Optimizing Decision-Making in Multi-Agent RL with CPT

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Introduction

- Investigating Multi-Agent Reinforcement Learning (MARL) under Cumulative Prospect Theory (CPT)
- **Motivation:** Aligning autonomous agents with human decision-making biases
- **Key Questions:**
    - Do CPT-trained agents adhere to their utility and probability distortion functions?
    - How do CPT-guided agents optimize strategies in multi-agent games compared to those using traditional utility functions?
    - To what extent do agents adapt their strategies based on the utility functions of counterparties? What emergent dynamics arise in mixed populations of agents?

Background on CPT - Prospect Theory

Developed by Daniel Kahneman and Amos Tversky in 1979, Prospect Theory explains decision-making under risk and uncertainty:

- **Loss Aversion:** People tend to avoid losses more than acquiring equivalent gains.
- **Relative Evaluation:** Decisions are made based on relative differences rather than absolute outcomes.
- **Reference-Dependent:** Evaluations are based on outcomes relative to a reference point.

Background on CPT - Development of CPT

Cumulative Prospect Theory (CPT) extends the original framework to better handle multiple outcome probabilities:

- **Probability Weighting Function:** Captures the tendency to overweight small probabilities and underweight large probabilities.
- **Value Function:** Typically concave for gains and convex for losses, reflecting human risk preferences.

Implementation Strategy

Technical Approach & PyTorch Implementation

- **Policy Gradient Optimization with CPT:**
  - Integrates CPT-adjusted rewards and probability distortions.
  - Employs model-free learning using policy gradients.
- **Implementation Workflow:**
  1. Design a neural network for policy representation.
  2. Transform rewards using CPT functions.
  3. Compute policy gradients via automatic differentiation.
  4. Optimize policies using gradient ascent.

CPT-Adjusted Rewards

(1)

$$C(X) \;=\; \int_{-\infty}^{0} w^{+}\big(P(u(X) > z)\big)\,dz \;-\; \int_{0}^{\infty} w^{-}\big(P(u(X) > z)\big)\,dz.$$

(2)

$$\max_{\pi \in \Pi_{M,N}} \; C\Big(\sum_{t=0}^{H-1} r_t\Big).$$

- C: The CPT value capturing the decision-maker's distortion in perceiving gains and losses.
- $\pi \in \Pi_{M,N}$: A policy π chosen from the set $\Pi_{M,N}$ (e.g., all feasible memory-based policies).

Algorithms + Policy Gradient

Below is the Policy Gradient that we use to optimize the policy and solve our optimization problem.

$$\nabla_{\rho} J \;=\; \mathbb{E}\Big[\, \xi\big(\textstyle\sum_{\tau} r_{\tau}\big)\, \nabla_{\rho}\, \mu_{\tau}\big(a_{\tau} \mid Q_{\tau}(s_{\tau}, a_{\tau}; n)\big)\, \nabla_{a_{\tau}} Q_{\tau}\big(s_{\tau}, a_{\tau}; n\big) \Big].$$

$$\xi(V) \;=\; \int_{0}^{\max(V,0)} w^{+}\Big(P\big(u\big(\textstyle\sum_{\tau} r_{\tau}\big) > z\big)\Big)\, dz \;-\; \int_{0}^{\max(-V,0)} w^{-}\Big(P\big(u\big(\textstyle\sum_{\tau} r_{\tau}\big) > z\big)\Big)\, dz.$$

The algorithm we use is the Multi Agent Deep Deterministic Policy Gradient (MADDPG)

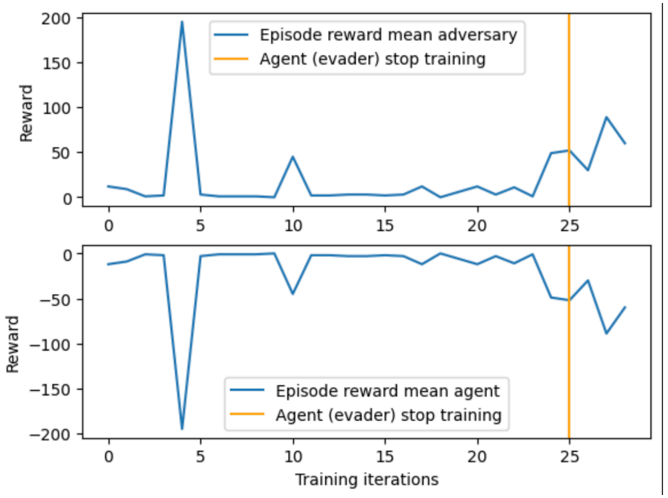
Competitive Environment - Overview

PettingZoo's **Simple Tag** Environment is a basic Multi-Agent Particle Environment (MPE) designed for competition between agents

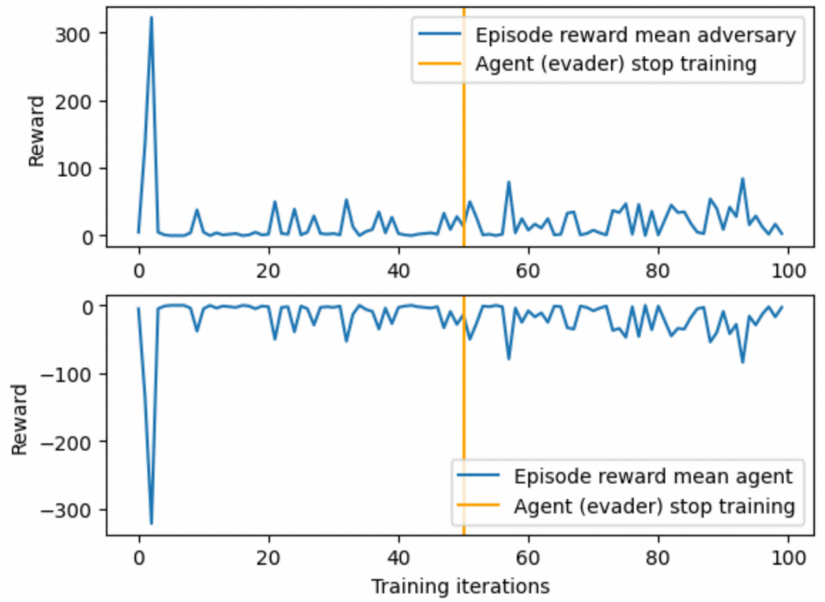
- **Objective**: Predators work to “tag” or catch the prey, while the prey’s goal is to evade capture.
- **Rewards**: Rewards are structured so that predators gain rewards when they successfully tag the prey, and the prey receives a penalty when caught.

Competitive Environment - Rewards

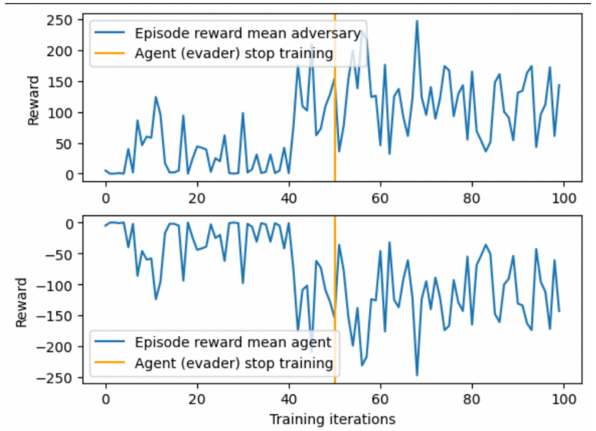
Baseline



Moderate CPT (Risk Seeking)



Extreme CPT (Risk Averse)



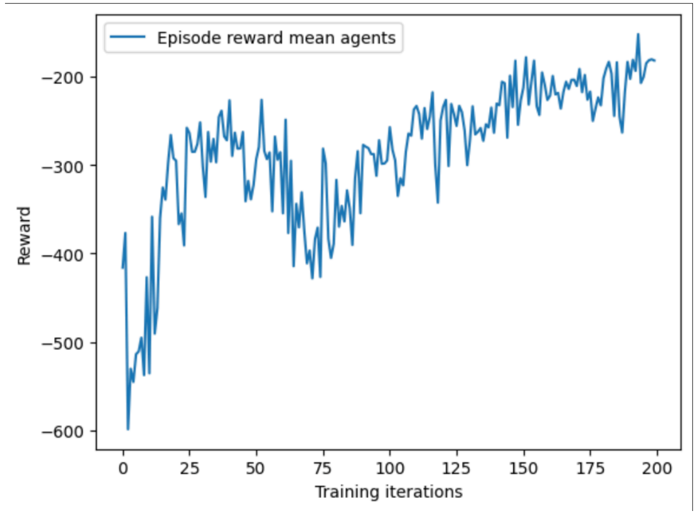
Cooperative Environment - Overview

PettingZoo's **Simple Spread** Environment is a basic Multi-Agent Particle Environment (MPE) designed for semi-collaboration between agents

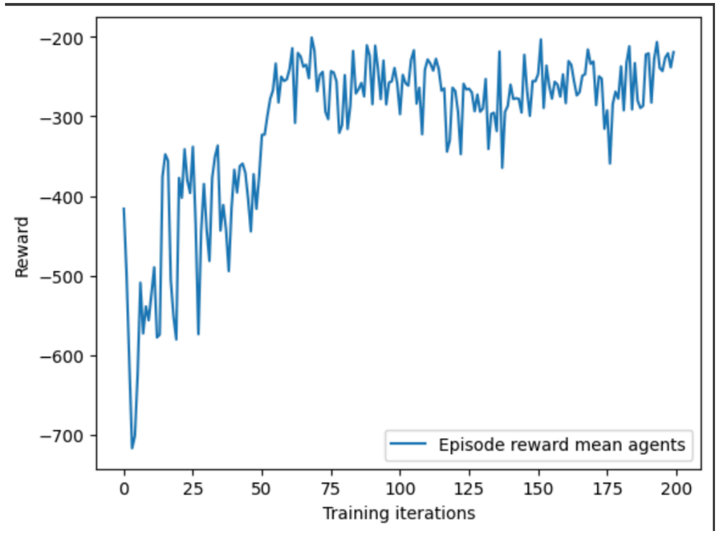
- **Objective**: The agents work cooperatively to cover all the landmarks. Their goal is to position themselves so that each landmark is “covered” by at least one agent, maximizing overall performance.
- **Rewards**: Rewards encourage efficient coverage of landmarks while also penalizing agents for collisions with one another, which promotes coordinated movement and spacing.

Cooperative Environment - Rewards

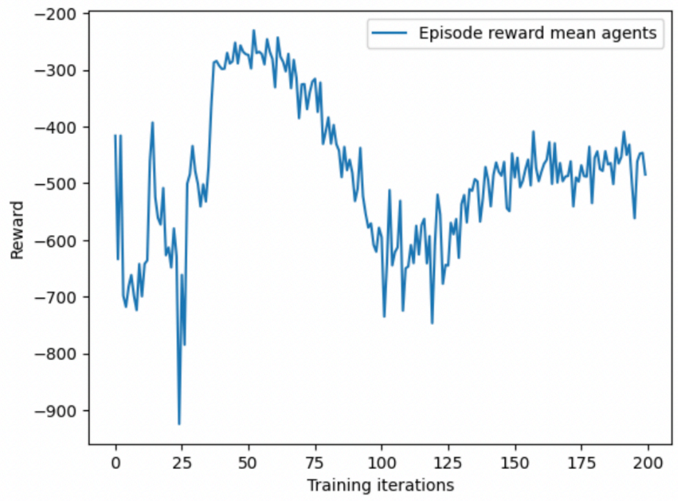
Baseline



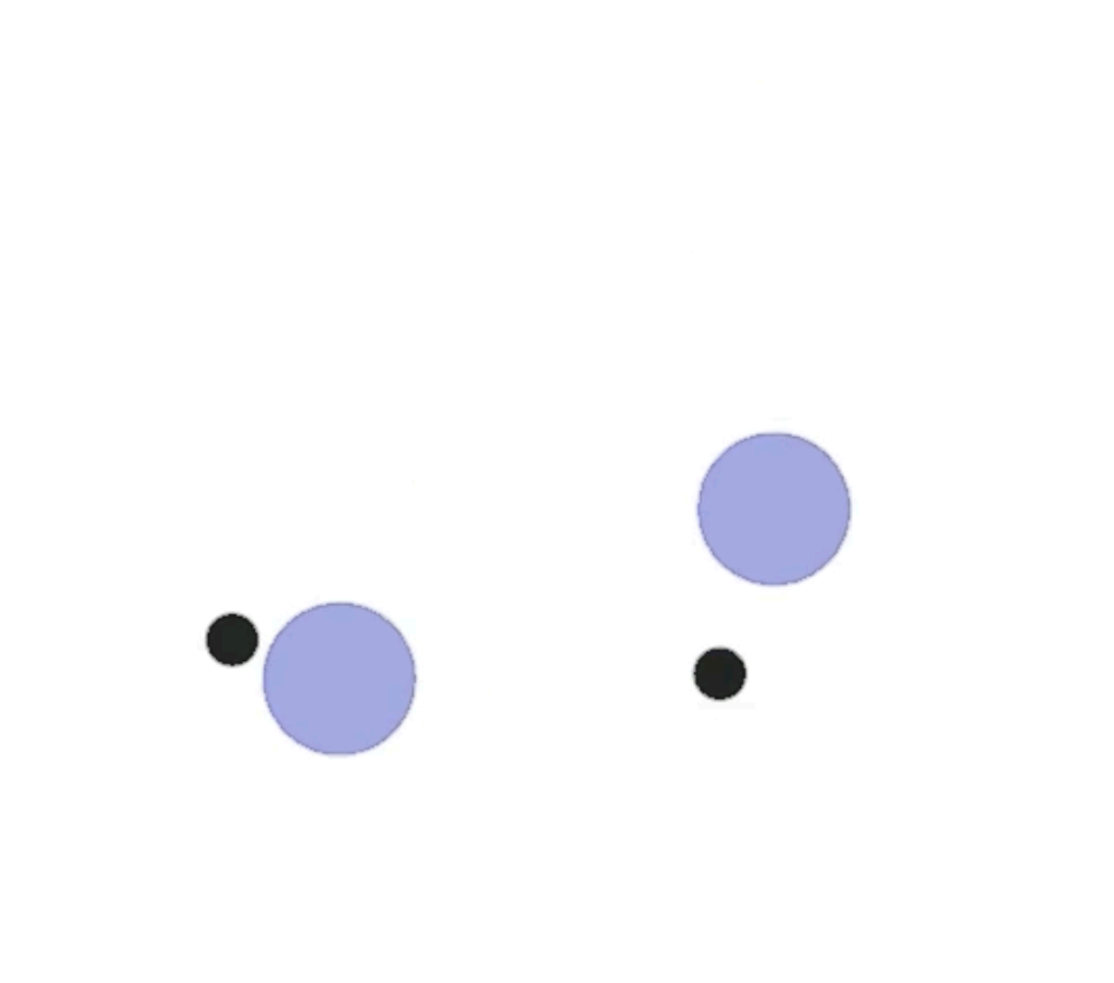
Moderate CPT



Extreme CPT



Cooperative Environment - Visualization of MPE

Baseline CPT	Extreme CPT
	

Next Steps & Challenges

Planned Improvements

- **Optimizing CPT Integration**
  - Attempt to try new probability weighting and value distortions
  - See the effect of new estimation methods for the value functions and integral
- **Implementing Discrete Competitive Environments**
  - Try the effect of the CPT-driven policy on an environment like Poker
  - Attempt to induce more interpretable CPT effects driven by Behavioral Economics Studies

Conclusion

Thank You! Questions?