May 2021

Identification of Emergent Collaborative Behaviors in Multi-Agent Systems

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362. Identification of Emergent Collaborative Behaviors in Multi-Agent Systems

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Background

Multi-Agent Reinforcement Learning (MARL) has been used to allow groups of autonomous agents to perform complex cooperative tasks such as stochastic games.

Prior Work

- MARL-trained teams display a variety of behaviors even when trained under identical conditions [1].
- These behaviors have been observed to be significantly coordinated [2].

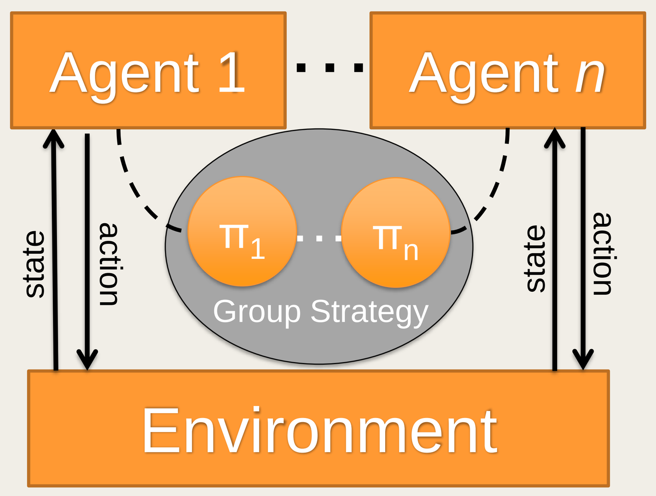


Figure 1: MARL Overview

Hypotheses

- Coordination is a useful measure of collaboration.
- MARL methods can produce emergent collaborative strategies.

Motivation

- Recent work has used neural networks to identify dynamical systems [3].
- No method is capable of completely identifying and describing collaboration.
- Developing a process for modeling collaborative strategies can lead to AI agents that are more adaptive to new teammates and changing environments.

Research Goals

1. Explore a method for describing the group behavior of a heterogeneous team performing a predator-prey pursuit task.
2. Asses if this method can provide insight into the collaborative strategies learned by MARL agents and inform future work.

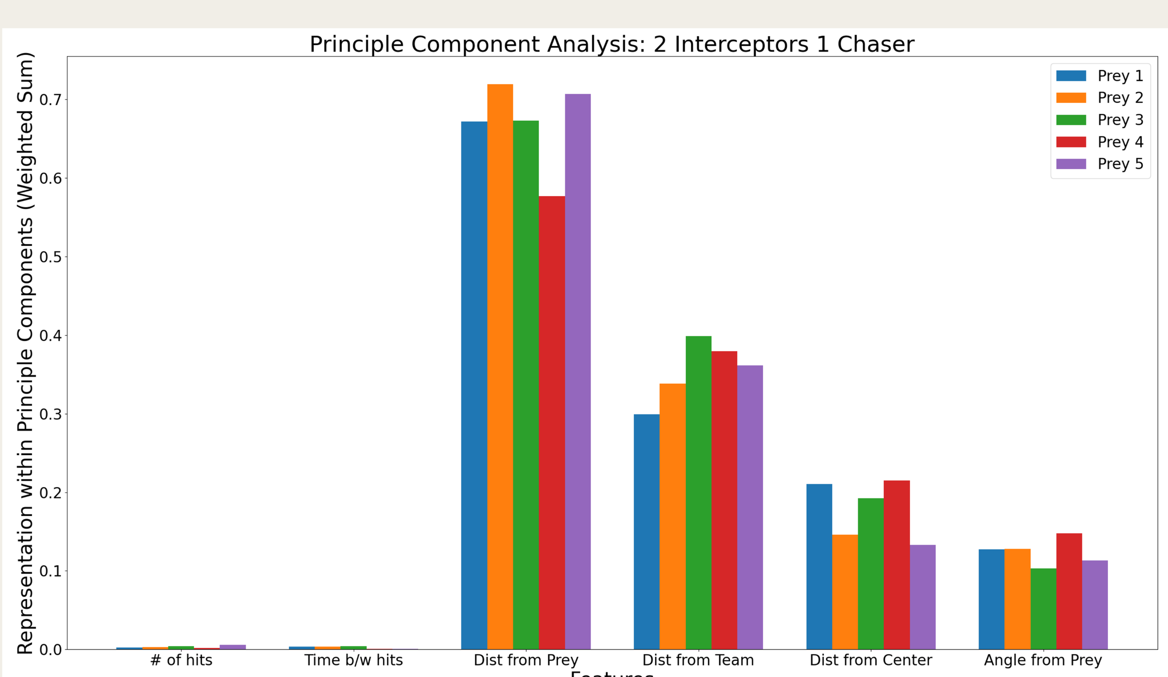
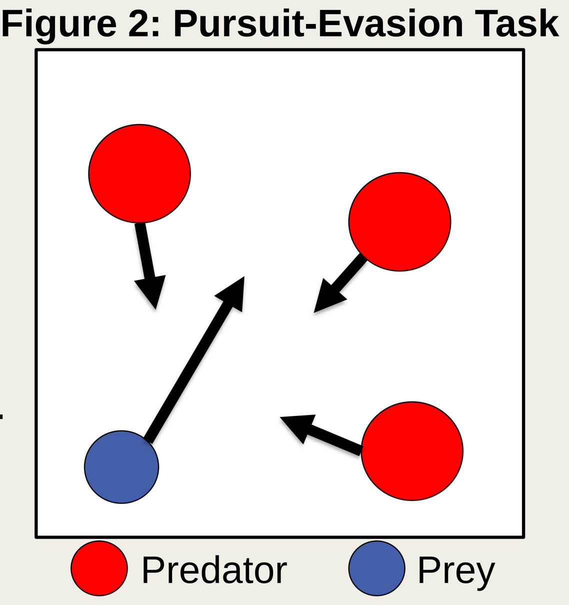


Figure 4: Principal Component Analysis Applied to Fixed-Strategy Team

Methods

Environment

Figure 2: Pursuit-Evasion Task



- Agents are simulated within a 2D particle environment utilizing the OpenAI Gym library [4].
- Agents play a continuous pursuit-evasion game **(Figure 2)**.

MARL Algorithm

- Agents are trained with the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) method [4].
- Uses the Centralized Training and Decentralized Execution (CTDE) paradigm.

Reward structure:

- Predators are equally rewarded when one of them collides with the prey.
- Prey receives the opposite reward.

Fixed Strategies

- Defined by simple algorithms
- Not coordinated with other predators
- Behaviors are easily described:
  - **Interceptor:** Agent calculates an interception trajectory based on the prey's current velocity.
  - **Chaser:** Agent heads directly towards the prey.
- Used for comparisons with unknown RL behaviors.

Experiment Process

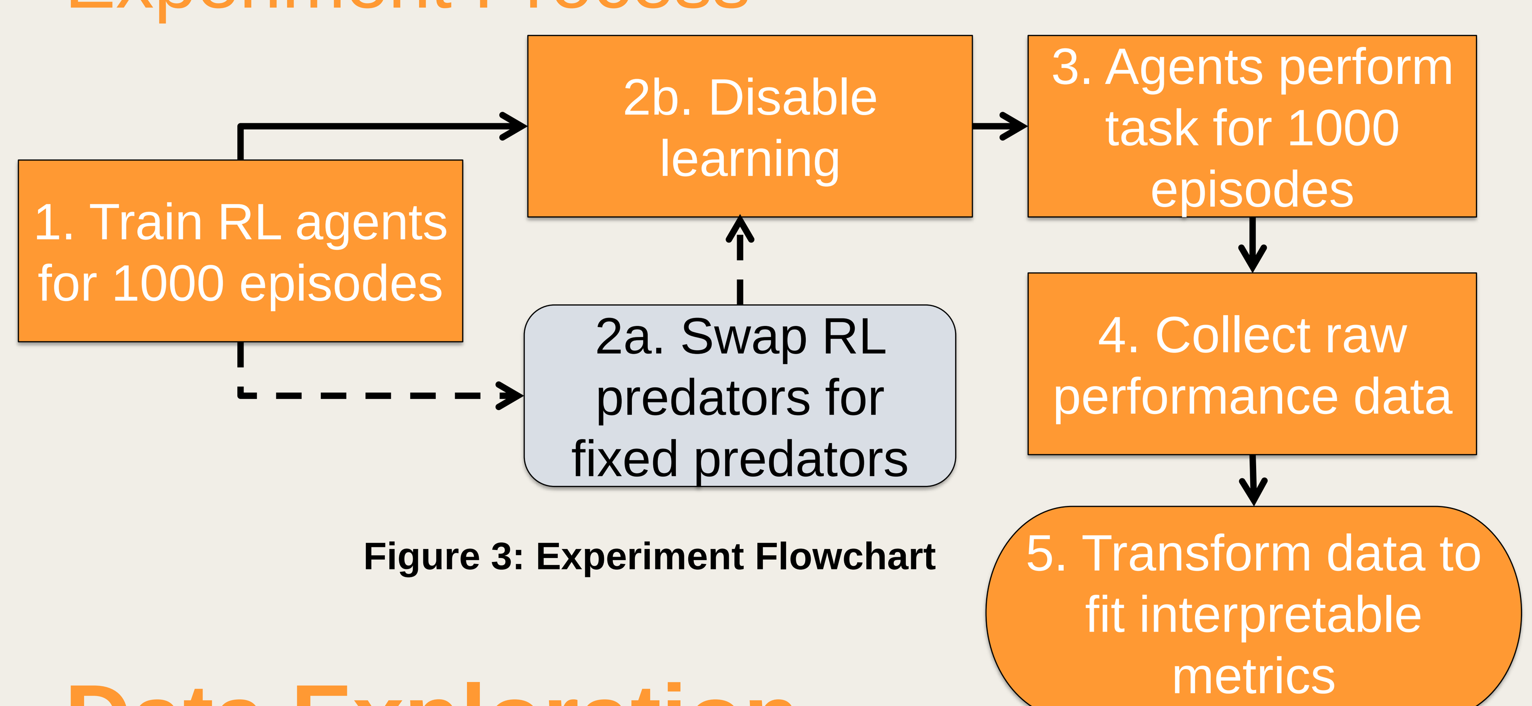


Figure 3: Experiment Flowchart

Data Exploration

- Selected several human-interpretable metrics that could describe the strategy of a predator agent.
- Applied principal component analysis **(Figure 4)** to determine which features were useful.
- **Key finding:** "Average Distance from Prey" feature was consistently the most variable between agents.
- Theorized that this feature is sufficient to differentiate between team strategies.

Results

- The extent of MARL agents' ability to adapt to their teammates can be inferred by observing the probability distributions formed by teams that contain a single MARL agent.
- By comparing these distributions to those from fixed strategy teams, the behavior of each RL agent becomes human-interpretable.

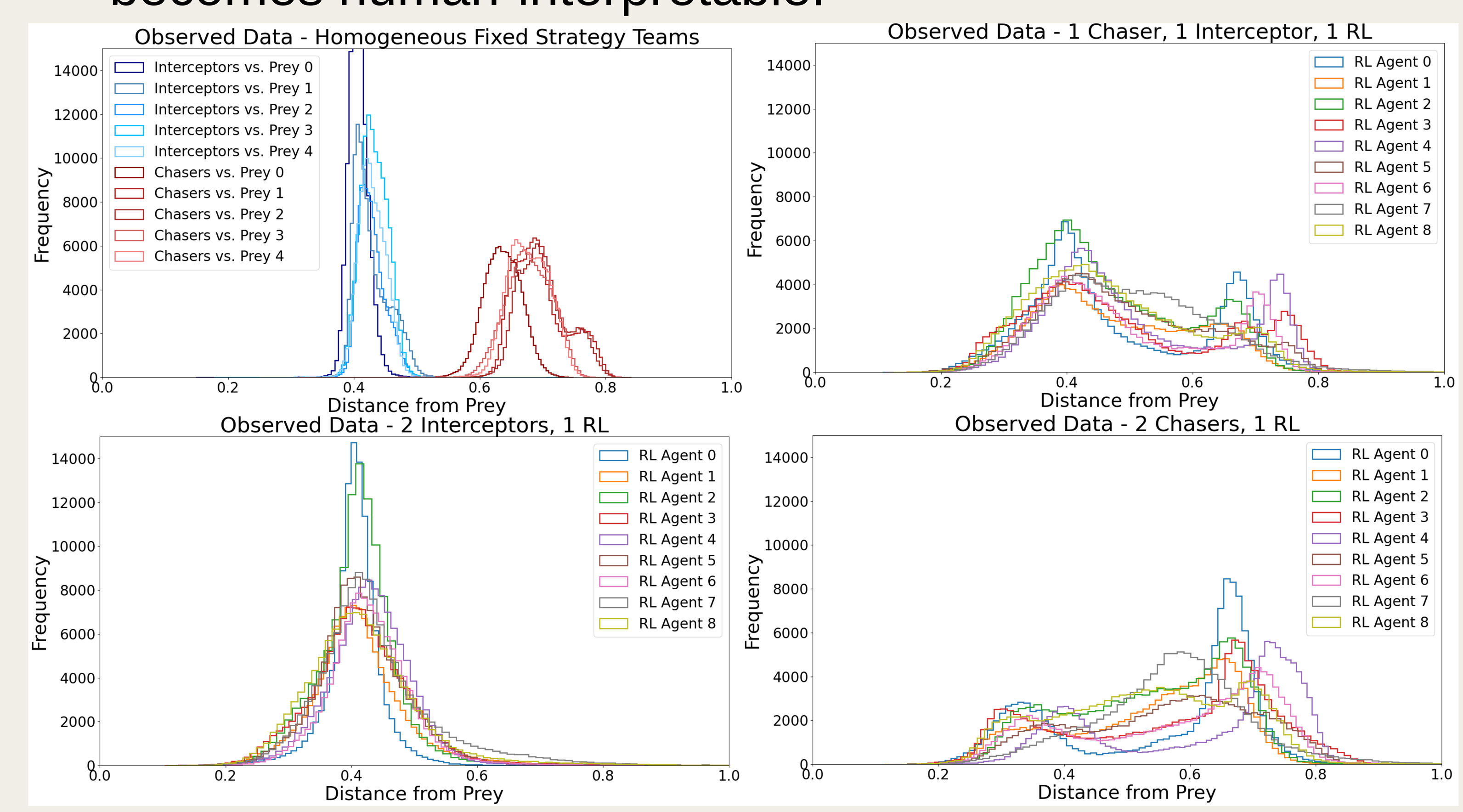


Figure 5: Probability Distributions of 'Distance from Prey' Feature for Various Predator Teams

- When paired with different combinations of fixed-strategy agents, MARL agents are observed to produce varied probability distributions.

Discussion

- Results indicate that MARL agents can assume different strategies to adapt to teammates.
- Investigating the process by which MARL agents are adapting to teammates can lead to an improved model of collaboration.
- This can lead to MARL agents that are able to intelligently form teams with other AI agents and human partners.

Future Work

- Train a classifier to identify team strategies by the multimodal probability distributions visible in Figure 5.
- Use findings from fixed strategy teams to investigate teams composed only of MARL agents.
- Create an agent that swaps between fixed strategies.

Works Cited

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