

A Combinatorial Look at Auctions

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 - VCG Mechanisms
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- 2 Allocate All
 - Allocate All Items
 - Large Range
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Auctions

We consider combinatorial auctions of m items to n bidders where we wish to maximize the social welfare.

- The VCG mechanism can be used for truthfulness
- An FPTAS can be used to approximate arbitrarily well
- Can we achieve efficiency and truthfulness *simultaneously*?

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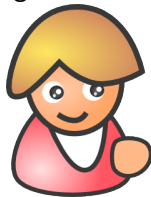
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The VCG Mechanism

- By participating in the auction, each bidder harms the others



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- To counter greed, each player is charged for this harm
- Intuitively, the player wants the social welfare maximized

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Example

Grouping all items into one lot, we can maximize over a range of size n . This yields a $1/n$ approximation.

MIR Example

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- By giving all items to one player, we do well when welfare is concentrated
- To do well when welfare is spread out, we can treat the auction as unit demand and solve exactly
- One of these gets at least a $\min(n, 2\sqrt{m})$ approximation

Proof of Approximation Ratio

We know that it gets at least n , so let's see that we get $2\sqrt{m}$

- In an optimal allocation, bidders get $\leq \sqrt{m}$ or $> \sqrt{m}$ items

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- If those with $> \sqrt{m}$ items get more welfare, giving all items to one bidder yields a \sqrt{m} approximation for the group

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The Model

- Each bidder has a valuation function v_i
- For each item j , bidder i has a value v_{ij}
- Each bidder i has a **budget** b_i
- For each subset $S \subseteq [m]$ of the items,

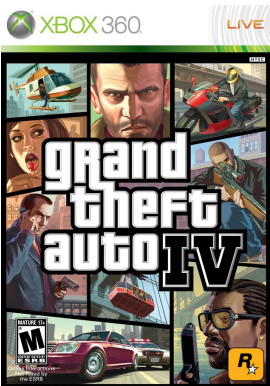
$$v_i(S) = \min \left(\sum_{j \in S} v_{ij}, b_i \right)$$

Example: Video Game Auction

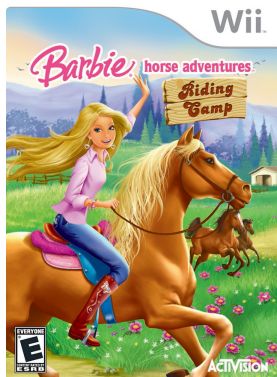


Value: 40

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Previous Work

- Inapproximability for Combinatorial Public Projects (Schapira, Singer, 2008)
- n -bidder auctions can't approximate better than $(n + 1)/2n$ (Mossel et al., 2009)

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- We show that n -bidder auctions can't beat $\min(n, m^{1/2-\epsilon})$
- The key to all of these was **VC dimension**

VC Dimension

- Consider a subset $R \subseteq 2^{[m]}$
- By restricting to $S \subset [m]$, we get a new set R_S

Example

If $\{2, 3, 5\} \in R$ and $S = \{1, 2, 5\}$, then $\{2, 5\} \in R_S$.

- The VC dimension is size of the largest S such that $R_S = 2^S$
- For 2-bidder auctions, this is like allocating S in every way

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Allocate All Items

Our work is based on a related proof for an easier case

- In auctions, items can be given to bidders or retained
- The social welfare is never harmed by giving out more items
- Doing so might result in not being maximal-in-range

Allocating All vs. Maximal-in-Range

Consider a 2 bidder, 2 item auction

Algorithm

- Let \mathcal{M} maximize value with item 1, retain item 2
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- \mathcal{M} gives item 1 to bidder 1
 - so \mathcal{M}' gives both items to bidder 1
 - but \mathcal{M}' has a range that includes giving each bidder one item

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We start by looking at 2-bidder MIR allocate all mechanisms

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- 1221 means bidder 1 values 1 and 4, bidder 2 values 2 and 3
- All values are 1 or 0, budgets are infinite
- Social welfare is just how well the vectors match

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- Fix an allocation r in the range
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- So it takes an exponentially large range to do well on all v

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- So there is a subset of δm items on which we can solve exactly
- Using this subset as advice, we can solve welfare maximization
- So approximating to $1/2 + \epsilon$ is impossible unless $NP \subseteq P/poly$

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Coverings

- Suppose we have an approximation ratio of $1/n + \epsilon$
- For every $v \in [n]^m$, some $r \in R$ matches $(1/n + \epsilon)m$ indices

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- For each S , T_S projects R to S
- T_S filters out $r \in R$ such that any $s \in S$ is unassigned
- $t \in T_S$ **covers** v if it is the projection of v to S

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Where are we now?

So we not only have a large range, but by focusing in on S , we have a large range that allocates all items.

Next, we deal with the difficulty of using the VC dimension with more than two bidders.

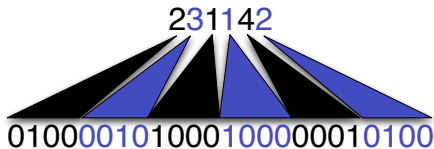
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- Using Sauer's lemma requires an exponential subset of $[2]^m$
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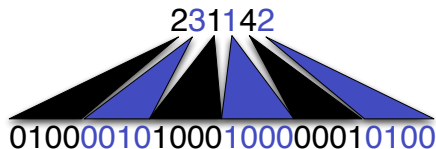
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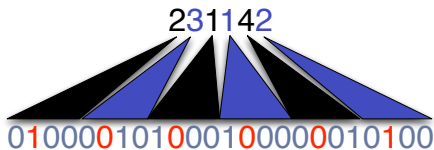
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- By sacrificing a factor of n , we can fix i

Now what do we know?

So we now see that the large range means that the range solves exactly over an auction with 2 bidders, one corresponding to a special bidder i and the rest forming a meta-bidder.

We do not know that this auction is hard yet, however, as the meta-bidder has a restricted class of valuations.

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- The meta-bidder has $b = \infty$, $v_j = a_j$
- For bidder i , $b = 2\tau$, $v_j = 2a_j$
- A subset sums to τ iff we get welfare $\sum_j a_j + \tau$

So if a maximal-in-range mechanism approximates the social welfare better than $\min(n, m^{1/2-\epsilon})$, subset sum has polynomial circuits.

Conclusions and Open Problems

- We showed that for any poly-bounded n , no poly-time MIR mechanism can beat $\min(n, m^{1/2-\epsilon})$
- This essentially solves the problem, as a $\min(n, 2\sqrt{m})$ approximation exists.
- The more general question of how well truthful mechanisms can perform is left open