERTISING

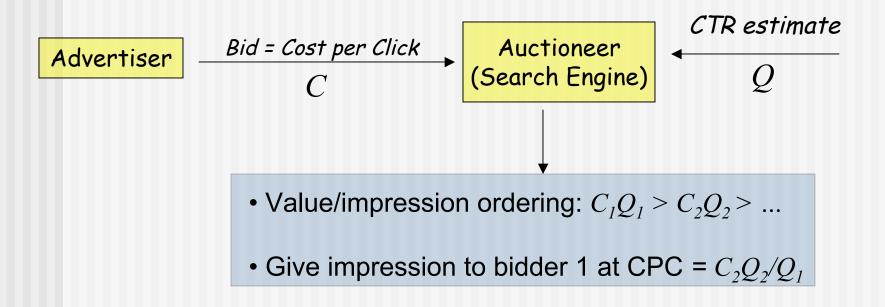
Pricing Models

- CPM (Cost per thousand impressions)
- CPC (Cost per click)
- CPA (Cost per acquisition)
- Conversion rates:
 - Click-through-rate (CTR), conversion from clicks to acquisitions, ...

Differences between these pricing models:

- Uncertainty in conversion rates:
 - Sparse data, changing rates, ...
- Stochastic fluctuations:
 - Even if the conversion rates were known exactly, the number of clicks/conversions would still vary, especially for small samples

SPONSORED SEARCH AUCTION

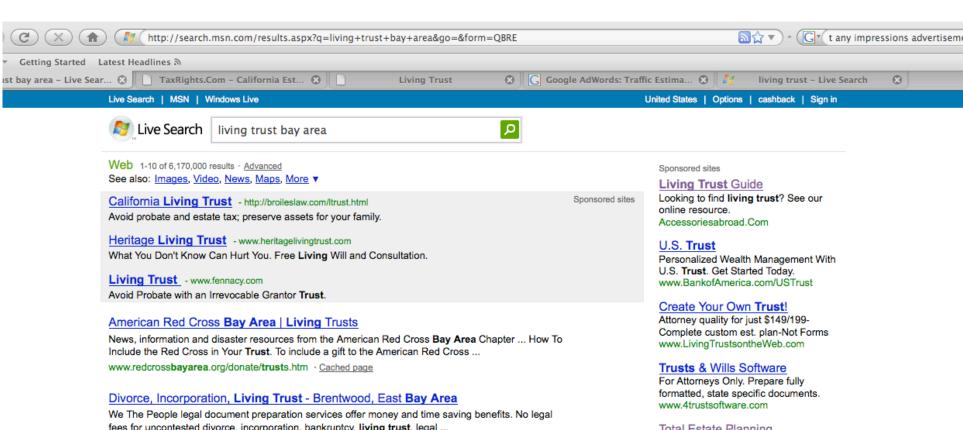


VCG Mechanism: Truthful for a single slot, assuming static CTR estimates
Can be made truthful for multiple slots [Vickrey-Clark-Groves, Myerson81, AGM06]
This talk will focus on single slot for proofs/examples

WHEN DOES THIS WORK WELL?

- High volume targets (keywords)
 - Good estimates of CTR

- What fraction of targets are high volume?
 - Folklore: a small fraction
 - Motivating problem:
 - How to better monetize the low volume keywords?



fees for uncontested divorce, incorporation, bankruptcy, living trust, legal ...

www.wtpeastbay.com/benefits.htm · Cached page

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Law: Certified Specialists in Estate Planning, Trust, and Probate Law ...

Anti-Bimbo Clause: Should your Living Trust allow your Spouse to change the "A Trust" after you die? Or should the A Trust be locked so she may spend it but when she dies, whatever ...

www.wwlaw.com · Cached page

Law Offices of Jason S. Buckingham, Inc. - San Francisco Bay Area ...

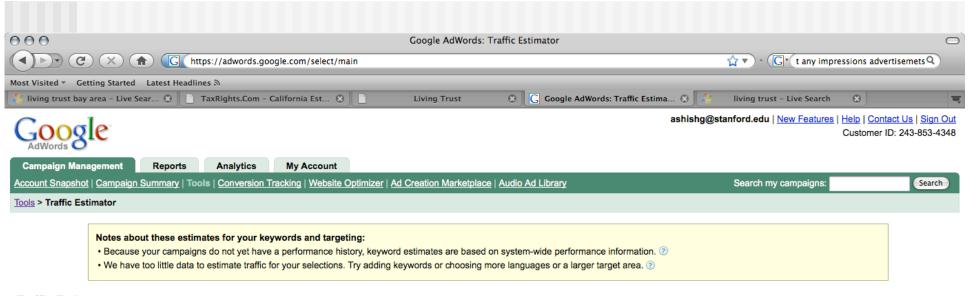
San Francisco Bay Area real estate, living trust, and business law firm. Flat fee legal services for real estate investors and business owners. Flat fee living trust packages ...

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Total Estate Planning

Donald L. Field, Jr., Attorney at Law, Tax/Estate Planning Since 1979 http://www.taxrights.com

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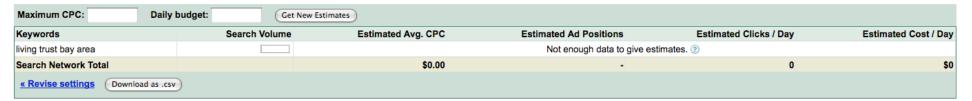


Traffic Estimator

« Revise settings | Download as .csv

All estimates are provided as a guideline, and are based on system-wide averages; your actual costs and ad positions may vary. To view estimates based on your keywords' performance history, use the Traffic Estimator within the appropriate ad group. Learn more

Average CPC: **\$0.00** (at a maximum CPC of \$0.05) Estimated clicks per day: **0** (at a daily budget of \$1.00) Estimates are based on your bid amount and geographical targeting selections. Because the Traffic Estimator does not consider your daily budget, your ad may receive fewer clicks than estimated.

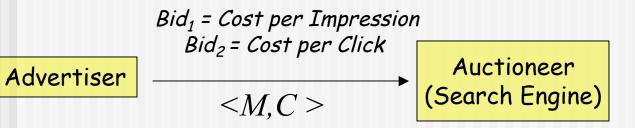


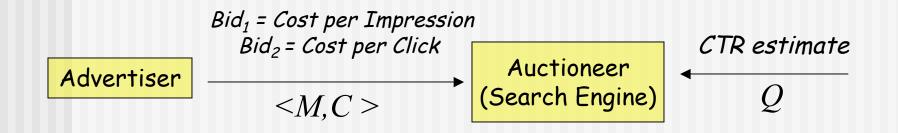
Estimates for these keywords are based on clickthrough rates for current advertisers. Some of the keywords above are subject to review by Google and may not trigger your ads until they are approved. Please note that your traffic estimates assume your keywords are approved.

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POSSIBLE SOLUTIONS

- Coarse ad groups to predict CTR:
 - Use performance of advertiser on possibly unrelated keywords
- Predictive models
 - Regression analysis/feature extraction
 - Taxonomies/clustering
 - Collaborative filtering
- Our approach: Devise richer pricing models





Bid₁ = Cost per Impression Bid2 = Cost per Click CTR estimate Auctioneer Advertiser (Search Engine) <*M*,*C* > • Advertiser's score $R_i = \max \{ M_i, C_i Q_i \}$

Advertiser

Bid₁ = Cost per Impression

Bid₂ = Cost per Click

Auctioneer

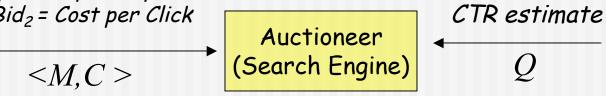
(Search Engine)

Q Q

- Advertiser's score $R_i = \max \{ M_i, C_i Q_i \}$
- Order by score: $R_1 > R_2 > \dots$

Bid₁ = Cost per Impression Bid₂ = Cost per Click

Advertiser



- Advertiser's score $R_i = \max \{ M_i, C_i Q_i \}$
- Order by score: $R_1 > R_2 > \dots$
- Give impression to bidder 1:
 - If $M_1 > C_1Q_1$ then charge R_2 per impression
 - If $M_1 < C_1Q_1$ then charge R_2/Q_1 per click

WHY SUCH A MODEL?

- Per-impression bid:
 - Advertiser's estimate or "belief" of CTR
 - May or may not be an accurate reflection of the truth
 - Backward compatible with cost-per-click (CPC) bidding

WHY SUCH A MODEL?

- Per-impression bid:
 - Advertiser's estimate or "belief" of CTR
 - May or may not be an accurate reflection of the truth
 - Backward compatible with cost-per-click (CPC) bidding
- Why would the advertiser know any better?
 - Advertiser aggregates data from various publishers
 - Has domain specific models not available to auctioneer
 - Is willing to pay a premium for internal experiments

BENEFITS

1. Search engine:

Better monetization of low volume keywords

2. Advertiser:

Opportunity to make the search engine converge to the correct CTR estimate *without paying a premium*

3. Technical:

- a) Truthful
- Accounts for risk characteristics of the advertiser
- c) Allows users to implement complex strategies

MULTIPLE SLOTS

- Show the top K scoring advertisers
 - □ Assume $R_1 > R_2 > ... > R_K > R_{K+1}...$
- Generalized Second Price (GSP) mechanism:
 - For the *i*th advertiser, if:
 - If $M_i > Q_i C_i$ then charge R_{i+1} per impression
 - If $M_i < Q_i C_i$ then charge R_{i+1} / Q_i per click

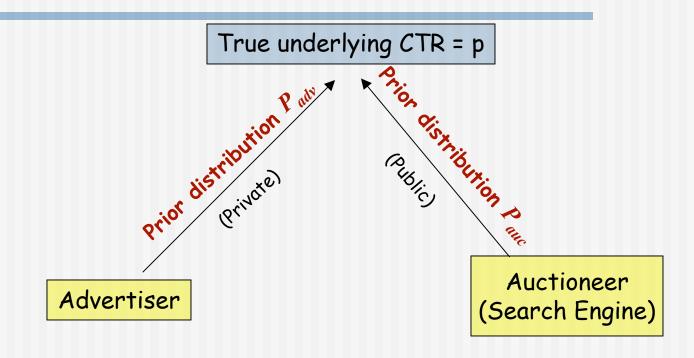
MULTIPLE SLOTS

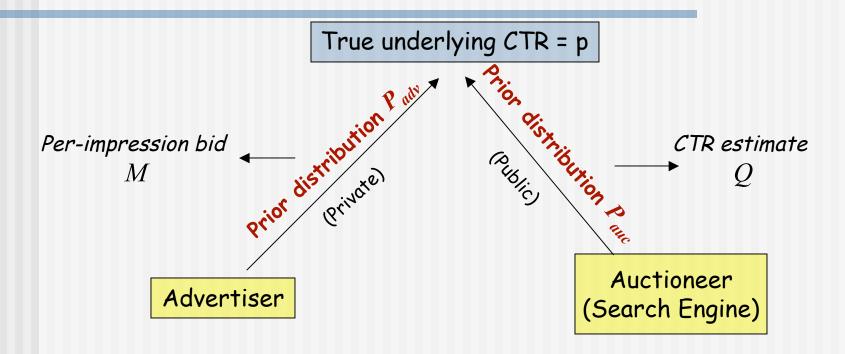
- Show the top K scoring advertisers
 - **a** Assume $R_1 > R_2 > ... > R_K > R_{K+1}...$
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 - If $M_i > Q_i C_i$ then charge R_{i+1} per impression
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- Can also implement VCG [Vickrey-Clark-Groves, Myerson81, AGM06]
 - Need separable CTR assumption
 - Details in the paper

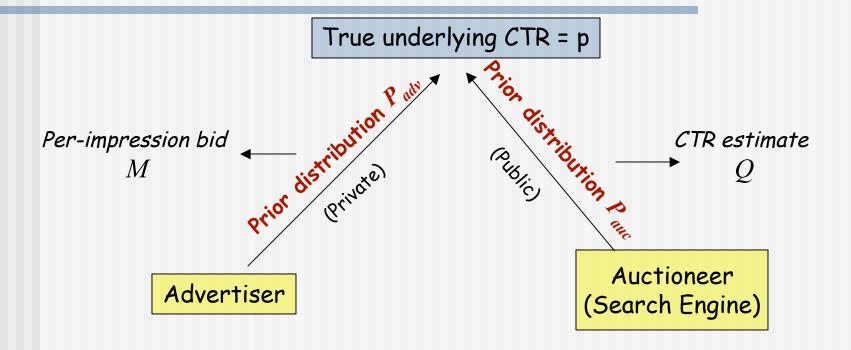
True underlying CTR = p

Advertiser

Auctioneer (Search Engine)







Each agent optimizes based on its current "belief" or prior:
Beliefs updated with every impression
Over time, become sharply concentrated around true CTR

WHAT IS A PRIDR?

- Simply models asymmetric information
 - □ Sharper prior \Rightarrow More certain about true CTR p
 - **E**[Prior] need not be equal to p
- Main advantage of per-impression bids is when:
 - Advertiser's prior is sharper than auctioneer's
 - Limiting case: Advertiser certain about CTR p
- Priors are only for purpose of analysis
 - Mechanism is well-defined regardless of modeling assumptions

TRUTHFULNESS

- lacktriangle Advertiser assumes CTR follows distribution P_{adv}
- Wishes to maximize expected profit at current step
 - **E**[P_{adv}] = x = Expected belief about CTR
 - Utility from click = C
 - \blacksquare Expected profit = Cx Expected price

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Let Cy = Per impression bid R_2 = Highest other score

If \max(Cy, CQ) < R_2 then Price = 0

Else:

If y < Q then: Price = x R_2/Q

If y > Q then: Price = R_2
```

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 - **E** $[P_{adv}] = x =$ Expected belief about CTR
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Bidding (Cx, C) is the dominant strategy

Regardless of Q used by auctioneer

Regardless of P_{adv} and true CTR p

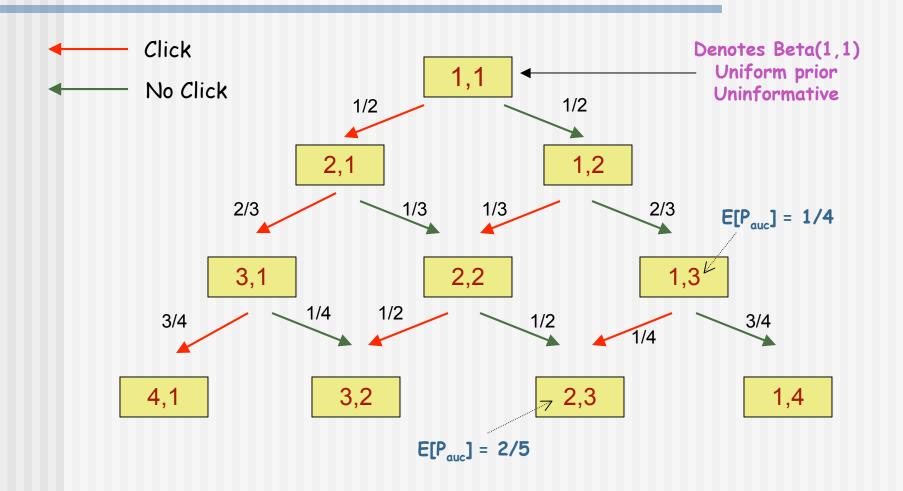
Elicits advertiser's "expected belief" about the CTR!

Holds in many other settings (more later)

CONJUGATE BETA PRIORS

- P_{auc} for advertiser $i = Beta(\alpha, \beta)$
 - α , β are positive integers
 - Conjugate of Bernoulli distribution (CTR)
 - Expected value = $\alpha/(\alpha + \beta)$
- Bayesian prior update:
 - \blacksquare Probability of a click at the next step is: $\alpha/(\alpha + \beta)$
 - If click, new P_{auc} (posterior) = $Beta(\alpha+1, \beta)$
 - □ If no click, new P_{auc} (posterior) = $Beta(\alpha, \beta+1)$

EVOLUTION OF BETA PRIORS



PROPERTIES

- Larger α , β ⇒ Sharper concentration around p
 - □ Uninformative prior: Beta(1,1) = Uniform[0,1]

- - Encodes auctioneer's "belief"
 - Could be different from true CTR p

CERTAIN ADVERTISER

- Knows true CTR p and bids rationally $(M_i = p_i)$
 - $P_{adv} = p_i$ with probability 1
 - $P_{auc} = Beta(\alpha_i, \beta_i)$ and $Q_i = \mathbf{E}[P_{auc}] = \alpha_i/(\alpha_i + \beta_i)$
- Revenue properties of auctioneer:
 - Worst case: 63% of CPC scheme
 - Canonical case: log n times better than CPC scheme
- Flexibility for advertiser:
 - lacksquare Can make P_{auc} converge to p without losing revenue
 - But pays huge premium for achieving this in CPC auction

BETTER MONETIZATION

- Illustrative Scenario: Low volume keywords
 - \blacksquare *n* advertisers, all click-utilities C = 1
 - □ All $P_{auc} = Beta$ (1, log n) so that $E[P_{auc}] = Q \approx 1 / \log n$
 - High variance prior
 - Some p_i close to 1 with high probability
 - \Box Per-impression bid will elicit this high p_i
 - CPC auction allocates slot to a random advertiser
- Theorem: Hybrid auction can generate $\log n$ times more revenue for auctioneer than existing CPC auction

FLEXIBILITY FOR ADVERTISERS

- Suppose advertiser certain about CTR = p
 - □ Assume C = 1 and Q < p
 - Bids truthfully and wins on per impression bids
- Hybrid scheme: Charged at most p per impression
 - Impressions shown repeatedly
 - lacktriangle Auctioneer's belief P_{auc} will converge to have mean p
 - Now, advertiser switches to CPC bidding
- Assume auctioneer's prior is $Beta(\alpha, \beta)$

$$Q = \alpha/(\alpha + \beta)$$

FLEXIBILITY FOR ADVERTISERS

- If CTR converges in T impressions resulting in N clicks:
 - $(\alpha + N)/(\alpha + \beta + T) \ge p$
 - □ Since $Q = \alpha/(\alpha + \beta) < p$, this implies $N \ge Tp$
 - □ Value gain = N; Payment for T impressions at most T * p
 - Hence, no loss in revenue to advertiser!
- In the existing CPC auction:
 - The advertiser would have to pay a huge premium for getting impressions and making the CTR converge

UNCERTAIN ADVERTISERS

- Advertiser should "pay premium" for CTR p resolving to a high value
 - What should her bidding strategy be?
 - Does it lead to a socially optimal mechanism?
- Key contribution:
 - Defining a Bayesian model for repeated auctions
 - Dominant strategy exists!

SEMI-MYDPIC ADVERTISER

- Maximizes discounted utility in contiguous time horizon in which she wins the auction
 - State of other advertisers stays the same during this time
 - Once she stops getting impressions, cannot predict future
 ... since future will depend on private information of other bidders!
 - Circumvents negative results in economics literature
- Private information with advertiser:
 - \Box Discount factor γ , value C_i and prior P_{adv}
 - Discount factor models varying optimization horizons
 - Strategic vs. myopic

DOMINANT HYBRID STRATEGY

- Bidder always has a dominant hybrid strategy
 - Bidding Index: Computation similar to the Gittins index
 - Bidder can optimize her utility by dynamic programming

DOMINANT HYBRID STRATEGY

- Bidder always has a dominant hybrid strategy
 - Bidding Index: Computation similar to the Gittins index
 - Bidder can optimize her utility by dynamic programming
- Socially optimal in many reasonable scenarios:
 - Myopic advertiser: Has $\gamma_i = 0$; trusts auctioneer's prior:
 - Pure per-click bidding implements the Gittins index policy
 - □ If advertiser is *certain* of CTR, and Q_i is an underestimate:
 - Bidding index = Per-impression bidding, which is socially optimal
 - Implementation needs both per-impression and per-click bids

SUMMARY

- Allow both per-impression and per-click bids
 - Same ideas work for CPM/CPC + CPA
- Significantly higher revenue for auctioneer
- Easy to implement
 - Hybrid advertisers can co-exist with pure per-click advertisers
 - Easy path to deployment/testing
- Many variants possible with common structure:
 - Optional hybrid bids
 - Use the "max" operator to compute score

OPEN QUESTIONS

- Some issues that may be exacerbated:
 - Whitewashing: Re-entering when CTR is lower than the default
 - Fake Clicks: Bid per impression initially and generate false clicks to drive up CTR estimate Q
 - Switch to per click bidding when slot is "locked in" by the high Q
- Analysis of semi-myopic model
 - Other applications of separate beliefs?
- Connections of Bayesian mechanisms to:
 - Regret bounds and learning

[Nazerzadeh, Saberi, Vohra '08]

Best-response dynamics

[Edelman, Ostrovsky, Schwarz '05]