Dynamic Resource Allocation to Strategic Agents under Cost Constraints

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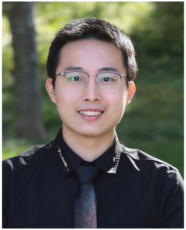

(project overseen by Prof. Negin Golrezaei and Prof. Patrick Jaillet)

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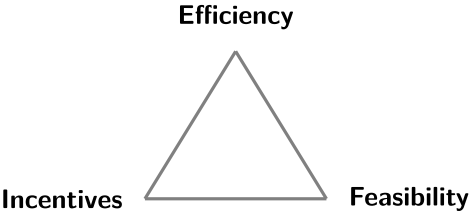
Question. Can all three be achieved simultaneously?

No “3-in-1” Approach in the Literature



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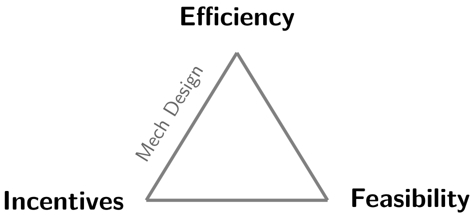

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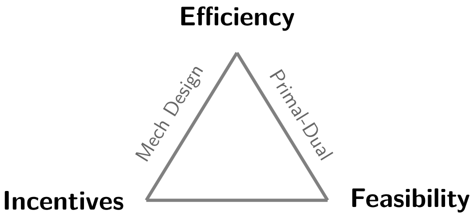

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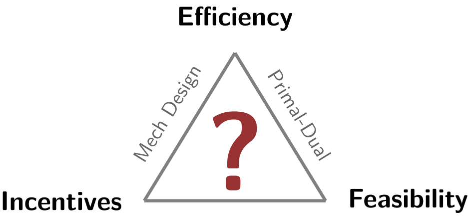
- **Efficiency + Incentives + Feasibility? No** unless super restrictive assumptions (*e.g.*, homogeneous agents [Yin et al., 2022] & "fair share"-like constraints & non-social-welfare objective [Gorokh et al., 2021]) **"Impossible triangle"?**



Standard Methods Fail: The Strategic Gap

Standard Primal-Dual Methods

Decide *dual* $\boldsymbol{\lambda}_1, \ldots, \boldsymbol{\lambda}_T$ ("shadow prices" for cost constraints)
Give dual-adjusted *primal allocation* ($\tilde{i}_t^* := \text{argmax}_i(v_{t,i} - \boldsymbol{\lambda}_t^\mathsf{T} \boldsymbol{c}_{t,i})$)

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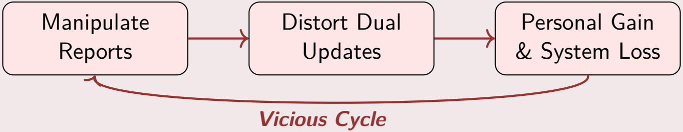

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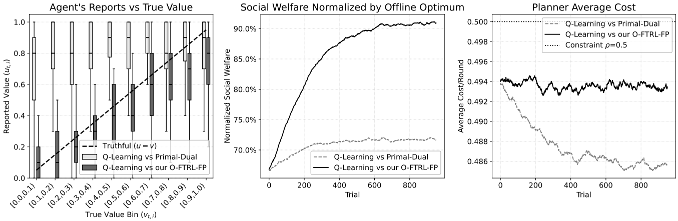
Manipulate Reports → Distort Dual Updates → Personal Gain & System Loss → Manipulate Reports

Vicious Cycle



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Main Result: $\widetilde{\mathcal{O}}(\sqrt{T})$ Social Welfare Regret & 0 Constr Violation

Regret. $\mathbb{E}[\sum_t (v_{t,i_t^*} - v_{t,i_t})] = \widetilde{\mathcal{O}}(\sqrt{T})$ ($\{i_t^*\} :=$ offline optimum)
Constr Violation. $\frac{1}{T} \sum_t \boldsymbol{c}_{t,i_t} \le \boldsymbol{\rho}$ *a.s.* (0 constraint violation)

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Theorem. $\widetilde{\mathcal{O}}(1)$ misreports & $\widetilde{\mathcal{O}}(1)$ misallocations per epoch

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Novel Online Learning Framework: O-FTRL-FP

Equip Optimistic FTRL [Rakhlin and Sridharan, 2013] with **Fixed Points**

Allow action-dependent predictions: If round-t loss func $f_t(x)$ depends on round-t action x_t, we allow $\hat{f}_t(x; x_t)$-style predictions instead of only $\tilde{f}_t(x)$

Main Results & Takeaway

Main Contribution

First dynamic mechanism achieving the **trilemma**:

- **Efficiency.** Optimal $\widetilde{\mathcal{O}}(\sqrt{T})$ regret (matching non-strategic LB)
- **Incentives.** Robust to strategic agents ($\exists$ near-truthful PBE)
- **Feasibility.** Zero constraint violation (with probability 1)

Key Techniques

- **Incentive-Aware Primal Allocations.** Novel mixture of lazy updates, uniform exploration, & dual-adjusted payments
- **Dual Learning via Predictions.** Truthful $\Rightarrow$ predictability (nearly) & novel O-FTRL-FP framework for online learning

Questions are more than welcomed!

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