Adaptive Incentive Design with Regret Minimization

24th European Control Conference, Reykjavík, Iceland

Georgios Vasileiou, Lantian Zhang, Prof. Silun Zhang

Motivation: Strategic Participation in the Control Loop

Cyber-physical systems interact with **strategic participants** $\rightarrow$ humans, firms, algorithms.

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Congestion control

Power-grid operation

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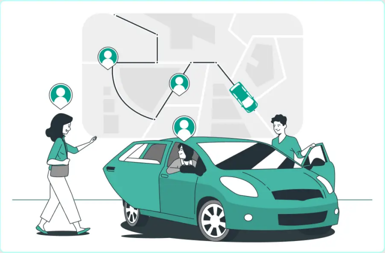
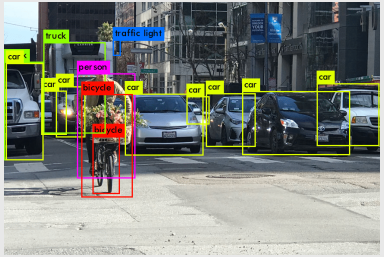


Ride-sharing markets



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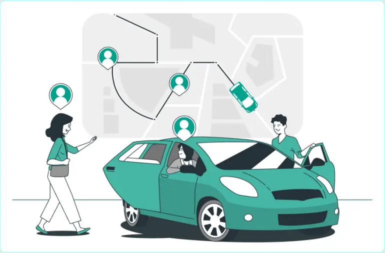

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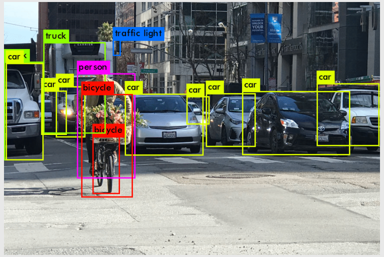

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- Self-interested agents
- **Indirectly influenced** $\rightarrow$ incentives

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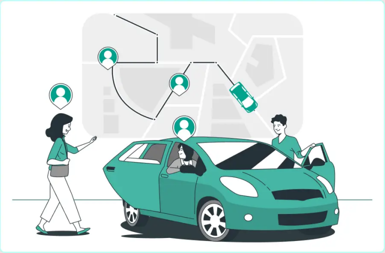

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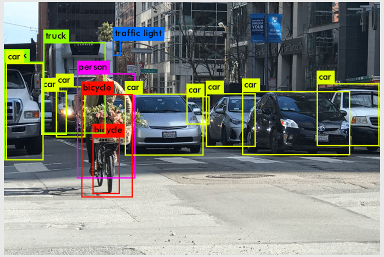

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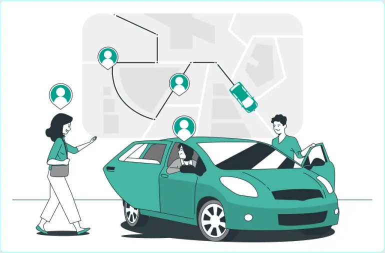

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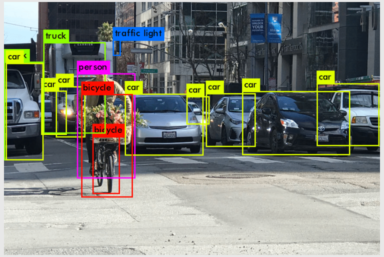

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Adaptive Control

Adaptive Incentive Design:
How do we choose incentives to steer agents to desirable outcomes?

Contents

Incentive Design Problems

Social cost Ψ
x: agent decision
u: payments

System Planner
$\min_{x\in\mathcal{X},u\in\mathbb{R}^n} \Psi(x,u)$

Agents
$\min_{x_i\in\mathcal{X}_i} \quad \ell_i(x)$

Zheng, Basar, *Existence and Derivation of Optimal Affine Incentive Schemes for Stackelberg Games with Partial Information*, Int J Control, 1982

Incentive Design Problems

System Planner

$\min_{x \in \mathcal{X}, u \in \mathbb{R}^n} \Psi(x, u)$

1 Announce

Contract γ

Agents

$\min_{x_i \in \mathcal{X}_i} \; (\ell_i(x) + \gamma_i(x))$

2 Competition

$x^* = \text{NE}\ (\gamma)$

$u^* = \gamma(x^*)$

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Reverse Stackelberg Game:
Choose $\gamma^* \in \mathcal{G}$: $(x^*, u^*) \in \arg\min_{(x,u)} \Psi(x,u)$

If ℓ_i are known,
Reverse Stackelberg game is one-shot solvable
(though optimizing over $\mathcal{G}$ is hard.)

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Adaptive Incentive Design: Closing the loop

$\hat{\Theta}_t$

System Planner

$\min_{x \in \mathcal{X}, u \in \mathbb{R}^n} \Psi(x, u)$

Estimator

$\hat{\Theta}_t = F_t(x_t^*, \gamma_t, \hat{\Theta}_{t-1})$

3

1 Announce

Contract γ_t

Agents

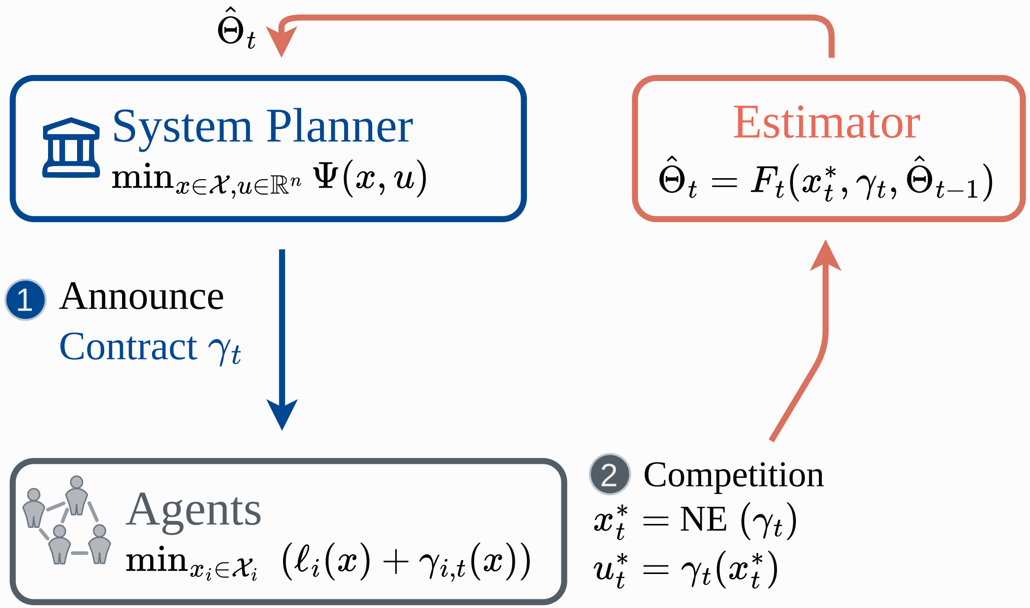
$\min_{x_i \in \mathcal{X}_i} \ (\ell_i(x) + \gamma_{i,t}(x))$

2 Competition

$x_t^* = \text{NE}\ (\gamma_t)$

$u_t^* = \gamma_t(x_t^*)$

Adaptive Incentive Design: Closing the loop



3

Design parameters:

1) **Estimator** $(\gamma_t, x_t^*) \mapsto \hat{\Theta}_t$
2) **Policy** $\hat{\Theta}_t \mapsto \gamma_{t+1}$

Adaptive Incentive Design:
Perform estimation + mechanism design over an unknown game, in feedback so that

$$\gamma_t \xrightarrow{t} \gamma^*$$

Connection to Literature

Relation to various perspectives

- **Stackelberg / Reverse Stackelberg Games.**
  - (Fudenberg et al., MIT Press, 1991) | Hierarchical leader-follower structure
  - (Ho et al., Automatica, 1982), (Basar et al., IEEE TAC, 1979) | Feedback, incentive controllabiltiy, credibility
  - (Jing et al., Springer, 1988), (Ho et al., IEEE TAC, 1981) | Information structure, multi-follower systems, and others...
- **Inverse Game Theory/ Inverse Variational Inequalities / Utility Learning.**
  - (Kuleshov et al., IEEE Conf WINE, 2015) | Consistent equilibria in succinct games
  - (Bertsimas et al., Mathematical Programming Ser. A, 2015) | Data-driven estimation of VI map
  - (Varian, Economic Journal, 2006) | Rationalizable behavior, axioms of revealed preference

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- **Equilibrium Steering and Stackelberg Learning** (recent, relevant)
  - (Ratliff et al., IEEE TAC, 2021) | *Adaptive incentive design*: Parametric cost identification as least-squares
  - (Balcan et al., ACM Conf Econ Comp, 2015), (Lauffer et al., IEEE TAC, 2024), | No-regret policies on finite preference or action spaces.
  - (Yorulmaz et al., CDC, 2025) | Equilibrium steering in Bayesian normal-form games
  - (Zhang et al., ACM Conf Econ Comp, 2024), (Zhang et al., ICLR, 2026) | Identification and steering in extensive form games with no-regret learners

Contents

Agents' Game

Agents minimize $\quad c_i^{\gamma}(x) = \ell_i(x_i, x_{-i}) + \gamma_i(x_i, p_i)$ subj. to $x_i \in \mathcal{X}_i$

Nominal costs

- **Convex game:** ℓ_i is C^2, convex and
- (Assumption) **Strongly Monotone.**
- Parameterization of agent costs

$$\frac{\partial \ell_i(x)}{\partial x_i} = \theta_i^{*\top} \Phi(x), \ \ \Phi(\cdot) \text{ monomial basis.}$$

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Affine incentives

$$\gamma_i(x_i, p_i) = p_i(x_i - x_i^{\dagger}) + \text{constant},$$

$x_i^{\dagger}$: planner's target.

Lemma (GV, LZ, SZ):
Under strong monotonicity, affine incentives are **point-wise optimal** in

$$\mathcal{G} = \{\gamma : C^2, \text{ separable, convex in } x_i\}$$

G. Vasileiou, L. Zhang, S. Zhang, *A No-Regret Framework for Adaptive Incentive Design*, Preprint arXiv:2606.02529, 2026.

Planner's Performance

Compared to an oracle

- Objective $\min \Psi(x,u)$ s.t. $x \in \mathcal{X}$, $u \in \mathbb{R}^n$ $\quad \rightarrow \quad (x^\dagger, u^\dagger) \in \operatorname{int} \mathcal{X} \times \mathbb{R}^n$
- In T rounds of interaction, the **regret of policy** $\{p(t)\}_{t=1}^T$ is

$$\mathcal{R}_T := \sum_{t=1}^{T} \left(\Psi(x(t), u(t)) - \Psi(x^\dagger, u^\dagger) \right)^2.$$

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RAID Problem: Design

$$\hat{\Theta}(t) = F_t\left(p(t), x(t), \hat{\Theta}(t-1)\right), \quad \text{(estimator)}$$

$$p(t+1) = G_t\left(\hat{\Theta}(t), p(t), x^\dagger, u^\dagger\right), \quad \text{(incentive policy)}$$

such that, almost surely,

1. $\lim_{t\to\infty} \hat{\Theta}(t) = \Theta^*$ **(strong consistency)** , and 2. $\mathcal{R}_t = o(t)$ **(sublinear regret)**.

Intermission: How do we learn from NE?

Costs $c_i^{\gamma}(x) = \ell_i(x) + \gamma_i(x_i, p_i)$
s.t. $x_i \in \mathcal{X}_i$

- **Definition (Incentivized Nash Equilibrium)**

Given incentive γ, strategy x^* is an INE if

$$c_i^{\gamma}(x_i^*, x_{-i}^*) \leq c_i^{\gamma}(x_i, x_{-i}^*), \ \forall x_i \in \mathcal{X}_i, \forall i \in [n].$$

$$\Longleftrightarrow$$

- Solves the **variational inequality** (VI)

$$\langle G(x^*, p), x - x^* \rangle \geq 0, \forall x \in \mathcal{X},$$
$$G(x, p) := \Theta^* \Phi(x) + p.$$

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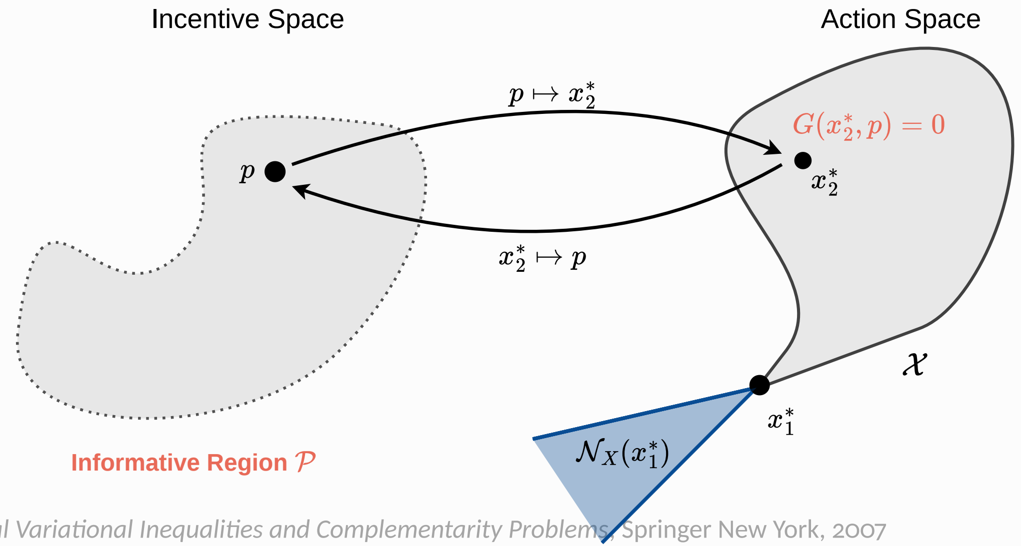

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Observation Model

$p(t)$: incentive issued
$\hat{p}(t)$: incentive observed

- **Unknowns:** Informative region $\mathcal{P}$, preferences Θ^*.
- **Available:** Action Space $\mathcal{X}$.
- **Noisy observations** $\{(\hat{p}(t), \hat{x}(t))\}_{t=1}^{T}$

$$\text{whenever } \hat{x}(t) \in \operatorname{int} \mathcal{X} : \quad \begin{cases} p(t) + v(t) & = -\Theta^* \Phi(\hat{x}(t)), \\ p(t) + e(t) & = \hat{p}(t), \end{cases}$$

where

$e(t)$ is a **measurement noise**

$v(t)$ is an **endogenous noise** $\rightarrow$ uncertainty on *best-response model*

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$v(t)$ is an **endogenous noise** $\rightarrow$ uncertainty on *best-response model*

Remark: $\{v(t)\}_t$ creates *correlation between the noise and the NE* $\rightarrow$ error-in-variables (EIV) regression problem. (Under review, 2026)

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RLS Estimator

For the measurement-noise model

Model $\forall t : \hat{x}(t) \in \operatorname{int} \mathcal{X}$,
$\hat{p}(t) = -\Theta^* \Phi(\hat{x}(t)) + e(t)$.

- Recursive least-squares (RLS), conditioned on *informative observations*

$$\hat{\Theta}(t) := \arg\min_{\Theta} \sum_{\tau \le t} \delta(\tau) \left\| \hat{p}(\tau) + \Theta \Phi(\hat{x}(\tau)) \right\|^2, \text{ where } \delta(\tau) = \mathbf{1}\{\hat{x}(\tau) \in \operatorname{int} \mathcal{X}\}.$$

Lai et al., The Annals of Statistics, 1982 | L. Zhang et al., *Stochastic Adaptive Control for Systems with Nonlinear Parameterization*, Preprint arXiv:2604.06980, 2026

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- Use *diminishing-excitation* sufficient condition

Lemma: Suppose strong monotonicity and $\{e(t)\}_t$ structure. Let $\lambda_{\min}(t) := \lambda_{\min}(\sum_\tau \delta(\tau)\Phi(\hat{x}(\tau))\Phi(\hat{x}(\tau))^\top)$. If $\lambda_{\min}(t) = \omega(\log t)$, then

$$\lim_{t\to\infty} \hat{\Theta}(t) = \Theta^* \text{ a.s.}$$

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Theorem: Under previous assumptions, if $\{p(t)\}_t$ is i.i.d. Gaussian, then $\lambda_{\min}(t) = \Omega(t)$ almost surely.

Key Technical Challenge $\rightarrow$ **Filtered regressors** $\mathbf{1}\{\hat{x}(t) \in \mathcal{X}\}\Phi(\hat{x}(t))$

- $\delta(t)$ filtering: Conditional expectation over *unknown* $\mathcal{P}$.
- Excitation must be preserved through the nonlinearity $p \mapsto \Phi \circ x^*(p)$.

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Faster than sufficient condition!

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The Incentive Policy

Use probing incentives whenever information is insufficient

Σ_t: RLS covariance matrix
$\lambda_{\min}(t)$: spectrum information matrix

- Switching policy:

$$p(t) = \begin{cases} \sim \mathcal{N}(0, \sigma_p^2 \mathbb{I}_n), & \text{if } \operatorname{tr}(\Sigma_t) > A(t)^{-1}, \\ -\hat{\Theta}(t-1)\Phi(x^\dagger), & \text{otherwise} \end{cases}$$

Exploration

Exploitation (Centrainty-equivalence design)

where

$$\Sigma_t := \left(\sum_{\tau \le t} \delta(\tau)\Phi(\hat{x}(\tau))\Phi(\hat{x}(\tau))^\top \right)^{-1},$$

and $A(t) := t^\gamma \log(t+1)$, $\gamma \in [1/2, 1)$.

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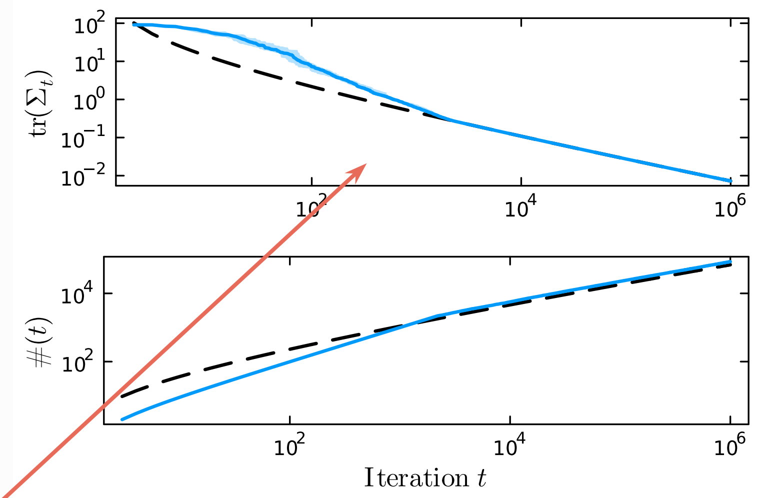

Switching threshold enables sufficient exploration
$\lambda_{\min}(t) = \Omega(t^\gamma \log t)$.

Convergence Results

The RAID Algorithm Converges with given rates

Theorem: Suppose strong monotonicity and $\{e(t)\}_t$ structure. For all parameters $\gamma \in [1/2, 1)$, the estimates $\{\hat{\Theta}(t)\}_t$ generated satisfy

$$\|\hat{\Theta}(t) - \Theta^*\|_F^2 = O\left(t^{-\gamma}\right) \text{ a.s.}$$

Moreover, the planner's regret over the generated incentive sequence $\{p(t)\}_t$ satisfies

$$\mathcal{R}_t = O\left(t^{\gamma} \log t\right) \text{ a.s.}$$

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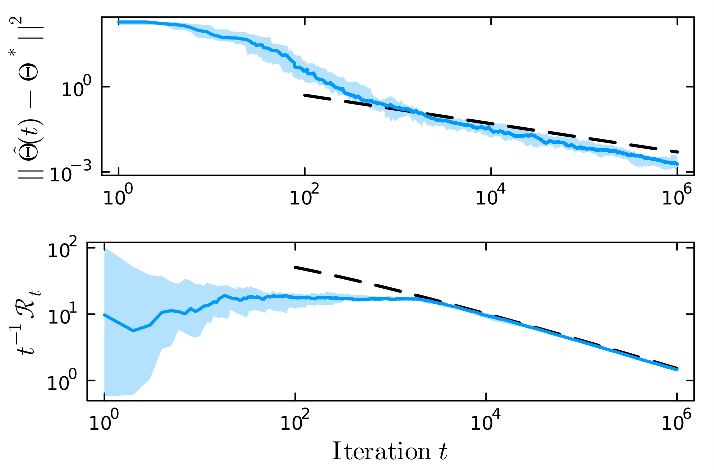
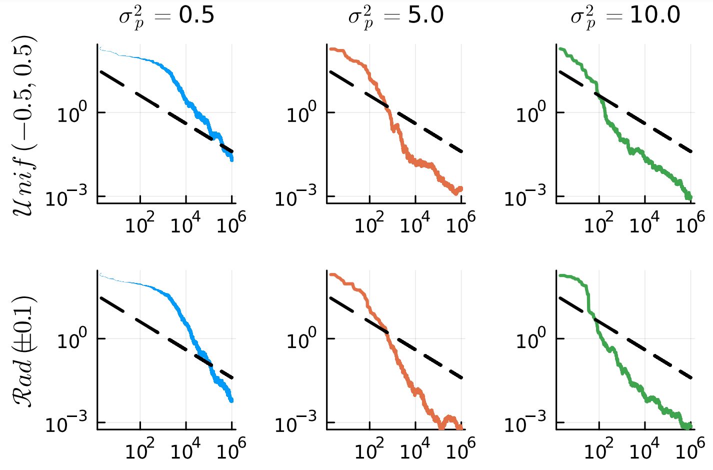
Numerical Verification

- Identification on 3-player game with 3rd-order polynomial costs

$$\ell_1(x) = 3(\tfrac{1}{6}x_1^3 + x_1^2 + x_1x_2 - x_1x_3 + x_1), \quad \ell_2(x) = 3(\tfrac{1}{6}x_2^3 + x_2^2 - x_1x_2 + x_2x_3 - x_2), \quad \ell_3(x) = 3(\tfrac{1}{6}x_3^3 + x_3^2 + x_1x_3 - x_2x_3 + x_3)$$



Convergence rates of the estimator and regret ($\gamma = 1/2$, black line indicates predicted rate).



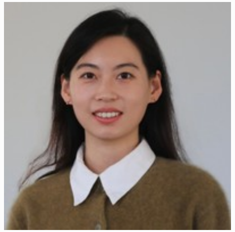
Performance under different measurement noise and probing variance.

Contents

Takeaways

1. *Adaptive Incentive Design* is a closed-loop regulator for strategic agents under information asymmetry: **regulate Nash equilibrium behavior** + **generate data for learning**.
2. This work proposes the **RAID Algorithm**:
   1. Achieves $O(t^{-\gamma})$ parameter estimation error and $O(t^{\gamma} \log t)$ regret.
   2. Active probing guarantees excitation.
   3. Sparsity of probing incentives produces strong consistency and sublinear regret.

Acknowledgements



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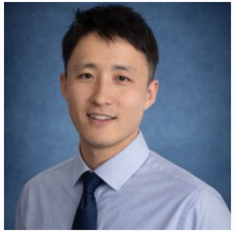

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Further details

Contact me

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