Introduction

Optimizing Decision-Making in Multi-Agent RL with CPT

- Investigating Multi-Agent Reinforcement Learning (MARL) under Cumulative Prospect Theory (CPT)
- Key motivation: **Aligning autonomous agents with human decision-making biases**
- Key Questions:
  - Do CPT trained agents work follow their utility and probability distortion functions?
  - How do CPT-guided agents optimize strategies in multi-agent games, and how do their behaviors differ from 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. Explains how people make decisions when faced with risk and uncertainty:

- People tend to avoid losses over acquiring equivalent gains (loss aversion).
- People evaluate choices based on relative differences rather than absolute similarities.
- People think in terms of expected utility relative to a reference point.

Background on CPT - Development of CPT

CPT provides a more robust framework for dealing with outcomes that have multiple possible probabilities, avoiding ranking issues and ensuring consistency in decision-making processes through nonlinear functions.

- Probability weighting function - captures the empirical observation that people tend to overweight small probabilities and underweight large probabilities
- Value function - concave for gains and convex for losses

Implementation Strategy

Technical Approach & PyTorch Implementation

- **Policy Gradient Optimization with CPT**
  - CPT-adjusted rewards & probability distortions
  - Model-free learning using policy gradients
- **Implementation Workflow**:
  i. Design neural network for policy representation
  ii. Transform rewards using CPT functions
  iii. Compute policy gradients using automatic differentiation
  iv. 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)

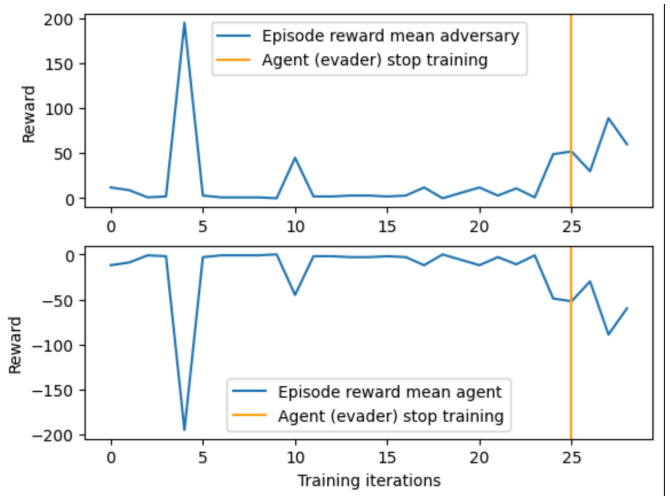
Competitive Environment - Overview

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

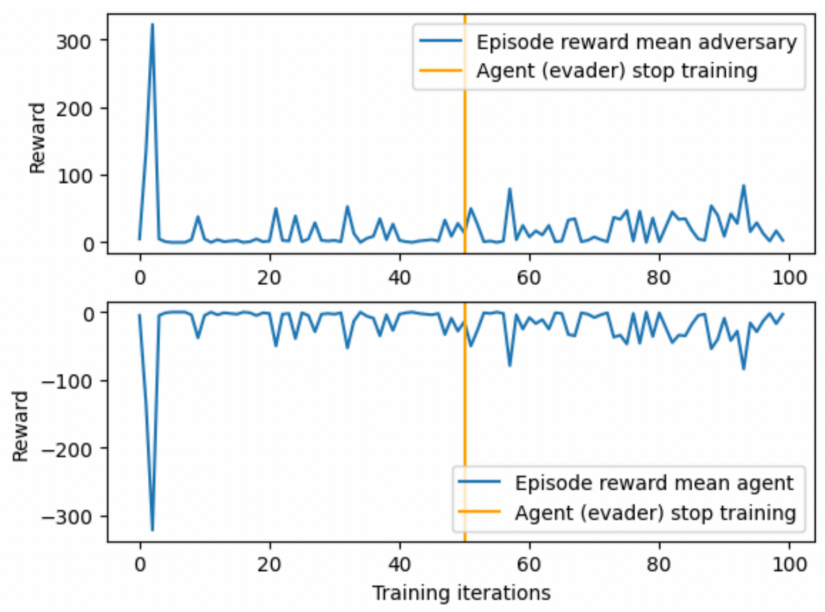
- **Objective**: Predators work to “tag” or catch the prey, while the prey’s goal is to evade capture.
- **Rewards**: Rewards are structured so that predators gain rewards when they successfully tag the prey, and the prey receives a penalty when caught.

Competitive Environment - Rewards

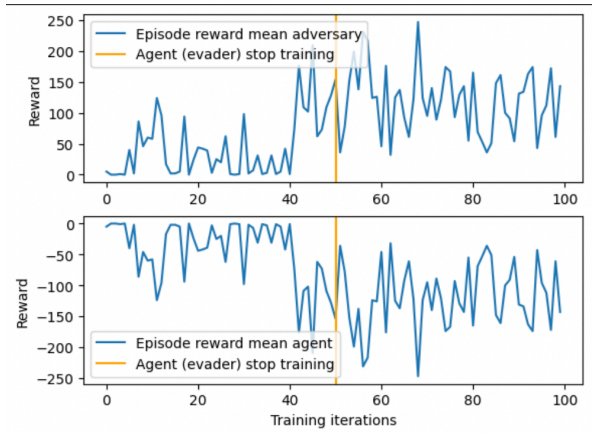
Baseline



Moderate CPT (Risk Seeking)

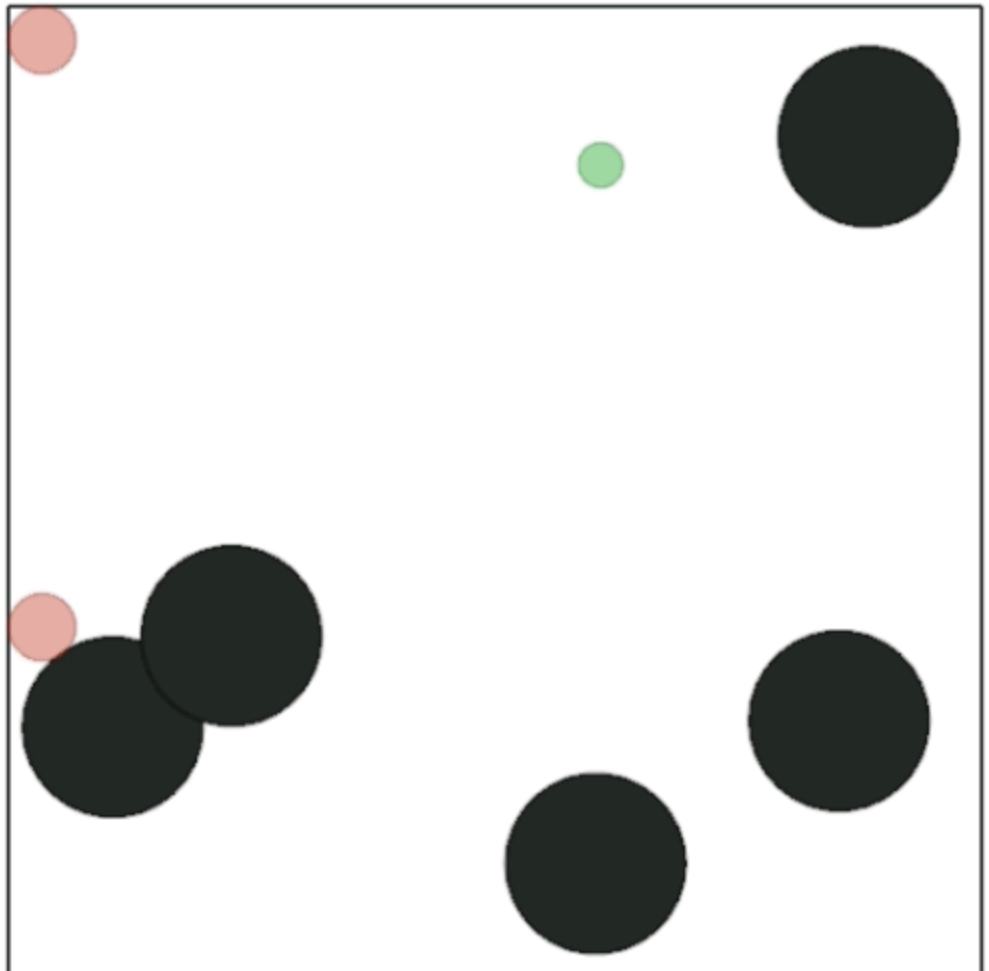


Extreme CPT (Risk Averse)



Competitive Environment - Visualization of MPE

Extreme CPT



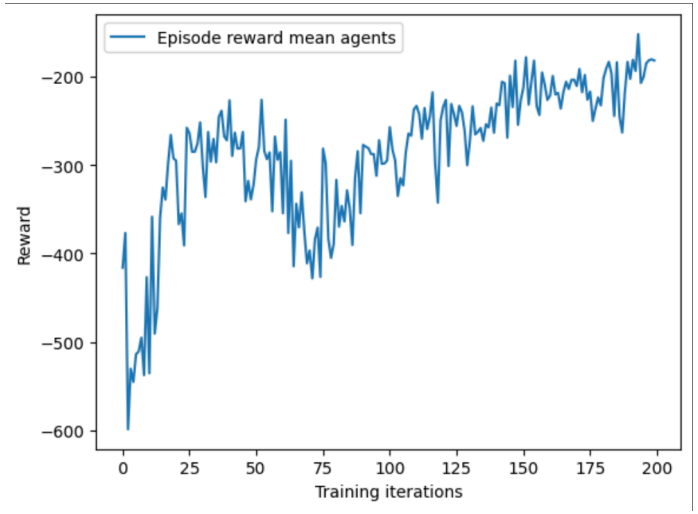
Cooperative Environment - Overview

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

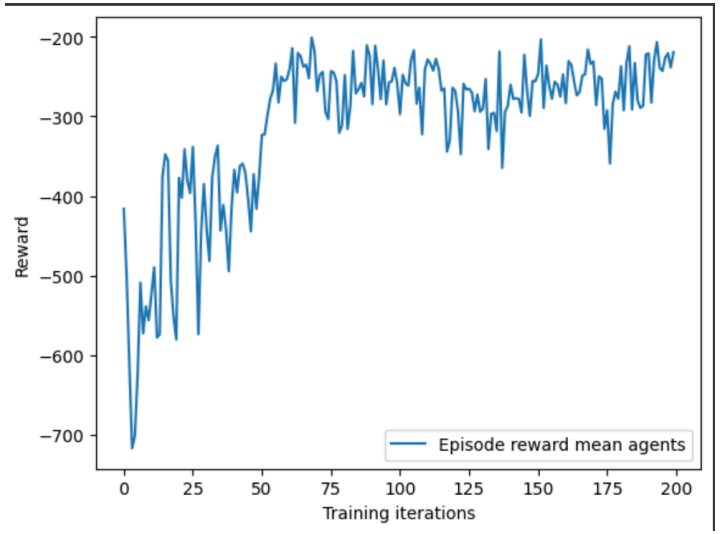
- **Objective**: The agents work cooperatively to cover all the landmarks. Their goal is to position themselves so that each landmark is “covered” by at least one agent, maximizing overall performance.
- **Rewards**: Rewards encourage efficient coverage of landmarks while also penalizing agents for collisions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

Cooperative Environment - Rewards

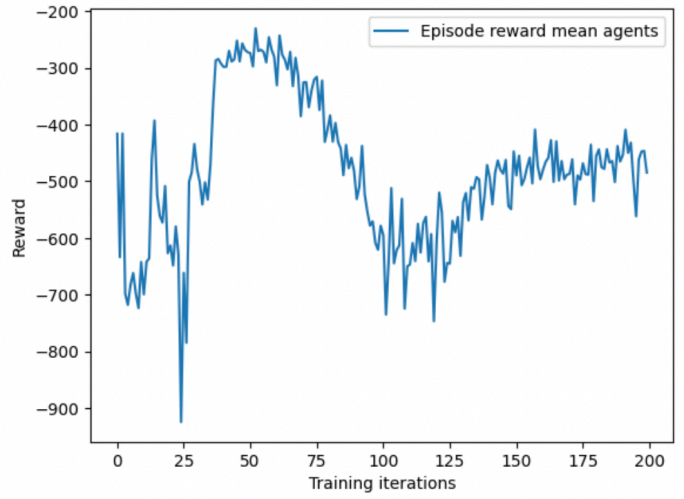
Baseline



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?