

Persuading a Learning Agent Generalized Principal-Agent Problem with a Learning Agent

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Introduction

Many economic problems have a *principal-agent* structure, where a principal commits to a strategy first, then an agent **best responds**:

- Contract Design
- Bimatrix Stackelberg Game
- Information Design (Bayesian Persuasion)

However:

- Oftentimes, the principal cannot commit,
- and the agent does not best respond.
- Nowadays, we have machine learning agents.

This work studies *principal-agent problems with a learning agent*: Can the principal do better than the classical problem where the agent best responds?

(Classical) Generalized Principal-Agent Problem

Proposed by Myerson (1982) & Gan-Han-Wu-Xu (2024):

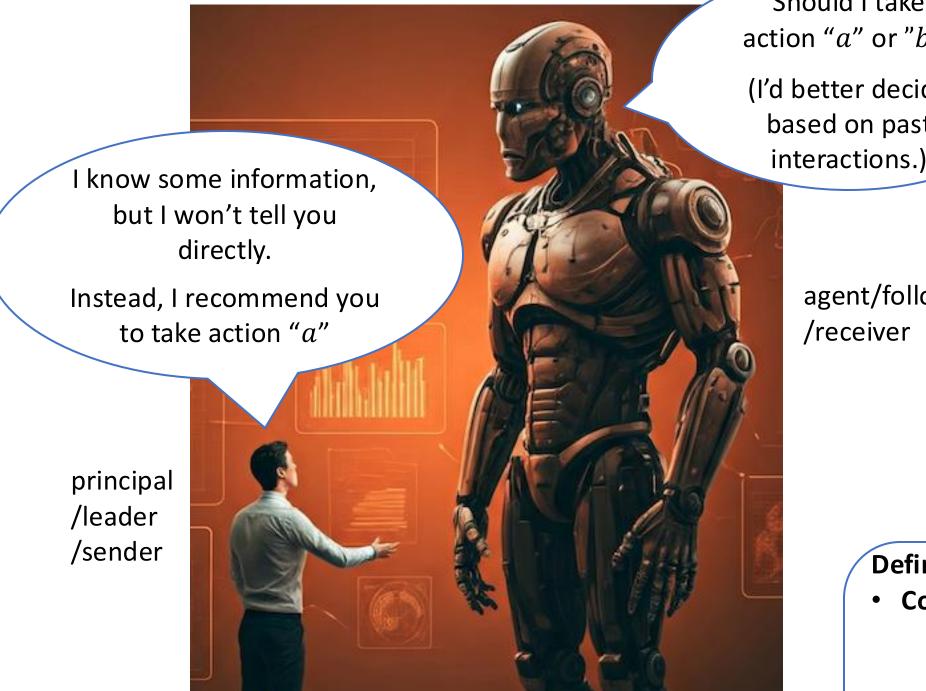
- The principal commits to a strategy $\pi = (q_s, x_s)_{s \in S}$:
 - S is a finite set of signals/recommendations.
 - $(q_s)_{s \in S}$ is a distribution over S: $\sum_{s \in S} q_s = 1$
 - $x_s \in \mathcal{X}$ is a decision associated with signal s.
- The agent chooses a strategy $\rho: \mathcal{X} \to A$
 - A is a finite set of actions of the agent.
 - Best response:

$$\rho(x_s) \in \operatorname{argmax}_{a \in A} v(x_s, a)$$

Principal and agent obtain (expected) utility

$$\mathbb{E}_{s \sim q} \left[u(x_s, \rho(x_s)) \right], \qquad \mathbb{E}_{s \sim q} \left[v(x_s, \rho(x_s)) \right]$$

• u(x,a), v(x,a) are assumed to be linear in $x \in \mathcal{X}$



Examples

- In Contract Design,
 - Action *a* leads to one of *n* outcomes.
- $x_s = (p_1, ..., p_n)$ is a payment vector (contract). $\mathcal{X} = \mathbb{R}^n_+$
- In Bimatrix Stackelberg Game,
 - $x_s \in \mathcal{X} = \Delta(\text{rows})$ is the leader's mixed strategy. Follower chooses a column a.
- In *Information Design*,
 - There is an unknown state of the world $\omega \sim \text{prior } \mu$
 - $x_s \in \mathcal{X} = \Delta(\Omega)$ is the posterior distribution of ω induced by signal s
 - Constraint: $\sum_{s \in S} q_s x_s = \mu$

Should I take action "a" or "b"? (I'd better decide based on past

swapped

agent/follower /receiver

Our Problem: Learning Agent

Instead of best-responding, we consider an agent who learns which action to take for each signal.

T rounds of interactions. In each round t,

- Based on history, the agent chooses a (randomized) strategy $\rho^t: S \to \Delta(A)$
- The principal chooses a strategy $\pi^t = (q_s^t, x_s^t)_{s \in S}$
- A signal $s^t \sim q^t$ is sampled, then:
 - the principal makes decision $x^t = x_{s^t}^t$
 - the agent samples action $a^t \sim \rho^t(s^t)$
- The two players' total expected utility: $\mathbb{E}\left[\sum_{t=1}^{T} u(x^t, a^t)\right]$ and $\mathbb{E}\left[\sum_{t=1}^{T} v(x^t, a^t)\right]$

Definition: The agent's learning algorithm satisfies

Contextual no-regret if

$$\forall d: S \to A, \qquad \mathbb{E}\left[\sum_{t=1}^{T} \left(v\left(x^{t}, d(s^{t})\right) - v\left(x^{t}, a^{t}\right)\right)\right] \leq \mathsf{CReg}(T) = o(T).$$

Contextual no-swap-regret if

$$\forall d: S \times A \to A, \qquad \mathbb{E}\left[\sum_{t=1}^{T} \left(v\left(x^{t}, d(s^{t}, a^{t})\right) - v\left(x^{t}, a^{t}\right)\right)\right] \leq \mathsf{CSReg}(T) = o(T).$$

Main Results: Under some regularity conditions (e.g., agent has no dominated actions),

- Against a contextual no-regret learning agent, the principal can obtain average utility at least $\left(\sqrt{\frac{\operatorname{ckeg}(T)}{T}}\right)$; U^* is the principal's optimal utility against a best-responding agent. $U^* - \Theta$
- Against a contextual no-swap-regret learning agent, the principal cannot obtain more utility than $U^* + O\left(\frac{\text{CSReg}(T)}{T}\right)$ (even if the principal can adapt to the agent's learning algorithm).
- For some contextual no-regret agent (MWU), the principal can obtain more than $U^* + \Omega(1)$.

Intuition: Consider the principal's signal s^t , together with the agent's algorithm's choice of action a^t , as a recommendation strategy $\tilde{\pi}$. No-swap-regret learning \Rightarrow the agent (approximately) best responds to $\tilde{\pi}$. No-regret learning does not always have this property.