

Online Competitive Auctions

Elias Koutsoupas
University of Athens / IAS

Haifa 2011.05.04

Joint work with George Pierrakos

Digital good auction

- We want to sell a digital good (with no replication cost)
- n bidders who have a **private valuation** for the good
- Objective: Maximize the profit

Types of auctions

Offline All bidders are present

Online Bidders appear online

Digital good auction

- We want to sell a digital good (with no replication cost)
- n bidders who have a **private valuation** for the good
- Objective: Maximize the profit

Types of auctions

Offline All bidders are present

Online Bidders appear online

Digital good auction

- We want to sell a digital good (with no replication cost)
- n bidders who have a **private valuation** for the good
- Objective: Maximize the profit

Types of auctions

Offline All bidders are present

Online Bidders appear online

Digital good auction

- We want to sell a digital good (with no replication cost)
- n bidders who have a **private valuation** for the good
- Objective: Maximize the profit

Types of auctions

Offline: All bidders are present

Online: Bidders appear online

Digital good auction

- We want to sell a digital good (with no replication cost)
- n bidders who have a **private valuation** for the good
- Objective: Maximize the profit

Types of auctions

Offline All bidders are present

Online Bidders appear online

Digital good auction

- We want to sell a digital good (with no replication cost)
- n bidders who have a **private valuation** for the good
- Objective: Maximize the profit

Types of auctions

Offline All bidders are present

Online Bidders appear online

Digital good auction

- We want to sell a digital good (with no replication cost)
- n bidders who have a **private valuation** for the good
- Objective: Maximize the profit

Types of auctions

Offline All bidders are present

Online Bidders appear online

How to model uncertainty?

Models

Adversarial The input is designed by a powerful adversary who knows the algorithm and tailors the set of bids to defeat it

Stochastic There is a known or unknown probability distribution.

- Independent bids: Each bid is selected independently from the others
- Correlated bids: The probability distribution is for all bids and not for each one separately

Random-order (online) The adversary selects the set of bids and they are presented in a random order, as in the **secretary problem**

How to model uncertainty?

Models

Adversarial The input is designed by a powerful adversary who knows the algorithm and tailors the set of bids to defeat it

Stochastic There is a known or unknown probability distribution.

- Independent bids: Each bid is selected independently from the others
- Correlated bids: The probability distribution is for all bids and not for each one separately

Random-order (online) The adversary selects the set of bids and they are presented in a random order, as in the **secretary problem**

How to model uncertainty?

Models

Adversarial The input is designed by a powerful adversary who knows the algorithm and tailors the set of bids to defeat it

Stochastic There is a known or unknown probability distribution.

- Independent bids: Each bid is selected independently from the others
- Correlated bids: The probability distribution is for all bids and not for each one separately

Random-order (online) The adversary selects the set of bids and they are presented in a random order, as in the **secretary problem**

How to model uncertainty?

Models

Adversarial The input is designed by a powerful adversary who knows the algorithm and tailors the set of bids to defeat it

Stochastic There is a known or unknown probability distribution.

- Independent bids: Each bid is selected independently from the others
- Correlated bids: The probability distribution is for all bids and not for each one separately

Random-order (online) The adversary selects the set of bids and they are presented in a random order, as in the **secretary problem**

How to model uncertainty?

Models

Adversarial The input is designed by a powerful adversary who knows the algorithm and tailors the set of bids to defeat it

Stochastic There is a known or unknown probability distribution.

- Independent bids: Each bid is selected independently from the others
- Correlated bids: The probability distribution is for all bids and not for each one separately

Random-order (online) The adversary selects the set of bids and they are presented in a random order, as in the **secretary problem**

How to model uncertainty?

Models

Adversarial The input is designed by a powerful adversary who knows the algorithm and tailors the set of bids to defeat it

Stochastic There is a known or unknown probability distribution.

- Independent bids: Each bid is selected independently from the others
- Correlated bids: The probability distribution is for all bids and not for each one separately

Random-order (online) The adversary selects the set of bids and they are presented in a random order, as in the **secretary problem**

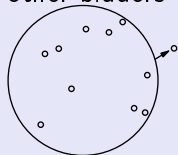
Some truthful offline auctions

Truthfulness

An auction is **truthful** if and only if the price offered to a bidder is independent of his bid

Some auctions

DOP (offline) To every bidder offer the optimal **single price** of the other bidders

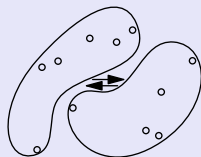


Some truthful offline auctions

Some auctions

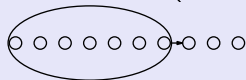
RSOP (offline)

- Partition the bidders randomly into two sets
- Find the optimal **single price** for each set and offer it to the bidders of the other set



SCS (offline) Similar to RSOP but try to extract the profit of each set instead of offering its optimal price

BPSF (online) To every bidder offer the optimal single price for the revealed bids (the online version of DOP)



How to evaluate an auction?

Notation: Let $b_1 > b_2 > \dots > b_n$ be the bids

Compare a mechanism against ?

- Sum of all bids: $\sum_i b_i$ (unrealistic)
- Optimal single-price profit: $\max_i i \cdot b_i$ (problem: highest bid impossible to get)
- A reasonable benchmark:

$$F^{(2)} = \max_{i \geq 2} i \cdot b_i$$

The **optimal** profit of

- a single-price auction
- which sells the good to at least 2 bidders

- This is the benchmark we adopt
- We call an algorithm ρ -competitive if its profit is at least $F^{(2)}/\rho$

How to evaluate an auction?

Notation: Let $b_1 > b_2 > \dots > b_n$ be the bids

Compare a mechanism against ?

- Sum of all bids: $\sum_i b_i$ (unrealistic)
- Optimal single-price profit: $\max_i i \cdot b_i$ (problem: highest bid impossible to get)
- A reasonable benchmark:

$$F^{(2)} = \max_{i \geq 2} i \cdot b_i$$

The **optimal** profit of

- a single-price auction
- which sells the good to at least 2 bidders

- This is the benchmark we adopt
- We call an algorithm ρ -competitive if its profit is at least $F^{(2)}/\rho$

How to evaluate an auction?

Notation: Let $b_1 > b_2 > \dots > b_n$ be the bids

Compare a mechanism against ?

- Sum of all bids: $\sum_i b_i$ (unrealistic)
- Optimal single-price profit: $\max_i i \cdot b_i$ (problem: highest bid impossible to get)
- A reasonable benchmark:

$$F^{(2)} = \max_{i \geq 2} i \cdot b_i$$

The **optimal** profit of

- a single-price auction
- which sells the good to at least 2 bidders

- This is the benchmark we adopt
- We call an algorithm ρ -competitive if its profit is at least $F^{(2)}/\rho$

How to evaluate an auction?

Notation: Let $b_1 > b_2 > \dots > b_n$ be the bids

Compare a mechanism against ?

- Sum of all bids: $\sum_i b_i$ (unrealistic)
- Optimal single-price profit: $\max_i i \cdot b_i$ (problem: highest bid impossible to get)
- A reasonable benchmark:

$$F^{(2)} = \max_{i \geq 2} i \cdot b_i$$

The **optimal** profit of

- a single-price auction
- which sells the good to at least 2 bidders

- This is the benchmark we adopt
- We call an algorithm ρ -competitive if its profit is at least $F^{(2)}/\rho$

How to evaluate an auction?

Notation: Let $b_1 > b_2 > \dots > b_n$ be the bids

Compare a mechanism against ?

- Sum of all bids: $\sum_i b_i$ (unrealistic)
- Optimal single-price profit: $\max_i i \cdot b_i$ (problem: highest bid impossible to get)
- A reasonable benchmark:

$$F^{(2)} = \max_{i \geq 2} i \cdot b_i$$

The **optimal** profit of

- a single-price auction
- which sells the good to at least 2 bidders

- This is the benchmark we adopt
- We call an algorithm ρ -competitive if its profit is at least $F^{(2)}/\rho$

How to evaluate an auction?

Notation: Let $b_1 > b_2 > \dots > b_n$ be the bids

Compare a mechanism against ?

- Sum of all bids: $\sum_i b_i$ (unrealistic)
- Optimal single-price profit: $\max_i i \cdot b_i$ (problem: highest bid impossible to get)
- A reasonable benchmark:

$$F^{(2)} = \max_{i \geq 2} i \cdot b_i$$

The **optimal** profit of

- a single-price auction
- which sells the good to at least 2 bidders

- This is the benchmark we adopt
- We call an algorithm ρ -competitive if its profit is at least $F^{(2)}/\rho$

How to evaluate an auction?

Notation: Let $b_1 > b_2 > \dots > b_n$ be the bids

Compare a mechanism against ?

- Sum of all bids: $\sum_i b_i$ (unrealistic)
- Optimal single-price profit: $\max_i i \cdot b_i$ (problem: highest bid impossible to get)
- A reasonable benchmark:

$$F^{(2)} = \max_{i \geq 2} i \cdot b_i$$

The **optimal** profit of

- a single-price auction
- which sells the good to at least 2 bidders

- This is the benchmark we adopt
- We call an algorithm ρ -competitive if its profit is at least $F^{(2)}/\rho$

How to evaluate an auction?

Notation: Let $b_1 > b_2 > \dots > b_n$ be the bids

Compare a mechanism against ?

- Sum of all bids: $\sum_i b_i$ (unrealistic)
- Optimal single-price profit: $\max_i i \cdot b_i$ (problem: highest bid impossible to get)
- A reasonable benchmark:

$$F^{(2)} = \max_{i \geq 2} i \cdot b_i$$

The **optimal** profit of

- a single-price auction
- which sells the good to at least 2 bidders

- **This is the benchmark we adopt**
- We call an algorithm ρ -competitive if its profit is at least $F^{(2)}/\rho$

How to evaluate an auction?

Notation: Let $b_1 > b_2 > \dots > b_n$ be the bids

Compare a mechanism against ?

- Sum of all bids: $\sum_i b_i$ (unrealistic)
- Optimal single-price profit: $\max_i i \cdot b_i$ (problem: highest bid impossible to get)
- A reasonable benchmark:

$$F^{(2)} = \max_{i \geq 2} i \cdot b_i$$

The **optimal** profit of

- a single-price auction
- which sells the good to at least 2 bidders

- **This is the benchmark we adopt**
- We call an algorithm ρ -**competitive** if its profit is at least $F^{(2)}/\rho$

Optimal competitive ratio for the **adversarial offline** case?

- Symmetric deterministic: unbounded
- Randomized: $\in [2.42, 3.24]$
- RSOP is 4.64-competitive
- Conjecture: RSOP is 4-competitive

(Goldberg-Hartline-Karlin-Saks-Wright, Hartline-McGrew)

Optimal competitive ratio for the stochastic case?

- Again $\in [2.42, 3.24]$
- Why the same? Because of Yao's lemma
- Theorem: For bid-independent distributions the answer is 2.42

Optimal competitive ratio for the **adversarial offline** case?

- Symmetric deterministic: unbounded
- Randomized: $\in [2.42, 3.24]$
- RSOP is 4.64-competitive
- Conjecture: RSOP is 4-competitive

(Goldberg-Hartline-Karlin-Saks-Wright, Hartline-McGrew)

Optimal competitive ratio for the stochastic case?

- Again $\in [2.42, 3.24]$
- Why the same? Because of Yao's lemma
- Theorem: For bid-independent distributions the answer is 2.42

Optimal competitive ratio for the **adversarial offline** case?

- Symmetric deterministic: unbounded
- Randomized: $\in [2.42, 3.24]$
- RSOP is 4.64-competitive
- Conjecture: RSOP is 4-competitive

(Goldberg-Hartline-Karlin-Saks-Wright, Hartline-McGrew)

Optimal competitive ratio for the stochastic case?

- Again $\in [2.42, 3.24]$
- Why the same? Because of Yao's lemma
- Theorem: For bid-independent distributions the answer is 2.42

Optimal competitive ratio for the **adversarial offline** case?

- Symmetric deterministic: unbounded
- Randomized: $\in [2.42, 3.24]$
- RSOP is 4.64-competitive
- Conjecture: RSOP is 4-competitive

(Goldberg-Hartline-Karlin-Saks-Wright, Hartline-McGrew)

Optimal competitive ratio for the stochastic case?

- Again $\in [2.42, 3.24]$
- Why the same? Because of Yao's lemma
- Theorem: For bid-independent distributions the answer is 2.42

Optimal competitive ratio for the **adversarial offline** case?

- Symmetric deterministic: unbounded
- Randomized: $\in [2.42, 3.24]$
- RSOP is 4.64-competitive
- Conjecture: RSOP is 4-competitive

(Goldberg-Hartline-Karlin-Saks-Wright, Hartline-McGrew)

Optimal competitive ratio for the stochastic case?

- Again $\in [2.42, 3.24]$
- Why the same? Because of Yao's lemma
- Theorem: For bid-independent distributions the answer is 2.42

Optimal competitive ratio for the **adversarial offline** case?

- Symmetric deterministic: unbounded
- Randomized: $\in [2.42, 3.24]$
- RSOP is 4.64-competitive
- Conjecture: RSOP is 4-competitive

(Goldberg-Hartline-Karlin-Saks-Wright, Hartline-McGrew)

Optimal competitive ratio for the stochastic case?

- Again $\in [2.42, 3.24]$
- Why the same? Because of Yao's lemma
- Theorem: For bid-independent distributions the answer is 2.42

Optimal competitive ratio for the **adversarial offline** case?

- Symmetric deterministic: unbounded
- Randomized: $\in [2.42, 3.24]$
- RSOP is 4.64-competitive
- Conjecture: RSOP is 4-competitive

(Goldberg-Hartline-Karlin-Saks-Wright, Hartline-McGrew)

Optimal competitive ratio for the stochastic case?

- Again $\in [2.42, 3.24]$
- Why the same? Because of Yao's lemma
- Theorem: For bid-independent distributions the answer is 2.42

Optimal competitive ratio for the **adversarial offline** case?

- Symmetric deterministic: unbounded
- Randomized: $\in [2.42, 3.24]$
- RSOP is 4.64-competitive
- Conjecture: RSOP is 4-competitive

(Goldberg-Hartline-Karlin-Saks-Wright, Hartline-McGrew)

Optimal competitive ratio for the stochastic case?

- Again $\in [2.42, 3.24]$
- Why the same? Because of Yao's lemma
- Theorem: For bid-independent distributions the answer is 2.42

Optimal competitive ratio for the adversarial offline case?

- Symmetric deterministic: unbounded
- Randomized: $\in [2.42, 3.24]$
- RSOP is 4.64-competitive
- Conjecture: RSOP is 4-competitive

(Goldberg-Hartline-Karlin-Saks-Wright, Hartline-McGrew)

Optimal competitive ratio for the stochastic case?

- Again $\in [2.42, 3.24]$
- Why the same? Because of Yao's lemma
- **Theorem:** For bid-independent distributions the answer is 2.42

Question for competitive auctions

Optimal online competitive ratio for the random-order case?

- Theorem: There is a generic transformation of offline auctions to online auctions, with only a loss of a factor of 2 in the competitive ratio.
- Competitive ratio $\in [4, 6.48]$
- Conjecture: The BPSF auction is 4-competitive

Previous work: Majiaghayi-Kleinberg-Parkes, in 2004 showed a very high competitive ratio

Question for competitive auctions

Optimal online competitive ratio for the random-order case?

- Theorem: There is a generic transformation of offline auctions to online auctions, with only a loss of a factor of 2 in the competitive ratio.
- Competitive ratio $\in [4, 6.48]$
- Conjecture: The BPSF auction is 4-competitive

Previous work: Majiaghayi-Kleinberg-Parkes, in 2004 showed a very high competitive ratio

Question for competitive auctions

Optimal online competitive ratio for the random-order case?

- Theorem: There is a generic transformation of offline auctions to online auctions, with only a loss of a factor of 2 in the competitive ratio.
- Competitive ratio $\in [4, 6.48]$
- Conjecture: The BPSF auction is 4-competitive

Previous work: Majiaghayi-Kleinberg-Parkes, in 2004 showed a very high competitive ratio

Question for competitive auctions

Optimal online competitive ratio for the random-order case?

- Theorem: There is a generic transformation of offline auctions to online auctions, with only a loss of a factor of 2 in the competitive ratio.
- Competitive ratio $\in [4, 6.48]$
- Conjecture: The BPSF auction is 4-competitive

Previous work: Majiaghayi-Kleinberg-Parkes, in 2004 showed a very high competitive ratio

Optimal online competitive ratio for the random-order case?

- Theorem: There is a generic transformation of offline auctions to online auctions, with only a loss of a factor of 2 in the competitive ratio.
- Competitive ratio $\in [4, 6.48]$
- Conjecture: The BPSF auction is 4-competitive

Previous work: Majiaghayi-Kleinberg-Parkes, in 2004 showed a very high competitive ratio

Stochastic case: worst-case distribution

- Suppose that the bids are drawn from a known probability distribution
- We can then design the auction with the best competitive ratio
- How high can it be?
- For which distribution?

Yao's lemma / minmax property

The competitive ratio of the worst-case distribution provides a (usually tight) lower bound for randomized algorithms in the worst-case input.

Stochastic case: worst-case distribution

- Suppose that the bids are drawn from a known probability distribution
 - We can then design the auction with the best competitive ratio
 - How high can it be?
 - For which distribution?

Yao's lemma / minmax property

The competitive ratio of the worst-case distribution provides a (usually tight) lower bound for randomized algorithms in the worst-case input.

Stochastic case: worst-case distribution

- Suppose that the bids are drawn from a known probability distribution
- We can then design the auction with the best competitive ratio
 - How high can it be?
 - For which distribution?

Yao's lemma / minmax property

The competitive ratio of the worst-case distribution provides a (usually tight) lower bound for randomized algorithms in the worst-case input.

Stochastic case: worst-case distribution

- Suppose that the bids are drawn from a known probability distribution
- We can then design the auction with the best competitive ratio
- How high can it be?
- For which distribution?

Yao's lemma / minmax property

The competitive ratio of the worst-case distribution provides a (usually tight) lower bound for randomized algorithms in the worst-case input.

Stochastic case: worst-case distribution

- Suppose that the bids are drawn from a known probability distribution
- We can then design the auction with the best competitive ratio
- How high can it be?
- For which distribution?

Yao's lemma / minmax property

The competitive ratio of the worst-case distribution provides a (usually tight) lower bound for randomized algorithms in the worst-case input.

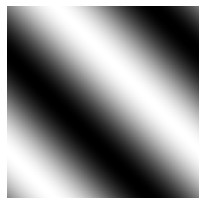
Stochastic case: worst-case distribution

- Suppose that the bids are drawn from a known probability distribution
- We can then design the auction with the best competitive ratio
- How high can it be?
- For which distribution?

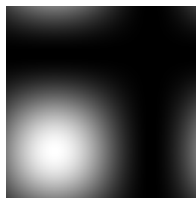
Yao's lemma / minmax property

The competitive ratio of the worst-case distribution provides a (usually tight) lower bound for randomized algorithms in the worst-case input.

Independent vs correlated distributions



correlated



i.i.d.

We will only consider i.i.d.'s or simply i.d's

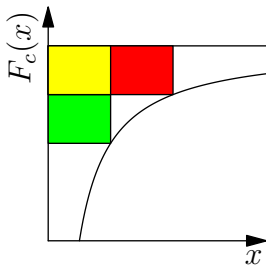
The equal-revenue distribution

The equal-revenue distributions

- The equal-revenue cumulative distributions are of the form

$$F_c(x) = \begin{cases} 0 & x < c \\ 1 - \frac{c}{x} & x \geq c \end{cases}$$

- It has profit $x(1 - F_c(x)) = c$ independent of the price offered



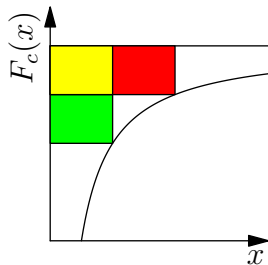
The equal-revenue distribution

The equal-revenue distributions

- The equal-revenue cumulative distributions are of the form

$$F_c(x) = \begin{cases} 0 & x < c \\ 1 - \frac{c}{x} & x \geq c \end{cases}$$

- It has profit $x(1 - F_c(x)) = c$ independent of the price offered



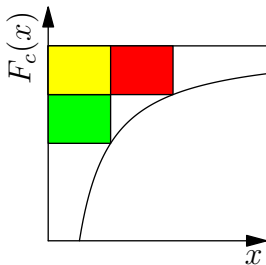
The equal-revenue distribution

The equal-revenue distributions

- The equal-revenue cumulative distributions are of the form

$$F_c(x) = \begin{cases} 0 & x < c \\ 1 - \frac{c}{x} & x \geq c \end{cases}$$

- It has profit $x(1 - F_c(x)) = c$ independent of the price offered



The worst-case independent distribution

Theorem

Among the independent distributions, the equal-revenue distributions have maximum competitive ratio.

Proof.

- Let F be a cumulative distribution with competitive ratio ρ
- The optimal pricing mechanism selects price p which maximizes $p(1 - F(p))$
- Let c be its profit
- Then for every x : $x(1 - F(x)) \leq c$, or equivalently, $F(x) \geq 1 - c/x$.
- Thus, $F(x)$ dominates the equal-revenue distribution $F_c(x)$.



The worst-case independent distribution

Theorem

Among the independent distributions, the equal-revenue distributions have maximum competitive ratio.

Proof.

- Let F be a cumulative distribution with competitive ratio ρ
- The optimal pricing mechanism selects price p which maximizes $p(1 - F(p))$
- Let c be its profit
- Then for every x : $x(1 - F(x)) \leq c$, or equivalently, $F(x) \geq 1 - c/x$.
- Thus, $F(x)$ dominates the equal-revenue distribution $F_c(x)$.



The worst-case independent distribution

Theorem

Among the independent distributions, the equal-revenue distributions have maximum competitive ratio.

Proof.

- Let F be a cumulative distribution with competitive ratio ρ
- The optimal pricing mechanism selects price p which maximizes $p(1 - F(p))$
- Let c be its profit
- Then for every x : $x(1 - F(x)) \leq c$, or equivalently, $F(x) \geq 1 - c/x$.
- Thus, $F(x)$ dominates the equal-revenue distribution $F_c(x)$.



The worst-case independent distribution

Theorem

Among the independent distributions, the equal-revenue distributions have maximum competitive ratio.

Proof.

- Let F be a cumulative distribution with competitive ratio ρ
- The optimal pricing mechanism selects price p which maximizes $p(1 - F(p))$
- Let c be its profit
- Then for every x : $x(1 - F(x)) \leq c$, or equivalently, $F(x) \geq 1 - c/x$.
- Thus, $F(x)$ dominates the equal-revenue distribution $F_c(x)$.



The worst-case independent distribution

Theorem

Among the independent distributions, the equal-revenue distributions have maximum competitive ratio.

Proof.

- Let F be a cumulative distribution with competitive ratio ρ
- The optimal pricing mechanism selects price p which maximizes $p(1 - F(p))$
- Let c be its profit
- Then for every x : $x(1 - F(x)) \leq c$, or equivalently, $F(x) \geq 1 - c/x$.
- Thus, $F(x)$ dominates the equal-revenue distribution $F_c(x)$.



The worst-case independent distribution

Theorem

Among the independent distributions, the equal-revenue distributions have maximum competitive ratio.

Proof.

- Let F be a cumulative distribution with competitive ratio ρ
- The optimal pricing mechanism selects price p which maximizes $p(1 - F(p))$
- Let c be its profit
- Then for every x : $x(1 - F(x)) \leq c$, or equivalently, $F(x) \geq 1 - c/x$.
- Thus, $F(x)$ dominates the equal-revenue distribution $F_c(x)$.



The worst-case independent distribution

Theorem

Among the independent distributions, the equal-revenue distributions have maximum competitive ratio.

Proof.

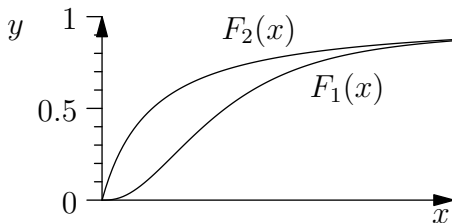
- Let F be a cumulative distribution with competitive ratio ρ
- The optimal pricing mechanism selects price p which maximizes $p(1 - F(p))$
- Let c be its profit
- Then for every x : $x(1 - F(x)) \leq c$, or equivalently, $F(x) \geq 1 - c/x$.
- Thus, $F(x)$ dominates the equal-revenue distribution $F_c(x)$.



Lemma

Let F_1, F_2 be two cumulative distributions with $F_1(x) \leq F_2(x)$ for every x . Let also $G : \mathbb{R}^n \rightarrow \mathbb{R}$ be a function which is **non-decreasing** in all its variables. Then

$$E_{b \in F_1^n}[G(b)] \geq E_{b \in F_2^n}[G(b)]$$



The proof of the lemma

- For a single variable the proof depends on the following property of integrals

$$\int_0^{\infty} F'(x)G(x) dx = \int_0^{\infty} (1 - F(x))G'(x) dx + G(0)$$

- For many variables, we can apply this inductively
- The independence of variables is crucial for the induction

- The benchmark $F^{(2)}(b)$ is non-decreasing in each bid
- Therefore the equal-revenue distributions have maximum competitive ratio

The proof of the lemma

- For a single variable the proof depends on the following property of integrals

$$\int_0^{\infty} F'(x)G(x) dx = \int_0^{\infty} (1 - F(x))G'(x) dx + G(0)$$

- For many variables, we can apply this inductively
- The independence of variables is crucial for the induction

- The benchmark $F^{(2)}(b)$ is non-decreasing in each bid
- Therefore the equal-revenue distributions have maximum competitive ratio

The proof of the lemma

- For a single variable the proof depends on the following property of integrals

$$\int_0^{\infty} F'(x)G(x) dx = \int_0^{\infty} (1 - F(x))G'(x) dx + G(0)$$

- For many variables, we can apply this inductively
- The independence of variables is crucial for the induction

- The benchmark $F^{(2)}(b)$ is non-decreasing in each bid
- Therefore the equal-revenue distributions have maximum competitive ratio

The proof of the lemma

- For a single variable the proof depends on the following property of integrals

$$\int_0^{\infty} F'(x)G(x) dx = \int_0^{\infty} (1 - F(x))G'(x) dx + G(0)$$

- For many variables, we can apply this inductively
- The independence of variables is crucial for the induction

- The benchmark $F^{(2)}(b)$ is non-decreasing in each bid
- Therefore the equal-revenue distributions have maximum competitive ratio

The proof of the lemma

- For a single variable the proof depends on the following property of integrals

$$\int_0^{\infty} F'(x)G(x) dx = \int_0^{\infty} (1 - F(x))G'(x) dx + G(0)$$

- For many variables, we can apply this inductively
- The independence of variables is crucial for the induction

- The benchmark $F^{(2)}(b)$ is non-decreasing in each bid
- Therefore the equal-revenue distributions have maximum competitive ratio

The proof of the lemma

- For a single variable the proof depends on the following property of integrals

$$\int_0^{\infty} F'(x)G(x) dx = \int_0^{\infty} (1 - F(x))G'(x) dx + G(0)$$

- For many variables, we can apply this inductively
- The independence of variables is crucial for the induction

- The benchmark $F^{(2)}(b)$ is non-decreasing in each bid
- Therefore the equal-revenue distributions have maximum competitive ratio

The proof of the lemma

- For a single variable the proof depends on the following property of integrals

$$\int_0^{\infty} F'(x)G(x) dx = \int_0^{\infty} (1 - F(x))G'(x) dx + G(0)$$

- For many variables, we can apply this inductively
- The independence of variables is crucial for the induction

- The benchmark $F^{(2)}(b)$ is non-decreasing in each bid
- Therefore the equal-revenue distributions have maximum competitive ratio

The competitive ratio of independent distributions

- [GHKSW06] has shown that if b_1, \dots, b_n are drawn from the equal-revenue distribution F_1 , the expected value of $F^{(2)}$ is

$$n \cdot \left(1 - \sum_{i=2}^n \left(\frac{-1}{n} \right)^{i-1} \cdot \frac{i}{i-1} \cdot \binom{n-1}{i-1} \right)$$

- The competitive ratio ranges from 2 (when $n = 2$) to 2.42 (when $n \rightarrow \infty$)

Conjecture

The optimal offline competitive ratio is 2.42

The competitive ratio of independent distributions

- [GHKSW06] has shown that if b_1, \dots, b_n are drawn from the equal-revenue distribution F_1 , the expected value of $F^{(2)}$ is

$$n \cdot \left(1 - \sum_{i=2}^n \left(\frac{-1}{n} \right)^{i-1} \cdot \frac{i}{i-1} \cdot \binom{n-1}{i-1} \right)$$

- The competitive ratio ranges from 2 (when $n = 2$) to 2.42 (when $n \rightarrow \infty$)

Conjecture

The optimal offline competitive ratio is 2.42

The competitive ratio of independent distributions

- [GHKSW06] has shown that if b_1, \dots, b_n are drawn from the equal-revenue distribution F_1 , the expected value of $F^{(2)}$ is

$$n \cdot \left(1 - \sum_{i=2}^n \left(\frac{-1}{n} \right)^{i-1} \cdot \frac{i}{i-1} \cdot \binom{n-1}{i-1} \right)$$

- The competitive ratio ranges from 2 (when $n = 2$) to 2.42 (when $n \rightarrow \infty$)

Conjecture

The optimal offline competitive ratio is 2.42

The competitive ratio of independent distributions

- [GHKSW06] has shown that if b_1, \dots, b_n are drawn from the equal-revenue distribution F_1 , the expected value of $F^{(2)}$ is

$$n \cdot \left(1 - \sum_{i=2}^n \left(\frac{-1}{n} \right)^{i-1} \cdot \frac{i}{i-1} \cdot \binom{n-1}{i-1} \right)$$

- The competitive ratio ranges from 2 (when $n = 2$) to 2.42 (when $n \rightarrow \infty$)

Conjecture

The optimal offline competitive ratio is 2.42

The online problem

Assumptions

- Unknown bids $b_1 > b_2 > \dots > b_n$
- They arrive in order $b_{\pi_1}, \dots, b_{\pi_n}$, where π is a random permutation
- For each bid we offer a take-it-or-leave price
- We assume that we learn the actual bid
- The bidders cannot control their arrival time

Question

- What is the best price $p(b_{\pi_1}, \dots, b_{\pi_{i-1}})$ to offer to b_{π_i} ?

The online problem

Assumptions

- Unknown bids $b_1 > b_2 > \dots > b_n$
- They arrive in order $b_{\pi_1}, \dots, b_{\pi_n}$, where π is a random permutation
- For each bid we offer a take-it-or-leave price
- We assume that we learn the actual bid
- The bidders cannot control their arrival time

Question

- What is the best price $p(b_{\pi_1}, \dots, b_{\pi_{i-1}})$ to offer to b_{π_i} ?

Assumptions

- Unknown bids $b_1 > b_2 > \dots > b_n$
- They arrive in order $b_{\pi_1}, \dots, b_{\pi_n}$, where π is a random permutation
- For each bid we offer a take-it-or-leave price
- We assume that we learn the actual bid
- The bidders cannot control their arrival time

Question

- What is the best price $p(b_{\pi_1}, \dots, b_{\pi_{i-1}})$ to offer to b_{π_i} ?

The online problem

Assumptions

- Unknown bids $b_1 > b_2 > \dots > b_n$
- They arrive in order $b_{\pi_1}, \dots, b_{\pi_n}$, where π is a random permutation
- For each bid we offer a take-it-or-leave price
- We assume that we learn the actual bid
- The bidders cannot control their arrival time

Question

- What is the best price $p(b_{\pi_1}, \dots, b_{\pi_{i-1}})$ to offer to b_{π_i} ?

The online problem

Assumptions

- Unknown bids $b_1 > b_2 > \dots > b_n$
- They arrive in order $b_{\pi_1}, \dots, b_{\pi_n}$, where π is a random permutation
- For each bid we offer a take-it-or-leave price
- **We assume that we learn the actual bid**
- The bidders cannot control their arrival time

Question

- What is the best price $p(b_{\pi_1}, \dots, b_{\pi_{i-1}})$ to offer to b_{π_i} ?

The online problem

Assumptions

- Unknown bids $b_1 > b_2 > \dots > b_n$
- They arrive in order $b_{\pi_1}, \dots, b_{\pi_n}$, where π is a random permutation
- For each bid we offer a take-it-or-leave price
- **We assume that we learn the actual bid**
- **The bidders cannot control their arrival time**

Question

- What is the best price $p(b_{\pi_1}, \dots, b_{\pi_{i-1}})$ to offer to b_{π_i} ?

The online problem

Assumptions

- Unknown bids $b_1 > b_2 > \dots > b_n$
- They arrive in order $b_{\pi_1}, \dots, b_{\pi_n}$, where π is a random permutation
- For each bid we offer a take-it-or-leave price
- **We assume that we learn the actual bid**
- **The bidders cannot control their arrival time**

Question

- What is the best price $p(b_{\pi_1}, \dots, b_{\pi_{t-1}})$ to offer to b_{π_t} ?

Assumptions

- Unknown bids $b_1 > b_2 > \dots > b_n$
- They arrive in order $b_{\pi_1}, \dots, b_{\pi_n}$, where π is a random permutation
- For each bid we offer a take-it-or-leave price
- **We assume that we learn the actual bid**
- **The bidders cannot control their arrival time**

Question

- What is the best price $p(b_{\pi_1}, \dots, b_{\pi_{t-1}})$ to offer to b_{π_t} ?

Natural (?) pricing algorithms

Pricing algorithms

- MIN, MEAN, MEDIAN: unbounded competitive ratio
- Why? Consider bids $1, 1, 0, 0, \dots, 0$

Theorem

The algorithm (MAX) which offers the maximum revealed bid has competitive ratio $k/(H_k - 1)$, where $F^{(2)} = kb_k$.

Proof.

The exact (!) profit of MAX is

$$\frac{1}{2}b_2 + \dots + \frac{1}{n}b_n$$



The ratio $k/(H_k - 1)$ is not bad for small values of k (it is less than 4 for $k \leq 5$).

Natural (?) pricing algorithms

Pricing algorithms

- MIN, MEAN, MEDIAN: unbounded competitive ratio
- Why? Consider bids $1, 1, 0, 0, \dots, 0$

Theorem

The algorithm (MAX) which offers the maximum revealed bid has competitive ratio $k/(H_k - 1)$, where $F^{(2)} = kb_k$.

Proof.

The exact (!) profit of MAX is

$$\frac{1}{2}b_2 + \dots + \frac{1}{n}b_n$$



The ratio $k/(H_k - 1)$ is not bad for small values of k (it is less than 4 for $k \leq 5$).

Natural (?) pricing algorithms

Pricing algorithms

- MIN, MEAN, MEDIAN: unbounded competitive ratio
- Why? Consider bids $1, 1, 0, 0, \dots, 0$

Theorem

The algorithm (MAX) which offers the maximum revealed bid has competitive ratio $k/(H_k - 1)$, where $F^{(2)} = kb_k$.

Proof.

The exact (!) profit of MAX is

$$\frac{1}{2}b_2 + \dots + \frac{1}{n}b_n$$



The ratio $k/(H_k - 1)$ is not bad for small values of k (it is less than 4 for $k \leq 5$).

Natural (?) pricing algorithms

Pricing algorithms

- MIN, MEAN, MEDIAN: unbounded competitive ratio
- Why? Consider bids $1, 1, 0, 0, \dots, 0$

Theorem

The algorithm (MAX) which offers the maximum revealed bid has competitive ratio $k/(H_k - 1)$, where $F^{(2)} = kb_k$.

Proof.

The exact (!) profit of MAX is

$$\frac{1}{2}b_2 + \dots + \frac{1}{n}b_n$$



The ratio $k/(H_k - 1)$ is not bad for small values of k (it is less than 4 for $k \leq 5$).

Natural (?) pricing algorithms

Pricing algorithms

- MIN, MEAN, MEDIAN: unbounded competitive ratio
- Why? Consider bids $1, 1, 0, 0, \dots, 0$

Theorem

The algorithm (MAX) which offers the maximum revealed bid has competitive ratio $k/(H_k - 1)$, where $F^{(2)} = kb_k$.

Proof.

The exact (!) profit of MAX is

$$\frac{1}{2}b_2 + \dots + \frac{1}{n}b_n$$



The ratio $k/(H_k - 1)$ is not bad for small values of k (it is less than 4 for $k \leq 5$).

Natural (?) pricing algorithms

Pricing algorithms

- MIN, MEAN, MEDIAN: unbounded competitive ratio
- Why? Consider bids $1, 1, 0, 0, \dots, 0$

Theorem

The algorithm (MAX) which offers the maximum revealed bid has competitive ratio $k/(H_k - 1)$, where $F^{(2)} = kb_k$.

Proof.

The exact (!) profit of MAX is

$$\frac{1}{2}b_2 + \dots + \frac{1}{n}b_n$$



The ratio $k/(H_k - 1)$ is not bad for small values of k (it is less than 4 for $k \leq 5$).

Transforming an offline mechanism to online

How to transform an offline algorithm to online

- Simply run the offline algorithm for the set of revealed bids and the current (unrevealed bid)
- For example, the online version of DOP is the BPSF auction
- Is it good? We compare with $F^{(2)}$ of all bids

Theorem

The competitive ratio of the online algorithm is at most $k/(k-1) \leq 2$ times greater than the offline competitive ratio, where $F^{(2)} = kb_k$.

Transforming an offline mechanism to online

How to transform an offline algorithm to online

- Simply run the offline algorithm for the set of revealed bids and the current (unrevealed bid)
- For example, the online version of DOP is the BPSF auction
- Is it good? We compare with $F^{(2)}$ of all bids

Theorem

The competitive ratio of the online algorithm is at most $k/(k-1) \leq 2$ times greater than the offline competitive ratio, where $F^{(2)} = kb_k$.

Transforming an offline mechanism to online

How to transform an offline algorithm to online

- Simply run the offline algorithm for the set of revealed bids and the current (unrevealed bid)
- For example, the online version of DOP is the BPSF auction
- Is it good? We compare with $F^{(2)}$ of all bids

Theorem

The competitive ratio of the online algorithm is at most $k/(k-1) \leq 2$ times greater than the offline competitive ratio, where $F^{(2)} = kb_k$.

Transforming an offline mechanism to online

How to transform an offline algorithm to online

- Simply run the offline algorithm for the set of revealed bids and the current (unrevealed bid)
- For example, the online version of DOP is the BPSF auction
- Is it good? We compare with $F^{(2)}$ of **all** bids

Theorem

The competitive ratio of the online algorithm is at most $k/(k-1) \leq 2$ times greater than the offline competitive ratio, where $F^{(2)} = kb_k$.

Transforming an offline mechanism to online

How to transform an offline algorithm to online

- Simply run the offline algorithm for the set of revealed bids and the current (unrevealed bid)
- For example, the online version of DOP is the BPSF auction
- Is it good? We compare with $F^{(2)}$ of **all** bids

Theorem

The competitive ratio of the online algorithm is at most $k/(k-1) \leq 2$ times greater than the offline competitive ratio, where $F^{(2)} = kb_k$.

- Let ρ be the offline competitive ratio
- Let $F^{(2)}(b_1, \dots, b_n) = k \cdot b_k$
- Expected online profit at step $t = \frac{1}{t} \cdot$ expected offline profit of the first t bids
- With probability $\frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}}$ the first t bids have m of the high k bids
- offline profit $\geq \frac{1}{\rho} \cdot m \cdot b_k$, **when** $m \geq 2$
- Putting everything together

$$\begin{aligned} \text{online profit} &\geq \sum_{t=2}^n \sum_{m=2}^{\min\{t,k\}} \frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}} \cdot \frac{1}{t\rho} \cdot mb_k \\ &= \frac{k-1}{\rho} b_k = \frac{k-1}{k} \cdot \frac{1}{\rho} \cdot F^{(2)} \end{aligned}$$

- Let ρ be the offline competitive ratio
- Let $F^{(2)}(b_1, \dots, b_n) = k \cdot b_k$
- Expected online profit at step $t = \frac{1}{t} \cdot$ expected offline profit of the first t bids
- With probability $\frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}}$ the first t bids have m of the high k bids
- offline profit $\geq \frac{1}{\rho} \cdot m \cdot b_k$, **when** $m \geq 2$
- Putting everything together

$$\begin{aligned}
 \text{online profit} &\geq \sum_{t=2}^n \sum_{m=2}^{\min\{t,k\}} \frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}} \cdot \frac{1}{t\rho} \cdot mb_k \\
 &= \frac{k-1}{\rho} b_k = \frac{k-1}{k} \cdot \frac{1}{\rho} \cdot F^{(2)}
 \end{aligned}$$

- Let ρ be the offline competitive ratio
- Let $F^{(2)}(b_1, \dots, b_n) = k \cdot b_k$
- Expected online profit at step $t = \frac{1}{t} \cdot$ expected offline profit of the first t bids
- With probability $\frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}}$ the first t bids have m of the high k bids
- offline profit $\geq \frac{1}{\rho} \cdot m \cdot b_k$, **when** $m \geq 2$
- Putting everything together

$$\begin{aligned}
 \text{online profit} &\geq \sum_{t=2}^n \sum_{m=2}^{\min\{t,k\}} \frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}} \cdot \frac{1}{t\rho} \cdot mb_k \\
 &= \frac{k-1}{\rho} b_k = \frac{k-1}{k} \cdot \frac{1}{\rho} \cdot F^{(2)}
 \end{aligned}$$

- Let ρ be the offline competitive ratio
- Let $F^{(2)}(b_1, \dots, b_n) = k \cdot b_k$
- Expected online profit at step $t = \frac{1}{t} \cdot$ expected offline profit of the first t bids
- With probability $\frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}}$ the first t bids have m of the high k bids
- offline profit $\geq \frac{1}{\rho} \cdot m \cdot b_k$, **when** $m \geq 2$
- Putting everything together

$$\begin{aligned}
 \text{online profit} &\geq \sum_{t=2}^n \sum_{m=2}^{\min\{t,k\}} \frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}} \cdot \frac{1}{t\rho} \cdot mb_k \\
 &= \frac{k-1}{\rho} b_k = \frac{k-1}{k} \cdot \frac{1}{\rho} \cdot F^{(2)}
 \end{aligned}$$

- Let ρ be the offline competitive ratio
- Let $F^{(2)}(b_1, \dots, b_n) = k \cdot b_k$
- Expected online profit at step $t = \frac{1}{t} \cdot$ expected offline profit of the first t bids
- With probability $\frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}}$ the first t bids have m of the high k bids
- offline profit $\geq \frac{1}{\rho} \cdot m \cdot b_k$, **when** $m \geq 2$
- Putting everything together

$$\begin{aligned}
 \text{online profit} &\geq \sum_{t=2}^n \sum_{m=2}^{\min\{t,k\}} \frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}} \cdot \frac{1}{t\rho} \cdot mb_k \\
 &= \frac{k-1}{\rho} b_k = \frac{k-1}{k} \cdot \frac{1}{\rho} \cdot F^{(2)}
 \end{aligned}$$

- Let ρ be the offline competitive ratio
- Let $F^{(2)}(b_1, \dots, b_n) = k \cdot b_k$
- Expected online profit at step $t = \frac{1}{t} \cdot$ expected offline profit of the first t bids
- With probability $\frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}}$ the first t bids have m of the high k bids
- offline profit $\geq \frac{1}{\rho} \cdot m \cdot b_k$, **when** $m \geq 2$
- Putting everything together

$$\begin{aligned}
 \text{online profit} &\geq \sum_{t=2}^n \sum_{m=2}^{\min\{t,k\}} \frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}} \cdot \frac{1}{t\rho} \cdot mb_k \\
 &= \frac{k-1}{\rho} b_k = \frac{k-1}{k} \cdot \frac{1}{\rho} \cdot F^{(2)}
 \end{aligned}$$

- Let ρ be the offline competitive ratio
- Let $F^{(2)}(b_1, \dots, b_n) = k \cdot b_k$
- Expected online profit at step $t = \frac{1}{t} \cdot$ expected offline profit of the first t bids
- With probability $\frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}}$ the first t bids have m of the high k bids
- offline profit $\geq \frac{1}{\rho} \cdot m \cdot b_k$, **when** $m \geq 2$
- Putting everything together

$$\begin{aligned}
 \text{online profit} &\geq \sum_{t=2}^n \sum_{m=2}^{\min\{t,k\}} \frac{\binom{t}{m} \binom{n-t}{k-m}}{\binom{n}{k}} \cdot \frac{1}{t\rho} \cdot mb_k \\
 &= \frac{k-1}{\rho} b_k = \frac{k-1}{k} \cdot \frac{1}{\rho} \cdot F^{(2)}
 \end{aligned}$$

Theorem

The online competitive ratio is between 4 and 6.48

Why?

- The lower bound comes from specific cases: 2 distinct bids or $b = (2 + \epsilon, 2 - \epsilon, 1)$
- For the upper bound, take the offline auction of Hartline-McGrew with competitive ratio 3.24 and transform it into an online auction

Conjecture

The online competitive ratio is 4. Stronger: BPSF has competitive ratio 4.

Theorem

The online competitive ratio is between 4 and 6.48

Why?

- The lower bound comes from specific cases: 2 distinct bids or $b = (2 + \epsilon, 2 - \epsilon, 1)$
- For the upper bound, take the offline auction of Hartline-McGrew with competitive ratio 3.24 and transform it into an online auction

Conjecture

The online competitive ratio is 4. Stronger: BPSF has competitive ratio 4.

Theorem

The online competitive ratio is between 4 and 6.48

Why?

- The lower bound comes from specific cases: 2 distinct bids or $b = (2 + \epsilon, 2 - \epsilon, 1)$
- For the upper bound, take the offline auction of Hartline-McGrew with competitive ratio 3.24 and transform it into an online auction

Conjecture

The online competitive ratio is 4. Stronger: BPSF has competitive ratio 4.

Theorem

The online competitive ratio is between 4 and 6.48

Why?

- The lower bound comes from specific cases: 2 distinct bids or $b = (2 + \epsilon, 2 - \epsilon, 1)$
- For the upper bound, take the offline auction of Hartline-McGrew with competitive ratio 3.24 and transform it into an online auction

Conjecture

The online competitive ratio is 4. Stronger: BPSF has competitive ratio 4.

Theorem

The online competitive ratio is between 4 and 6.48

Why?

- The lower bound comes from specific cases: 2 distinct bids or $b = (2 + \epsilon, 2 - \epsilon, 1)$
- For the upper bound, take the offline auction of Hartline-McGrew with competitive ratio 3.24 and transform it into an online auction

Conjecture

The online competitive ratio is 4. Stronger: BPSF has competitive ratio 4.

"Almost" 4-competitive

- Let $F^{(2)} = k \cdot b_k$
- MAX has competitive ratio $\frac{k}{H_{k-1}} \leq 4$ for $k \leq 5$
- Online-SCS has competitive ratio $\frac{k}{k-1} \left(\frac{1}{2} - \binom{k-1}{\lfloor k-1 \rfloor} \cdot 2^{-k} \right)^{-1}$, which is less than 4 for $k \geq 5$.
- If we know k , we can achieve 4-competitiveness.

"Almost" 4-competitive

- Let $F^{(2)} = k \cdot b_k$
- MAX has competitive ratio $\frac{k}{H_{k-1}} \leq 4$ for $k \leq 5$
- Online-SCS has competitive ratio $\frac{k}{k-1} \left(\frac{1}{2} - \binom{k-1}{\lfloor k-1 \rfloor} \cdot 2^{-k} \right)^{-1}$, which is less than 4 for $k \geq 5$.
- If we know k , we can achieve 4-competitiveness.

"Almost" 4-competitive

- Let $F^{(2)} = k \cdot b_k$
- MAX has competitive ratio $\frac{k}{H_{k-1}} \leq 4$ for $k \leq 5$
- Online-SCS has competitive ratio $\frac{k}{k-1} \left(\frac{1}{2} - \binom{k-1}{\lfloor k-1 \rfloor} \cdot 2^{-k} \right)^{-1}$, which is less than 4 for $k \geq 5$.
- If we know k , we can achieve 4-competitiveness.

"Almost" 4-competitive

- Let $F^{(2)} = k \cdot b_k$
- MAX has competitive ratio $\frac{k}{H_{k-1}} \leq 4$ for $k \leq 5$
- Online-SCS has competitive ratio $\frac{k}{k-1} \left(\frac{1}{2} - \binom{k-1}{\lfloor k-1 \rfloor} \cdot 2^{-k} \right)^{-1}$, which is less than 4 for $k \geq 5$.
- If we know k , we can achieve 4-competitiveness.

"Almost" 4-competitive

- Let $F^{(2)} = k \cdot b_k$
- MAX has competitive ratio $\frac{k}{H_{k-1}} \leq 4$ for $k \leq 5$
- Online-SCS has competitive ratio $\frac{k}{k-1} \left(\frac{1}{2} - \binom{k-1}{\lfloor k-1 \rfloor} \cdot 2^{-k} \right)^{-1}$, which is less than 4 for $k \geq 5$.
- If we know k , we can achieve 4-competitiveness.

Offline auctions

No offline symmetric deterministic auction has bounded competitive ratio [GHKSW06]

Online auctions

- Order seems to matter!
- BPSF has bounded competitive ratio (open!)

Offline auctions

No offline symmetric deterministic auction has bounded competitive ratio [GHKSW06]

Online auctions

- Order seems to matter!
- BPSF has bounded competitive ratio (open!)

Offline auctions

No offline symmetric deterministic auction has bounded competitive ratio [GHKSW06]

Online auctions

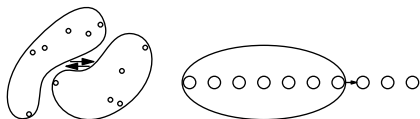
- Order seems to matter!
- BPSF has bounded competitive ratio (open!)

Offline auctions

No offline symmetric deterministic auction has bounded competitive ratio [GHKSW06]

Online auctions

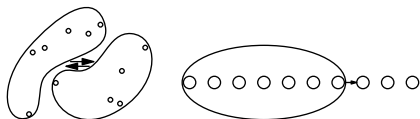
- Order seems to matter!
- BPSF has bounded competitive ratio (open!)



- Let $S = \{b_{j_1} > b_{j_2} > \dots > b_{j_r}\}$, a subset of bids
- Define $y(S) = \max\{1 \cdot b_{j_1}, 2 \cdot b_{j_2}, \dots, r \cdot b_{j_r}\}$ the optimal single price profit of S
- Define $z(S)$ the profit from offering the optimal single price of S to the other side
- $z(S) = (j_i - i)b_{j_i}$, where $i = \operatorname{argmax} y(S)$

$$\text{RSOP} = \sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot 2^{-(n-1)}$$

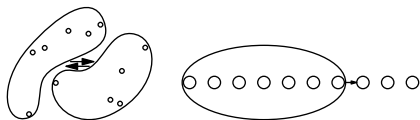
$$\text{BPSF} = \sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot \binom{n-1}{|S|}^{-1} \cdot n^{-1}$$



- Let $S = \{b_{j_1} > b_{j_2} > \dots > b_{j_r}\}$, a subset of bids
- Define $y(S) = \max\{1 \cdot b_{j_1}, 2 \cdot b_{j_2}, \dots, r \cdot b_{j_r}\}$ the optimal single price profit of S
- Define $z(S)$ the profit from offering the optimal single price of S to the other side
- $z(S) = (j_i - i)b_{j_i}$, where $i = \operatorname{argmax} y(S)$

$$\text{RSOP} = \sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot 2^{-(n-1)}$$

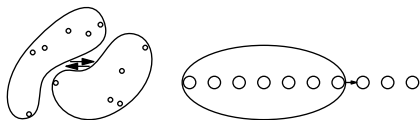
$$\text{BPSF} = \sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot \binom{n-1}{|S|}^{-1} \cdot n^{-1}$$



- Let $S = \{b_{j_1} > b_{j_2} > \dots > b_{j_r}\}$, a subset of bids
- Define $y(S) = \max\{1 \cdot b_{j_1}, 2 \cdot b_{j_2}, \dots, r \cdot b_{j_r}\}$ the optimal single price profit of S
- Define $z(S)$ the profit from offering the optimal single price of S to the other side
- $z(S) = (j_i - i)b_{j_i}$, where $i = \operatorname{argmax} y(S)$

$$\text{RSOP} = \sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot 2^{-(n-1)}$$

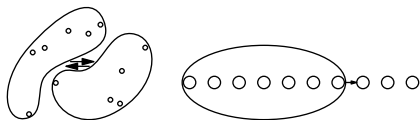
$$\text{BPSF} = \sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot \binom{n-1}{|S|}^{-1} \cdot n^{-1}$$



- Let $S = \{b_{j_1} > b_{j_2} > \dots > b_{j_r}\}$, a subset of bids
- Define $y(S) = \max\{1 \cdot b_{j_1}, 2 \cdot b_{j_2}, \dots, r \cdot b_{j_r}\}$ the optimal single price profit of S
- Define $z(S)$ the profit from offering the optimal single price of S to the other side
- $z(S) = (j_i - i)b_{j_i}$, where $i = \operatorname{argmax} y(S)$

$$\text{RSOP} = \sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot 2^{-(n-1)}$$

$$\text{BPSF} = \sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot \binom{n-1}{|S|}^{-1} \cdot n^{-1}$$



- Let $S = \{b_{j_1} > b_{j_2} > \dots > b_{j_r}\}$, a subset of bids
- Define $y(S) = \max\{1 \cdot b_{j_1}, 2 \cdot b_{j_2}, \dots, r \cdot b_{j_r}\}$ the optimal single price profit of S
- Define $z(S)$ the profit from offering the optimal single price of S to the other side
- $z(S) = (j_i - i)b_{j_i}$, where $i = \operatorname{argmax} y(S)$

$$\text{RSOP} = \sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot 2^{-(n-1)}$$

$$\text{BPSF} = \sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot \binom{n-1}{|S|}^{-1} \cdot n^{-1}$$

Conjecture

RSOP is 4-competitive. Equivalently, for every set of bids b :

$$\sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot 2^{-(n-1)} \geq y(b_2, b_2, b_3, \dots, b_n)$$

Conjecture

BPSF is 4-competitive. Equivalently, for every set of bids b :

$$\sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot \binom{n-1}{|S|}^{-1} \cdot n^{-1} \geq y(b_2, b_2, b_3, \dots, b_n)$$

Conjecture

RSOP is 4-competitive. Equivalently, for every set of bids b :

$$\sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot 2^{-(n-1)} \geq y(b_2, b_2, b_3, \dots, b_n)$$

Conjecture

BPSF is 4-competitive. Equivalently, for every set of bids b :

$$\sum_{S \subseteq \{b_2, \dots, b_n\}} z(S) \cdot \binom{n-1}{|S|}^{-1} \cdot n^{-1} \geq y(b_2, b_2, b_3, \dots, b_n)$$

A coupling argument

S	#of b_2 's	#of b_3 's	#of b_4 's
$b_2b_3b_4$	b_2	$2b_3$	$3b_4$
b_2b_3	b_2	$2b_3$	-
b_2b_4	b_2	-	$2b_4$
b_2	b_2	-	-
b_3b_4	-	b_3	$2b_4$
b_3	-	b_3	-
b_4	-	-	b_4
/	-	-	-
Σ # ib's	$2*2b_2$	$2*3b_3$	$2*4b_4$

Diagrammatic annotations: Red arrows on the left point to rows $b_2b_3b_4$, b_2b_3 , b_2b_4 , and b_2 . Red circles highlight the b_2 entries in the third, fourth, and fifth rows, and the b_3 entries in the fifth and sixth rows. Red arrows connect the circled b_2 in the third row to the circled b_3 in the fifth row, and the circled b_2 in the fourth row to the circled b_3 in the sixth row.

$$\sum_{\substack{S \in \{b_2, \dots, b_n\} \\ b_2 \in S}} y(S) \geq$$

$$\sum_{\substack{S \in \{b_2, \dots, b_n\} \\ b_i \in S}} y(S) =$$

$$2^{n-i} \sum_{j=0}^{i-2} \binom{i-2}{j} \cdot (j+1) \cdot b_i =$$

$$2^{n-3} \cdot i \cdot b_i$$

Lemma

$$\sum_{\substack{S \in \{b_2, \dots, b_n\} \\ b_2 \in S}} y(S) \geq 2^{n-3} \cdot F(2)$$

Relations between z and y

Conjecture

$$\sum_{S \in \{b_2, \dots, b_n\}} z(S) \geq \sum_{\substack{S \in \{b_2, \dots, b_n\} \\ b_2 \in S}} y(S)$$

This will show that RSOP is 4-competitive

Conjecture

$$\sum_{S \in \{b_3, \dots, b_n\}} z(S) \geq \sum_{S \in \{b_3, \dots, b_n\}} y(S)$$

The second conjecture implies the first because

$$z(b_{j_1}, \dots, b_{j_r}) \geq y(b_{j_1}, \dots, b_{j_r}) - y(b_{j_2}, \dots, b_{j_r})$$

Relations between z and y

Conjecture

$$\sum_{S \in \{b_2, \dots, b_n\}} z(S) \geq \sum_{\substack{S \in \{b_2, \dots, b_n\} \\ b_2 \in S}} y(S)$$

This will show that RSOP is 4-competitive

Conjecture

$$\sum_{S \in \{b_3, \dots, b_n\}} z(S) \geq \sum_{S \in \{b_3, \dots, b_n\}} y(S)$$

The second conjecture implies the first because

$$z(b_{j_1}, \dots, b_{j_r}) \geq y(b_{j_1}, \dots, b_{j_r}) - y(b_{j_2}, \dots, b_{j_r})$$

Relations between z and y

Conjecture

$$\sum_{S \in \{b_2, \dots, b_n\}} z(S) \geq \sum_{\substack{S \in \{b_2, \dots, b_n\} \\ b_2 \in S}} y(S)$$

This will show that RSOP is 4-competitive

Conjecture

$$\sum_{S \in \{b_3, \dots, b_n\}} z(S) \geq \sum_{S \in \{b_3, \dots, b_n\}} y(S)$$

The second conjecture implies the first because

$$z(b_{j_1}, \dots, b_{j_r}) \geq y(b_{j_1}, \dots, b_{j_r}) - y(b_{j_2}, \dots, b_{j_r})$$

Open problems

- Prove or disprove that the worst-case distribution is bid-independent
- Prove that BPSF is 4-competitive
- Prove that RSOP is 4-competitive

Open problems

- Prove or disprove that the worst-case distribution is bid-independent
- Prove that BPSF is 4-competitive
- Prove that RSOP is 4-competitive

Open problems

- Prove or disprove that the worst-case distribution is bid-independent
- Prove that BPSF is 4-competitive
- Prove that RSOP is 4-competitive

Open problems

- Prove or disprove that the worst-case distribution is bid-independent
- Prove that BPSF is 4-competitive
- Prove that RSOP is 4-competitive

Thank you!