Learning in Stackelberg Games with Non-Myopic Agents


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Principal-Agent Problems

- **Principal** commits to action; **agent** best responds
- Principal aims to find an optimal commitment
- Captures many settings of **economic design**

Defender vs. **attacker**
(Stackelberg security games)

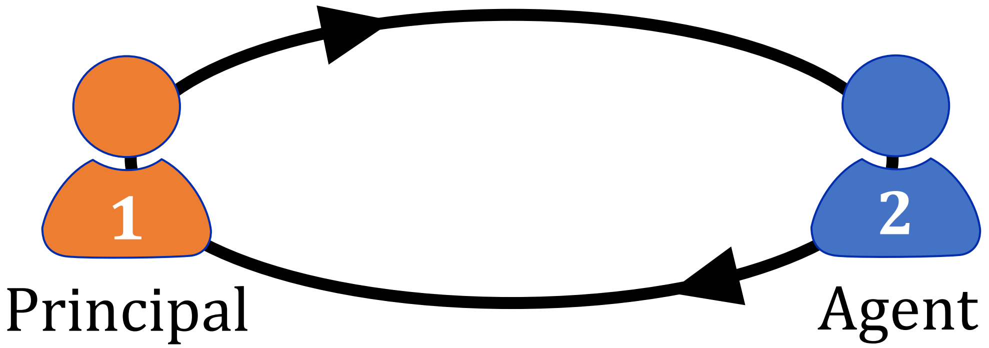
Seller vs. **buyer**
(Demand learning)

Decision-maker vs. **applicant**
(Strategic classification)

Principal-Agent Learning

But agent preferences are typically unknown!

⇒ Principal must **learn** and **adapt** from repeated interactions



Typical assumption: **myopic agent** who always best responds

⇒ Stationary learning problem with (semi-)bandit feedback

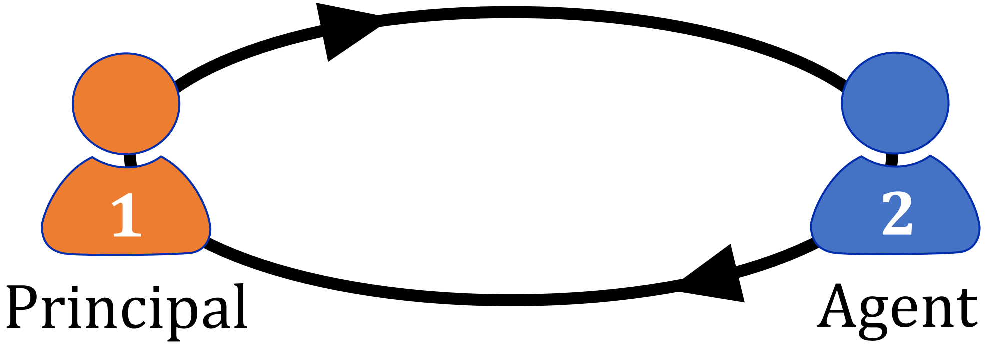
- Security games (Letchford et al., '09; Blum et al., '14), demand learning (Kleinberg-Leighton, '03; Besbes-Zeevi, '09), strategic classification (Dong et al., '18; Chen et al., '20)

Challenge: Non-Myopic Agents

What happens with **non-myopic** agents?

- Agent actions optimize long-run payoff
- Agents may not best respond—and may have incentive to mislead!

  (E.g., agent could mimic another type)



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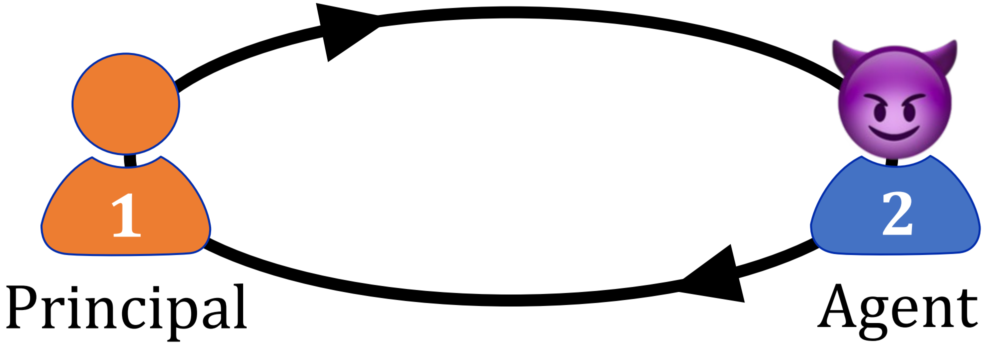

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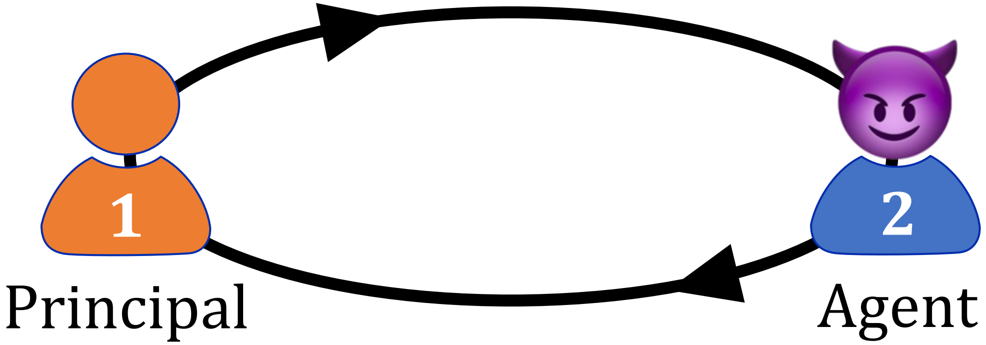

Common model of non-myopic agents:

- Not arbitrarily patient (shorter-lived than principal; present bias)
- Receive discounted utility

$\Rightarrow$ Do not deviate from best response as much (or for as long)

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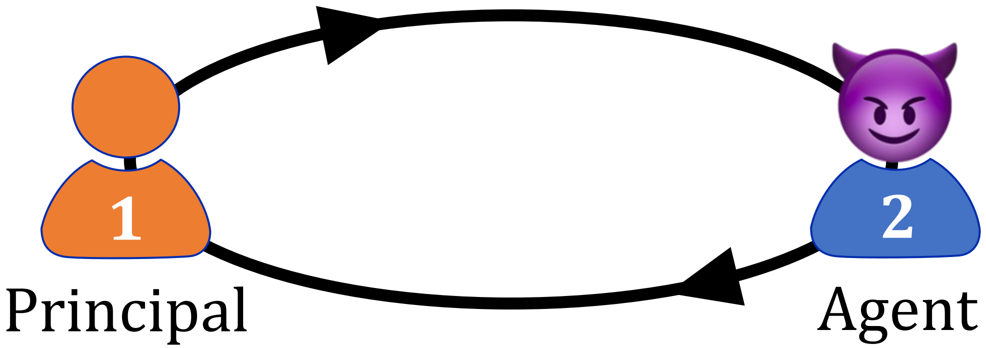

Questions

1. What are **principled ways** to learn from non-myopic agents?
2. How do insights for learning from myopic agents apply?

Our Contributions

Reduction framework: Non-myopic to myopic learning with:

- Minimal reactivity: Incentivize low deviation from best response
  - Achieved by delaying principal reaction to agent behavior
- Robustness: Learn effectively from approximate best responses

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Principled reduction via delayed feedback and batched queries
(Almost) optimal algorithm for batched stochastic bandits

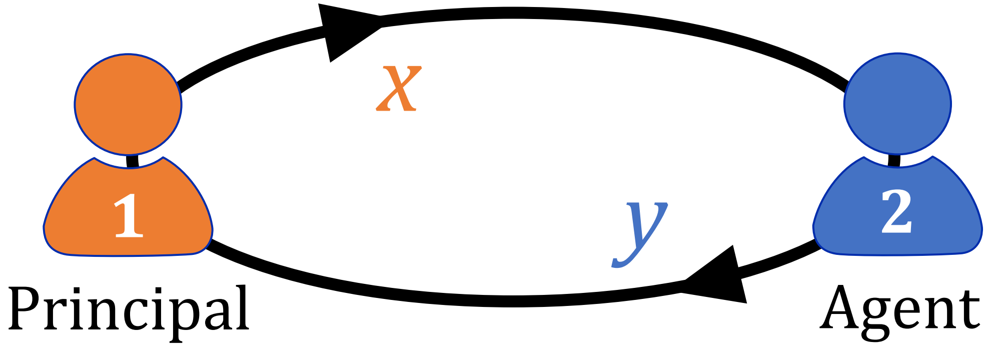
(Almost) optimal myopic learning for Stackelberg security games

Model

Principal-Agent Learning

Repeat over T rounds:

1. **Principal** commits to action $x \in \mathcal{X}$
2. **Agent** responds with action $y \in \mathcal{Y}$
3. Both parties observe x and y
4. Principal, agent receive payoffs $u(x, y)$, $v(x, y)$, respectively



Agent behavior: Choose actions to maximize γ-discounted payoff

$$\mathbb{E}\left[\sum_t \gamma^t \cdot v(x_t, y_t) \mid \text{principal policy}\right].$$

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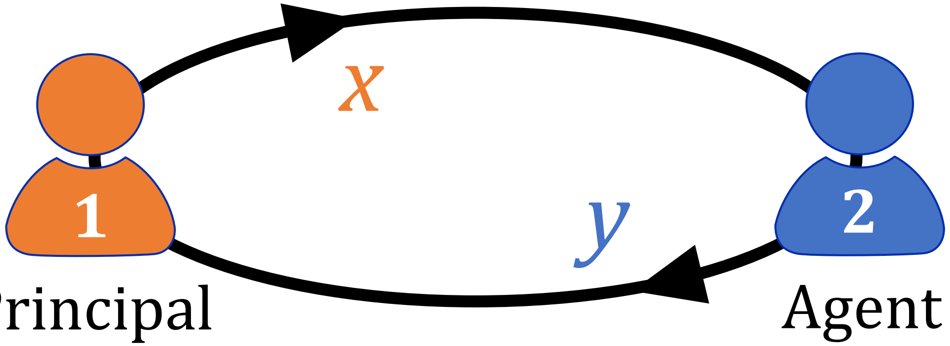

Principal goal: Minimize Stackelberg regret for **unknown** agent v:

Agent's best response

$$\underbrace{\max_{x \in \mathcal{X}} u(x, \mathrm{BR}(x))}_{\text{Stackelberg payoff}} - \underbrace{\mathbb{E}\left[\frac{1}{T}\sum_{t=1}^{T} u(x_t, y_t)\right]}_{\text{Algorithm payoff}}$$

Example: Stackelberg Security Games

Repeat over T rounds:

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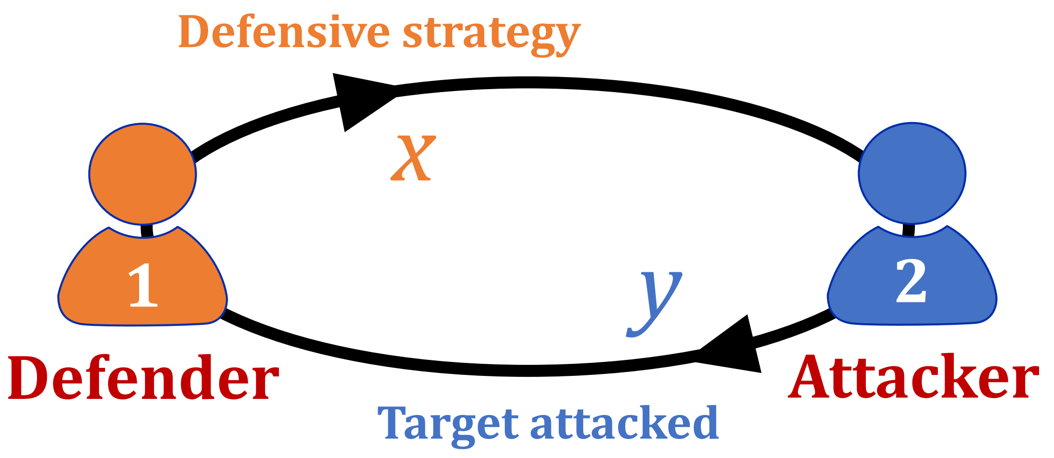
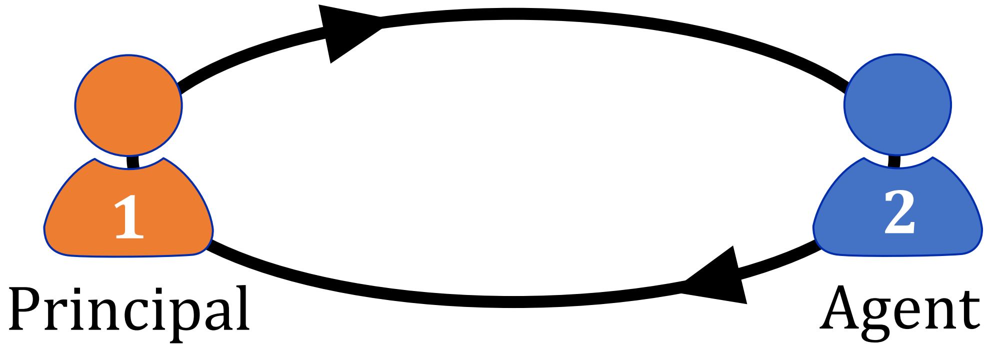
Expected payoff; depends only on attacked target and whether it was defended



Reduction

Non-Myopic Learning via Delayed Feedback

Policy is ***D*-delayed** if it only uses feedback from ≥ D rounds ago



Non-Myopic Learning via Delayed Feedback

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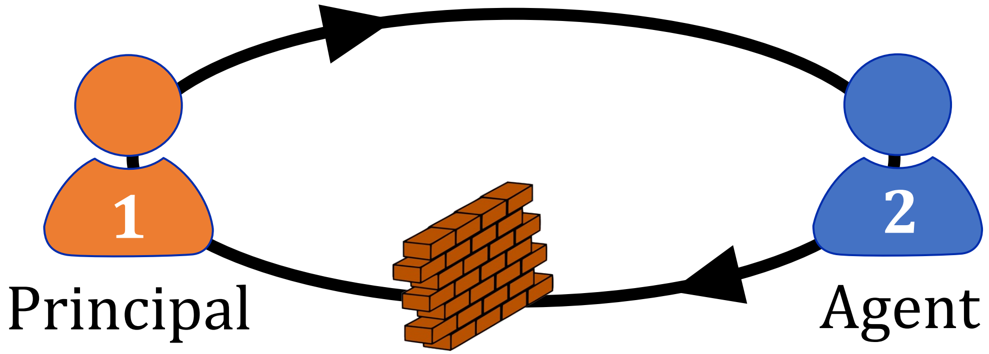
- Delay acts as information barrier!

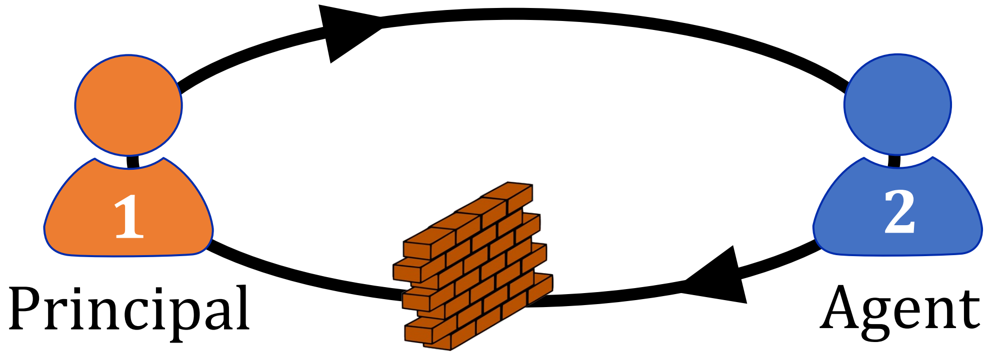


Non-Myopic Learning via Delayed Feedback

Policy is ***D*-delayed** if it only uses feedback from $\geq D$ rounds ago

- Delay acts as information barrier!

Principal delaying $\Rightarrow$ **lower reactivity**
$\Rightarrow$ less incentive for agent deviation



Proposition. If policy is D-delayed, then an γ-discounting agent will play an ε-approximate best response for $\varepsilon = \gamma^D/(1-\gamma)$:

$$v(x, y) \geq \max_{y' \in \mathcal{Y}} v(x, y') - \varepsilon$$

Non-Myopic Learning via Delayed Feedback

We reduce non-myopic learning to algorithm design desiderata:

1. **Robust** (to ε-approximate best response) bandit learning
2. Efficient bandit learning with ***D*-delayed feedback**

Minimize Stackelberg regret $\max_{x \in \mathcal{X}} u(x, \mathrm{BR}(x)) - \mathbb{E}\left[\frac{1}{T}\sum_{t=1}^{T} u(x_t, y_t)\right]$

x_t a function of $(x_1, y_1), \ldots, (x_{t-D}, y_{t-D})$

y_t is an ε-approximate best response

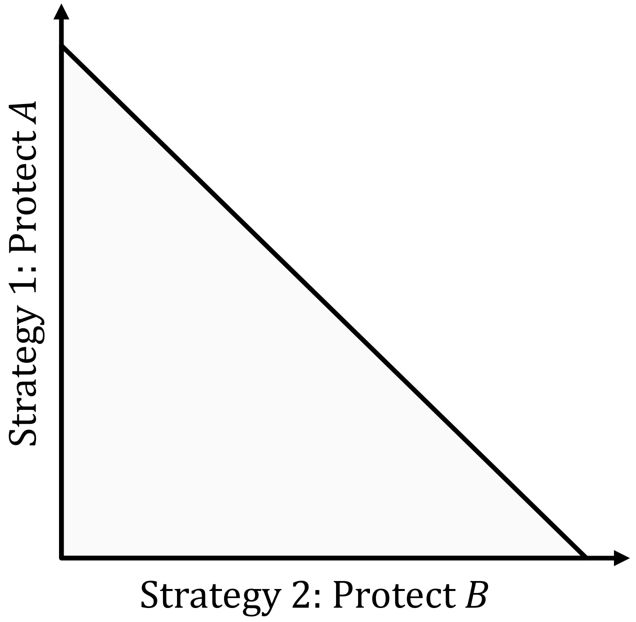
Robust Bandit Learning

(applied to Stackelberg security games)

Stackelberg security games

Targets = $\{A, B\}$

Defenses $\mathcal{X}$ = distributions over $\{\emptyset, A, B\}$



Stackelberg security games

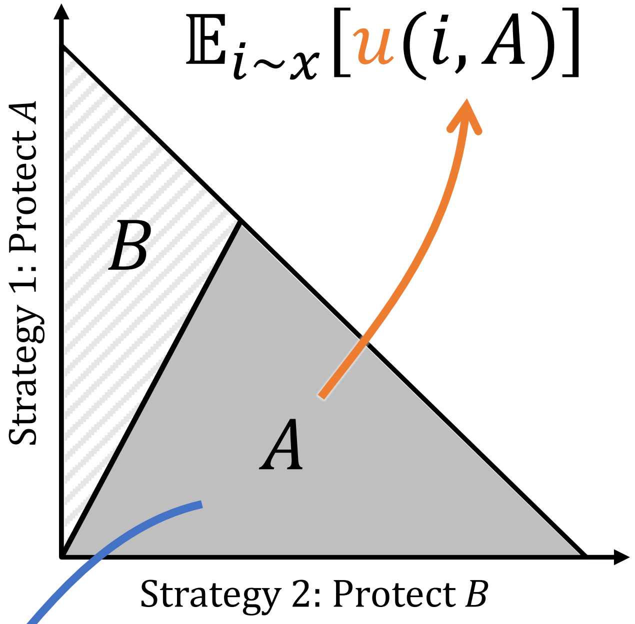
Targets = $\{A, B\}$

Defenses $\mathcal{X}$ = distributions over $\{\emptyset, A, B\}$

- Payoffs given by attacked target and whether it was defended

Defender objective:

$$\mathbb{E}_{i\sim x}[u(i, A)]$$

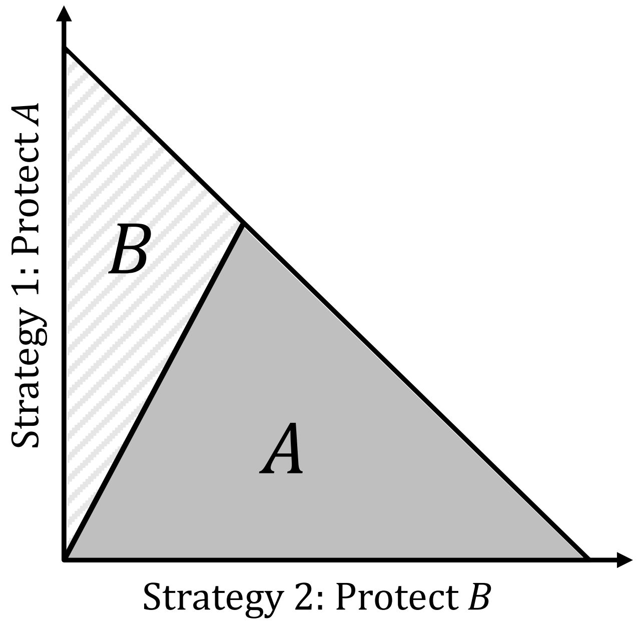


Agent choice:

$$\mathbb{E}_{i\sim x}[v(i, B)] \le \mathbb{E}_{i\sim x}[v(i, A)]$$

Robust (Myopic) Learning in Security Games

Identify **optimal algorithm** CLINCH for learning in security games



Traditionally:

- Run learning subroutine for each of n regions
- For each region, run generic (costly) learning algo

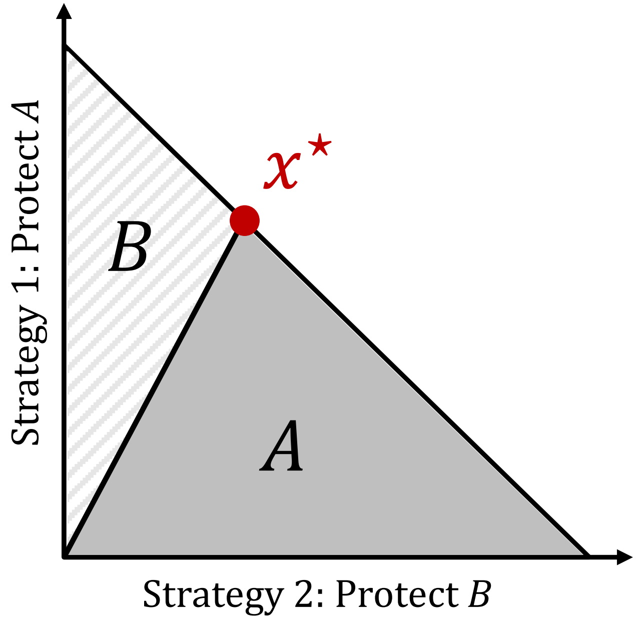
Our approach:

- Identify **structural properties** (⇒ solving single region suffices!)
- Apply **"cutting-plane"**-type optimization (Grünbaum's theorem)

Key Structural Property of Security Games

Principal's optimal action $x^\star \in \mathcal{X}$ satisfies:

- Agent **indifferent** between all protected targets
- $x^\star$ also **minimizes agent's payoff**
- $x^\star$ is the intersection of **all non-empty regions**



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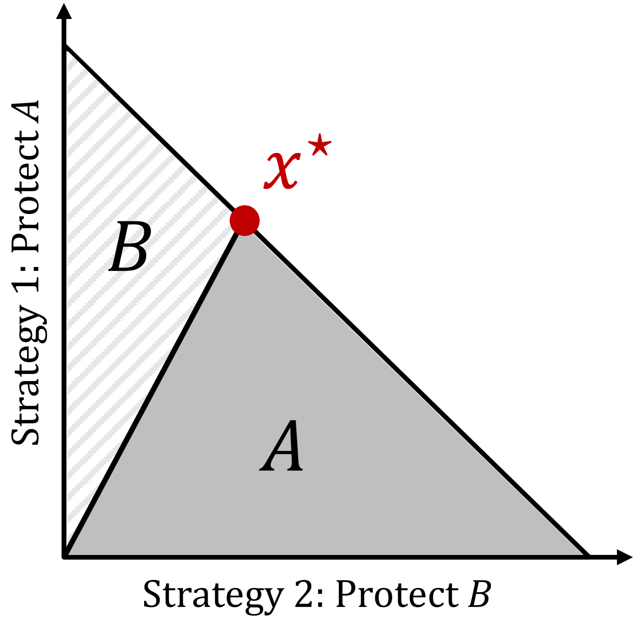


Robustness: feedback always points "towards" $x^\star$

Theorem. CLINCH finds a δ-approx. equilibrium with $O(N \log(N/\delta))$ queries to an (approx.) best response oracle

Bandits with Delayed Feedback

(applied to multi-armed bandits)

Efficient Bandit Learning with Delayed Feedback

Naïve solution: Repeat each action D times $\Rightarrow$ up to D times regret

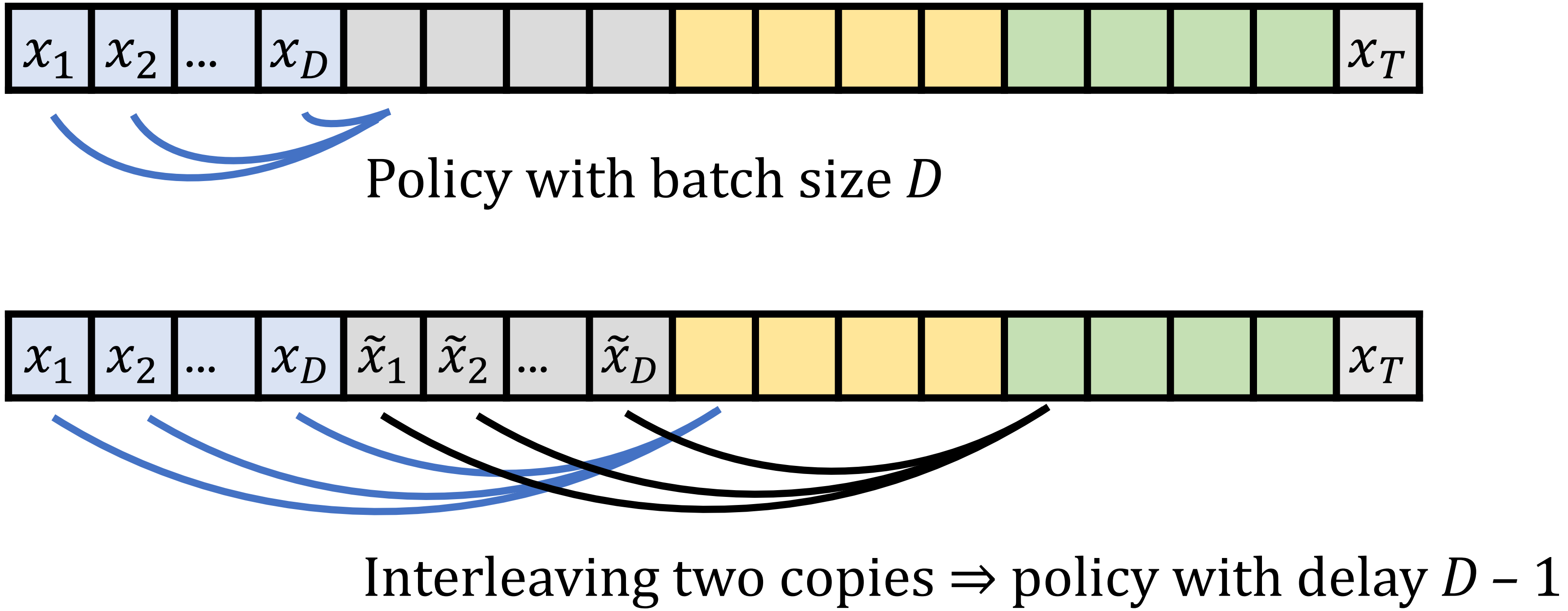
- Always works, but often suboptimal

Better: Show bandits with delays **equivalent to batched bandits**:

- Batch size B = submit B queries simultaneously
- Dependent delay sequences $\Rightarrow$ independent batches
- Well-studied setting (and thus a nice target for reduction)

Proposition. Algorithm with delay D and regret $R \Rightarrow$ algorithm with batch size D and regret $O(R)$, and vice versa.

Efficient Bandit Learning with Delayed Feedback



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Stochastic Multi-Armed Bandits

Naïve B-batched regret bound: $B \cdot \log(T/B) \sum_i \frac{1}{\Delta_i}$

Idea: Exploration of ActiveArmElimination **parallelizable**

- Allows for parallelization within each batch
- Fewer "wasted" queries

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B-batched ActiveArmElimination (ours): $B \log K + \log(T) \sum_i \frac{1}{\Delta_i}$

$\Rightarrow$ For demand learning, handles much more patient agents

Summary

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