Payment Rules through Discriminant-Based Classifiers

by Paul Dütting, Felix Fischer, Pichayut Jirapinyo, John K. Lai, Benjamin Lubin and David C. Parkes

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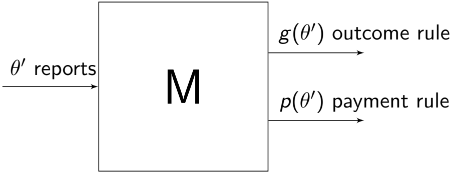
Classical Approach for Mechanism Design

Classical Approach



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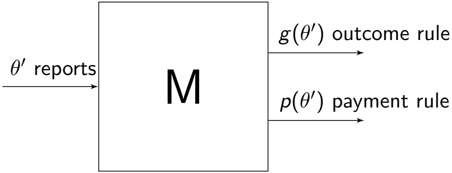
1. Impose incentive compatibility (IC) constraint (DSIC, BNIC)



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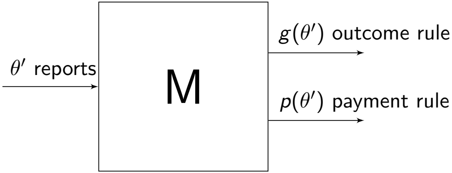

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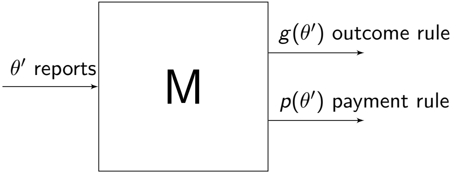

Challenges

- Analytical Complexity
- Exclusion of Mechanisms
- Computational Complexity

New Approach for Mechanism Design

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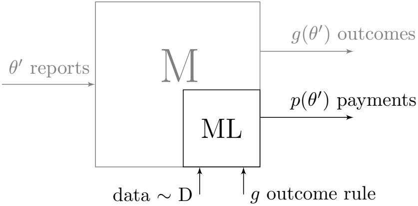

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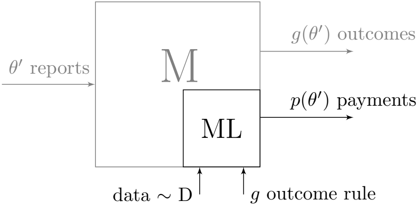

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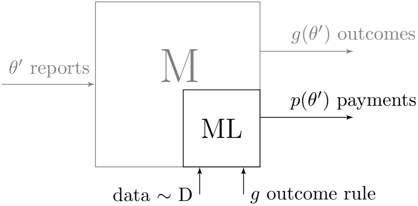
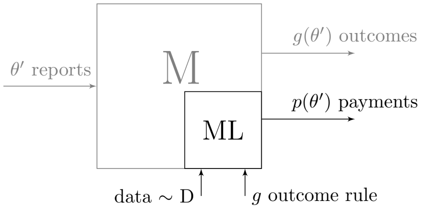


New Approach for Mechanism Design

New Approach

1. Define an outcome rule g (e.g. optimal outcome rule)
2. Sample data from a type distribution D
3. Use *Machine Learning (ML)* to find a payment rule p that minimizes ex-post regret



Ex-Post Regret

ex-post regret an agent has for truthfully reporting in a given instance is the amount by which its utility could be increased through a misreport.

$$rgt_i(\theta_i, \theta'_{-i}) = \max_{\theta'_i \in \Theta_i} \underbrace{u_i((\theta'_i, \theta'_{-i}), \theta_i)}_{\text{utility misreport}} - \underbrace{u_i((\theta_i, \theta'_{-i}), \theta_i)}_{\text{utility truthful report}}$$

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- $\mathbb{E}(gain) < cost(\text{strategic behaviour})$ → *agents are assumed to report truthfully*

Payment Rules from Multi-Class Classifiers

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$$h_w(x) \in \arg\max_{y \in Y} f_w(x, y)$$

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Discriminant-Based Classifier: $h_w(\theta) \in \arg\max_{o_i \in \Omega_i} \; w_i v_i(\theta_i, o_i) \quad + \quad w_{-i}^T \psi(\theta_{-i}, o_i)$

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Payment Rule

$$p_w(\theta) = (t_w(\theta_{-1}, g_1(\theta)), t_w(\theta_{-2}, g_2(\theta)), ..., t_w(\theta_{-n}, g_n(\theta)))$$

Truthful Mechanisms with a Perfect Classifier

Theorem (3.2)

Let g be an agent symmetric outcome rule, h_w an admissible classifier, and p_w the payment rule corresponding to h_w. If h_w is a perfect classifier for the partial outcome rule g_1, then the mechanism (g, p_w) is strategyproof.

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But what happens when $\mathrm{h_w}$ **is not a perfect classifier?**
minimizing *generalization error* of the classifier $\Rightarrow$
minimizing *expected ex-post regret* of the mechanism.

Example: Single Item Auction

Discriminant-Based Classifier: $h_w(\theta) \in \arg\max_{o_1 \in \Omega_1} w_1 v_1(\theta_1, o_1) \; + \; w_{-1}^T \psi(\theta_{-1}, o_1)$

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the outcome matching the outcome rule of the *Single Item Auction*

$$g_1(\theta) = \begin{cases} \textit{allocate} & \text{if} \quad \text{agent 1 has the highest bid} \\ \textit{not allocate} & \text{else} \end{cases}$$

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plugging this into the associated price function $\rightarrow$ second price payment rule

$$t_w(\theta_{-1}, o_1) = -\frac{1}{w_1} w_{-1}^T \psi(\theta_{-1}, o_1) = max(\theta_{-1})$$

Example: Single Item Auction Instance

$$h_w(\theta) = \arg\max_{o_i} \underbrace{1 * v_i(\theta_i, o_i)}_{\text{left part}} + \underbrace{\begin{cases} -max(\theta_{-1}) & \text{if } o_i = 1 \\ 0 & \text{if } o_i = 0 \end{cases}}_{\text{right part}}$$

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	Outcome	Left Part	Right Part	Classifier	Optimal
Agent 1	$o_1 = 1$				
	$o_1 = 0$				
Agent 2	$o_2 = 1$				
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Agent 1	$o_1 = 1$	$v_1(\theta_1, 1) = 6$			
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Agent 2	$o_2 = 1$	$v_2(\theta_2, 1) = 8$			
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	$o_1 = 0$	$v_1(\theta_1, 0) = 0$	0	$0 - 0 = 0$	
Agent 2	$o_2 = 1$	$v_2(\theta_2, 1) = 8$	6	$8 - 6 = 2$	
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Structural Support Vector Machine (SSVM)

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Learn weight vector w by training SSVM using:

$$\text{training data: } \{(\theta^1, o_1^1), (\theta^2, o_1^2), ..., (\theta^\ell, o_1^\ell)\}$$

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SSVM Optimization Problem

$$\begin{aligned}
\underset{w,\xi}{\text{minimize}} \quad & \frac{1}{2}\|w\|^2 + \frac{C}{\ell}\sum_{k=1}^{\ell}\xi^k \\
\text{subject to} \quad & (w_1 v_1(\theta_1^k, o_1^k) + w_{-1}^T \psi'(\theta_{-1}^k, o_1^k)) - (w_1 v_1(\theta_1^k, o_1) + w_{-1}^T \psi'(\theta_{-1}^k, o_1)) \\
& \geq \mathcal{L}(o_1^k, o_1) - \xi^k \text{ , } \forall k = 1, ..., \ell \text{ , } o_1 \in \Omega_1 \\
& \xi^k \geq 0 \text{ , } \forall k = 1, ..., \ell
\end{aligned}$$

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Remarks

Valid Price Function if $w_1 > 0$

Flexible Payment Structure with ψ

Problems of the computed Payment Rule

Negative Payments

computed payments p_w can be negative $\rightarrow$ normalize payments

Violation of Individual Rationality

truthful report leads to *utility* < 0 $\rightarrow$

- introduce payment offsets
- adjust the loss function $\mathcal{L}$
- introduce deallocation

Multi-Minded Combinatorial Auctions

Multi-Minded CAs

- r items $\{A, B, ...\}$
- n agents $\{1, 2, ..., n\}$
- express valuation for bundles
- each agent interested in at most b bundles

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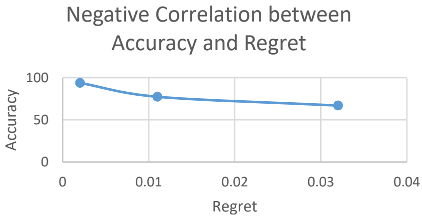
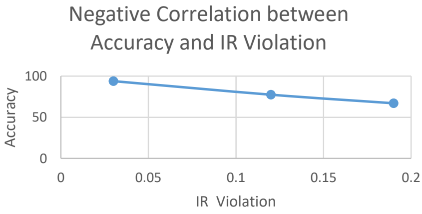
In Terms of the Framework

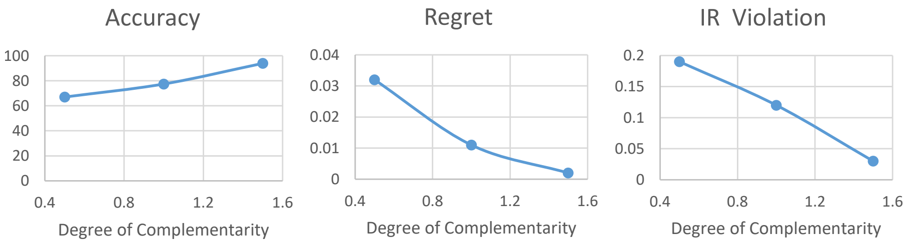
- type $\theta_i = (v_i(\emptyset), v_i(A), v_i(B), v_i(C), v_i(AB), v_i(AC), v_i(BC), v_i(ABC))$
- type profile $\theta = (\theta_1, \theta_2, ..., \theta_n)$
- outcome $o_1 = 101$
- type distribution D with parameter to control correlation and complementarity between items

Correlation between Accuracy and Regret / IR Violation





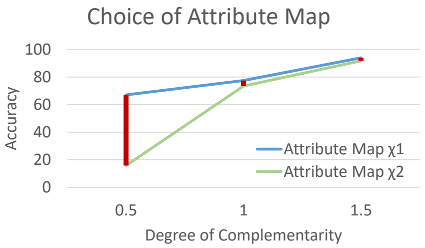
Degree of Complementarity

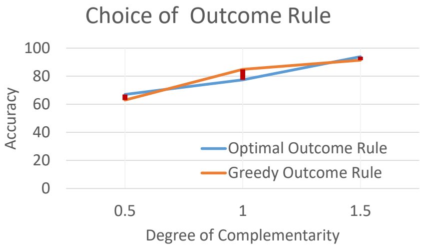


low degree of complementarity: $v(AB) \approx v(A) + v(B)$

high degree of complementarity: $v(AB) \gg v(A) + v(B)$

Choice of Outcome Rule and Attribute Map





Training Set Size and IR Fixes

Training Set Size: more training data leads to better results

IR Fixes:

$$\left.\begin{array}{l}\text{- payment offset}\\ \text{- adjusting loss function}\\ \text{- introducing deallocation}\end{array}\right\}\text{IR - Violation}\downarrow \qquad \text{Regret}\uparrow$$

Conclusion

Challenges of Classical Mechanism Design

- Analytical Complexity
- Exclusion of Mechanisms
- Computational Complexity

Conclusion

Challenges of Classical Mechanism Design

- Analytical Complexity
- Exclusion of Mechanisms
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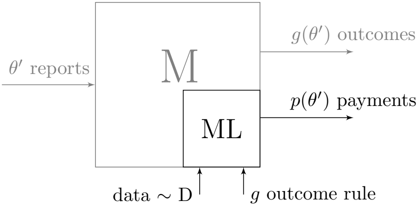
Conclusion

- introduce new paradigm for computational mechanism design
- shown encouraging experimental results
- further directions of interest that have to be investigated in the future

Discussion - Overview

New Approach



Remarks

- train a classifier for the outcome
- use special structure of the classifier to extract a payment rule
- the better the classifier for the given outcome rule, the less incentive an agent has for not reporting truthfully