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# Advertising on the Web

CS246: Mining Massive Datasets

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# Announcements

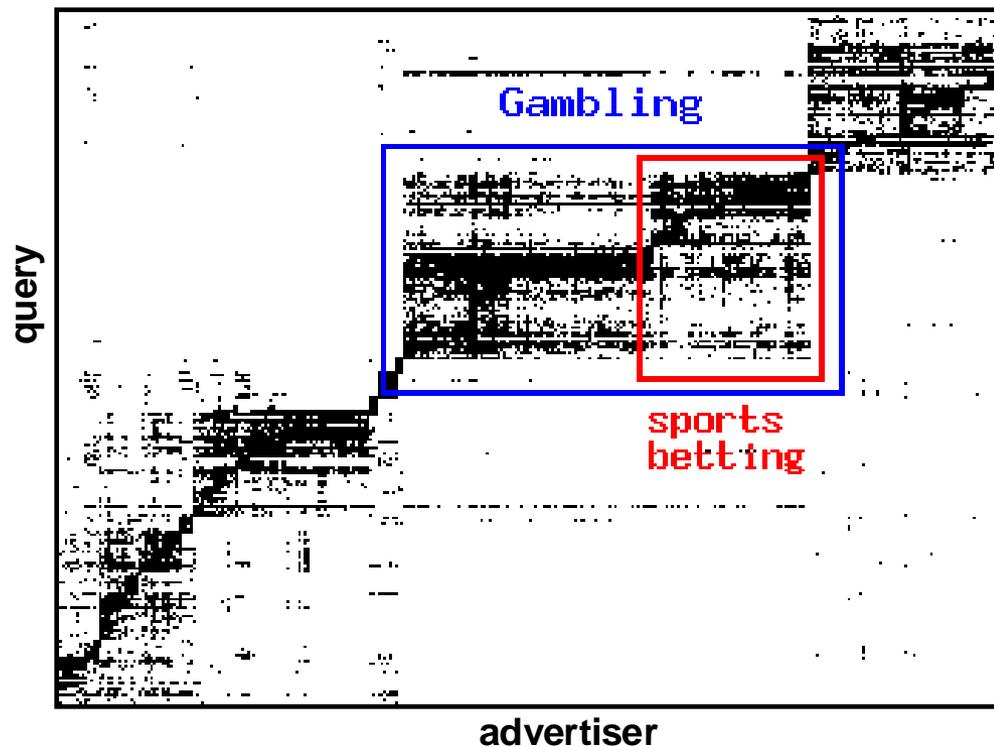
- HW 4 and Colab 8 are due Thursday (3/6)
- Practice Final Exam will be posted on Thursday (3/6) (likely on Ed)

# Online Algorithms

- **Classic model of algorithms**
  - You get to see the entire input, then compute some function of it
  - In this context, “**offline** algorithm”
- **Online Algorithms**
  - You get to see the input one piece at a time, and need to make irrevocable decisions along the way
  - **Similar to the data stream model**

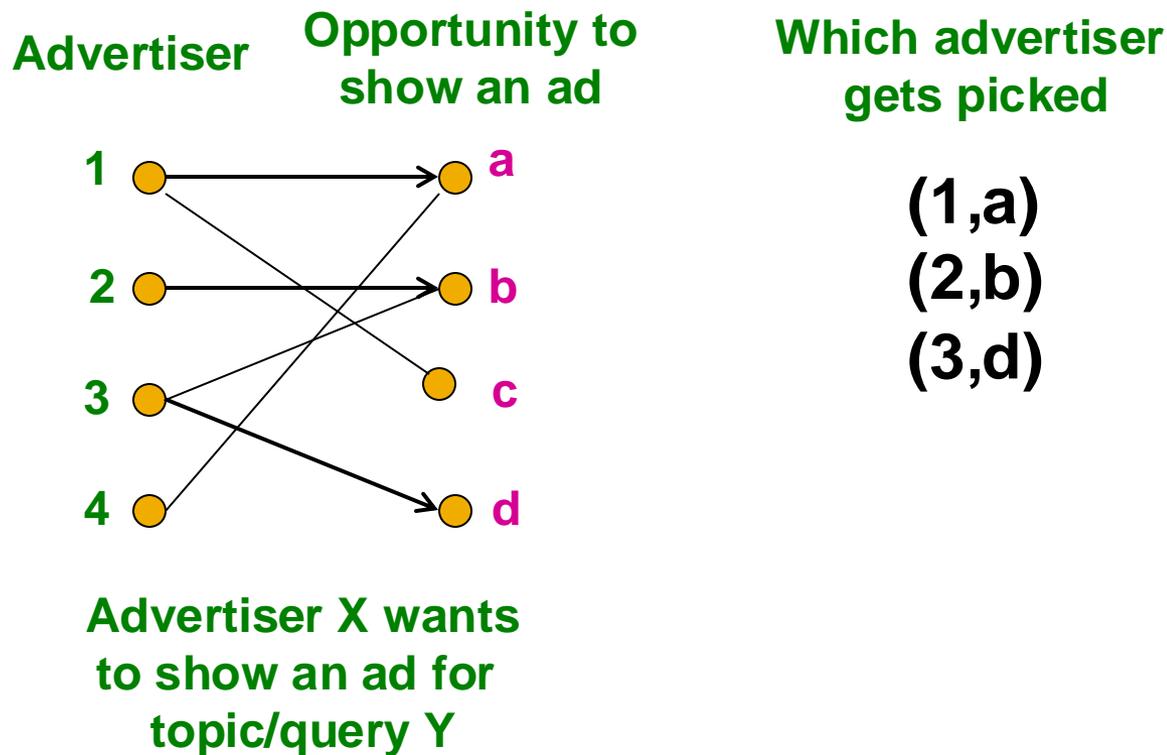
# Sponsored Search: Ads

- Query-to-advertiser graph:



[Andersen, Lang: Communities from seed sets, 2006]

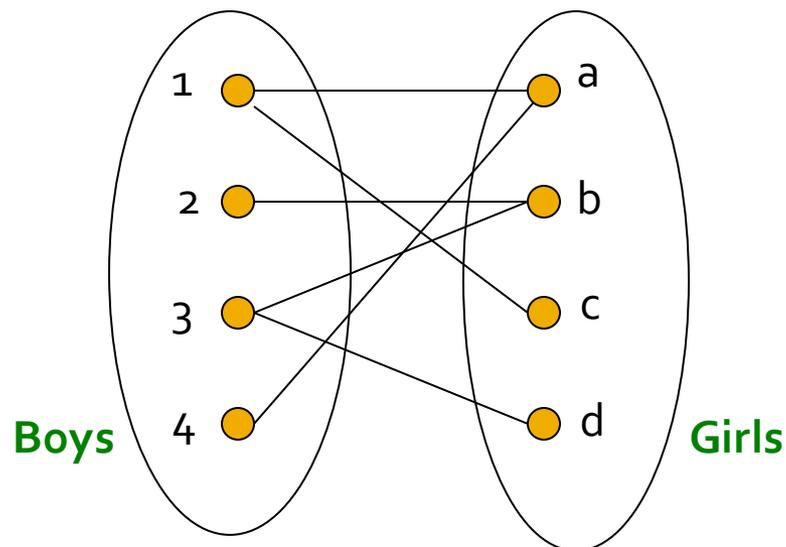
# Graph Matching for Advertising



**This is an online problem:** We have to make decisions as queries/topics show up. We do not know what topics will show up in the future.

# Online Bipartite Matching

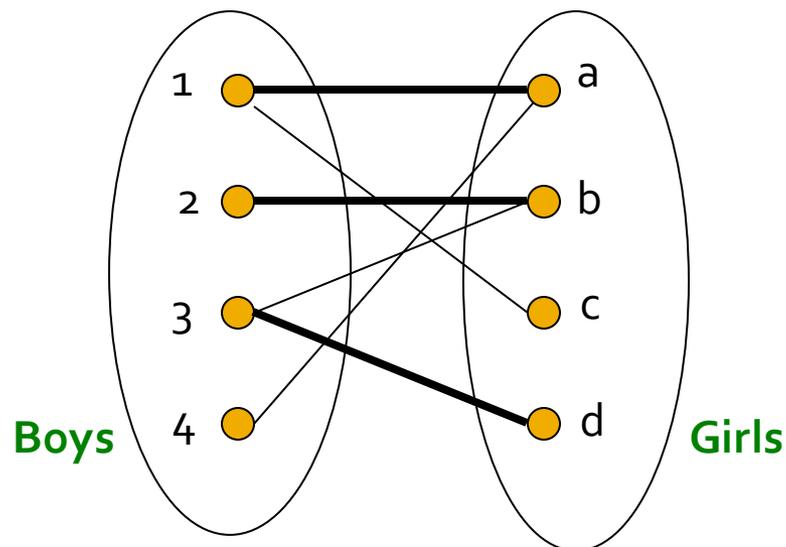
# Example: Bipartite Matching



**Nodes: Boys and Girls; Links: Preferences**  
**Goal: Match boys to girls so that the most preferences are satisfied**

Note: edges are only preferences with no weight or order.

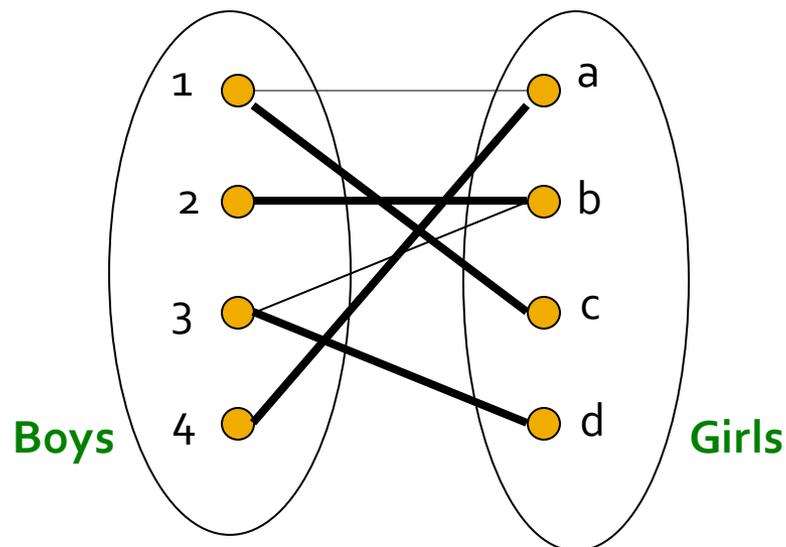
# Example: Bipartite Matching



$M = \{(1,a), (2,b), (3,d)\}$  is a **matching**  
**Cardinality of matching =  $|M| = 3$**

Matching means that we are not using any vertex twice

# Example: Bipartite Matching



$M = \{(1,c), (2,b), (3,d), (4,a)\}$  is a  
**perfect matching**

**Perfect matching** ... all vertices of the graph are matched

**Maximum matching** ... matching that contains the largest possible number of matches

# Matching Algorithm

- **Problem:** Find a maximum matching for a given bipartite graph
  - A perfect one if it exists
- There is a polynomial-time offline algorithm based on augmenting paths (Hopcroft & Karp 1973, [http://en.wikipedia.org/wiki/Hopcroft-Karp\\_algorithm](http://en.wikipedia.org/wiki/Hopcroft-Karp_algorithm))
- **But what if we do not know the entire graph upfront?**

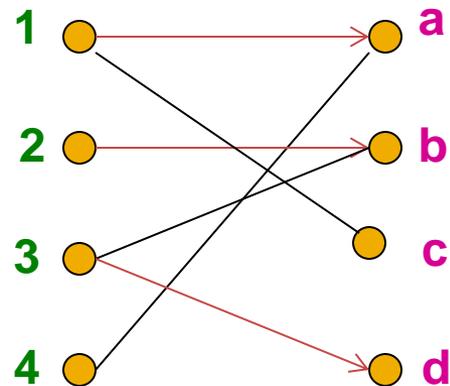
# Online Graph Matching Problem

- Initially, we are given the set **boys**
- In each **round**, **one girl's choices are revealed**
  - That is, the girl's **edges** are revealed
- **At that time, we have to decide to either:**
  - Pair the **girl** with a **boy**
  - Do not pair the **girl** with any **boy**
- **Example of application:**

Assigning tasks to servers

Note: Matching means that we are not using any girl or boy twice

# Online Graph Matching: Example



**(1,a)**  
**(2,b)**  
**(3,d)**

# Greedy Algorithm

- **Greedy algorithm for the online graph matching problem:**
  - Pair the new girl with **any** eligible boy
    - If there is none, do not pair the girl
- **How good is the algorithm?**

# Competitive Ratio

- For input  $I$ , suppose greedy produces matching  $M_{greedy}$  while an optimal matching is  $M_{opt}$

**Competitive ratio =**

$$\min_{\text{all possible inputs } I} (|M_{greedy}| / |M_{opt}|)$$

(what is greedy's worst performance over all possible inputs  $I$ )

# Analyzing the Greedy Algorithm

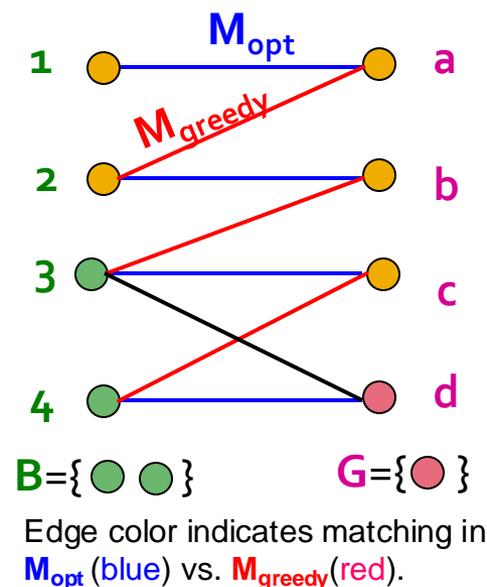
- Consider a case:  $M_{greedy} \neq M_{opt}$
- Consider the set  $G$  of girls matched in  $M_{opt}$  but not in  $M_{greedy}$

- (1) By definition of  $G$ :  

$$|M_{opt}| \leq |M_{greedy}| + |G|$$

- (2) Define set  $B$  of boys linked to girls in  $G$ 
  - Notice boys in  $B$  are already matched in  $M_{greedy}$ . Why?
    - If there would exist such non-matched (by  $M_{greedy}$ ) boy adjacent to a non-matched girl then greedy would have matched them

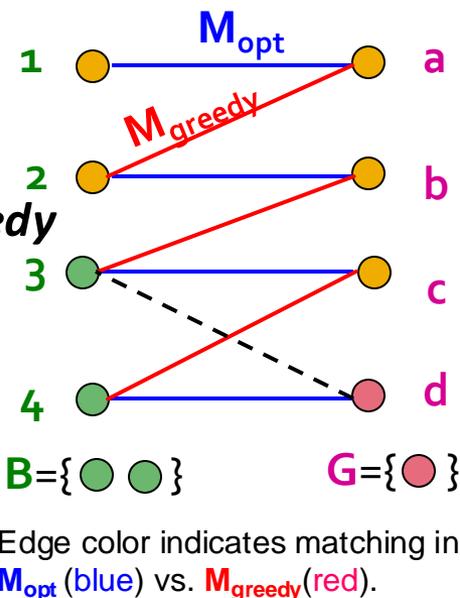
So:  $|M_{greedy}| \geq |B|$



# Analyzing the Greedy Algorithm

## ■ Summary so far:

- Girls  $G$  matched in  $M_{opt}$  but not in  $M_{greedy}$
- Boys  $B$  adjacent to girls in  $G$
- (1)  $|M_{opt}| \leq |M_{greedy}| + |G|$
- (2)  $|M_{greedy}| \geq |B|$



- Optimal matches all girls in  $G$  to (some) boys in  $B$ 
  - (3)  $|G| \leq |B|$
- Combining (2) and (3):
  - (4)  $|G| \leq |B| \leq |M_{greedy}|$

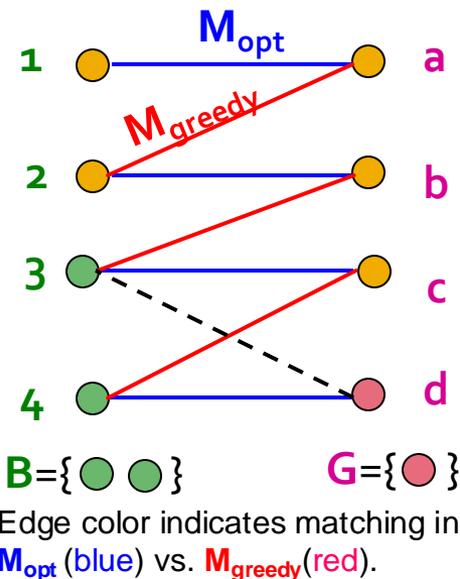
# Analyzing the Greedy Algorithm

- So we have:

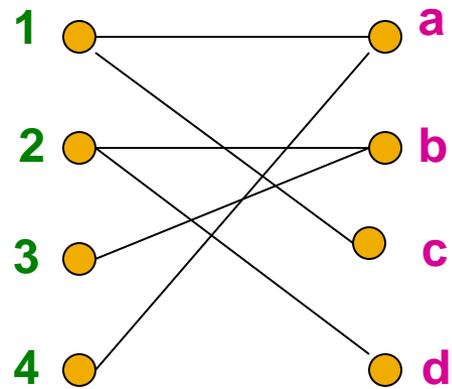
- (1)  $|M_{opt}| \leq |M_{greedy}| + |G|$
- (4)  $|G| \leq |B| \leq |M_{greedy}|$

- Combining (1) and (4):

- Worst case is when  $|G| = |B| = |M_{greedy}|$
- $|M_{opt}| \leq |M_{greedy}| + |M_{greedy}|$
- Then  $|M_{greedy}| / |M_{opt}| \geq 1/2$



# Worst-case Scenario



(1,a)

(2,b)

# Web Advertising

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# History of Web Advertising

- **Banner ads (1995-2001)**

- Initial form of web advertising

- Popular websites charged \$X for every 1,000

“impressions” of the ad

- Called “CPM” rate

(Cost per thousand impressions)

- Modeled similar to TV, magazine ads

- From **untargeted** to **demographically targeted**

- **Low click-through rates**

- Low ROI for advertisers

The screenshot shows the homepage of The New York Times. Several elements are highlighted with red boxes: a small banner ad in the top left corner; the 'NO DIRECT' button in the search bar; a large banner ad for 'A Group's Experience Speaks for Users' featuring a photo of a group of people; a smaller banner ad for 'Occupancy Protests Complain of Police Surveillance'; and a large green banner ad for Audible.com promoting 'HEAR GREAT BOOKS PERFORMED BY HOLLYWOOD'S FINEST' with a 'GO NOW' button. The page also displays various news headlines, market data, and a navigation menu.

**CPM...cost per mille**  
**Mille...thousand in Latin**

# Performance-based Advertising

- **Introduced by Overture around 2000**
  - Advertisers **bid on search keywords**
  - When someone searches for that keyword, the **highest bidder's ad is shown**
  - Advertiser is charged only if the ad is clicked on
- Similar model adopted by Google with some changes around 2002
  - Called **Adwords**

# Ads vs. Search Results

## Web

Results 1 - 10 of about 2,230,000 for **geico**. (0.04 sec)

### [GEICO Car Insurance. Get an auto insurance quote and save today ...](#)

GEICO auto insurance, online car insurance quote, motorcycle insurance quote, online insurance sales and service from a leading insurance company.

[www.geico.com/](#) - 21k - Sep 22, 2005 - [Cached](#) - [Similar pages](#)

[Auto Insurance](#) - [Buy Auto Insurance](#)

[Contact Us](#) - [Make a Payment](#)

[More results from www.geico.com »](#)

### [Geico, Google Settle Trademark Dispute](#)

The case was resolved out of court, so advertisers are still left without legal guidance on use of trademarks within ads or as keywords.

[www.clickz.com/news/article.php/3547356](#) - 44k - [Cached](#) - [Similar pages](#)

### [Google and GEICO settle AdWords dispute | The Register](#)

Google and car insurance firm GEICO have settled a trade mark dispute over ... Car insurance firm GEICO sued both Google and Yahoo! subsidiary Overture in ...

[www.theregister.co.uk/2005/09/09/google\\_geico\\_settlement/](#) - 21k - [Cached](#) - [Similar pages](#)

### [GEICO v. Google](#)

... involving a lawsuit filed by Government Employees Insurance Company (GEICO). GEICO has filed suit against two major Internet search engine operators, ...

[www.consumeraffairs.com/news04/geico\\_google.html](#) - 19k - [Cached](#) - [Similar pages](#)

## Sponsored Links

### [Great Car Insurance Rates](#)

Simplify Buying Insurance at Safeco

See Your Rate with an Instant Quote

[www.Safeco.com](#)

### [Free Insurance Quotes](#)

Fill out one simple form to get multiple quotes from local agents.

[www.HometownQuotes.com](#)

### [5 Free Quotes. 1 Form.](#)

Get 5 Free Quotes In Minutes!

You Have Nothing To Lose. It's Free

[sayyessoftware.com/Insurance](#)

Missouri

# Web 2.0

- **Performance-based advertising works!**
  - Multi-billion-dollar industry
- **Interesting problem:**  
**Which ads to show for a given query?**
  - (Today's lecture)
- **If I am an advertiser, which search terms should I bid on and how much should I bid?**
  - (Not focus of today's lecture)

# AdWords Problem

- A stream of queries arrives at the search engine:  $q_1, q_2, \dots$
- Several advertisers bid on each query
- When query  $q_i$  arrives, search engine must pick a subset of advertisers to show their ads
- **Goal: Maximize search engine's revenues**
  - **Simple solution:** Instead of raw bids, use the “expected revenue per click” (i.e., Bid\*CTR)
- **Clearly we need an online algorithm!**

# The Adwords Innovation

Advertiser	Bid	CTR	Bid * CTR
A	\$1.00	1%	1 cent
B	\$0.75	2%	1.5 cents
C	\$0.50	2.5%	1.25 cents

Click through  
rate

Expected  
revenue

# The Adwords Innovation

Advertiser	Bid	CTR	Bid * CTR
B	\$0.75	2%	1.5 cents
C	\$0.50	2.5%	1.25 cents
A	\$1.00	1%	1 cent

Instead of sorting advertisers by bid, sort by expected revenue

# Limitations of Simple Algorithm

Instead of sorting advertisers by bid, sort by expected revenue

Advertiser	Bid	CTR	Bid * CTR
B	\$0.75	2%	1.5 cents
C	\$0.50	2.5%	1.25 cents
A	\$1.00	1%	1 cent

## Challenges:

- CTR of an ad is unknown
- Advertisers have limited budgets and bid on multiple queries

# Complications: Budget

- **Two complications:**
  - Budget
  - CTR of an ad is unknown

## 1) Budget: Each advertiser has a limited budget

- Search engine guarantees that the advertiser will not be charged more than their daily budget
  - The Ad Pacing problem:
    - Advertiser's ad works well on a popular query
    - Advertiser has a small budget and the budget gets exhausted quickly
    - Observing a click and recording it takes much longer and thus the advertiser gets a lot of free impressions/clicks

# Complications: CTR

- **2) CTR (Click-Through Rate): Each ad-query pair has a different likelihood of being clicked**
  - **Advertiser 1** bids \$2 on query A, click probability = 0.1
  - **Advertiser 2** bids \$1 on query B, click probability = 0.5
- **CTR Prediction:**
  - ML models that predict the propensity of user clicking on a particular ad.
  - **Further complications: We will not cover:**
    - **1) CTR is position dependent:**
      - Ad #1 is clicked more than Ad #2

# Complications: CTR

- **Complications we will cover:**

- **2) Exploration vs. exploitation**

**Exploit:** Should we keep showing an ad for which we have good estimates of click-through rate?

**or**

**Explore:** Shall we show a brand new ad to get a better sense of its click-through rate?

# Online Algorithms

## The BALANCE Algorithm

# Adwords Problem

## ■ Given:

- 1. A set of bids by advertisers for search queries
- 2. A click-through rate for each advertiser-query pair
- 3. A budget for each advertiser (say for 1 month)
- 4. A limit on the number of ads to be displayed with each search query

## ■ Respond to each search query with a set of advertisers such that:

- 1. The size of the set is no larger than the limit on the number of ads per query
- 2. Each advertiser has bid on the search query
- 3. Each advertiser has enough budget left to pay for the ad if it is clicked upon

# Greedy Algorithm

- **Our setting: Simplified environment**
  - There is **1** ad shown for each query
  - All advertisers have the same budget  **$B$**
  - All ads are equally likely to be clicked
  - Bid value of each ad is the same ( **$=\$1$** )
- **Simplest algorithm is greedy:**
  - For a query pick any advertiser who has bid **1** for that query
  - **Competitive ratio of greedy is  $1/2$**

# Bad Scenario for Greedy

- **Two advertisers A and B**
  - **A** bids on query **x**, **B** bids on **x** and **y**
  - Both have budgets of **\$4**
- **Query stream: x x x x y y y y**
  - Worst case greedy choice: **B B B B \_ \_ \_ \_**
  - Optimal: **A A A A B B B B**
  - **Competitive ratio =  $\frac{1}{2}$**
- **This is the worst case!**
  - **Note:** Greedy algorithm is deterministic – it always resolves draws in the same way

# BALANCE Algorithm [MSVV]

- **BALANCE** Algorithm by Mehta, Saberi, Vazirani, and Vazirani
  - **For each query, pick the advertiser with the largest unspent budget**
    - Break ties arbitrarily (**but in a deterministic way**)

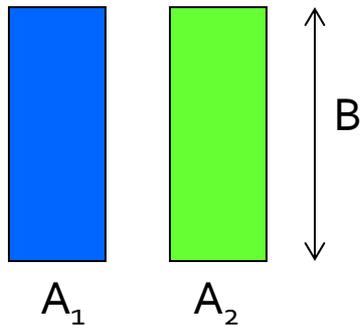
# Example: BALANCE

- **Two advertisers A and B**
  - A bids on query  $x$ , B bids on  $x$  and  $y$
  - Both have budgets of \$4
- **Query stream:  $x x x x y y y y$**
- **BALANCE choice: A B A B B B \_ \_**
  - Optimal: A A A A B B B B
- **In general: For BALANCE on 2 advertisers**  
**Competitive ratio =  $\frac{3}{4}$**

# Analyzing BALANCE

- **Consider simple case (w.l.o.g.):**
  - 2 advertisers,  $A_1$  and  $A_2$ , each with budget  $B$  ( $\geq 1$ )
  - Optimal solution exhausts both advertisers' budgets
- **BALANCE must exhaust at least one budget:**
  - **If not, we can allocate more queries**
    - Whenever BALANCE makes a mistake (both advertisers bid on the query), advertiser's unspent budget only decreases
    - Since optimal exhausts both budgets, one will for sure get exhausted
  - Assume BALANCE exhausts  $A_2$ 's budget, but allocates  $x$  queries fewer than the optimal
    - **So revenue of BALANCE =  $2B - x$**  (where OPT is  $2B$ )
  - **Let's work out what  $x$  is!**

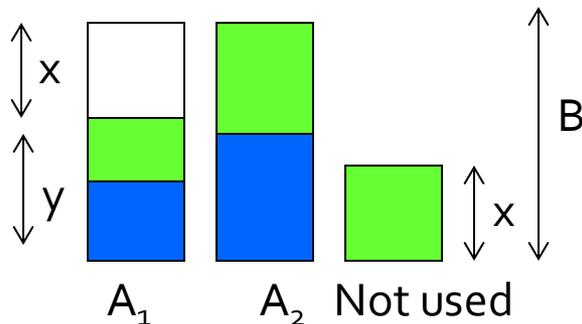
# Analyzing Balance



■ Queries allocated to  $A_1$  in optimal solution

■ Queries allocated to  $A_2$  in optimal solution

**Opt revenue =  $2B$**



Balance allocation

**Balance revenue =  $2B - x = B + y$**

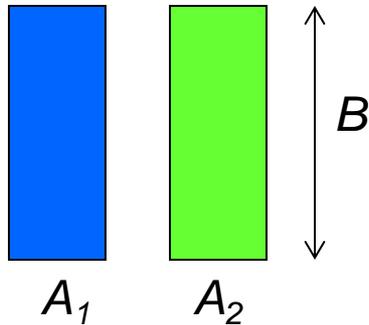
**We claim  $y \geq x$**  (next slide).

Balance revenue is minimum for  $x=y=B/2$ .

Minimum Balance revenue =  $3B/2$ .

Competitive Ratio =  $3/4$ .

# Analyzing BALANCE: What's $x$ ?

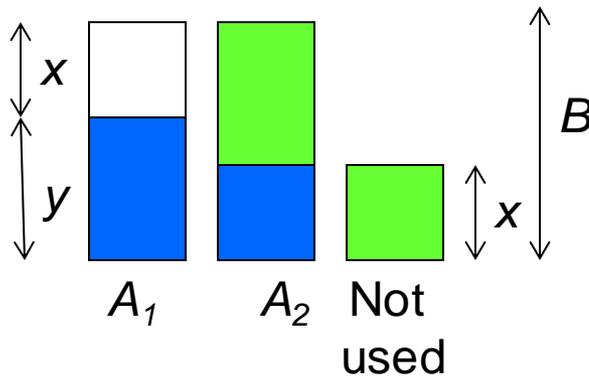


- Queries allocated to  $A_1$  in the optimal solution
- Queries allocated to  $A_2$  in the optimal solution

Optimal revenue =  $2B$

Assume Balance gives revenue =  $2B - x = B + y$

**Assume we exhausted  $A_2$ 's budget**



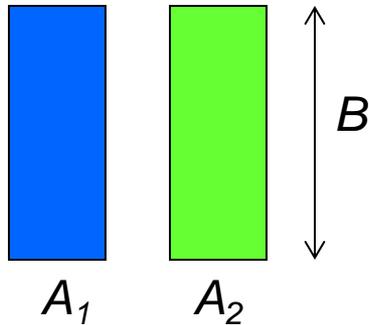
**Notice: Unassigned (not used) queries should be assigned to  $A_2$**  (since if we could assign them to  $A_1$  we would since we still have the budget)

**Goal: Show we have  $y \geq B/2$**

**Case 1)** BALANCE assigns  $\geq B/2$  blue queries to  $A_1$ .

Then trivially,  $y \geq B/2$

# Analyzing BALANCE: What's $x$ ?



- Queries allocated to  $A_1$  in the optimal solution
- Queries allocated to  $A_2$  in the optimal solution

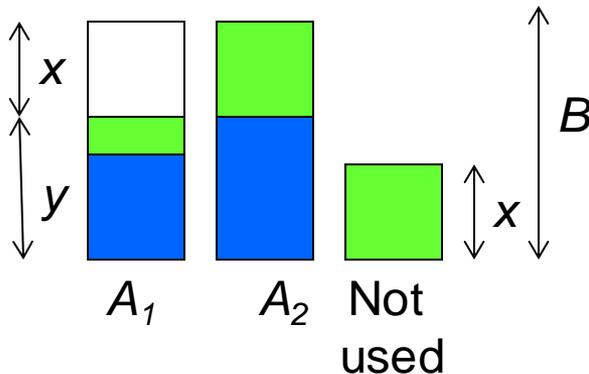
Optimal revenue =  $2B$

Assume Balance gives revenue =  $2B - x = B + y$

**Assume we exhausted  $A_2$ 's budget**

**Unassigned queries should be assigned to  $A_2$**   
(if we could assign to  $A_1$  we would since we still have the budget)

**Goal: Show we have  $y \geq B/2$**



**Balance revenue is minimum for  $x = y = B/2$**

Minimum Balance revenue =  $3B/2$

**Competitive Ratio:  $BAL/OPT = 3/4$**

**Case 2)** BALANCE assigns  $>B/2$  blue queries to  $A_2$ .

Consider the last blue query assigned to  $A_2$ .

At that time,  $A_2$ 's unspent budget must have been at least as big as  $A_1$ 's.

That means at least as many queries have been assigned to  $A_1$  as to  $A_2$ .

At this point, we have already assigned at least  $B/2$  queries to  $A_2$ .

So,  $x \leq B/2$  and  $x + y = B$  then  $y > B/2$

# BALANCE: General Result

- In the general case, worst competitive ratio of BALANCE is  $1 - 1/e = \text{approx. } 0.63$ 
  - $e = 2.7182$
  - Interestingly, no online algorithm has a better competitive ratio!
- Let's see the worst case example that gives this ratio

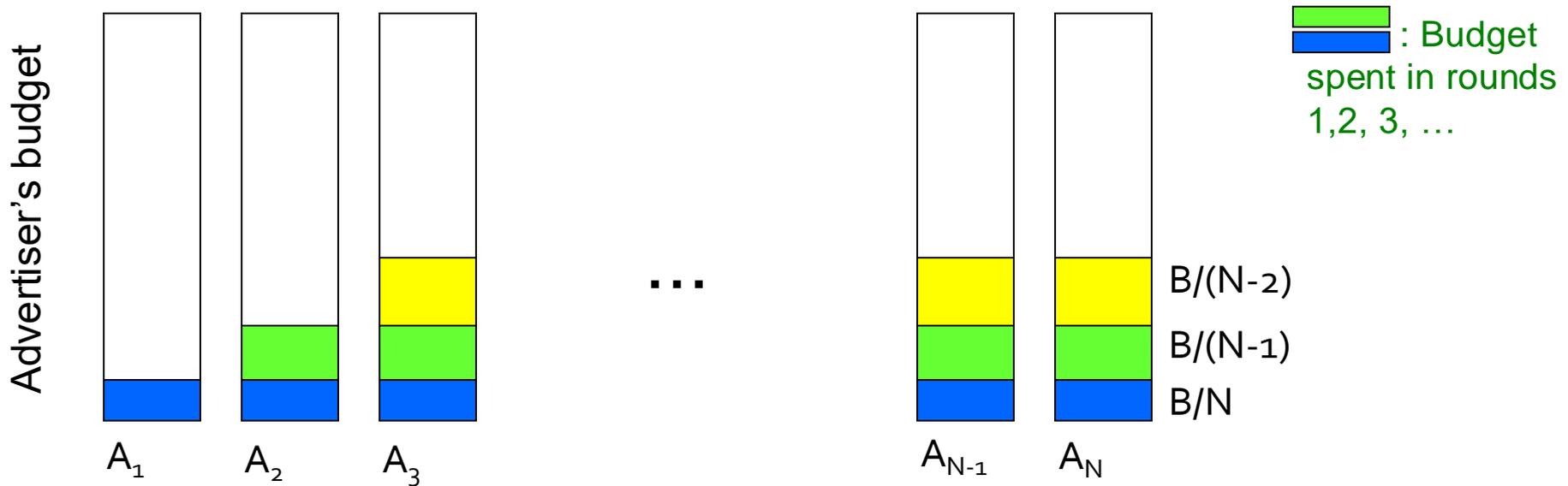
# Worst case for BALANCE

- **$N$  advertisers:**  $A_1, A_2, \dots, A_N$ 
  - Each with budget  $B > N$
- **Queries:**
  - $N \cdot B$  queries appear in  $N$  rounds of  $B$  queries each
- **Bidding:**
  - Round 1 queries: bidders  $A_1, A_2, \dots, A_N$
  - Round 2 queries: bidders  $A_2, A_3, \dots, A_N$
  - Round  $i$  queries: bidders  $A_i, \dots, A_N$
- **Optimum allocation:**

Allocate all round  $i$  queries to  $A_i$

  - Optimum revenue  $N \cdot B$

# BALANCE Allocation

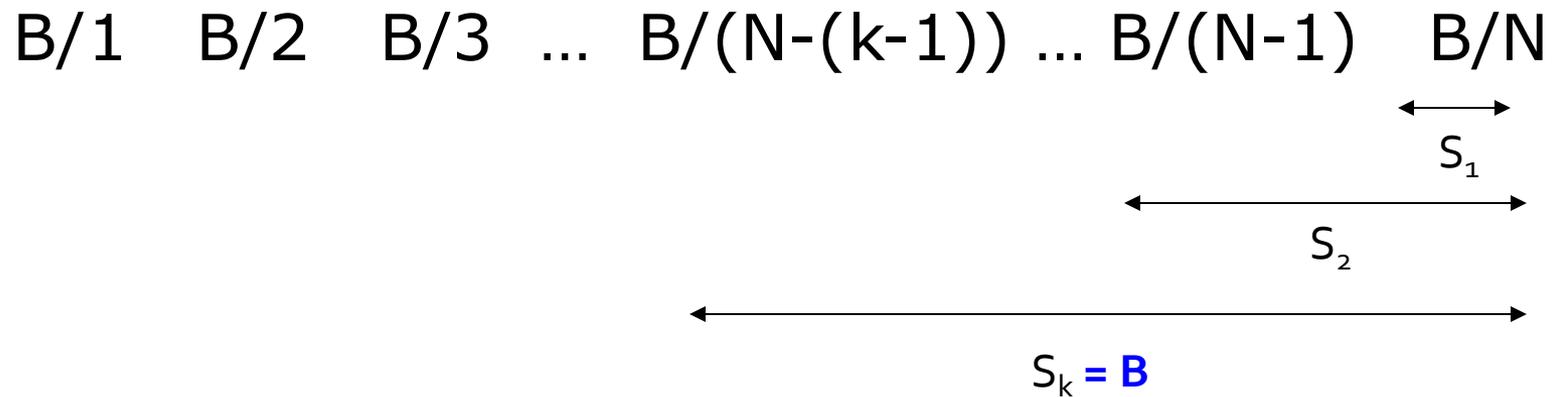


BALANCE assigns each of the queries in round 1 to  $N$  advertisers. After  $k$  rounds, **sum of allocations**  $S_k$  to each of advertisers

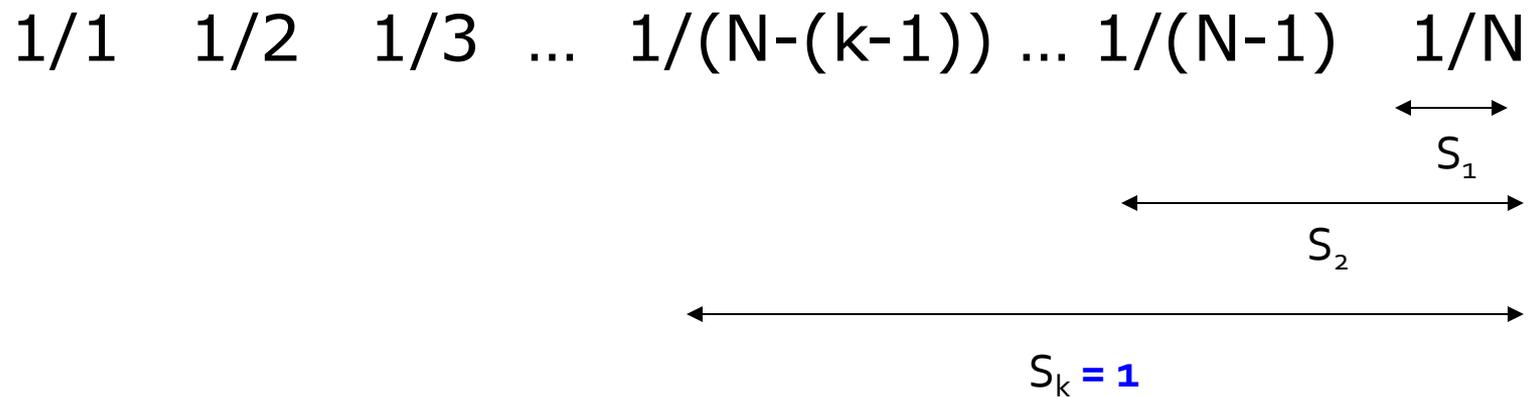
$$A_1, \dots, A_N \text{ is } S_k = S_{k+1} = \dots = S_N = \sum_{i=1}^k \frac{B}{N-(i-1)}$$

**If we find the smallest  $k$  such that  $S_k \geq B$ , then after  $k$  rounds we cannot allocate any queries to any advertiser**

# BALANCE: Analysis

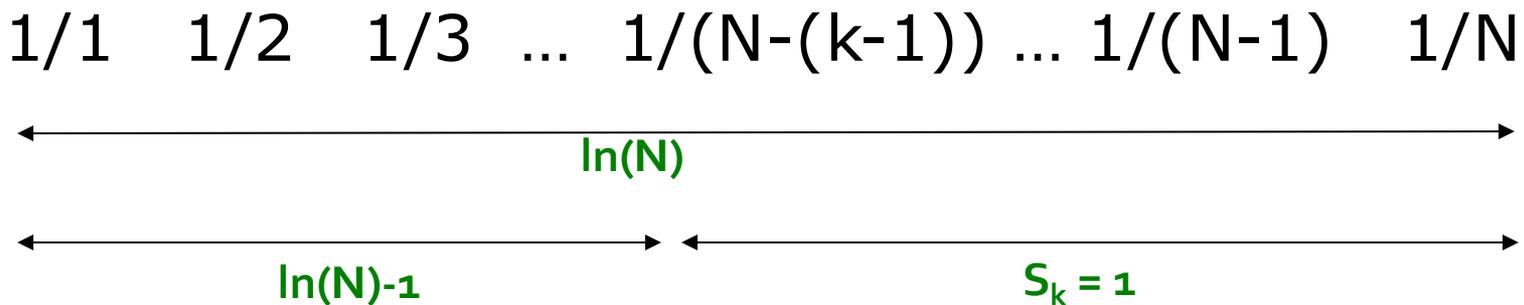


Can divide everything by B:



# BALANCE: Analysis

- **Fact:**  $H_n = \sum_{i=1}^n 1/i \approx \ln(n)$  for large  $n$ 
  - Result due to Euler



- $S_k = 1$  implies:  $H_{N-k} = \ln(N) - 1 = \ln\left(\frac{N}{e}\right)$
  - We also know:  $H_{N-k} = \ln(N - k)$
  - So:  $N - k = \frac{N}{e}$
  - Then:  $k = N\left(1 - \frac{1}{e}\right)$
- N* terms sum to  $\ln(N)$ .  
Last  $k$  terms sum to 1.  
First  $N-k$  terms sum to  $\ln(N-k)$  but also to  $\ln(N)-1$

# BALANCE: Analysis

- So after the first  $k=N(1-1/e)$  rounds, we cannot allocate a query to any advertiser
- Revenue =  $B \cdot N (1-1/e)$
- Competitive ratio =  $1-1/e$
- Note: So far we assumed:
  - All advertisers have the same budget  $B$
  - All advertisers bid 1 for the ad
  - (but each advertiser can bid on any subset of ads)

# General Version of the Problem

- **Arbitrary bids and arbitrary budgets!**
- Consider we have 1 query  $q$ , advertiser  $i$ 
  - Bid =  $x_i$
  - Budget =  $b_i$
- **In a general setting BALANCE can be terrible**
  - Consider two advertisers  $A_1$  and  $A_2$
  - $A_1: x_1 = 1, b_1 = 110$
  - $A_2: x_2 = 10, b_2 = 100$
  - Consider we see **10** instances of  $q$
  - BALANCE always selects  $A_1$  and earns **10**
  - Optimal earns **100**

# Generalized BALANCE

- **Arbitrary bids:** consider query  $\mathbf{q}$ , bidder  $i$ 
  - Bid =  $x_i$
  - Budget =  $b_i$
  - Amount spent so far =  $m_i$
  - Fraction of budget left over  $f_i = 1 - m_i/b_i$
  - Define  $\psi_i(\mathbf{q}) = x_i(1 - e^{-f_i})$
- Allocate query  $\mathbf{q}$  to bidder  $i$  with largest value of  $\psi_i(\mathbf{q})$
- **Same competitive ratio  $(1 - 1/e) = 0.63$**