CSCI 357: Algorithmic Game Theory Lecture 6: Sponsored Ad Markets (Theory vs Practice)

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Announcements and Logistics

- Assignment 3 due by 11 pm Thursday
- **Partner work** guidelines are similar to pair programming: solve problems logically together, one person drives writing with alternation
- 2 questions both about surplus maximization and Myerson's payments
 - Intuition about critical bids/ approximation approach of AGT
 - Change in **Wed office hours** for next two weeks
- If you cannot make it to office hours, just reach out on Slack
- Workload distribution and learning in this class
 - Goal with partner assignments



Announcements and Logistics

- Assignment 2: feedback will be returned later this week
- Assignment 4 will also be a partner assignment
 - Simulation assignment to understand sponsored ad auctions
 - Need your Github IDs to share starter code: watch out for google form
- Not too many lines of code: but need to understand the simulation infrastructure
 - Goal: simulate simple auctions and do empirical analysis of how revenue/utility of agents
 - How do strategic agents reach eqm in a repeated auction setting?



Instructor Masking in Lectures

would like your feedback: <u>https://tinyurl.com/357mask</u> (please fill it before next class)

"Starting next Monday, February 21, instructors may unmask in class if they believe it will enhance instruction and if they maintain a safe distance."

Midterm 1: Save the Date March 12

- Pencil-paper exam, ~3 ish hours
- Can take it any time on (Sat) March 12
 - You have to be on campus
 - Pick up the exam from my office and return there
- If you have a conflict please reach out asap
- Open book, open notes
- Reasoning behind format
 - Goal to not be memory or time constrained

Questions?

HW 2 Rewind:

- Sealed-bid SP vs ascending clock auction (w public/private drop out)
 - In both cases, truthfulness is dominant strategy
 - Pros and cons?
- In public dropout, there is more transparency compared to sealed bid
 - Sealed bid requires everyone to trust the auctioneer
- Ascending auctions do not reveal value of winning bidder to others
- Extra information in public dropout can be used by bidders
 - Can help them learn the price/value of others but that can sometimes lead to undesirable competitive behavior

on (w public/private drop out) Int strategy





Last Time

- Myerson's lemma for single parameter settings:
 - Says allocation can be made DSIC iff it is monotone
 - Gives unique DSIC payment rule

$$p_i(z, \mathbf{b}_{-\mathbf{i}}) = z \cdot x_i(z, \mathbf{b}_{-\mathbf{i}}) - \int_0^z x_i(z, \mathbf{b}_{-\mathbf{i}}) dz_i(z, \mathbf$$

• We applied this rule to sponsored search auctions and derived the theoretical DSIC payment rule

Fotal payment:
$$p_i(\mathbf{b}) = \sum_{j=i}^k \left(b_{j+1} \cdot (\alpha_j - \alpha_{j+1}) \right) = b_{i+1}(\alpha_i - \alpha_{i+1}) + p_{i+1}(\mathbf{b})$$

$f_i(z, \mathbf{b}_{-\mathbf{i}}) dz$

Recursive definition might help think about it!



Today: Theory vs Practice

- What happens in the practice of sponsored search auctions
 - Rich history
 - Theory has often predicted behavior in practice pretty well
- Downsides of DSIC payment rules given by Myerson?
 - Can be complicated and hard to explain
 - Can be computationally expensive (as you will see in HW 3)
- Do we even need them? Does strategic bidding actually take place?
 - If so, how bad is it?
- Today: what happens in sponsored ad auctions in practice

Why Study Digital Ad Markets

The New York Times

THE ON TECH NEWSLETTER

Google and Facebook's Ad Empires

The tech giants talk a lot about the "metaverse" and cloud computing. What really powers them is selling us socks.



By Rapapawn

Google, Facebook, and Amazon to account for 64% of US digital ad spending this year

Article by Sara Lebow | Nov 3, 2021

"<u>AdSense</u> counts more than **2 million content publishers** as customers. Approved publishers can enter their Google code onto their sites or videos, and advertisers bid to show up **in** those ad slots in auctions. If a publisher's content displays an ad through AdSense, that publisher receives <u>68% of the</u> <u>revenue</u> recognized by Google in connection with that service."

https://www.cnbc.com/2021/05/18/how-does-google-make-moneyadvertising-business-breakdown-.html

Sponsored Search Auction

- We have k ad slots and n bidders (advertisers)
- Each add slot *i* has a "click through rate" α_i that models the number of clicks generated by the slot
- We assume that $\alpha_1 \geq \alpha_2 \geq \ldots \geq \alpha_k$
- Bidders have a **private value** v_i per click
 - Bidder *i*'s value for being assigned slot *j* is $v_i \cdot \alpha_j$
- Each bidder submits a "bid-per-click" (amount they are willing to pay per click)
- Auction collects the bid profile $\mathbf{b} = (b_1, \dots, b_n)$ and outputs an allocation rule $\mathbf{x}(\mathbf{b})$ (who gets what slot) and payment rule $\mathbf{p}(\mathbf{b})$ (who pays what)

Truthful Mechanism (VCG)

- Also called the Vickrey-Charles-Grove or VCG mechanism
- Surplus maximizing allocation:
 - Rank bidders by the bid value $b_1 \ge$
 - Assign slot *i* to bidder *i*, where $1 \leq i$
- Payment rule:
 - We have derived this using Myerson's lemma • Total payment of bidder *i* who is assigned slot *i* is $\sum_{k=1}^{k} \left(b_{j+1} \cdot (\alpha_j - \alpha_{j+1}) \right)$ • Per click payment of bidder *i* in slot *i* is thus $\sum_{j=i}^{k} \left(\frac{b_{j+1}}{\alpha_i} \cdot (\alpha_j - \alpha_{j+1}) \right)$

$$b_2 \ge \dots \ge b_n$$

 $i \le k$

VCG Payments Example

- Suppose bidders bid truthfully, what should they pay?
- Would bidder 1 have an incentive to underbid and obtain the second slot at a lower price?

Value per click v_i



$$\frac{1}{\alpha_i} \sum_{j=i}^k \left(b_{j+1} \cdot (\alpha_j - \alpha_{j+1}) \right)$$

Payment per click
$$p_i$$
 $\alpha_i(v_i - p_i)$
 $p_1 = 6.5$ $u_1 = 0.35$
 $p_2 = 4$ $u_2 = 0.25$
 $p_3 = 0$ $u_3 = 0$

VCG Payments Example • $p_1 = \frac{1}{0.1} \left(9(0.1 - 0.05) + 4(0.05) \right)$ • $p_2 = \frac{1}{0.05} \left(4(0.05 - 0) \right)$



 $\frac{1}{\alpha_i} \sum_{j=i}^{\kappa} \left(b_{j+1} \cdot (\alpha_j - \alpha_{j+1}) \right)$

$\alpha_i(v_i - p_i)$ Value per click v_i Payment per click p_i $u_1 = 0.35$ $p_1 = 6.5$ $u_2 = 0.25$ $p_{2} = 4$ $v_3 = 4$ $p_3 = 0$ $u_3 = 0$

VCG Payments Example

- $u_1 = 10 \cdot 0.1 (9(0.1 0.05) + 4(0.05)) = 0.35$
- Would bidder 1 have an incentive to underbid and obtain the second slot at a lower price?





VCG Payments Example

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VCG is Strategyproof

- $u_1 = 10 \cdot 0.1 (9(0.1 0.05) + 4(0.05)) = 0.35$
- Would bidder 1 have an incentive to underbid and obtain the second slot at a lower price?





 $b_1 = 8_{10}$

 $v_{2} = 9$

VCG is Strategyproof

•
$$p'_1 = \frac{1}{0.05} \left(4(0.05) \right) = 4$$

- $u_1' = 10 \cdot 0.05 4(0.05)$
- $u_1 u_1' = 10(0.1 0.05) 9(0.1 0.05) \ge 0$



Generalizes to $(v_1 - v_2)(\alpha_1 - \alpha_2)$ which is always positive: intuition why VCG mechanism is DSIC

 $p'_1 = 4$



Sponsored Search Practice

- Auction is run every second (rather than once)
- Bidders can adjust their bids based on history, time of the day etc

Sponsored Search: Practice

- Auction is run every second (rather than once)
- Bidders can adjust their bids based on history, time of the day etc
- In late 90s, Yahoo was the main search engine with ads
 - Used first-price auctions
 - We will analyze first-price auctions in next lecture
 - But what do you think bidders would do in such a "repeated auction"

Strategic bidder behavior in sponsored search auctions

Benjamin Edelman^a, Michael Ostrovsky^{b,*}

First Price vs Second Price?

- What are some pros/cons of each format?
- What is the benefit of first-price auction?
- What is a downside of second price?
 - Even if it is public ascending clock?

Sponsored Search: Practice

Authors looked at data and observed sawtooth bidding pattern



Strategic bidder behavior in sponsored search auctions Benjamin Edelman^a, Michael Ostrovsky^{b,*}

Generalized Second Price Auction

- Developed by Google in 2002 in response to the bidding wars
- Attempt to enforce truthful behavior by generalizing Vickrey (second price auctions)
- Collect bids-per-click $\mathbf{b} = (b_1, \dots, b_n)$
- GSP allocation rule: same as VCG
 - Order and reindex such that $b_1 \ge b_2 \ge \ldots \ge b_n$
 - Assign slot *i* to bidder *i*, where $1 \le i \le k$
- The price-per-click for bidder who is assigned slot *i*:
 - "Critical bid": the minimum amount they could have bid to obtain slot i
 - This is just b_{i+1} the bid of the person below i
- For a single slot this is truthful, but what if we have more than one slot?

- In a GSP auction, it is not the dominant strategy of bidders to bid their true value-per-click
- Idea. Incentive to underbid to acquire fewer clicks at a reduced price.
- Consider the following example
 - Say bidders 2 & 3 bid truthful, does bidder 1 have a useful deviation?



 $v_1 = 10$

 $v_{2} = 9$

- In a GSP auction, it is not the dominant strategy of bidders to bid their true value-per-click
- Suppose bidder 2 and 3 are truthful
- What are the prices of each bidder?
- What is the current utility of bidder 1?



 $v_1 = 10$ $p_1 = 9$ $u_1 = 0.1$ $v_{2} = 9$ $p_{2} = 4$ $v_3 = 4$ $p_3 = 0$

- In a GSP auction, it is not the dominant strategy of bidders to bid their true value-per-click
- Suppose bidder 2 and 3 are truthful, does bidder 1 have a useful deviation?



- In a GSP auction, it is not the dominant strategy of bidders to bid their true value-per-click
- Suppose bidder 2 and 3 are truthful, does bidder 1 have a useful deviation?



Being untruthful improves utility!

= 9	$p_2 = 8$	
= 8 = 10	<i>p</i> ₁ ' = 4	$u'_1 = 0.05(10)$ = 0.3
= 4	$p_3 = 0$	



Analyzing GSP's Equilibrium

- Not being strategyproof, makes GSP more difficult to analyze
- Its properties have been extensively studied computer scientists and economists (Varian, Edelman, Ostrovsky, and Schwarz)
- They formulate the auction as a complete-information game and make the following simplifying assumption:
 - Bidders know each other's value (Complete-information game)
 - Argument in favor: reasonable if bidders can observe patterns of bidding behavior of market competitors
 - Search engines often provide "market data", price points, etc. sc reasonable for advertisers to learn the market
- Easier to analyze using **Nash equilibrium**

ALL MODELS ARE WRONG, BUT SOME **ARE USEFUL**

GEORGE E P BOX



GSP Nash Equilibrium

GSP's Nash Equilibrium

- Turns out even with simplifying assumptions, still many challenges:
 - Turns out GSP has **many** Nash equilibria
 - Some of which aren't "good": that is, not reasonable to assume that players will play such an equilibrium
 - How do we choose between the various Nash?
- Formally, the utility of bidders is
 - $u_i(\mathbf{b}) = \alpha_i(v_i p_i)$ if bidder *i* receives slot $j \neq \emptyset$ where p_i is the price-per-click of slot j
 - Utility is 0 is bidder receives no slot
- At a Nash equilibrium, bidders must not be increase their utility by unilaterally deviating to a different bid b_i , keeping b_{-i} fixed

Formalizing Nash Eq Conditions

- Suppose bidder i who current has slot i deviates to b'_i to obtain a higher (better) slot j < i, then
 - How big should b'_i be to win?
 - Beat out b_i but below b_{i-1} that is, $b_i < b_i$
 - What is the payment-per-click it has to make for slot j?

•
$$p_j = b_j$$

• Expected utility from this deviation:

•
$$\alpha_j(v_i - b_j)$$

• To be in a Nash equilibrium, this deviation must not be profitable:

•
$$\alpha_i(v_i - b_{i+1}) \ge \alpha_j(v_i - b_j)$$
 for eve

$$b_i' < b_{j-1}$$

ery higher slot j < i

Formalizing Nash Eq Conditions

- Suppose bidder i who current has slot i deviates to b'_i to obtain a lower (worse) slot j > i, then
 - How big should b'_i be to win slot j?
 - Just above b_{i+1} but below b_i , that is, $b_{i+1} < b'_i < b_i$
 - What is the payment-per-click it has to make for slot j?

•
$$p_j = b_{j+1}$$

• Expected utility from this deviation:

•
$$\alpha_j(v_i - b_{j+1})$$

• To be in a Nash equilibrium, this deviation must not be profitable:

•
$$\alpha_i(v_i - b_{i+1}) \ge \alpha_j(v_i - b_{j+1})$$
 for e

every lower slot i > i

Summary: Nash Equilibrium

 For an assignment between bidders and slots to be a Nash equilibrium, the following two conditions must hold

 $\alpha_i(v_i - b_{i+1}) \ge \alpha_i(v_i - b_i)$ for every higher slot j < i

 $\alpha_i(v_i - b_{i+1}) \ge \alpha_i(v_i - b_{i+1})$ for every lower slot j > i

• We can verify best response for bidder 2:

• Deviate up to slot 1 at price \$4 or deviate down to slot 3 at price \$1



 $v_1 = 4$ $b_1 = 4$ $p_1 = 2.1$ $p_{2} = 2$ $p_3 = 1$

 $v_3 = 1$ $b_4 = 1$ $u_2 = 0.18(10 - 2) = 1.44$



- Suppose bidder 2 targets and wins slot 1, whats the price?
 - $p_1 = 4$
- Utility goes down, no incentive to deviate





 $v_3 = 1$ $b_4 = 1$ $u'_2 = 0.2(10 - 4) = 1.2$

- Suppose bidder 2 targets and wins slot 3, whats the price?
 - $p_3 = 1$
- Utility goes down, no incentive to deviate





 $v_3 = 1$ $b_4 = 1$ $u'_2 = 0.1(10 - 1) = 0.9$

- Can verify similarly for other bidders
- This bid profile is a **Nash equilibrium**, but is it a good one?
 - Does not maximize surplus! Economically inefficient outcome



 $p_1 = 2.1$ $p_{2} = 2$ $p_3 = 1$

Envy-Free Nash Equilibrium

Envy-Free Outcome

- The challenge in analyzing GSP is that there can be multiple equilibria
 - How do bidders select---depends on which equilibria is more plausible and reached by a straightforward bidding strategy
- Envy-free outcome. We say that a bid profile $\mathbf{b} = (b_1, \dots, b_n)$ where $b_1 \ge b_2 \ge \ldots \ge b_n$ is **envy-free** if for every bidder *i*

$$\alpha_i(v_i - b_{i+1}) \ge \alpha_j(v_i - b_{j+1})$$

- Interpretation: (current price-per-click of slot j is $p_i = b_{i+1}$)
 - each bidder *i* is as happy getting its current slot at its current price as it would be getting any other slot at that slot's current price

Envy-Free Outcome

• Envy-free outcome. We say that a bid profile $\mathbf{b} = (b_1, \dots, b_n)$ where $b_1 \ge b_2 \ge \ldots \ge b_n$ is **envy-free** if for every bidder *i*

$$\alpha_i(v_i - b_{i+1}) \ge \alpha_j(v_i - b_{i+1})$$

- **Exercise.** Envy-free outcome \implies bids in GSP are value ordered, that is, $v_1 \ge v_2 \ge \ldots \ge v_n$ for bids $b_1 \ge b_2 \ge \ldots \ge b_n$
- We want to show: envy-free outcomes are a subset of Nash equilibrium
- Remember Nash equilibrium conditions:
 - $\alpha_i(v_i b_{i+1}) \ge \alpha_i(v_i b_j)$ for every higher slot j < i
 - $\alpha_i(v_i b_{i+1}) \ge \alpha_i(v_i b_{i+1})$ for every lower slot j > i

 $b_{i+1})$

Envy-Free Outcome is a Nash Eq

- Lemma. An envy-free outcome of the GSP auction must be a Nash equilibrium
- Proof. We showed the GSP outcome is a Nash equilibrium if the following conditions hold for each bidder *i*:
 - $\alpha_i(v_i b_{i+1}) \ge \alpha_j(v_i b_j)$ for every higher slot j < i
 - $\alpha_i(v_i b_{i+1}) \ge \alpha_j(v_i b_{j+1})$ for every lower slot j > i
- At an envy-free outcome we have for each bidder ${\it i}$
 - $\alpha_i(v_i b_{i+1}) \ge \alpha_j(v_i b_{j+1})$
- Since $b_{j+1} < b_j$ we have that
 - $\alpha_i(v_i b_{i+1}) \ge \alpha_j(v_i b_{j+1}) \ge \alpha_j(v_i b_{j+1})$

$$\alpha_j(v_i - b_j) \blacksquare$$

- Is this equilibrium envy free?
 - Consider bidder 2, does he envy slot 1 at its current price?
 - Utility from slot 1's current price: 0.2(10 2.1) = 1.58



Greater than current utility of **1.44** (Not envy free)

- $p_1 = 2.1$
- $p_{2} = 2$
- $p_3 = 1$

 $v_3 = 1$ $b_4 = 1$ $u_2 = 0.18(10 - 2) = 1.44$



GSP: An Envy-Free Equilibrium

• Verify that the following outcome is envy free

• No bidder envies a different slot at its current price





Many Envy-Free Equilibrium

- Can you come up with another bid profile that is envy free?
 - Of course 1 can increase his bid without affecting anything
 - Lets assume wlog $b_1 = v_1$





• Now how about bidder 2? Can they bid higher? Is that envy-free?





• Bidder 2 can increase their bid and raise bidder 1's price!





- Why not bid $b_2 = \$9.99$ and increase the price for bidder 1 which can potentially drive that bidder out of future auctions?
- What can go wrong?



 $v_1 = 10$ $b_1 = 10$ $p_1 = 9.99$ $v_2 = 4$ $b_2 = 9.99$ $p_2 = 1.5$ $v_3 = 2$ $b_3 = 1.5$ $p_3 = 1$

- Why not bid $b_2 = \$9.99$ and increase the price for bidder 1 which can potentially drive that bidder out of future auctions?
- Potential concern. Bidder 1 could retaliate and "jam" bidder 2 by bidding 9.98 which would put bidder 1 in slot 1 at price 9.98



- $p_1 = 9.99$ $p_2 = 1.5$ $p_3 = 1$

- Why not bid $b_2 = \$9.99$ and increase the price for bidder 1 which can potentially drive that bidder out of future auctions?
- Potential concern. Bidder 1 could retaliate and "jam" bidder 2 by bidding 9.98 which would put bidder 1 in slot 1 at price 9.98



 $v_2 = 4$ $b_2 = 9.99$ $p_1 = 9.98$ $v_1 = 10$ $b_1 = 9.98$ $p_2 = 1.5$ $p_3 = 1$

• Idea. Bidders will prefer highest bids amongst those that achieve the same position as it drives up the price of their competitors



Balanced Bidding

• For bidder i, a balanced bid in slot i (for slots $2, \ldots, k$) is the largest bid b_i for which

$$\underbrace{\alpha_i(v_i - b_{i+1})}_{\text{utility current position}}$$

- Does such a bid b_i always exist?
 - As long as $b_{i+1} \leq v_i$ and $\alpha_i < \alpha_{i-1}$, the
- For bidders that have no slot assigned, what is the highest they should bid without any threat of retaliation (and non-negative utility)?
 - Their true value

$$\sum_{i=1}^{\alpha_{i-1}(v_i - b_i)}$$
 utility in case of retaliation

en yes (
$$b_{i+1} < b_i \le v_i$$
)

Credit: Textbook by Parkes and Seuken



Balanced Bidding

- We say a bid profile $\mathbf{b} = (b_1, b_2, \dots, b_n)$ satisfies the balanced bidding requirement if
 - The following holds for bidder *i* for $2 \le i \le m$

$$\alpha_i(v_i - b_{i+1})$$

utility current position

- Any unassigned bidder bids their true value
- Notice that for value ordered bids, the balanced bidding requirement defines a unique bid profile (up to the indifference of the top bidder)



Credit: Textbook by Parkes and Seuken



Balanced Bidding Strategies

• b_i must be the highest bid such that bidder i is indifferent between remaining in slot i and having bidder i - 1 retaliate



Balanced Bidding Strategies

- Bid b_3 must be the highest bid such that bidder 3 is indifferent between remaining in slot 2 and having bidder 1 retaliate
- $0.1(2-1) = 0.18(2-b_3) \implies b_3 = ?$

Balanced Bidding Strategies

- Bid b_2 must be the highest bid such that bidder 2 is indifferent between remaining in slot 2 and having bidder 1 retaliate:
 - $0.18(4 13/9) = 0.2(4 b_2) =$

$$\implies b_2 = 17/10$$

 $p_1 = 17/10$

- $v_2 = 4$ $b_2 = 17/10$ $p_2 = 13/9$
- $v_3 = 2$ $b_3 = 13/9$ $p_3 = 1$

Compare to VCG

Compute the VCG payments for this example • Exercise:

These are exactly the VCG payments!!!

$p_1 = 17/10$

- $v_2 = 4$ $b_2 = 17/10$ $p_2 = 13/9$
- $v_3 = 2$ $b_3 = 13/9$ $p_3 = 1$

Bigger Picture

Figure adapted from Textbook by Parkes and Seuken

Bigger Picture

- Lots of Nash equilibrium, some are inefficient and seem unlikely
- Envy-free (solution concept) in GSP \implies Nash equilibrium in GSP
- Lots of envy-free Nash still! Which ones are likely to be played?
 - The ones that emerge out of a reasonable "best response dynamics"
- Balanced bidding: **locally** envy free (no one wants to swap with one above)
- What we need to show:
 - Balanced bidding is in fact envy free
- GSP with balanced bidding gets exactly the same outcome (allocation, payments) as VCG with truthful biding!