Incentive Engineering in the Internet Age

David C. Parkes
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Mechanism design theory

- Leonid Hurwicz (1960, 1972)
  - communication system, incentive compatibility
Mechanism design theory

- Leonid Hurwicz (1960, 1972)
  - communication system, incentive compatibility
- Eric Maskin (1977)
  - Nash implementation
Mechanism design theory

- Leonid Hurwicz (1960, 1972)
  - communication system, incentive compatibility
- Eric Maskin (1977)
  - Nash implementation
- Roger Myerson (1979, 1981)
  - Bayesian mechanism design
What can be achieved, in principle, by a market system despite agent self interest and private information?
Example: Median Mechanism
(Moulin’80)
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(Moulin’80)
Example: Median Mechanism  
(Moulin’80)
Example: Single item auction
(Vickrey’61)
Direct Revelation Mechanism

(Hurwicz’60, ’72)

agents \( \theta_1, \ldots, \theta_N \)

\( M \)

outcome rule \( f(\theta) \)

payments

\( \theta \) types
Rules of Encounter
(Rosenschein and Zlotkin 1994; Ephrati and Rosenschein AAAI‘91)

• “As distributed systems of computers play an increasingly important role in society, it will be necessary to consider ways in which these machines can be made to interact effectively…”
Rules of Encounter
(Rosenschein and Zlotkin 1994; Ephrati and Rosenschein AAAI‘91)

• “As distributed systems of computers play an increasingly important role in society, it will be necessary to consider ways in which these machines can be made to interact effectively… Adjusting the rules of public behavior (the rules of the game) by which the programs must interact can influence the private strategies that designers set up in their machines.”
“Maybe I can bid as high as $0.21...”
• “… they’ll pay programmers to develop sophisticated models of their opponents’ bidding strategies… put energy into trying to discover relevant information about their opponents…

    Ultimately, this sort of effort drains resources that might be better spent elsewhere…”
Task negotiation

Agents will flip a coin to decide who delivers all the letters.
Task negotiation

Post Office

They then agree that agent 2 delivers to f and e.
An Economics View
(Varian 1995)

• “… hyper-rationality may actually be [an] appropriate model for software agents…

  The whole framework of game theory and mechanism design may well find its most exciting and practical application with computerized agents rather than human agents.”
Early Sponsored Search
(Goto 1998)

• Bids are *per click* on a search keyword
• Rank by bid. First price.

$12  pay $12
$10
$6

Autobidders: Bid minimal amount to maintain current position
Churn...
(Edelman and Ostrovsky, 2007)
Fix: Generalized Second Price

pay $10 → $12
pay $6 → $10
... → $6

Stability (not full SP)
(1) user relevance, (2) revenue, (3) ad quality
World Design for Self-interested Agents
Mechanism = Algorithm
Example: Combinatorial Auction
(Rassenti, Smith and Bulfin, 1982)
Good Progress

• Compact and expressive bidding languages
  – e.g., OR-of-XOR (Sandholm’99), OR* (Fujishima et al.’99, Nisan’00), $L_{GB}$ (Boutilier & Hoos ’01)

• Scalable winner determination
  – exact algorithms via heuristic search (Fujishima et al.’99, Sandholm’99)
  – tractable special cases (Rothkopf et al.’98)

• Preference elicitation
  – iterative CAs (Parkes & Ungar’00), learning theory (Lahaie & Parkes’04), querying (Hudson & Sandholm’03)
  – regret-based methods (Hyafil & Boutilier’06)
An “EconCS” agenda
(Nisan and Ronen’99, Lehmann et al.’99)

- Can’t just substitute heuristic algorithms into mechanisms and retain strategyproofness
- Led to a cottage industry in “algorithmic mechanism design”
  - Econ: incentive constraints
  - CS: computational constraints
- Exciting progress
Reasoning about SP mechanisms is hard 😞
SP

econ optimal

constrained AMD
(Likhodedov and Sandholm ’04, Guo & Contizer ’08)

poly time, best approx ratio
Heuristic MD

state-of-art computational approach
Example: Dynamic Knapsack

m concert tickets to sell. probabilistic model
Agent type: quantity, value, \([a,d]\) interval

ONLINE STOCHASTIC COMBINATORIAL OPTIMIZATION
(van Hentenryck and Bent’06)

exogenous uncertainty
(P. & Duong ‘07, Constantin & P.’09)

inputs → OSCO → \( g^t(v^{1..t}) \) → \( x^t \)

samples

model

monotonicity
(P. & Duong ‘07, Constantin & P.’09)

inputs → OSCO → PAY

\[ g^t(v^{1..t}) \]

samples → model

monotonicity

critical value

\[ x^t, p^t \]
(P. & Duong ‘07, Constantin & P.’09)

inputs \xrightarrow{\text{OSCO}} \quad \text{check} \quad \xrightarrow{\text{PAY}} \quad x^t, p^t

samples \xrightarrow{\text{model}} \quad \text{critical value} \quad \text{sensitivity analysis}

performance (eff):
81.5\% best fixed price
89.5\% OSCO + ironing
95.2\% OSCO

Parkes
AAAI’10
Relaxing away from SP…

• We like SP for reasons of
  – equity (Roth’03, Pathak and Sonmez’08)
  – simplify reasoning
  – can predict properties of the mechanism
Relaxing away from SP...

• We like SP for reasons of
  – equity (Roth’03, Pathak and Sonmez’08)
  – simplify reasoning
  – can predict properties of the mechanism

• But it is generally hard to obtain

• And, can be provably bad along other dimensions 😞
  • e.g., CAs with complements
    (Ausubel & Milgrom’06, Rastegeri, Condon, & Leyton-Brown’10)
Approx Incentive Alignment

• A satisfactory answer will:
  – allow for comparison of mechanisms
  – allow for a larger design space
  – still provide predictable behavior
Old Favorite: Min Max Regret

- Regret = best utility – actual utility
- Maximally SP: minimizes max regret across agents on every instance
- $\epsilon$-SP: max regret $\leq \epsilon$
Example: Comb. Exchange

• Airlines buying and selling landing slots
Example: Comb. Exchange

- Airlines buying and selling landing slots

- $p_{vcg,i} = \text{bid} - \text{marginal contribution} (\Delta_{vcg})$
Example: Comb. Exchange

- Airlines buying and selling landing slots

- $p_{vcg,i} = \text{bid} - \text{marginal contribution} = (\Delta_{vcg} )$

- Runs at a deficit in a CE 😞
- Impose $\sum p_i \geq 0$
Two mechanism rules
(Parkes, Kalagnanam and Eso ‘01)
Two mechanism rules

(Parkes, Kalagnanam and Eso ‘01)

\[ \Delta_{vcg} \]

Threshold rule
(min max regret)

Small rule
max #(regret=0)
# Approximate BNE Analysis

(Lubin & Parkes ’09)

<table>
<thead>
<tr>
<th>Rule</th>
<th>strategy</th>
<th>efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>VCG</strong></td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Two Triangle</td>
<td>0.1</td>
<td>0.4</td>
</tr>
<tr>
<td>Threshold</td>
<td>14.6</td>
<td>27.2</td>
</tr>
<tr>
<td>Small</td>
<td>0.0</td>
<td>0.1</td>
</tr>
<tr>
<td>No Discount</td>
<td>62.3</td>
<td>80.9</td>
</tr>
</tbody>
</table>

(For BNE, see Vorobeychik & Wellman’08, Rabinovich, Gерding, Polukarov & Jennings’09)
Distributional View: Payoffs

Discount Distribution by Rule

"reference mechanism"
KL-divergence\((\pi, \pi_{v cg})\)
correlates to BNE/EFF
Regret Quantiles

Inverse CDF of Available Gain

look at $F(\text{regret} \leq \epsilon)$ and max regret
From Events to Platforms

- eBay, sponsored search, display advertising on Facebook, etc. are all *dynamic* problems:
  - Dynamic population
  - Learning by agents
  - Learning by the mechanism
  - Uncertain supply

- Need incentive engineering to coordinate “always on” dynamic systems
Loosely coupled MDPs
Theory: Dynamic VCG

• **Support Optimal MDP policies**

• **With dynamic population, static types**
  – *includes dynamic Cas*
  – P. & Singh ‘03, P., Singh & Yanovsky’04

• **With static population, dynamic types**
  – *includes Bayesian optimal learning*
  – Bergemann & Valimaki ’08

• **Unified view**
  – Cavallo, P. & Singh’09
Skill Acquisition Example

(Cavallo & Parkes’08)

EV=11.1

\[ \beta = 0.75 \]
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\[ \beta = 0.75 \]

\[ \text{payment } (1 - \beta) 11.1 = 2.78 \]
Skill Acquisition Example

(Cavallo & Parkes’08)

EV = 11.1

payment

(1 - β) 11.1 = 2.78

β = 0.75
Skill Acquisition Example

(Cavallo & Parkes’08)

EV=11.1

payment \((1-\beta)8 = 2\)

\(\beta = 0.75\)

EV=18

payment \((1-\beta)11.1 = 2.78\)

\(\beta = 0.75\)
Skill Acquisition Example

(Cavallo & Parkes’08)

$$EV=11.1$$

$$\beta = 0.75$$

$$payment \ (1-\beta) \ 11.1 = 2.78$$
Skill Acquisition Example

(Cavallo & Parkes'08)

\[ EV = 11.1 \]

1/2

6

\[ (1 - \beta) \times 8 = 2 \]

1/2

2

payment

1/2

6

40

\[ \beta = 0.75 \]

1/2

0

EV = 18

1/2

8

1/2

40

payment

11.1 = 2.78 + 6 = 8.78

Parkes

AAAI'10
Dynamic-VCG: Scaling-up

• Need optimal-in-range policies

$$\pi^* \in \arg \max_{\pi \in \Pi} V^\pi(s)$$

⇒ an interesting meta-problem

(see Gerding, Stein, Larson, Rogers & Jennings’10)
Back to tasks...

They then agree that agent 2 delivers to f and e.
Crowdsourcing Platforms

- **Amazon Mechanical Turk**
  - online labor market for “human intelligence tasks” (e.g., data cleaning)

- **InnoCentive** (innovation marketplace)
  - 150+ seekers, 180,000+ solvers, $$ prizes
  - 900+ challenges
  - e.g., “Sustainable Packaging for Developing World”

- **TopCoder** (code development)
  - 250,000+ workers, $$ to first and second-best
  - e.g., NASA/HBS/LBS “MedKit optimization”
The Longitude Prize
http://www.nmm.ac.uk/harrison

• Royal Observatory
  – founded in 1675 to solve the “longitude problem”
  – sailors could measure local time from sun, with an accurate reference time, could compute longitude
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- Royal Observatory
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- Won by John Harrison (1693-1776)
  - started work in 1730, awarded prize at age 79 in 1773
But rapid integration of partial solutions from multiple sources is new
NetFlix Prize
When Gravity and Dinosaurs Unite

\[ y(x) = g(y_1(x), \ldots, y_K(x)) \]

meta-features

www.the-ensemble.com

~volinsky/netflix/bpc.html

Grand Prize Team

(Fall 2007)

When Gravity and Dinosaurs Unite

(Jan 2009, share 2/3 prize for final 1% improvement)

Gravity

Dinosaur Planet

+0.21% Bertino
+0.14% Sill
+0.06% Nabutovsky
+0.08% Sill
+0.19%

June 26, 2009

Opera Solutions

The Ensemble +0.43%

Vandelay Industries!

=10.10% improvement
July 26, 2009

Parkes

AAAi’10
DARPA “Red Balloons”

- Ten 8’ red balloons, 30.5 m in air
- $40,000 prize (for latitude and longitude)
- Competition @ 10am, December 5, 2009
DARPA “Red Balloons”

- Ten 8’ red balloons, 30.5 m in air
- $40,000 prize (for latitude and longitude)
- Competition @ 10am, December 5, 2009
- Won by 6:52pm!
MIT: Recursive Incentive Scheme

Recruited 5,400 individuals in 36 hours
One-time “supply chain”

![Recursive Incentive Scheme Diagram]

Anmol Madan, Galen Pickard, Riley Crane, Alex ("Sandy") Pentland, Wei Pan, and Manuel Cebrian
Environment Design

(Zhang & Parkes’08)
Role for AI

AI + crowdsourcing \approx A New Kind of Firm

finally put the AI into the mechanical Turk?
Example: TopCoder

- Workers on TC get a score for a submission
  - correctness, docs, flexibility, extendability
  - combines to an aggregate “coder rating”
Example: TopCoder
(Archak’10)

- Workers on TC get a score for a submission
  - correctness, docs, flexibility, extendability
  - combines to an aggregate “coder rating”
- Skilled contestants tend to enter early
  - an implicit coordination mechanism
  - signaling game
Generalized Task Markets
(Shahaf & Horvitz’10)
Example: Language Translation
(Shahaf & Horvitz’10)

- 388 participants, 70 countries, random trans. tasks
- Assign tasks to coalitions to maximize final quality while respecting capacity constraints
Example: Policy Teaching
(Zhang & Parkes’08, Zhang, Parkes & Chen’09)

$\text{MDP} \quad \text{observe} \quad \pi \quad \text{perturb} \quad R \rightarrow R + \Delta \quad \text{Target policy} \quad \pi_T$
Example: Policy Teaching
(Zhang & Parkes’08, Zhang, Parkes & Chen’09)

MDP  observe $\pi$  perturb $R \rightarrow R + \Delta$  Target policy $\pi_T$

$\text{IRL} \cap \text{IRL}^\pi_T(B)$

$(R + \Delta) \in \text{IRL}^{\pi'}$

Multi-agent Policy Teaching?
(Rabinovich, Dufton, Larson & Jennings’10)
“target earnings” shows preference for amounts divisible by 5 cents.
Hutong Karma

By midmorning, the vendors are out. They pedal through the alley on three-wheeled carts, each announcing his product with a trademark cry. The beer woman is the loudest, singing out again and again, ”Maaaaiiiiii piiiijuuuuuuu!”... The rice man’s refrain is higher-pitched; the vinegar dealer occupies the lower registers. ... The sounds are soothing, a reminder that even if I never left my doorway again life would be sustainable, albeit imbalanced. I would have cooking oil, soy sauce, and certain vegetables and fruit in season. In winter, I could buy strings of garlic. ...

On an average day, a recycler passes through every half hour, riding a flat-bed tricycle. ... Not long ago, I piled some useless possessions in the entryway of my apartment ... A stack of old magazines sold for sixty-two cents; a burned-out computer cord went for a nickel. Two broken lamps were seven cents, total. A worn-out pair of shoes: twelve cents. Two broken Palm Pilots: thirty-seven cents.

Computational Sustainability through “Sharing Markets”
Sharing Markets

• Goal: use AI and electronic markets to transform our use of resources
• Support “microtransactions”.
• For well functioning systems, need for:
  – scrip (Friedman, Halpern & Kash’06)
  – reputation (Friedman, Resnick & Sami’07)
  – accounting (Seuken, Tang & Parkes’10)

... and handle complexity!
Hidden Markets
(Seuken, Jain, Tan & Czerwinski ’10, Seuken, Jain & Parkes’10)
Hidden Markets
(Seuken, Jain, Tan & Czerwinski ’10, Seuken, Jain & Parkes’10)

Example: P2P backup

UI Design

Market Design
Summary

• MD theory is beautiful but severely stretched by Internet scale systems
• Provide useful formalism, but to make real progress in AI we’ll need to move beyond
• Emphasized here three things:
  – heuristic approaches for MD
  – dynamic coordination opportunities
  – future: intelligent task and sharing markets
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www.eecs.harvard.edu/econcs
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