Intractability in Algorithmic Game Theory

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How Theory CS Can Contribute

Unsurprising fact: very rich tradition and literature on mechanism design and equilibria in economics.

- largely "Bayesian" (i.e., average-case) settings
- emphasizes exact solutions/characterizations
- usually ignores communication/computation

What we have to offer:

- 1. worst-case guarantees
- 2. approximation bounds
- 3. computational complexity

Overview

Part I: Algorithmic Mechanism Design

- goal: design polynomial-time protocols so that selfinterested behavior leads to socially desirable outcome
- intractability from joint computational, incentive constraints

Part II: Revenue-Maximizing Auctions

- Information-theoretic intractability
- Interpolation of worst-case, average-case analysis
- Part III: Complexity of Computing Equilibria
- Computing Nash equilibria is PPAD-complete
- Interpretations and open questions

References

- FOCS 2010 tutorial, "How to Think About Algorithmic Mechanism Design"
 - video available from my home page
- CACM July 2010 survey article, "Algorithmic Game Theory".

review articles

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A new era of theoretical computer science addresses fundamental problems about auctions, networks, and human behavior.

BY TIM ROUGHGARDEN

Algorithmic Game Theory

An eBay Single-Good Auction



winner = highest bidder above reserve price
 price = max{second-highest bid, reserve}

Truthful Auctions

Claim: a second-price auction (like eBay) is truthful

- bidding your maximum willingness to pay (your "value") is "foolproof" (a *dominant strategy*)
- i.e., your utility (value price) is at least as large with a truthful bid as with any other bid

Proof idea: truthful bid equips the auctioneer (who knows all the bids) to bid optimally on your behalf.

A More Complex Example

Setup: n bidders, m houses.

each bidder i has private value
 v_{ii} for house j, wants ≤ 1 house.

Analog of 2nd-price auction:

every bidder submits bid for every house



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- compute a max-value matching
- charge suitable payments so that bidding true values is dominant strategy for every bidder (relatively simple calculation: this can be done)

Another More Complex Example

Setup: n bidders, m goods.

 bidder i has private value v_i for known subset S_i of goods



- every bidder submits a bid for the bundle it wants
- compute a max-value packing
- charge suitable payments so that bidding true values is dominant strategy for every bidder (relatively simple calculation: this can be done)

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[Nisan/Ronen 99] For as many optimization problems as possible, design a mechanism:

- runs in polynomial time
- every player has a dominant strategy
- dominant strategies yield near-optimal outcome

Examples: Can maximize welfare (sum of values) exactly in single-item and matching problems.

special cases of the "VCG mechanism"

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Obvious approach:

- 1. every bidder submits bids
- 2. compute an approximately max-value solution using best-known approximation algorithm
- 3. charge suitable payments so that bidding true values is dominant strategy for every bidder

goal: runs in poly-time, dominant strategies yield near-optimal outcome holy grail: match approximation factor of best approximation algorithm.

Problem [Nisan/Ronen 00] for all but a special type of approximation algorithms, *no payments make truthful bidding a dominant strategy.*

How to think about algorithmic mechanism design: designing truthful mechanisms boils down to designing algorithms in a certain "restricted computational model".

The Punch Line

Theorem(s): Joint intractability of computational and game-theoretic constraints often much more severe than that of either constraint by itself.

- 1st compelling example: [Papadimitriou/Schapira/Singer FOCS 08]
 - O(1)-approximation with only poly-time or GT constraints, Ω(poly(n))-approximation with both
 - blends Robert's theorem, probabilistic method, Sauer-Shelah Lemma, and a clever embedding of 3SAT
- state of the art (2011-12): Dobzinski, Dughmi, Vondrak

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Reference

- Jason Hartline, "Approximation in Economic Design", book in preparation, 2013.

Welfare vs. Revenue

Question: why should revenue maximization be different than welfare-maximization?

- Answer: welfare defined *extrinsic* to the auction, payments generated by auction itself.
 - □ in 2nd-price auction, payments only means to an end
- clear what "maximum-possible welfare" means
- not clear what "max-possible revenue" means

Example: Multi-Unit Auctions

Setup: n bidders, k identical goods.

- bidder i has private "valuation" v_i for a good
- $v_i = maximum willingness to pay$

Design space: decide on:

(1) at most k winners; and (2) selling prices.

Example: Vickrey auction.

top k bidders win; all pay (k+1)th highest bid

Variant: Vickrey with a reserve. [≈extra bid by seller]

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Goal: design an auction A for which:

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Problem: too strong, not useful.

- all auctions A are terrible [no constant α is possible]
- optimal" auction for this benchmark is uninteresting

Classic Optimal Auctions

Example: 1 bidder, 1 item, v ~ known distribution F

- want to choose optimal reserve price p
- expected revenue of p: p(1-F(p))
 - given F, can solve for optimal p^{*}

• e.g.,
$$p^* = \frac{1}{2}$$
 for v ~ uniform[0,1]

but: what about k,n >1 (with i.i.d. v_i's)?

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- need minor "regularity" condition on F
- but: what about k,n >1 (with i.i.d. v_i 's)?

Theorem: [Myerson 81] auction with max expected revenue is second-price with above reserve p^{*}.
note p^{*} is *independent of k and n*

Prior-Independent Auctions

New goal: [Dhangwatnotai/Roughgarden/Yan EC 10] prove results of the form:

"Theorem: for every distribution D: $E_{v\sim D}[rev(A(v))] \ge (E_{v\sim D}[rev(OPT_{D}(v))])/a"$ (for a hopefully small constant a)

Prior-Independent Auctions

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"Theorem: for every distribution D (in some set C): $E_{v\sim D}[rev(A(v))] \ge (E_{v\sim D}[rev(OPT_D(v))])/a"$ (for a hopefully small constant a)

Interpretation of C: provides knob to tune "optimality vs. robustness" trade-off.

 a single auction that is simultaneously near-optimal across many average-case settings.

Bulow-Klemperer Theorem

Setup: single-item auction. Let D be a valuation distribution. [Needs to be "regular".]

Theorem: [Bulow-Klemperer 96]: for every n≥1:

E[2nd-price revenue] E[OPT_D's revenue]

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Usual interpretation: small increase in competition more important than running optimal auction.
Also: 2nd-price ≈ a good prior-independent auction!

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Part III: Complexity of Computing Equilibria

- *Computing Nash equilibria is PPAD-complete*
- Interpretations and open questions

Reference

 T. Roughgarden, Computing Equilibria: A Computational Complexity Perspective, survey for Economic Theory, 2010.

Example: Prisoner's Dilemma

	cooperate	defect
cooperate	5, 5	0, 10
defect	10, 0	1, 1

Example: Prisoner's Dilemma



Example: Penalty Kick Game



Example: Penalty Kick Game



(unique) Nash equilibrium: kicker and goalie each pick a strategy uniformly at random

The 2-Nash Problem

Input: a bimatrix game (one pair of integer payoffs per entry of an m×n matrix). (Nash 51] or by Lemke-Howson algorithm Output: a Nash equilibrium. (any one will do)

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Question: How to amass evidence of intractability?

The 2-Nash Problem

- Input: a bimatrix game (one pair of integer payoffs per entry of an m×n matrix). [Nash 51] or by Lemke-Howson algorithm
- Output: a Nash equilibrium. (any one will do)
- Fact: no polynomial-time algorithm is known.
- Question: How to amass evidence of intractability?
- NP-hard?: Not unless NP=coNP.
 - decision version is trivial, only search version is hard







Answer: PPAD [Papadimitriou 90]





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Theorem: [Chen/Deng/Teng 06], extending [Daskalakis/ Goldberg/Papadimitriou 05] 2-Nash is PPAD-complete.



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Question: That's a great result. But how hard is PPAD, really?

Is PPAD Intractable?

Evidence of intractability (FP≠PPAD):

- several very smart people have worked on a few complete problems
- oracle separation [Beame/Cook/Edmonds/ Impagliazzo/Pitassi 98], black-box lower bounds for fixed points [Hirsch/Papadimitriou/Vavasis 89]

But: no known "complexity earthquakes" if FP=PPAD ("just" a bunch of new poly-time algorithms for several tough problems).



Is PPAD Intractable?

Possible research directions:

- find a subexponential-time algorithm for the 2-Nash problem
- relate PPAD-hardness to better-understood hardness notions (existence of one-way functions?)
- relate PPAD (or PLS, etc.) to BQP
- potentially easier for positive results: approximate Nash equilibria (solvable in n^{O(log n)} time [Lipton/Markakis/Mehta 03])
- convincing implications for economic analysis?



Conclusions

Algorithmic Mechanism Design

- intractability from joint computational, incentive constraints
- new direction: "Bayes-Nash" implementations

Revenue-Maximizing Auctions

- Interpolation of worst-case, average-case analysis
- When are good prior-independent auctions possible?

Complexity of Computing Equilibria

- How hard is PPAD?
- Stronger connections to economic analysis?