Adaptive Auctions in Advertising

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Outline

1. Background
2. Hypothesis, data and assumptions
3. Auction mechanisms and the multi-armed bandit algorithm
4. Preliminary results and comments

Background

How do search-ads auctions work?

Keywords Choice and Bidding

- Advertiser choses a set of keywords related to a product / service is selling.
- Advertiser places a bid for each keyword.

Ads display

- When a user's search query matches one keyword, a set of ads is displayed.
- Ads are ranked by bids.
- Ad with higher bid is placed in the "best" position.

Payment

- If user clicks on an ad, that advertiser is charged the bid (or a function of it) of the advertiser that is immediately below it in the ranking (**second-price auction**).

Background

- **General Setting**
  - **Problem:** Selecting a sequence of auction designs that maximizes the auctioneer's revenue over the course of an episode.
  - **Learning Process:** For each keyword, the algo revises the design parameters periodically in response to observed bidder behaviors.
  - In addition to varying some parameter values, we also implement the algorithm with two different auction types - **GSP and VCG.**
  - We then compare the results of the adaptive mechanism with the ones of a traditional fixed mechanism.

- **Why are we doing this?**
  - **Key challenge** for sellers of advertisement: Identification of the best "design" to **maximize revenue.**
  - Different designs can lead to widely **differing outcomes.**
  - **Electronic Auction Markets:** Availability of large amounts of data offers an opportunity for learning and adaptation of parameters over a sequence of auctions.
  - **Keyword auctions:** Available periodically and can be auctioned sequentially over time. Lends itself nicely for an adaptive mechanism approach.

Hypothesis

- According to Edelman et al (2007), in any locally envy-free equilibrium of GSP, the total expected revenue to the seller is at least as high as in the dominant-strategy equilibrium of the VCG auction.

- The adaptive auction mechanism generates greater revenue for the auctioneer with respect to a fixed auction mechanism (in line with the observations from Pardoe et al, 2010)

Data

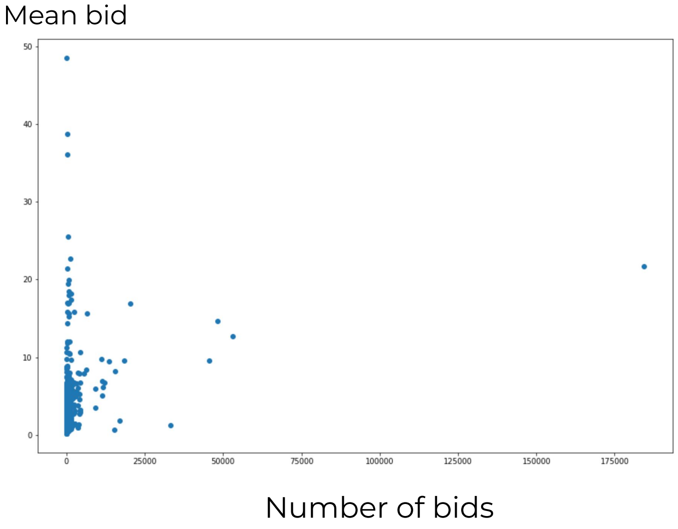
- **Yahoo! Search Marketing advertiser bids**
  - Top 1,000 phrases by volume from June 2002 to June 2003
  - Timestamp, Phrase ID, Account ID, Price, Auto
  - Originally 6,918,838 auctions (timestamp, Phrase ID pair)

- **Additional Restrictions**
  - At least 3 unique bidders: generate variation between GSP and VCG payments
  - All bids placed are autobids: assume away attention parameters
  - 87,309 auctions over 731 phrases

Summary Stats

- Bids on a specific phrase (regardless of auction)

PHRASE_ID	count	mean	std	min	25%	50%	75%	max
1	184274.0	21.698402	8.215513	0.05	16.5300	19.050	26.1100	50.00
2	53070.0	12.675019	4.500716	0.05	9.8200	12.520	15.8400	39.52
89	48288.0	14.634550	4.347557	0.05	13.2900	13.940	14.6500	50.00
11	45545.0	9.582153	2.905149	0.05	7.8600	9.480	11.1600	35.01
589	33315.0	1.252793	0.383837	0.05	1.0700	1.260	1.5400	3.01
...	...	...	...	...	...	...	...	...
531	4.0	1.395000	0.856757	0.11	1.3850	1.815	1.8250	1.84
443	4.0	1.777500	1.143398	0.10	1.5250	2.250	2.5025	2.51
444	4.0	1.455000	0.896753	0.11	1.4450	1.895	1.9050	1.92
195	4.0	0.657500	0.371697	0.10	0.6550	0.840	0.8425	0.85
882	4.0	0.315000	0.023805	0.29	0.2975	0.315	0.3325	0.34



Assumptions

- **Ex ante, bidders do not know the auction design**
  - Bidders do not know seller's reserve price
  - Bidders do not know how many other bidders will win the auction

- **Additional assumptions made on bids**
  - Bids are independent: no collusion
  - Bidders do not change their bids regardless of auction design

Auction Designs - GSP Varian et al. (2013)

- Generalization of the second price auction (given multiple slots, instead of a single slot) - truth-telling is not a dominant strategy
- Let v_s be the value of a click to an advertiser in slot s = 1..S, and let x_s be the clickthrough rate associated with the slot
- Revealed preferences of an advertiser who purchases slot s would indicate that he/she prefers that slot to the other slots (i.e. slot t), represented by:

  $$\mathbf{v_s x_s - p_s x_s \geq v_s x_t - p_t x_t}$$

- Therefore, advertisers with higher values get more prominent slots

- Assuming that the slots have been ordered, starting with the most clicked first, such that $x_1 > x_2 > \ldots > x_S$, the GSP auction will result in a price being charged for each slot
- in the three slot case, the GSP auction would yield the following payments:
  - $\mathbf{p_1 x_1 = v_2(x_1 - x_2) + p_2 x_2}$
  - $\mathbf{p_2 x_2 = v_3(x_2 - x_3) + p_3 x_3}$
  - $\mathbf{p_3 x_3 = v_4 x_3}$
- Implementation: ordered bidders by their valuation and applied the formula above retrieve the prices charged for each slot

Auction Designs - VCG Varian et al. (2013)

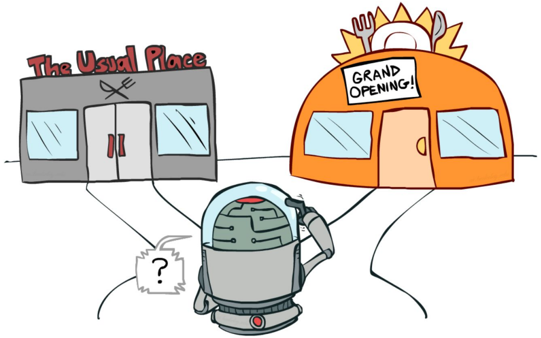
- Vickrey Clarke Groves (VCG) mechanism - bidding the true value is a dominant strategy for all players
- Each bidder pays the externality which he/she imposes on the other bidders
- Derivation:
  - If advertiser 1 participates in auction, the total payment made by the other advertisers is $\mathbf{v_2x_2 + v_3x_3}$
  - If advertiser 1 does not participate in the auction, the other advertisers will all move up one position and pay $\mathbf{v_2x_1+v_3x_2+v_4x_3}$
  - Therefore the harm which is imposed on the other advertiser by advertiser 1 is the difference i.e. $\mathbf{v_2(x_1-x_2)+v_3(x_2-x_3)+v_4x_3}$
- The VCG payment in the three slot case would be as follows:
  - $\mathbf{p_1x_1 = v_2(x_1-x_2)+v_3(x_2-x_3) + v_4x_3}$
  - $\mathbf{p_2x_2 = v_3(x_2-x_3)+v_4x_3}$
  - $\mathbf{p_3x_3 = v_4x_3}$
- Implementation: ordered bidders based on their bids, and calculated the VCG payment based on formula above

Adaptive Algorithm - Idea

- Based on Multi-Armed Bandit Problem by Robbins (1952):
  - “Gambler has to decide which of *k* slot machines to play in a sequence of trials so as to maximize the overall reward”

- For online auctions:
  - Seller has to decide which of *k* auction designs to pick in a sequence of auctions (*episode*) so as to **maximize the overall revenue.**

- Basic Idea: For each auction in an episode -
  - **Explore** - Select a design that has not been chosen yet
  - **Exploit** - Select a ‘previously chosen’ design which is estimated to be most profitable.
  - Start: Explore More → End: Exploit More



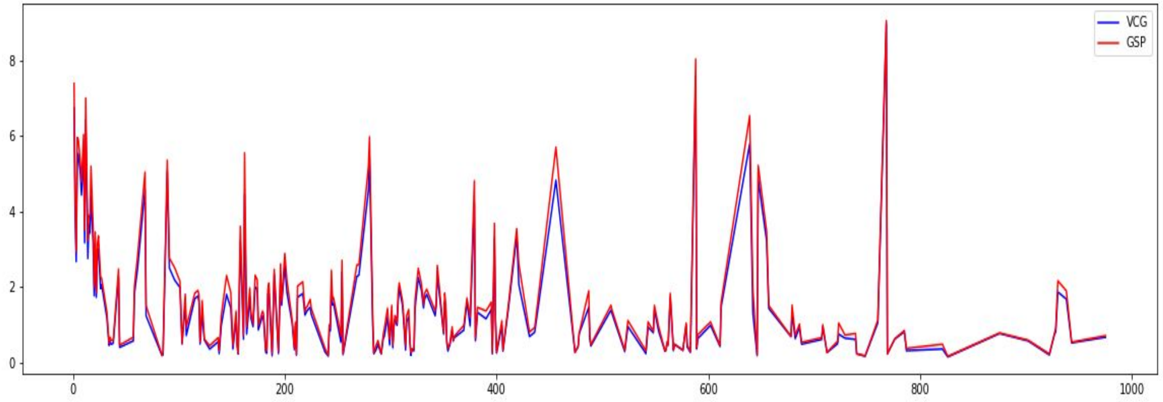
(Image source: UC Berkeley AI course slides, lecture 11)

Adaptive Algorithm - Implementation

- Following Pardoe et al (2010)
- Each search phrase (*phrase_id*) has a set of auctions → 1 episode / phrase
- Seller has a choice of k auction designs - by varying
  - **Type** (i.e. VCG or GSP)
  - **Reserve Price**
  - **Number of Slots**
- Steps
  - Estimate expected revenue of each auction design
  - For each auction in an episode:
    - Calculate probability of selecting auction design *(Boltzmann Distribution)*
      - Temperature (High → Low)
      - Estimated expected revenue
    - Select auction design *at random* from distribution
    - Run auction
    - Update expected revenue for selected design

Results

- Fixed mechanisms - VCG vs GSP
- Compared Average Revenue for around 240 phrase ids (Episodes), each of which has more than 60 auctions and each auction containing more than 3 unique bidders
- Assuming Reserve Price and Ads Cost as 0
- For our data, we get average revenue pretty close to each other for VCG and GSP, with GSP generating slightly better average revenue.



Results

Phrase Id: 1, Ads Cost: 1

- 8 Fixed Mechanisms vs 1 Adaptive Bandit Algorithm
- 2870 Auction Groups
- Without any prior info, Bandit algorithm explores and exploits designs such that it is able to generate total revenue over an episode close to the total revenue generated by the best auction design
- On convergence, the maximum probability is assigned to the last auction design

Design Type	Total Revenue
Adaptive Multi-Armed Bandit Algorithm	11873.52
Auction Type: VCG, Number of Slots: 3, Reserved Price: 15	9247.09
Auction Type: VCG, Number of Slots: 2, Reserved Price: 15	10797.94
Auction Type: GSP, Number of Slots: 3, Reserved Price: 15	11314.01
Auction Type: GSP, Number of Slots: 2, Reserved Price: 15	11993.61
Auction Type: VCG, Number of Slots: 3, Reserved Price: 10	10369.64
Auction Type: VCG, Number of Slots: 2, Reserved Price: 10	11873.52
Auction Type: GSP, Number of Slots: 3, Reserved Price: 10	12212.09
Auction Type: GSP, Number of Slots: 2, Reserved Price: 10	12805.14

Results

Phrase Id: 2, Ads Cost: 0.5

- 8 Fixed Mechanisms vs 1 Adaptive Bandit Algorithm
- 1790 Auction Groups
- Without any prior info, Bandit algorithm explores and exploits designs such that it is able to generate total revenue over an episode close to the total revenue generated by the best auction design
- On convergence, the maximum probability is assigned to the last auction design

Design Type	Total Revenue
Adaptive Multi-Armed Bandit Algorithm	5222.30
Auction Type: VCG, Number of Slots: 3, Reserved Price: 10	3410.16
Auction Type: VCG, Number of Slots: 2, Reserved Price: 10	4119.30
Auction Type: GSP, Number of Slots: 3, Reserved Price: 10	4496.86
Auction Type: GSP, Number of Slots: 2, Reserved Price: 10	4651.32
Auction Type: VCG, Number of Slots: 3, Reserved Price: 5	4355.95
Auction Type: VCG, Number of Slots: 2, Reserved Price: 5	4951.47
Auction Type: GSP, Number of Slots: 3, Reserved Price: 5	5218.02
Auction Type: GSP, Number of Slots: 2, Reserved Price: 5	5296.75

Limitations

- Adaptive mechanisms could lead to long-term strategic bidding behavior by the bidders, ie., a bidder intentionally bids low to make the reserve price be lower in the future. We are not considering this point in our evaluation.

- Without real-time data, it's difficult to accurately predict how the algorithm would converge to the best design with dynamic data.

- Bidders will bid differently, depending on whether the VCG and GSP mechanism is used. Our data is based on first price auction, however, we utilize this data for simulation purposes and assume that bidders will bid in the similar way for GSP/VCG to generate our results.

Future Steps & Conclusion

- Given multiple designs, adaptive bandit algorithm is able to select designs such that generated total revenue is close to maximum.
- GSP performs at least as good as VCG (assuming bids are same for both) but unlike VCG, truthfulness is not a dominant strategy for GSP (Edelman et al, 2007)
    - In a real-time setting, VCG has the benefit of truthfulness but there may be high costs for transitioning from GSP to VCG.
- Our approach also shows how strategically varying other parameters, beside auction type, can change the overall revenue.

Future Steps:
- Add more designs
- Compare with first price auction (as Yahoo! Data uses this)
- Run adaptive algorithm for all phrase ids and compare performance with fixed mechanism
- Look for any patterns in the best auction design across phrase ids

Do you have any suggestions?

References

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