

# Computation and Incentives in Public Projects

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# Outline

1 Background

2 Unit-Demand

3 Coverage

4 Summary and Conclusions

# Public Projects

A combinatorial public project is a game in which the goal is to choose  $k$  items from a set of  $m$  to provide for shared use among  $n$  agents.

# Public Projects

A combinatorial public project is a game in which the goal is to choose  $k$  items from a set of  $m$  to provide for shared use among  $n$  agents.

This differs from an auction in that allocated items are shared.

## Definition (Social Welfare)

Suppose that each agent  $i$  gets value  $v_i(S)$  for allocation  $S$ . Then the **social welfare** of  $S$  is

$$\sum_i v_i(S)$$

# History

- Public projects were first studied by Papadimitriou, Schapira and Singer in a 2008 FOCS paper titled *On the Hardness of Being Truthful*
- Our results use techniques from this paper to achieve hardness results for approximating social welfare with maximal-in-range mechanisms
- These techniques were also used in a recent paper in SODA 2010, *Limits on the Social Welfare of Maximal-In-Range Auction Mechanisms* by Buchfuhrer, Dughmi, Fu, Kleinberg, Mossel, Papadimitriou, Schapira, Singer and Umans.

# Maximal-in-Range (MIR)

## Definition (Maximal-in-Range)

An allocation algorithm is **maximal-in-range** if there exists some range  $R$  such that the algorithm always outputs an allocation from  $R$  that maximizes the social welfare.

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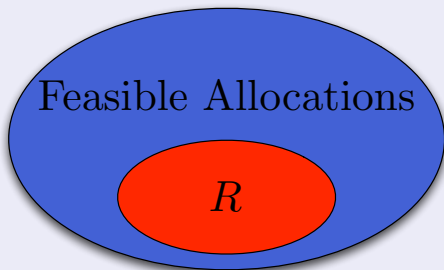


Feasible Allocations

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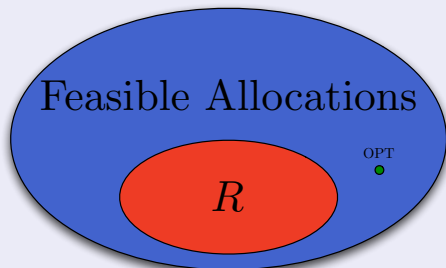




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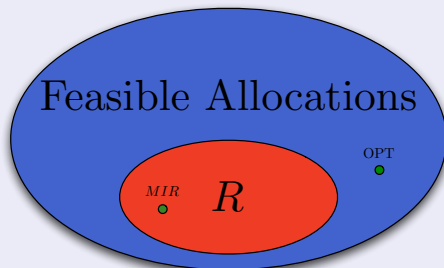
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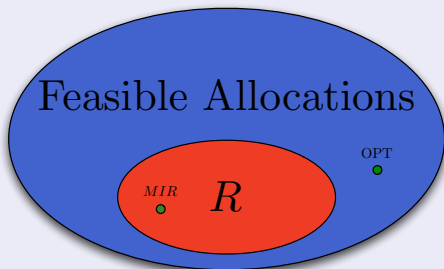
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- An algorithm can be implemented truthfully via VCG iff it is MIR
- For sufficiently general valuations, VCG is the only truthful mechanism

# Performance of MIR mechanisms

## Theorem (sketch)

*A maximal in range allocation algorithm for any NP-hard combinatorial public project cannot approximate the welfare with a ratio better than  $\sqrt{m}$  unless  $NP \subseteq P/poly$ .*

## Proof scheme.

- A mechanism that gets better than a  $\sqrt{m}$  ratio requires an exponential range for sufficiently expressive valuation classes (PSS 08)



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- A mechanism that gets better than a  $\sqrt{m}$  ratio requires an exponential range for sufficiently expressive valuation classes (PSS 08)
- By Sauer's lemma, an exponential range must contain a polynomial-sized subset  $S^*$  of items allocated in every way
- We construct instances in which it is NP-hard to determine which members of  $S^*$  should be selected. These follow fairly directly from the proofs of NP-hardness. □

# Embedding NP-hard problems into $S^*$

Suppose we have an NP-hardness reduction to the problem

## Example

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We simply embed  $[m]$  into  $S^*$  and set social welfare

$$v'(S = S_1 \cup S_2) = v(S_1) + \epsilon|S_2|$$

where  $S_1 \subseteq S^*, S_2 \subset [m'] \setminus S^*$



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### Lemma

*The auction after this embedding has social welfare  $v([m]) + \epsilon(k' - k)$  iff there is a set  $S \subseteq [m], |S| = k$  such that  $v(S) = v([m])$ .*

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# Definition

## Definition (Unit-Demand Valuation)

An agent with a unit-demand valuation has private values  $w_j$  for each item  $j$ , and has total value

$$v_i(S) = \max_{j \in S} w_j$$

for set  $S$ .

In auctions, unit-demand agents are trivial.

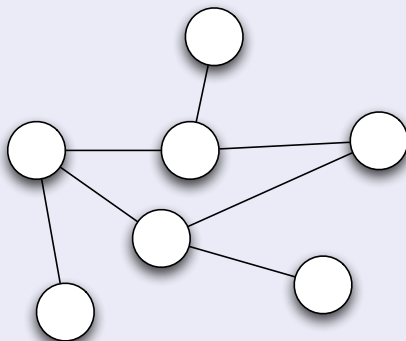
# NP hardness

## Theorem

*The public project problem with unit-demand agents is NP-hard.*

## Proof by picture

Reduction from vertex cover:



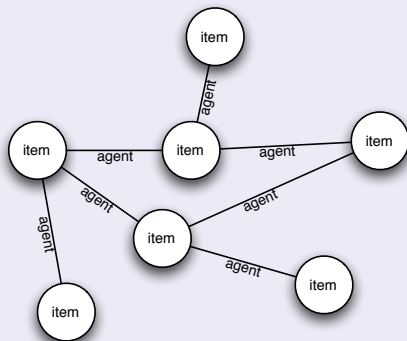
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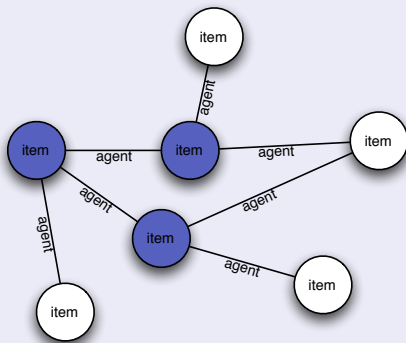
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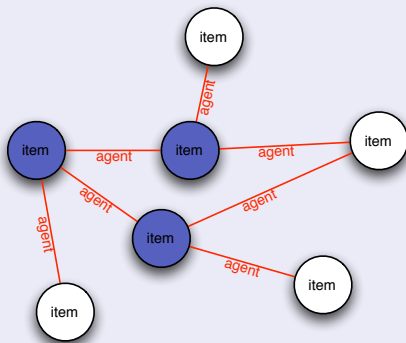
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## 2- $\{0, 1\}$ Unit-Demand

### Definition (2- $\{0, 1\}$ Unit-Demand)

An agent has a 2- $\{0, 1\}$  unit-demand valuation if for some two items  $i, j$ :

$$v(S) = \begin{cases} 1 & i \in S \vee j \in S \\ 0 & \text{otherwise} \end{cases}$$

The previous proof showed hardness for 2- $\{0, 1\}$  unit-demand agents, as an agent is satisfied if one of the items chosen corresponds to one of the 2 endpoints of his edge.



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## Recall

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Choose the  $k$  items corresponding to the vertices of highest degree

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## Proof.

- The number of edges covered is at least half the sum of degrees
- There's no benefit to lying □

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# Definition

## Definition (Coverage Valuation)

An agent with a coverage valuation associates a set  $T_j$  with each item  $j$ , and has value

$$v_i(S) = \left| \bigcup_{j \in S} T_j \right|$$

for set  $S$ .

# NP hardness

## Theorem

*The public projects problem with a single coverage valuation agent is NP-hard.*

## Definition (max- $k$ -cover)

**Input:** Several sets  $T_1, \dots, T_m$

**Goal:** Find a set  $S \subseteq [m], |S| = k$  maximizing  $|\bigcup_{j \in S} T_j|$

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Wait a second...

## Theorem

*No truthful poly-time mechanism for public projects can achieve better than a  $\sqrt{m}$  approximation unless  $NP \subseteq P/poly$ .*

## Proof.

- Our results show hardness for VCG to do better than  $\sqrt{m}$
- For a single agent, any mechanism must be maximal-in-range to be truthful, so VCG is all there is □

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# Summary of Results

## Computational Results

valuation class	no. of agents	appx. ratio $r$
unit-demand	constant	$r = 1$
	$n$	$r = 1 - \frac{1}{e}$ [New]
multi-unit-demand	1, 2	$r = 1$ [New]
	3	$\frac{2}{3}$ [New] $\leq r < 1$ [New]
	$\geq 4$	$1 - \frac{1}{e}$ [10] $\leq r < 1$ [New]
	$\geq 10$	$1 - \frac{1}{e}$ [10] $\leq r < 1 - \epsilon$ (no PTAS)[New]
	$n$	$r = 1 - \frac{1}{e}$ [New]
capped additive	1	$r = 1$
	constant $\geq 2$	$r = 1 - \epsilon$ (FPTAS) [New]
	$n$	$r = 1 - \frac{1}{e}$ [New]
fractionally-subadditive	constant	$r = 1$
	$n$	$\max\{\frac{1}{n}, \frac{1}{\sqrt{m}}\}$ [16] $\leq r \leq 2^{-\frac{\log^{1-\gamma} n}{6}}$ [New]

## Truthful Results

valuation class	no. of agents	Truthful appx. ratio $r$	VCG-based appx. ratio $r$
2- $\{0,1\}$ unit-demand	$n$	$\frac{1}{2} \leq r < 1$ [New]	$r = \frac{1}{\sqrt{m}}$ [New]
unit-demand	$n$	?	
multi-unit-demand	3	$\frac{2}{3} \leq r < 1$ [New]	
	$n$	?	
capped-additive	$\geq 2$	?	
coverage	1	$r = \frac{1}{\sqrt{m}}$ [New]	
fractionally-subadditive	$n$	?	

# Conclusions and Open Problems

- Public projects are hard even for simple classes of valuations, allowing for mechanism design to be explored on simpler problems than in auctions
- Can we improve upon the VCG mechanism in simple public projects?
- The requirement of truth can be too much even for a single agent
- Can we define a satisfying substitute for truth in these situations?