relAI

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in Reliable AI

Deep Reinforcement Learning Agents learn Predatory Pricing

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Motivation

- Complex economic models have been infesible to analyse until recently
- **Reinforcement Learning** (RL) can solve complex decision making problems

⟹ What if RL controls economic agents?

Dynamic Oligopoly Model

Agents are companies competing in an oligopoly over multiple rounds:

Require:
Set of agents $\mathcal{N} = \{1, \dots, N\}$
Number of rounds T
For each agent i: initial demand D_1^i, unit production cost c_i, policy π_i, observation function Φ_i
for $t = 1, 2, \dots, T$ **do**
  for $i \in \mathcal{N}$ **do**
    i observes $o_t^i = \Phi_i(s_t) = \Phi_i(t, D_t^1, \dots, D_t^N)$
    i selects a price $p_t^i \sim \pi_i(o_t^i)$
    i sells quantity $D_t^i - p_t^i$
    i receives reward $r_t^i = (p_t^i - c_i)(D_t^i - p_t^i)$
  end for
  Compute the average price as $\bar{p}_t = \frac{1}{N} \sum_{j \in \mathcal{N}} p_t^j$
  for $i \in \mathcal{N}$ **do**
    Compute the price difference $\Delta p_t^i = p_t^i - \bar{p}_t$
    Transition demand to $D_{t+1}^i = D_t^i - \Delta p_t^i$
    Optionally, drop out i if $D_{t+1}^i < c_i$ (see Eq. (2))
  end for
end for
Reward each agent i with $U_i = \sum_{t=1}^{T} r_t^i$

The dropout mechanism removes unprofitable companies from the game

⟹ **Discontinuous game dynamics**

⟹ no analytical solutions with dropouts

Equilibrium Learning

Nash equilibria (NE) are strategy fixed points where no player gains by deviating:

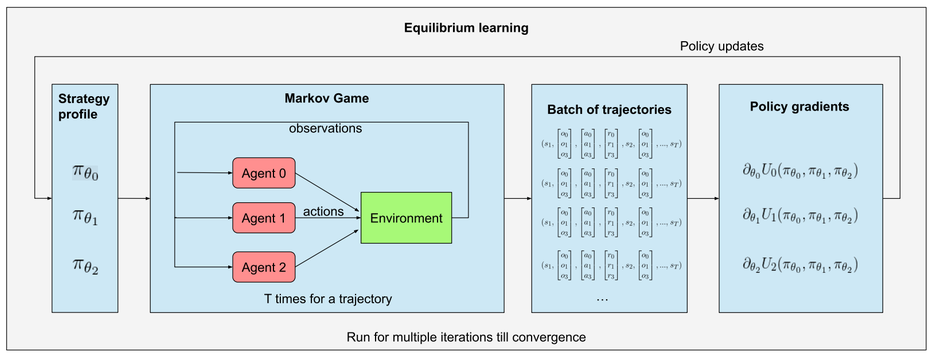
$$\sup_{\pi_i \in \Sigma_i} U_i(\pi_i, \pi_{-i}^*) - U_i(\pi_{\mathcal{N}}^*) \leq \varepsilon \quad \forall i \in \mathcal{N}$$

Proximity to equilibrium is measured by

$$\mathcal{L}_{\text{bf}} = \sum_{i \in \mathcal{N}} \sup_{\pi_i \in \Sigma_i^K} U_i(\pi_i, \pi_{-i}) - U_i(\pi_i, \pi_{-i})$$

where $\sup_{\pi_i \in \Sigma_i^K} U_i(\pi_i, \pi_{-i})$ is approximated by a brute force algorithm.

Each company is controlled by a RL agent aiming to maximize its profit:



We use REINFORCE (or its variants) to update all agents' policies simultaneously:

$$\theta_i \leftarrow \theta_i + \alpha \nabla_{\theta_i} U_i(\pi_{\theta_i}, \{\pi_{\theta_j}\}_{j \in \mathcal{N} \setminus \{i\}})$$

⟹ Hopefully converges to NE

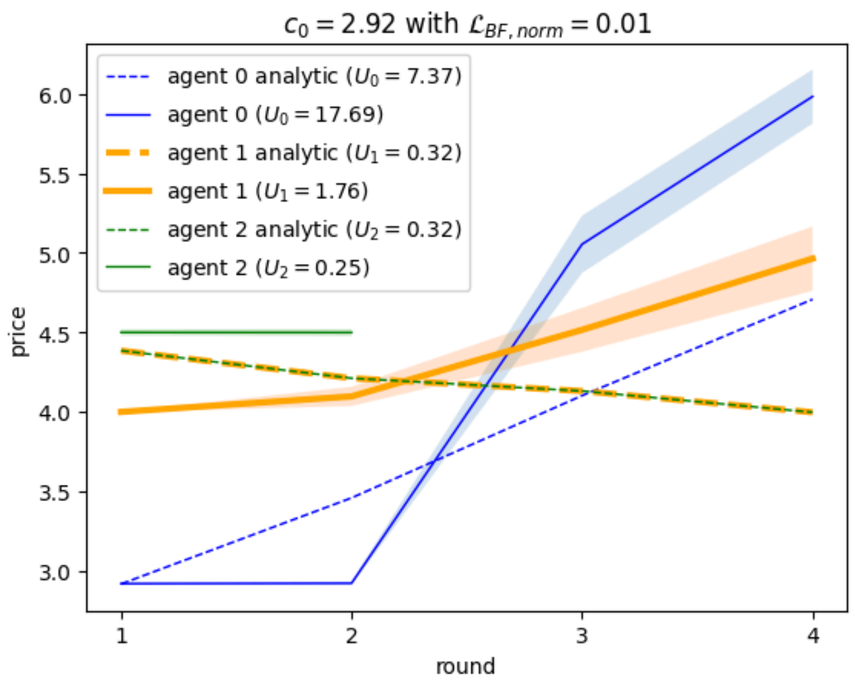
Results

Setup

- $N = 3$ companies, $T = 4$ rounds
- Proximal Policy Optimization (PPO) for RL
- Company 0 produces cheaper than 1 and 2

Findings

- Firm 0 learns **predatory pricing**, first lowering prices to drive out competitors
- The result is a verified approximate NE



Broader implications

- Our methodology finds approximate NE complex games without analytical solutions
- Brute-force verification is required due to lack of convergence guarantees in MARL

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