

CS599: Algorithm Design in Strategic Settings
Fall 2012

Lecture 4: Prior-Free Single-Parameter Mechanism
Design

Instructor: Shaddin Dughmi

- HW out, due Friday 10/5
 - Very hard (I think)
 - Discuss together and with me (but write up independently)

Outline

- 1 Recap
- 2 Objectives and Constraints in Mechanism Design
- 3 Single-Parameter Problems
 - Example Problems
 - General Definition
- 4 Characterization of Incentive-compatible Mechanisms
- 5 Exercises

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Motivated by impossibilities, we agreed to focus on settings where monetary payments can be used to align incentives.

The Quasi-linear Setting

Formally, $\mathcal{X} = \Omega \times \mathbb{R}^n$.

- Ω is the set of **allocations**
- For $(\omega, p_1, \dots, p_n) \in \mathcal{X}$, p_i is the payment from (or to) player i . and player i 's utility function $u_i : T_i \times \mathcal{X} \rightarrow \mathbb{R}$ takes the following form

$$u_i(t_i, (\omega, p_1, \dots, p_n)) = v_i(t_i, \omega) - p_i$$

for some **valuation function** $v_i : T_i \times \Omega \rightarrow \mathbb{R}$.

We say players have **quasilinear** utilities.

Example: Single-item Allocation

- $\Omega = \{e_1, \dots, e_n\}$
- $u_i(t_i, (\omega, p_1, \dots, p_n)) = t_i \omega_i - p_i$

The Mechanism Design Problem

Task of Mechanism Design in Quasilinear settings

Find a “good” **allocation rule** $f : T \rightarrow \Omega$ and **payment rule** $p : T \rightarrow \mathbb{R}^n$ such that the following mechanism is **incentive-compatible**:

- Solicit reports $\tilde{t}_i \in T_i$ from each player i (simultaneous, sealed bid)
- Choose allocation $f(\tilde{t})$
- Charge player i payment $p_i(\tilde{t})$

We think of the mechanism as the pair (f, p) .

Incentive Compatibility

Incentive-compatibility (Dominant Strategy)

A mechanism (f, p) is dominant-strategy truthful if, for every player i , true type t_i , possible mis-report \tilde{t}_i , and reported types t_{-i} of the others, we have

$$\mathbf{E}[v_i(t_i, f(t)) - p_i(t)] \geq \mathbf{E}[v_i(t_i, f(\tilde{t}_i, t_{-i})) - p_i(\tilde{t}_i, t_{-i})]$$

The expectation is over the randomness in the mechanism.

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The expectation is over the randomness in the mechanism.

Incentive-compatibility (Bayesian)

A mechanism (f, p) is Bayesian incentive compatible if, for every player i , true type t_i , possible mis-report \tilde{t}_i , the following holds in expectation over $t_{-i} \sim D|t_i$

$$\mathbf{E}[v_i(t_i, f(t)) - p_i(t)] \geq \mathbf{E}[v_i(t_i, f(\tilde{t}_i, t_{-i})) - p_i(\tilde{t}_i, t_{-i})]$$

The expectation is over randomness in both the mechanism and the other players' types.

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Question

What is a “good” mechanism?

Answer

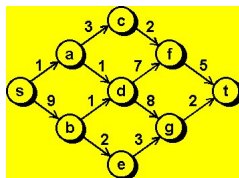
Depends what you are looking for.

- Researchers and practitioners have considered many **objectives** and hard **constraints** on desirable mechanisms.
- The task of mechanism design is then to find a mechanism maximizing the objective subject to the constraints.

Example: Single-minded Combinatorial Allocation

- n players, m non-identical items
- For each player, publicly known subset A_i of items the player desires
- Allocations: partitions of items among players
- Each player has type $v_i \in \mathbb{R}_+$, indicating his value for receiving a bundle including A_i (0 otherwise)
- Goal: Social welfare (sum of values of players who receive their desired bundles)

Shortest Path Procurement



- Players are edges in a network, with designated source/sink
- Player i 's private data (type): cost $c_i \in \mathbb{R}_+$
- Outcome: choice of s-t shortest path to buy, and payment to each player
- Utility of a player for an outcome is his payment, less his cost if chosen.

Goal: buy path with lowest total cost (welfare), or buy a path subject to a known budget, . . .

Example: Public Project

- Designer considering whether to build a project which costs designer C (public)
- n players, each with private type $v_i \in \mathbb{R}_+$, indicating value for project
- Outcome: Choice of whether or not to build project, and how much to charge each player.
- Possible goal: Build if $\sum_i v_i > C$, charging players enough to cover cost C

Constraints

- Incentive compatibility
- Polynomial-time
- Individual Rationality: never charge a player more than his (reported) value for an allocation.
- Nonnegative [Non-positive] Transfers: never pay [get paid by] a player
 - e.g. Combinatorial allocation, Shortest path procurement
- Budget constraints: sum of total payments to agents must respect budget
 - e.g. reverse (procurement) auctions
- Budget balance: sum of total payments must exceed cost of allocation
 - e.g. public project

Objectives: Prior-free

Given an instance of a mechanism design problem,

- An **objective** is a map from outcome (allocation and payments) to the real numbers.
- A **benchmark** is a real number “goalpost”

Single-item auction

- Objective: welfare, i.e. the value of the winning player.
- Benchmark: the maximum welfare over all allocations.

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Single-item auction

- Objective: welfare, i.e. the value of the winning player.
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In prior-free settings, we traditionally judge an algorithm by the worst-case ratio between the performance of the mechanism and the benchmark.

The **worst-case approximation ratio** of a mechanism is the maximum, over all inputs, of the benchmark divided by the objective of the outcome output by the mechanism.

Objectives: Bayesian

In the presence of a distribution over inputs, no need for a benchmark.

Judge a mechanism by the expected objective over the various inputs.

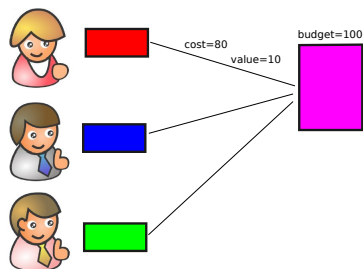
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We will begin our exploration of the space of mechanism design problems by restricting attention to

- Prior-free settings, with the goal of designing dominant-strategy truthful mechanisms
- Quasi-linear utilities, so our mechanisms will use payments
- Problems that are **single-parameter**

Example: Knapsack Allocation



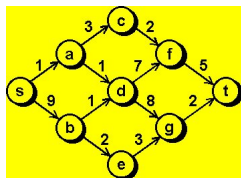
- n players, each player i with a task requiring c_i time
- Machine has total processing time B (public)
- Player i has (private) value v_i for his task

Must choose a welfare-maximizing feasible subset $S \subseteq [n]$ of the tasks to process, possibly charging players

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Goal: buy path with lowest total cost (welfare), or buy a path subject to a known budget, ...

Scheduling

- Designer has m jobs, with publicly known sizes p_1, \dots, p_m
- n players, each own a machine
- Player i 's type $t_i \in \mathcal{R}$ is time (cost) per unit job
- Outcome: schedule mapping jobs onto machines, and payment to each player
- Utility of a player for a schedule is his payment, less the total time spent processing assigned jobs

Goal: Find schedule minimizing **makespan**: the time at which all jobs are complete

Single-parameter Problems

Informally

- There is a single homogenous resource (items, bandwidth, clicks, spots in a knapsack, etc).
- There are constraints on how the resource may be divided up.
- Each player's private data is his "value (or cost) per unit resource."

Single-parameter Problems

Formally

- Each player i 's type is a single real number t_i . Player i 's type-space T_i is an interval in \mathbb{R} .
- Each outcome $\omega \in \Omega$ is a vector in \mathbb{R}^n .
- Player i 's valuation function is $v_i(t_i, x) = t_i x_i$

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Examples

- Single-item allocation: Ω is set of standard basis vectors, t_i is player i 's value for an item.
- Knapsack allocation: Ω is the set of indicator vectors of players who fit in the knapsack, t_i is player i 's value for being included.
- Scheduling: Ω is the set of possible load vectors, $-t_i$ is player i 's time per unit load.

Interpretation and Importance

- Models win/lose situations, and situations where a homogeneous resource is to be divided.
- Simple and pervasive
- Incentive-compatible mechanisms admit a simple and permissive characterization.

Outline

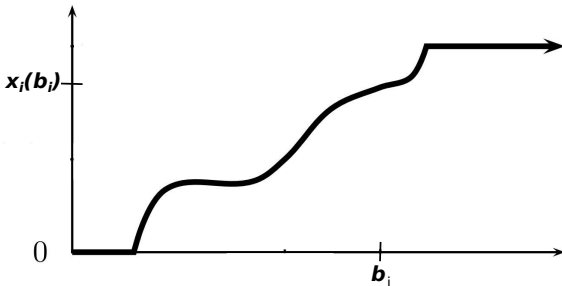
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Myerson's Lemma (Dominant Strategy)

A mechanism (x, p) for a single-parameter problem is dominant-strategy truthful if and only if for every player i and fixed reports b_{-i} of other players,

- $x_i(b_i)$ is a monotone non-decreasing function of b_i
- $p_i(b_i)$ is an integral of $b_i dx_i$. Specifically, when $p_i(0) = 0$ then

$$p_i(b_i) = b_i \cdot x_i(b_i) - \int_{b=0}^{b_i} x_i(b) db$$

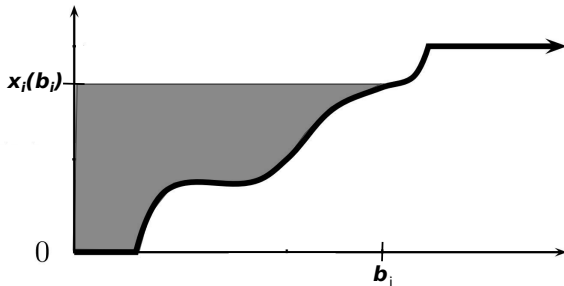


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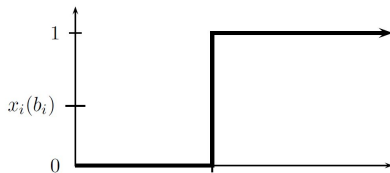
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Interpretation of Myerson's Lemma



Utilitarian Single-item Allocation

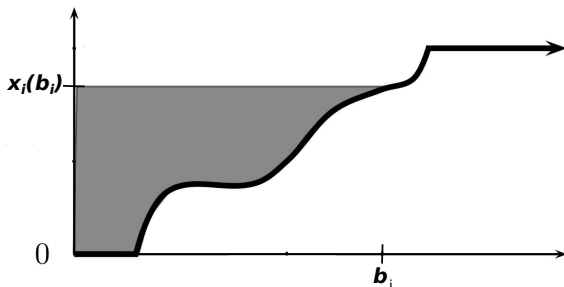
- Once a player wins, he remains a winner by increasing his bid (assuming other bids held fixed)
- The player must pay his **critical value** if he wins: the minimum bid he needs to win.
- Therefore, Vickrey is the unique welfare-maximizing, individually rational, single-item auction.

Same holds for every problem with a binary (win/lose) outcome per player.

Interpretation of Myerson's Lemma

More Generally

As player increases his bid, he pays for each additional chunk of resource at a rate equal to the minimum bid needed to win that chunk.



Figure

Monotonicity

- Assume for a contradiction that x_i is non-monotone. Let $b'_i > b_i$ with $x_i(b'_i) < x_i(b_i)$.
- Two cases:
 - 1 $b_i \cdot (x_i(b_i) - x_i(b'_i)) < p_i(b_i) - p_i(b'_i)$
Extra “value” gotten by reporting b_i truthfully is dominated by increase in price.
 - 2 $b_i \cdot (x_i(b_i) - x_i(b'_i)) \geq p_i(b_i) - p_i(b'_i)$
Then also $b'_i \cdot (x_i(b_i) - x_i(b'_i)) > p_i(b_i) - p_i(b'_i)$, and a player with true value b'_i prefers to mis-report b_i .

Payments

- Consider the utility of a player with type b_i reporting b'_i

$$b_i x_i(b'_i) - p_i(b'_i)$$

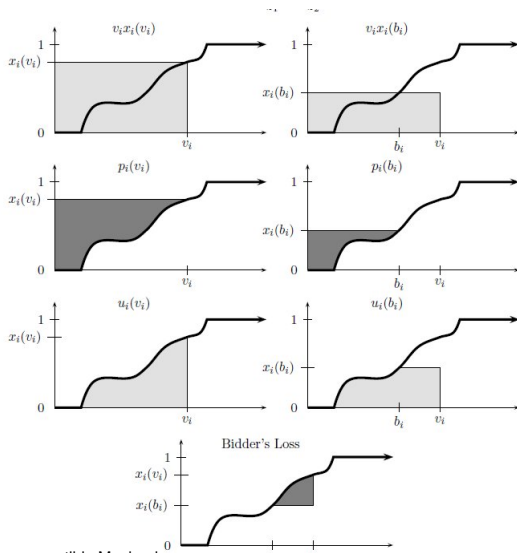
- For truthfulness, this expression must be maximized by setting $b'_i = b_i$
- This implies that the partial derivative w.r.t b'_i , evaluated at $b'_i = b_i$, is zero

$$b_i \frac{dx_i}{db_i}(b_i) - \frac{dp_i}{db_i}(b_i) = 0$$

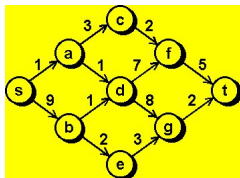
- Multiplying by db_i gives that p_i integrates $b_i dx_i$, as needed.

Proof: Sufficiency

Consider a player with true type v_i , and a possible mis-report $b_i < v_i$.
(Exercise: consider $b_i > v_i$)



Example: Dijkstra Shortest Path



- Monotonicity: If an edge in the shortest path decreases its cost, it remains in the shortest path
- Critical Payments: We pay each edge the maximum possible cost it could report and still remain in the shortest path.

Figure

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A seller (player 1) and buyer (player 2) are looking to trade a single item initially held by the seller.

- Type of each player i is his value v_i for the item
- Two outcomes:
 - No trade: $(1, 0)$
 - Trade: $(0, 1)$
- Welfare maximizing allocation rule:

Bilateral Trade

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Question

Assuming no payments in the event of no-trade, describe the payment rule of the welfare-maximizing mechanism.

We finally begin designing “interesting” mechanisms, specifically for problems that are NP-hard. The tricky part will be combining incentive-compatibility and polynomial-time.