



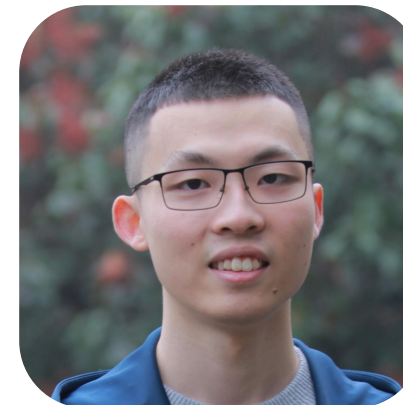
Bidder Selection Problem in Position Auctions: A Fast and Simple Algorithm via Poisson Approximation



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Bidder Selection in Online Ad Auction

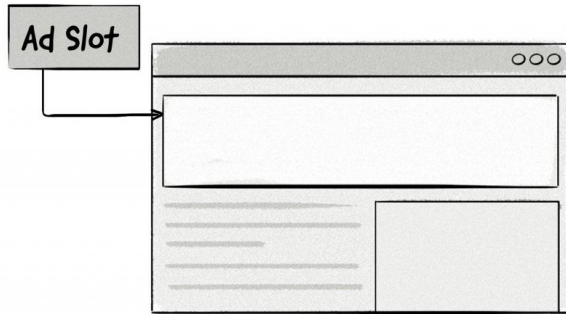
- Online ad auction
 - Ad company sells ad slots to advertisers
 - Real time and automated
- Bidder selection
 - Bidders' valuations are computed from a ML model
 - Running the model for all bidders: costly and slow
 - A prior distribution for each bidder is available
 - **Two-stage selection:** filter out a fraction of bidders, then run auction

Example Scenario

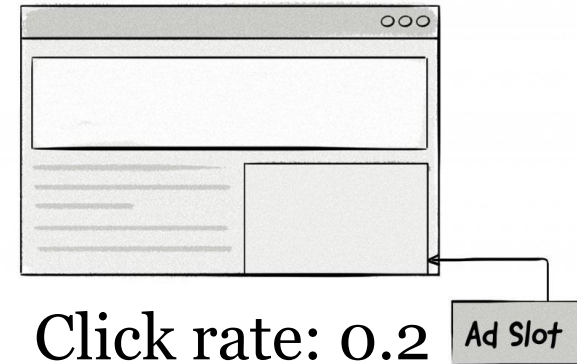
 

Example Scenario

ticket discount 



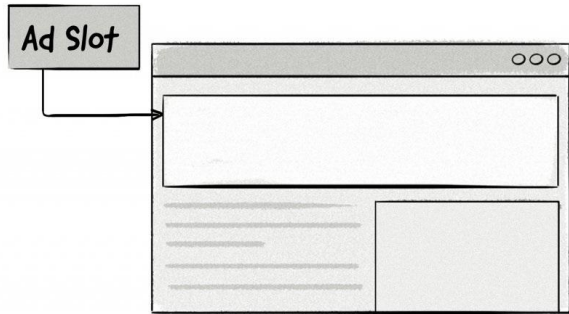
Click rate: 0.8



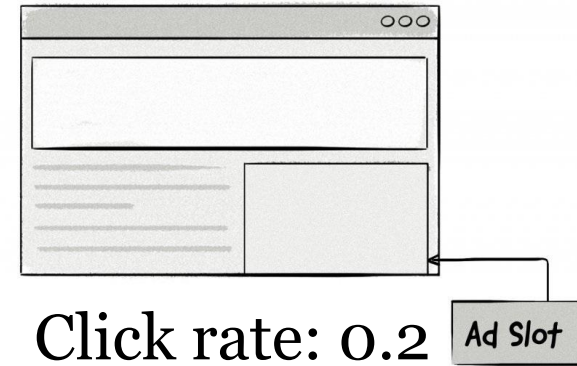
Click rate: 0.2

Example Scenario

ticket discount



Click rate: 0.8



Click rate: 0.2



Value: 5\$



Value: 1\$



Value: 3\$



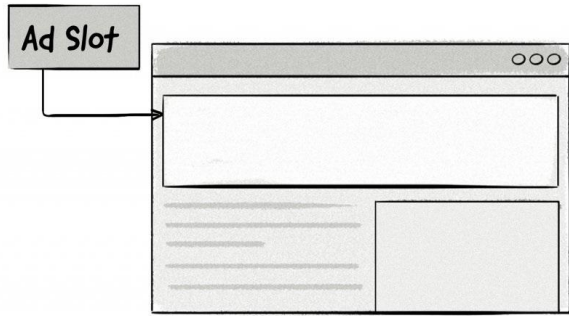
Value: 4\$



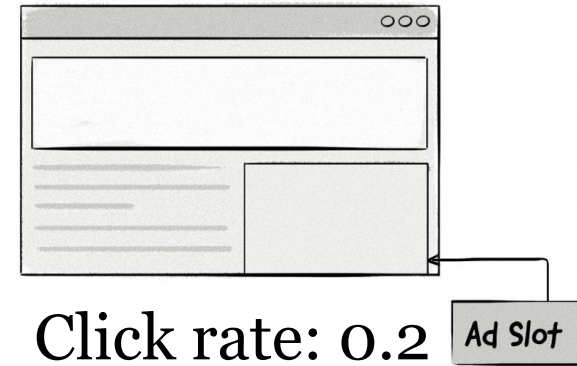
Value: 0.1\$

Example Scenario

ticket discount



Click rate: 0.8



Click rate: 0.2



Value: 5\$



Value: 1\$



Value: 3\$



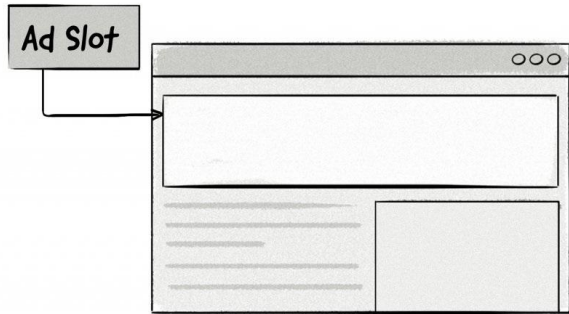
Value: 4\$



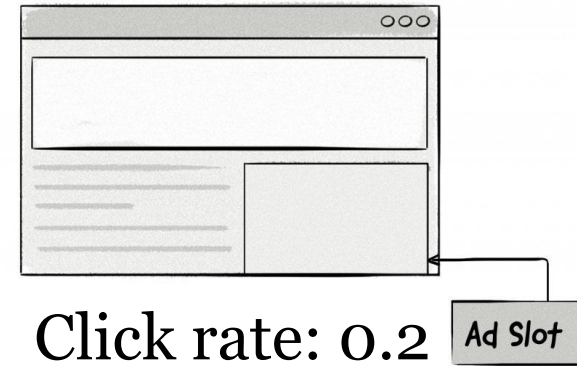
Value: 0.1\$

Example Scenario

ticket discount



Click rate: 0.8



Click rate: 0.2



$v_1 \sim D_1$



$v_2 \sim D_2$



$v_3 \sim D_3$



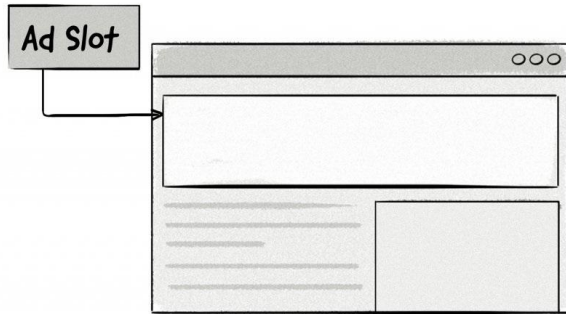
$v_4 \sim D_4$



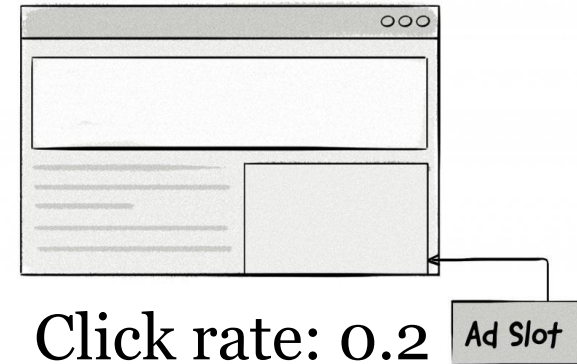
$v_5 \sim D_5$

Example Scenario

ticket discount



Click rate: 0.8



Click rate: 0.2



$v_1 \sim D_1$



$v_2 \sim D_2$



$v_3 \sim D_3$



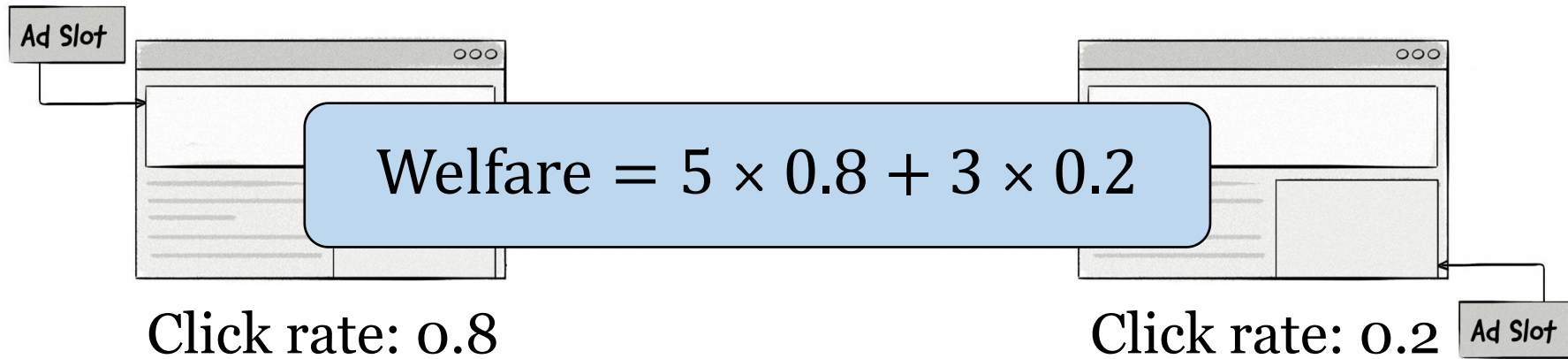
$v_4 \sim D_4$



$v_5 \sim D_5$

Example Scenario

ticket discount



Bidder Selection Problem (Single-Item)

- There are **n bidders** competing for an ad slot
 - Bidder i has value $v_i \sim D_i$ from an independent, known distribution

- We need to **choose k bidders**, maximizing

$$\mathbb{E}_{v_1, \dots, v_n} [\max \{v_i \mid \text{bidder } i \text{ is chosen}\}]$$

- Exact optimum is NP-hard; aim for **$(1 - \epsilon)$ -approximation**

Bidder Selection Problem (**Position Auction**)

- There are **n bidders** competing for **some ad slots**
 - Bidder i has value $v_i \sim D_i$ from an independent, known distribution
 - **There is a non-negative weight sequence $w_1 \geq w_2 \geq \dots \geq w_k$**
- We need to **choose k bidders**, maximizing

$$\mathbb{E}_{v_1, \dots, v_n} \left[\sum_{i=1}^k v_{(i)} w_i \right]$$

where $v_{(i)}$ is the i -th largest value among k chosen bidders

Previous Results on BSP

- Previous $(1 - \varepsilon)$ -approximation (PTAS) algorithms on BSP:
 - [CHLLL2016], [MNPR2020]: For **single-item auction**
 - [SS2021]: For **L -unit auctions** (i.e., position auctions with $w_i \in \{0, 1\}$)
- All of them are based on discretizing all possible distributions
 - Bad dependency on ε
$$2^{O(1/\varepsilon)^{O(1/\varepsilon)}}$$
 - Take years for small instances like $n = 3, k = 2, \varepsilon = 0.2$
 - Not implementable in practice

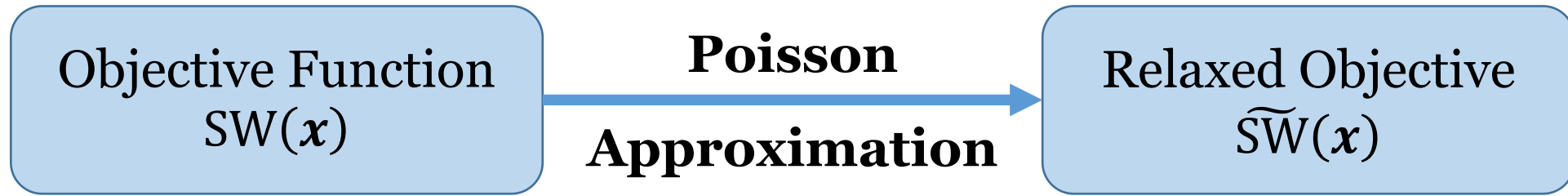
Our Results

- There is a **polynomial-time** algorithm for BSP choosing k bidders out of n with approximation ratio

$$1 - O(k^{-1/4})$$

- This implies a PTAS for BSP for general position auctions
- The algorithm is **easily implemented**, runs **fast** and obtains **high-quality solutions** in experiments

Main Technique: Poisson Approximation



- Relaxed objective $\widetilde{SW}(\mathbf{x})$ has 3 merits:
 1. **Good approximation** ratio: $1 - O(k^{-1/4})$
 2. **Convex**, thus easy to optimize
 3. **Works** for general **position auctions** (not only single-item)

Algorithm Framework

1. Poisson approximation gives the **relaxed objective** $\widetilde{SW}(\boldsymbol{x})$
2. Run **convex optimization** to find (a fractional solution) \boldsymbol{x} that maximizes $\widetilde{SW}(\boldsymbol{x})$
3. Use **rounding** techniques to transform \boldsymbol{x} to an integer solution

Experiments

- We test homebrew implementations of 3 algorithms (using python + standard convex libraries)
- On large instances ($n = 1000, k = 200$):

	Local Search	Greedy	Our Algorithm
Running Time	> 1 week	1 day	45 sec
(Relative) Welfare	N/A	97.38%	100.00%

- On all test cases, our algorithms shows **> 99% approximation** compared to the benchmarks (Local Search & Greedy)

Future Directions



- Bidder Selection Problem under different feasibility constraints
 - E.g., matroid, matching, and intersection of matroids
- Revenue maximization for other auction formats
- Improve the approximation ratio $1 - O(k^{-1/4})$