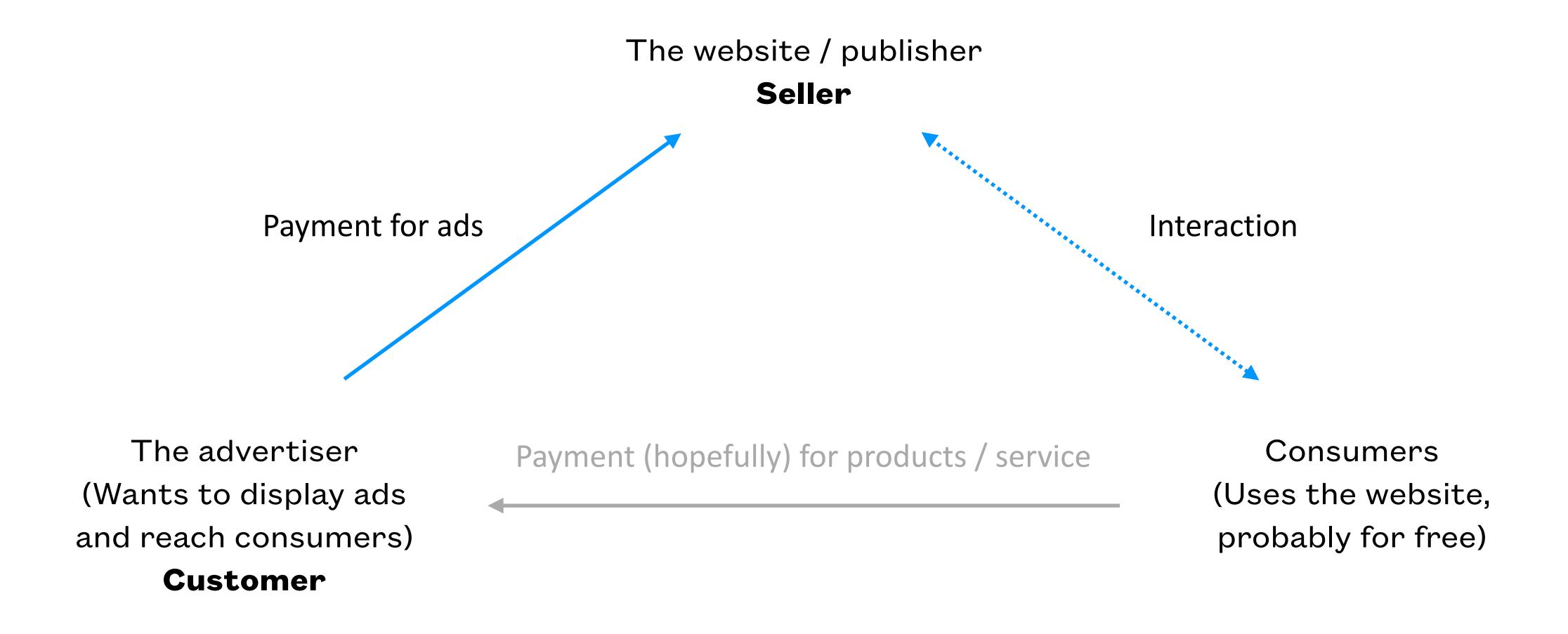
Advertising on the Web

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Online advertising

- Display ads
 - The primary method before search ads became popular
 - The host website charges fees for every 1000 "impressions" of ad
 - · Called "CPM" (cost per mile calculated as cost per 1000) rate
 - The advertiser pays the publisher when a user visits the website (and the ad is shown to the user)
 - · Based on the model used in TV, magazine ads
 - Many types (how they are displayed)
 - · Banner, Pop-up, Trick banner, Overlay, etc (we must have seen these all)
 - Untargeted, or demographically targeted
 - Low clickthrough rates
 - Low ROI for advertisers

The advertisement scenario



From cost-per-impression to cost-per-click





- Pay anyway, even if the user does not click
- Similar to TV (modernly streaming media), but in video viewers stay more glued to the screen

- Better option for the advertiser: pay only if the consumer clicked (showed initial interest) the ad (pay per click)
- The consumer's interest is the product
- (Pay only if you get the product)

For a history, read (recommended): https://www.launchpresso.com/what-happened-to-overture-com/

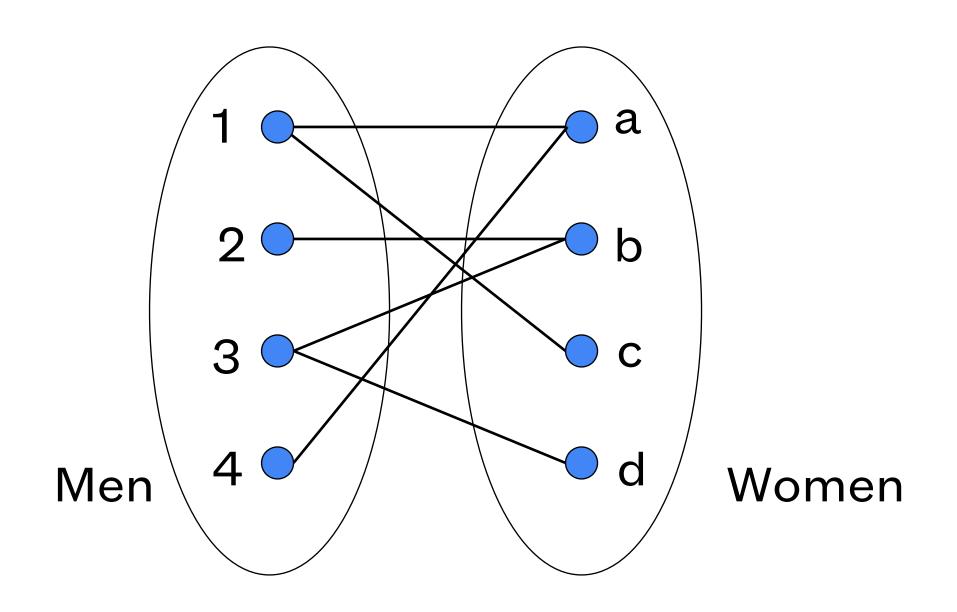
Search advertising

- Pay-per-click is seemingly good for the advertiser
- But guaranteed display of ads is no more profitable for the provider
 - What if some ads are almost never clicked on?
 - Website real estate space blocked, but no revenue
- Search ads: show ads based on what the user is interested in
 - Ads are relevant to the users \Longrightarrow much higher chance of clicking (ad revenue)
 - Good for advertisers too (their ads are targeted)
- The Adwords model
 - The advertisers bid on search queries: if my ad is shown when the user searched with keyword q, and the user clicks on my ad, I will pay \$b
 - For every search by some user (with query q), the search engine displays some of the ads that have a bid on the query

Online algorithms for search advertising

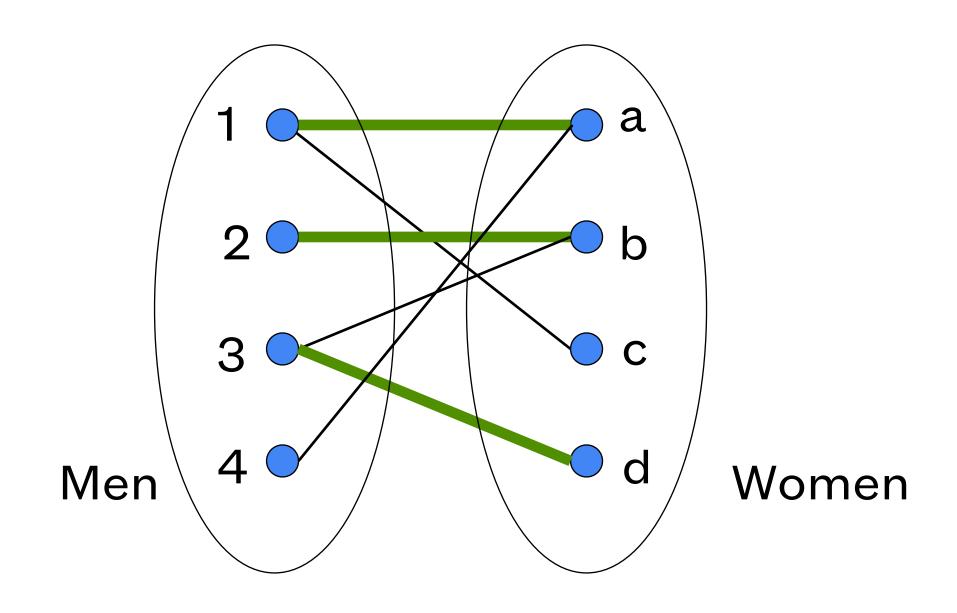
- Search advertising is a multi-billion-dollar industry
- Main technical problems:
 - Search engine: which ads to show for a search q?
 - Advertiser: which search terms should I bid on, and how much?
- Classic model of (offline) algorithms:
 - You get to see the entire input, then compute some function of it
- Online algorithm:
 - You get to see the input one piece at a time, and need to make irrevocable decisions along the way
 - Similar to data stream models

Background: bipartile matching



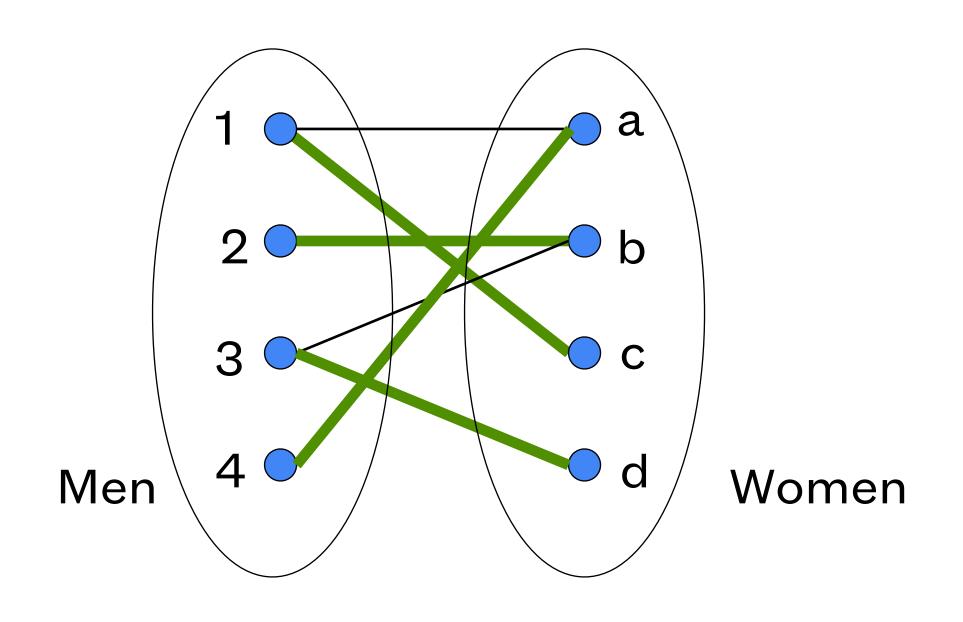
- A bipartile graph with two sets of nodes V_1 and V_2 with edges only across the sets
- A matching is a subset M of the edges such that no two edges in M have a common node
- In other words, a 1-1 pairing of men and women in the picture
- Goal: maximize the number of nodes paired this way

Maximal matching



- Example: $M = \{(1,a), (2,b), (3,d)\}$ is a matching
- Observe: no more edges can be added to M
 - So, M is a maximal matching
- Cardinality of M is 3
- Can there be another matching with a higher cardinality (in other words, is M a maximum cardinality matching?)

Maximum cardinality matching

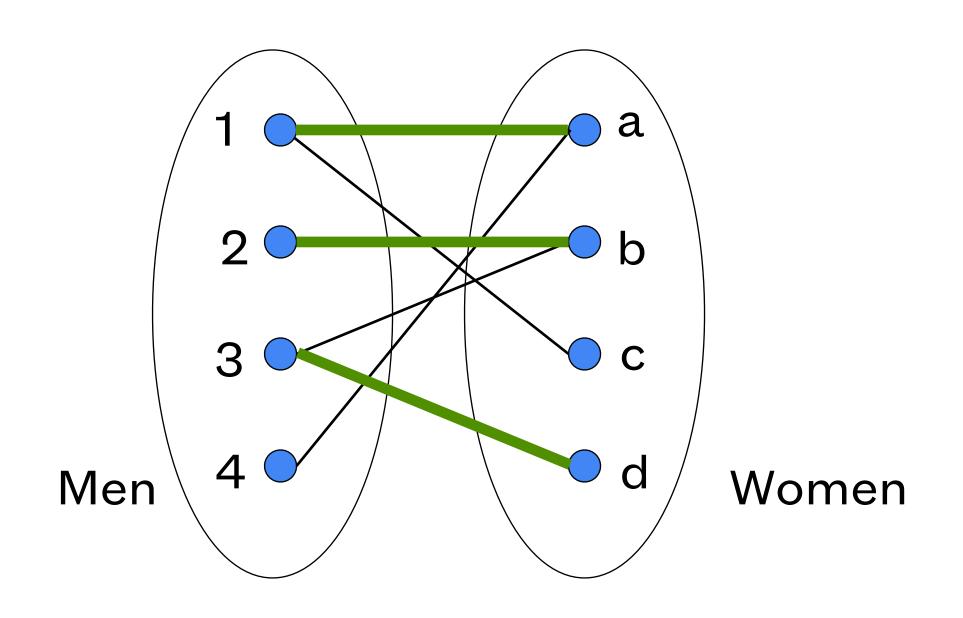


- Example 2: $M_2 = \{(1,c), (2,b), (3,d), (4,a)\}$ is a matching of cardinality 4
- M_2 is maximal as well as of maximal cardinality
- In fact M_2 is a perfect matching (all nodes are part of some edge of the matching)
- The problem we want to consider: given a bipartile graph, find a maximal cardinality matching (a perfect one if it exists)
- Offline: polynomial time algorithm exists
- Online: we don't have the entire graph initially

Online Matching

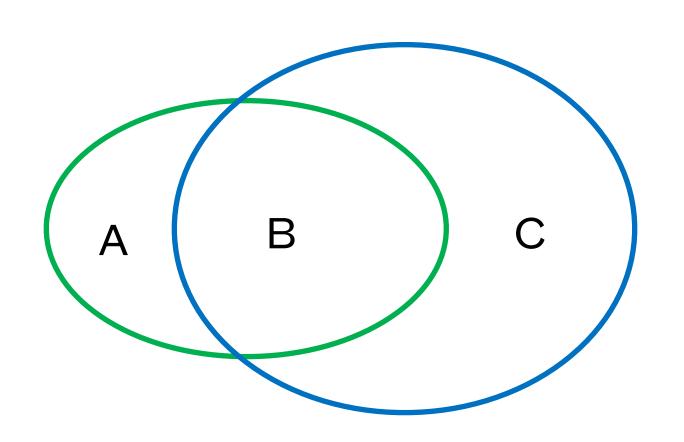
- Initially, we know the set of men
- In each round, one woman's set of choices is revealed
- At that time, we have to decide either to:
 - Pair the woman with a man among her choices
 - Don't pair the woman with any man
- Example applications:
 - Assigning tasks to servers
 - Web requests to threads
 - Assigning ads to search queries

The greedy algorithm



- The set of men are known
- As a new woman arrives with her choices, pair the woman with some man of her choice
 - If any such man is still available
- Simple to execute
- But how good (or bad) is this algorithm?
- Measured by the the competitive ratio of a matching algorithm
- If $M_{\mbox{greedy}}$ is a matching by the greedy algorithm and $M_{\mbox{opt}}$ is an optimal matching, then $\mbox{competitive ratio} = \min_{G} \{|M_{\mbox{greedy}}| / |M_{\mbox{opt}}|\}$ taken over all possible inputs G

The greedy algorithm has competitive ratio 1/2



- Let O be the optimal matching, and G the matches produced by a run of the greedy algorithm
- We need to show $2|G| \ge |O|$
- Consider the sets of women:

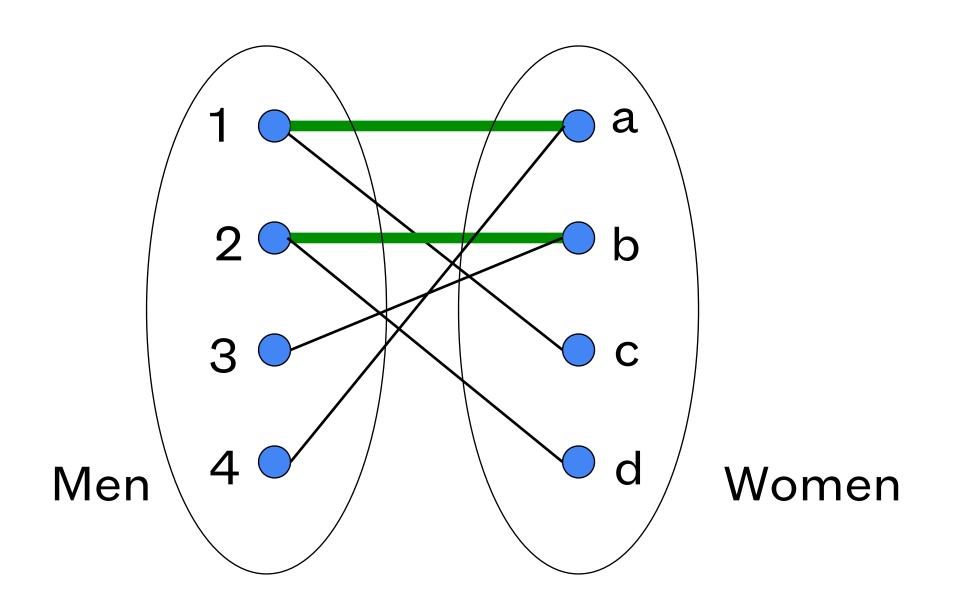
A: Matched in G, not in O

B: Matched in both

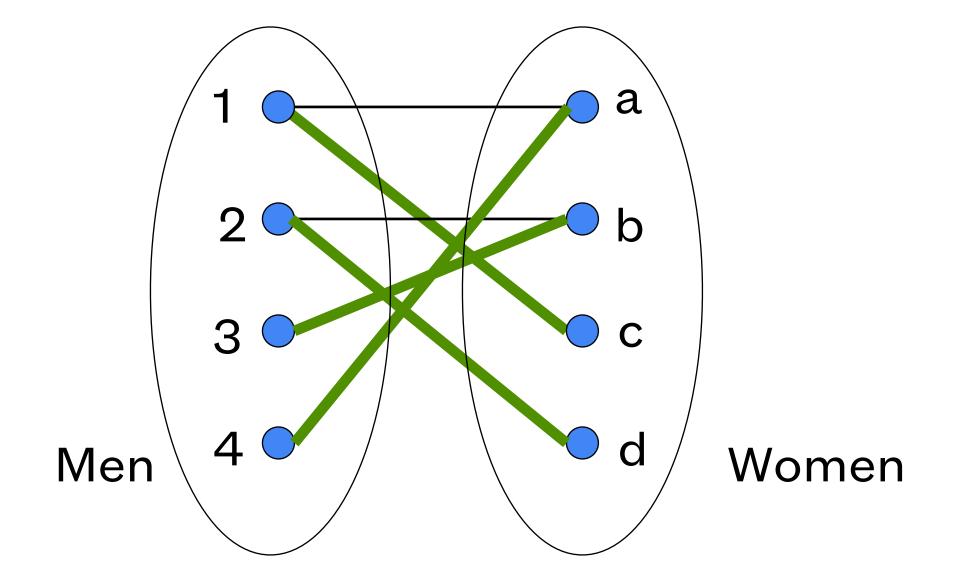
C: Matched in O, not in G

- ullet During the greedy matching, no woman in C could be matched (but they could be matched in O)
- In greedy every $w \in C$ her optimal match taken by another woman already
 - Those matches are taken by women in A and B
- So, $|A| + |B| \ge |C|$
- Then we have, 2|G| = 2|A| + 2|B| = |A| + |B| + |A| + |B| $\geq |B| + |C| = |O|$

The the worst case scenario is indeed 1/2



Greedy matching with cardinality 2



Optimal matching with cardinality 4

The 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 whose ads are shown (online)
- Goal: maximize the revenue of the search engine

The Adwords problem

- Goal: maximize the revenue of the search engine
- Further complication 1: each ad has a different likelihood of being clicked
- Example:
 - Advertiser 1 bids \$2, click probability = 0.1
 - Advertiser 2 bids \$1, click probability = 0.5
 - · Click-through rate measured by historical performance.
- Simple solution:
 - Instead of raw bids, use the expected revenue (bid X click-through rate)
 - However, for simplicity, we will use "bid" instead of bid X
 ctr in our algorithms
- Further complication 2: each advertiser has limited budget
- The search engine cannot charge the advertiser more than the set budget

Advertiser	Bid	CTR	Bid * CTR
A	\$1.00	1%	1 cent
В	\$0.75	2%	1.5 cents
C	\$0.50	2.5%	1.125 cents

Advertiser	Bid	CTR	Bid * CTR
3	\$0.75	2%	1.5 cents
	\$0.50	2.5%	1.125 cents
4	\$1.00	1%	1 cent

Adwords: simplified model

- Assume all bids are 0 or 1
- Each advertiser has the same budget
- Only one advertiser is chosen per query

Greedy algorithm on the simplified adwords problem

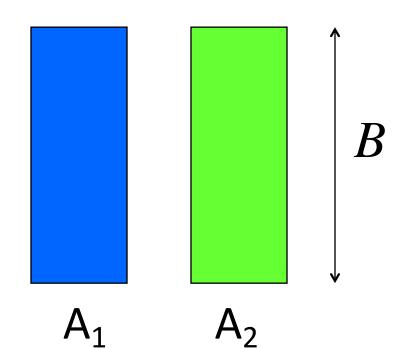
- Let's try the greedy algorithm:
 - Arbitrarily pick an eligible advertiser for each keyword
- Two advertisers A and B.
- A bids on query x, B bids on x and y
- Both have budgets of \$4.
- Query stream: x x x x y y y y
- Possible greedy choice: B B B B _ _ _ _
- Optimal: A A A A B B B B
- Competitive ratio = 1/2.
 - This is actually the worst case.

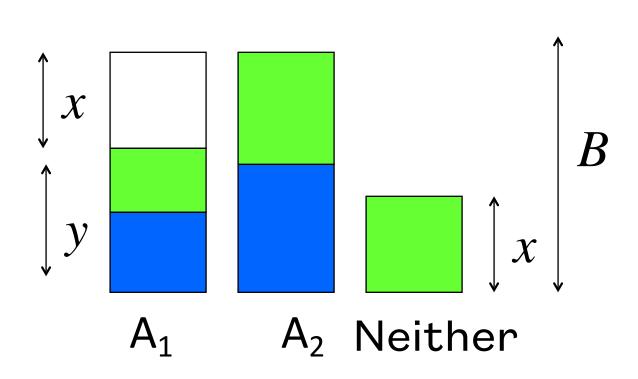
- Assume all bids are 0 or 1
- Each advertiser has the same budget
- Only one advertiser is chosen per query

Balance Algorithm

- Algorithm: for each query, pick the advertiser with the largest unspent budget who bid on this query
 - Break ties arbitrarily
- 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: B A B A B B _ _
- Optimal: A A A A B B B B
- Competitive ratio = 3/4

- Consider simple case: two advertisers A₁ and A₂
- Each with budget B > 1 (B is an even number)
- Consider the case where the optimal solution exhausts both advertisers' budgets.
 - i.e., optimal revenue to search engine = 2B.
- Balance must exhaust at least one advertiser's budget
 - If not, we can allocate more queries
 - Assume Balance exhausts A₂'s budget





Balance allocation

- Queries allocated to A₁ in optimal solution
- Queries allocated to A₂ in optimal solution

Optimal revenue = 2BBalance revenue = 2B - x = B + y

Note: only green queries can be assigned to neither. A blue query could have been assigned to A_1 .

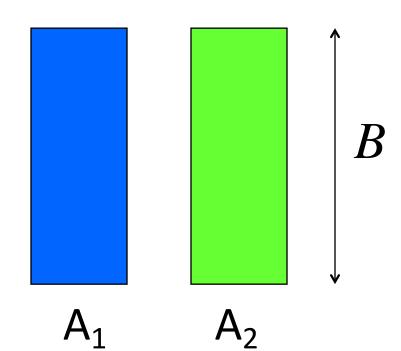
We claim: $y \ge x$

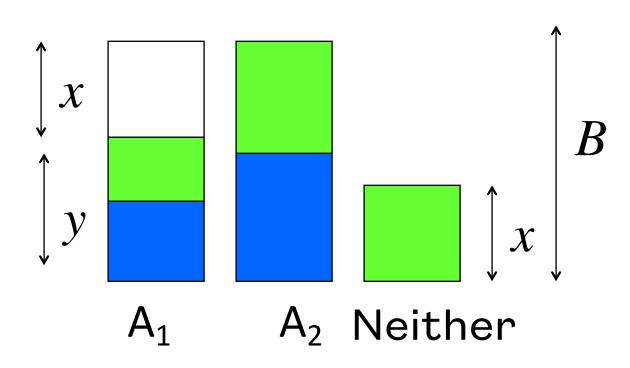
If we can prove that, then:

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

Minimum Balance revenue = 3B/2

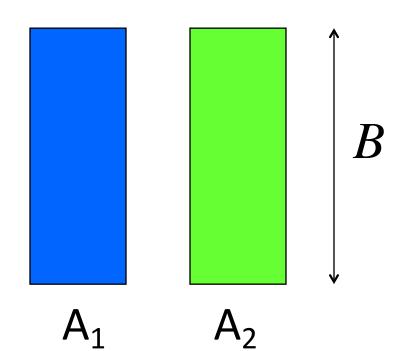
Competitive Ratio = 3/4

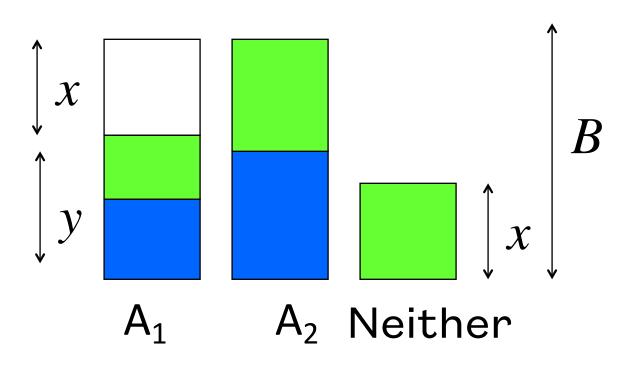




Balance allocation

- Queries allocated to A₁ in optimal solution
- Queries allocated to A₂ in optimal solution
- Case 1: At least half the blue queries are assigned to A₁ by Balance.
 - Then $y \ge B/2$, since the blues alone are $\ge B/2$
- Case 2: Fewer than half the blue queries are assigned to A_1 by Balance
 - Let q be the last blue query assigned by Balance to A₂





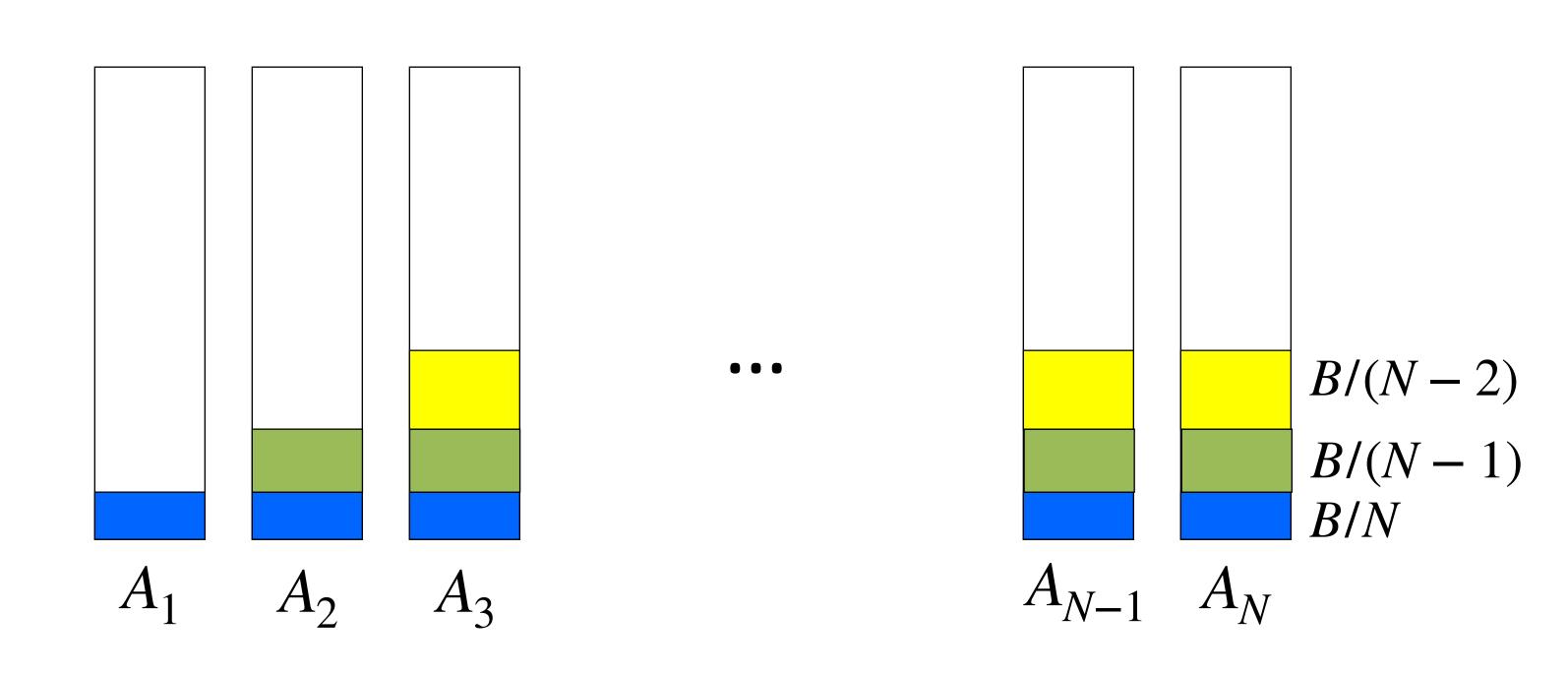
Balance allocation

- Queries allocated to A₁ in optimal solution
- Queries allocated to A₂ in optimal solution
- Since A_1 obviously bid on q, at that time, the budget of A_2 must have been at least as great as that of A_1 .
- Since more than half the blue queries are assigned to A_2 , at the time of q, A_2 's remaining budget was at most B/2
- Therefore so was A₁'s, which implies $x \le B/2$, and therefore $y \ge B/2$ and $y \ge x$
- Thus Balance uses $\geq 3B/2$

Many bidders: an example

- lacksquare N advertisers, each with budget B
- N distinct queries $q_1, q_2, ..., q_N$
- The *i*-th round: queries $q_i, q_i, ..., q_i$ (the same query q_i repeated B times)
- Total NB queries appear in N rounds
- Advertiser A_i bids on $q_1, q_2, ..., q_i$ only
- Bidders for round 1: all advertisers $A_1, A_2, ..., A_N$
- Bidders for round 2: all advertisers except A_1 , i.e., A_2, A_3, \ldots, A_N
- Bidders for round i: advertisers $A_i, A_{i+1}, ..., A_N$
- Bidders for round N: only A_N
- ullet Optimal allocation: all the queries in round i goes to A_i
 - Optimum revenue = NB (all budget exhausted)

Balance algorithm on this example



After k rounds, sum of allocations to each of A_k , ..., A_N is $S_k = S_{k+1} = ... = S_N$ $= \sum_{i=1}^k B/(N-i+1) = B \sum_{i=1}^k 1/(N-i-1)$

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

- The algorithm cannot allocate any queries after k rounds if $B\sum_{i=1}^{\infty} 1/(N-i+1) \ge B$,
- In other words, $\sum_{i=1}^{k} 1/(N-i+1) = \frac{1}{N} + \frac{1}{N-1} + \dots + \frac{1}{N-k+1} \ge 1$
- When does this happen?

Balance algorithm: competitive ratio

- Fact (Euler): $H_n = 1 + \frac{1}{2} + \dots + \frac{1}{n} \rightarrow \log_e n$ for large n
- We want to find k so that $\frac{1}{N} + \frac{1}{N-1} + \dots + \frac{1}{N-k+1} \ge 1$
- The condition is same as $\left(\frac{1}{N} + \frac{1}{N-1} + \dots + \frac{1}{2} + 1\right) \left(\frac{1}{N-k} + \frac{1}{N-k-1} + \dots + \frac{1}{2} + 1\right) \ge 1$
- For large n, the L.H.S. $\approx \log_e(N) \log_e(N-k) = \log_e\left(\frac{N}{N-k}\right)$, and we need that to be ≥ 1
- This happens when $(N-k)/N \le 1/e$, or $k \ge N(1-1/e)$
- Hence, no balance cannot make any further allocation after N(1-1/e) rounds
- Revenue (balance) = BN(1 1/e)
- The competitive ratio of balance is at best $(1 1/e) \approx 0.63$
- Results (Kalyanasundaram and Pruhs, 2000):
 - The competitive ratio of balance (where all advertisers have same budget) is indeed 1-1/e
 - No deterministic online algorithm can have a better competitive ratio

General case: when advertisers have different budgets

- Different bidders have different budgets
- The algorithm would allocate queries to the advertiser with largest unspent budget
- Suppose both A₁ and A₂ bid on query q
- Query stream: query q comes 10 times
- Balance will allocate all 10 queries to A₁
- Revenue: 10
- Optimal: allocate all 10 queries to A₂
- Revenue: 100
- Competitive ratio = 1/10
- In fact, we can make this ratio as small as we want by constructing curated examples

Bidder	Bid	Budget
A ₁	1	110
A ₂	10	100

Bidder	Bid	Budget
A ₁	1	210
A ₂	20	200

Generalized Balance

- Todo 1: Be biased in favor of higher bids
- Todo 2: Consider fraction of remaining budget, not absolute remaining budget
- Generalized balance
 - Suppose advertiser A_i has bid x_i (can be zero) for query q
 - Fraction of A_i 's budget currently remaining is f_i
 - Then define: $\Psi_i = x_i(1 e^{-f_i})$
 - Allocate query q to the advertiser for whom Ψ_i is maximum (break ties arbitrarily)
- Result: This algorithm achieves competitive ratio = $(1 1/e) \approx 0.63$

Sources and Acknowledgements

- 1. J. Leskovec, A. Rajaraman and J. Ullman. "Mining of massive datasets", Chapter 8. Cambridge University Press, 2011. http://www.mmds.org
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- 2. Tim. "What Happened To Overture.com?", May 2019: https://www.launchpresso.com/what-happened-to-overture-com/
- 3. B. Kalyanasundaram and K.R. Pruhs, "An optimal deterministic algorithm for b-matching," Theoretical Computer Science 233:1–2, pp. 319–325, 2000.
- 4. A Mehta, A. Saberi, U. Vazirani, and V. Vazirani, "Adwords and generalized on-line matching," IEEE Symp. on Foundations of Computer Science, pp. 264–273, 2005.