Tigers vs Deer - Collaborative Hunt

Autonomous Agents and Multi-Agent Systems

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ABSTRACT

This project aims to study and investigate efficient strategies for multi-agent collaboration in an environment characterized by predator-prey dynamics. In this system, tigers and deer act as agents with conflicting goals: tigers must collaborate to hunt deer for survival, while deer strive to evade capture and survive. By simulating a "Tigers vs Deer" scenario, we aim to explore how different coordination and cooperation mechanisms among agents impact their ability to achieve their objectives.

KEYWORDS

Predator-Prey, Artificial Intelligence, Multi-Agent, Autonomous Agents, Coordination, Cooperation, Adversarial, Decision Making, Belief-Desires-Intentions

1 INTRODUCTION

1.1 Motivation

Cooperative and conflicting interactions among agents, as observed in the Tigers vs. Deer environment, are prevalent in diverse real-world scenarios including gaming, ecosystem management, and business decision-making. By studying these dynamics within a controlled environment, we can gain valuable insights that parallel real-life struggles and problems.

The Tigers vs. Deer system serves as a microcosm of complex interactions, and our project seeks to harness these insights to develop effective coordination mechanisms and decision-making strategies that can be applied to real-world scenarios, thereby facilitating better understanding and management of cooperative and adversarial behaviors in multi-agent systems.

1.2 Related Work

Research in multi-agent systems (MAS) has explored various aspects of cooperative and adversarial behaviors among agents in dynamic environments. Cooperative hunting scenarios, similar to the Tigers vs Deer environment, have earned significant attention due to their relevance in understanding collaborative strategies and coordination mechanisms.

[1] A. A. Team et al., "Human-timescale adaptation in an open-ended task space," arXiv.org, https://arxiv.org/abs/2301.07608 (accessed Apr. 24, 2024).

[2] A. Bădică et al., "Multi-agent modelling and simulation of graph-based predator–prey dynamic systems: A BDI approach," Expert Systems, vol. 35, no. 5, Mar. 2018. doi:10.1111/exsy.12263 (accessed May 22, 2024).

Other notable works include studies on coordination mechanisms and communication strategies among agents. For example, the use of Nash equilibrium and social conventions in coordinating agent actions, as explored in various implementations of heuristic and role-based agents, highlights the significance of effective coordination in achieving optimal results in multi-agent systems.

In the context of ecological modeling, predator-prey interactions have been extensively studied to understand the balance and sustainability of ecosystems. These studies often employ MAS to simulate realistic scenarios where agents must adapt to changing conditions and develop strategies to survive and thrive. Such research provides valuable parallels to the Tigers vs Deer environment, where the goal is to explore how coordination and collaboration among agents can lead to successful hunting and evasion strategies.

1.3 Problem Definition and Relevance

The Tigers vs. Deer environment reflects cooperative and adversarial interactions seen in real-world scenarios. For example, in ecosystems, predators collaborate to hunt deer, while deer species evade capture. Similarly, in business, firms form alliances to achieve objectives while strategizing against competitors. The primary challenge lies in implementing a multi-agent system that optimizes and enables effective coordination among tigers to form alliances and successfully achieve their primary goal - surviving by hunting deer, while also considering strategies to allow collaboration between deer, ensuring greater survival of the species. This involves several key components:

- **Predator-Prey Dynamics:** Tigers and deer have distinct goals and behaviours, with tigers aiming to catch deer and deer trying to evade tigers.
- **Resource Management:** Predators need to manage their energy in order to survive, needing to feed on deer to stay alive, adding a layer of complexity to their interactions.
- **Environment Complexity:** The environment includes various obstacles, influencing the strategies and movements of both tigers and deer.

The relevance of this study lies in its potential applications across multiple domains. In ecology, it can help in developing better wildlife management strategies; In robotics, it can contribute to the development of more efficient algorithms for autonomous systems operating in dynamic and uncertain environments. Furthermore, in the field of artificial intelligence, it provides a robust framework for testing and improving multi-agent systems.

For reference of the code-base project, check: https://magent2.farama.org/environments/tiger_deer/

1.4 Objectives

- Determine how coordination among tigers influences their hunting success rate.
- Analyze the efficiency of different hunting strategies for tigers.
- Investigate collaborative strategies among deer to enhance their survival rates.
- Evaluate the role of 'family' structures in deer populations in increasing deer diversity and strategic complexity.
- Examine how robust the tigers' and deer's strategies are to noise or errors in communication and perception.

1.5 Implementation Details

To successfully build and simulate the Tigers vs. Deer environment, we utilized the programming language Python due to its extensive modules and support for scientific computing and artificial intelligence. Key modules employed include:

- **Gym:** This module was used for developing and managing the multi-agent environment. The environment was modified based on the environment provided during the practical lectures, and served as a robust base for our multi-agent system, which we adapted to include more complex interactions and dynamics specific to our project goals. To achieve the final environment solution, Gym provided a flexible and extensible framework that allowed us to create a customized environment where tigers and deer interact according to predefined rules and dynamics.
- **Numpy and Scipy:** These modules were essential for performing mathematical operations and data manipulation. Scipy was used for distance computations, while Numpy provided support for efficient numerical calculations and array operations.
- **Matplotlib:** For data visualization, Matplotlib was utilized. It enabled us to plot and compare results obtained from different strategies and algorithms, facilitating a clear and comprehensive analysis of the performance and behaviors of the agents.

To ensure that the agents (tigers and deer) could effectively interact within this environment, we employed object-oriented programming. This approach allowed us to model the internal states and behaviors of the agents through methods and attributes, providing a structured and modular way to define agent characteristics and interactions.

2 APPROACH

2.1 Agents

The agents have only partial observation capabilities, necessitating communication with their peers to inform their strategies. Their actions aim to maximize their survivability while considering the decisions made by other agents, as these directly impact the state of the environment. Our project comprises two major agent classes: Tigers and Deer. Additionally, if family settings are enabled, there will be two distinct families of Deer, one with enhanced vision and one with enhanced speed. A detailed description of each type of agent follows:

Tigers: Tigers start with 2 HP, which is the maximum possible HP, and lose 0.1 HP at every step they do not consume a deer, dying when their HP reaches 0. They have a default vision range of 3 units, allowing them to observe deer within this range in all directions. Tigers can move 1 unit in any direction per step, provided the unit is vacant, or they can stay still. When a deer is consumed, the tigers involved in the kill are rewarded with 1 HP. Each tiger can communicate its absolute position to all other living tigers and can share deer sightings with the ones they can see. Tigers aren't able to differentiate the deer by families and need to collaborate and coordinate in pairs to hunt down every deer. In sum:

$$TigerCommunication(x,y)_{id} = \begin{cases} \{(deer_{x_i}, deer_{y_i}) \mid \text{for all } i\} & \text{if } (\alpha) \\ (x,y,n) & \text{if } (\beta) \end{cases} \tag{1}$$

(α) Tiger is seen

(β) Tiger is not seen, where n is the number of prey seen

Deer: Deer do not experience HP decay over time; however, they die immediately once caught by the tigers. Each deer can communicate its absolute position to all other living deer in its family and can share predator sightings with the deer they can observe. This enables deer to collaborate within their family by sharing the tigers' positions, ensuring a greater chance of survival. The distinct features of the deer families allow us to investigate notable strengths or weaknesses in each family. The family with enhanced vision has a greater detection range, while the family with enhanced speed can move more quickly to evade predators. The families detailed description is as following:

- Family 1: Deer from this family have a vision range that is 3 units greater than that of the Tigers and the Deer from Family 2. They can move 1 unit in any direction per step, provided the unit is vacant, or they can remain still. This enhanced vision allows them to detect predators from a greater distance, improving their chances of evasion and survival.
- Family 2: Deer from this family have the ability to move 2 units per step, provided the units are vacant, unlike the Tigers and the Deer from Family 1, which can only move 1 unit per step. If there are not enough vacant units in the desired direction, they can move 1 unit or remain still. This enhanced mobility allows them to evade predators at a much faster rate, significantly improving their chances of survival.

$$DeerCommunication(x,y)_{id} = \begin{cases} \{(tiger_{x_i}, tiger_{y_i}) \mid \text{for all } i\} & \text{if } (\alpha) \\ (x,y,n) & \text{if } (\beta) \end{cases} \tag{2}$$

(α) Deer is seen

(β) Deer is not seen, where n is the number of tiger seen

We can characterize the agents as:

- **Autonomous:** The agents are able to act independently and thus determine how to achieve their delegated goals.
- **Reactive:** The agents are susceptible to changes in the environment and execute their decision-making accordingly.
- **Cooperative:** The agents cooperate with members of their own class to achieve their goals.
- **Rational:** The agents execute actions that maximize their survivability.
- **Mobile:** The agents have the ability to change their location in the environment.

2.2 Environment

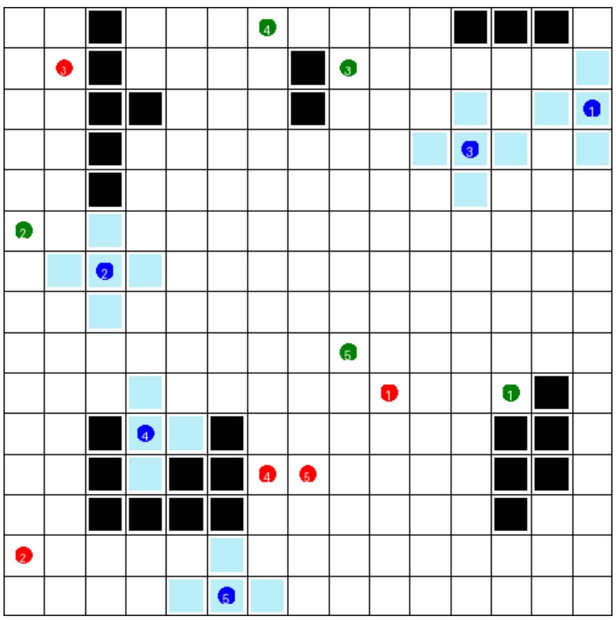

Figure 1: Tigers vs Deer System Environment

As demonstrated on Figure 1, the environment consists of a $2D$ grid with dimensions $X \times Y$, accommodating various agents and random obstacles. On the fragment presented we are utilizing a 15×15 grid size, with 15 agents in total: 5 Tigers, 10 Deer (5 from each family), represented by blue, red, and green respectively, and randomly placed obstacles around the grid. Depending on their class, agents may move 0, 1 or even 2 units horizontally or vertically at a time. The size of the grid is malleable by the user and so is the number of obstacles and the number of each type of agent. We can characterize the environment as:

- **Discrete:** The environment operates discretely, allowing agents to perform one of the following finite actions at each time step: Move up, down, left, right or do nothing;
- **Dynamic:** The agent's actions and decision-making impact the system and the decision of other agent's as well, making the environment dynamic.
- **Non-deterministic:** The actions aren't guaranteed to result in a calculated result, and there is uncertainty associated with the actions, therefore the environment isn't deterministic.
- **Episodic:** The system is executed in episodes which are composed by steps: each episode can be concluded when a certain number of steps is concluded (by default 100) or when a certain type of agent has been completely eliminated. The episodes are independent of each other and a new execution generates a new episode.
- **Inaccessible:** The agents have partial observability and aren't able to access the complete state of the environment, being restricted at each step to their own observations, the absolute positions of the members of their class and the observations of the members of their class that they can observe.

At each step the environment can described as:

$$EnvironmentState = \{[observation], [HP_T], [status_T], [status_{D_F1}], [status_{D_F2}]\} \quad (3)$$

$$\begin{aligned} [observation] \quad & \text{Observations of all agents} \\ [HP_T] \quad & \text{Array with tiger's health points} \\ [status_T] \quad & \text{Array with life status of Tigers} \\ [status_{D_F1}] \quad & \text{Array with life status of Family 1's Deer} \\ [status_{D_F2}] \quad & \text{Array with life status of Family 2's Deer} \end{aligned}$$

The actions that can be performed are:

$$ActionSpace = \{\text{Up, Down, Left, Right, Stay Still}\} \quad (4)$$

And the observation for each agent is:

$$ObservationSpace = \{(x, y), [(T_{x_i}, T_{y_i})], [(D_{x_j}, D_{y_j})], [(W_{x_k}, W_{y_k})]\} \quad (5)$$

$$\begin{aligned} (x, y) \quad & \text{Current position of the agent} \\ (T_{x_i}, T_{y_i}) \quad & \text{Positions of the visible tigers the agent sees} \\ (D_{x_j}, D_{y_j}) \quad & \text{Positions of the visible prey the agent sees} \\ & \textit{(only those from its family if the agent is a deer)} \\ (W_{x_k}, W_{y_k}) \quad & \text{Positions of the walls the agent sees} \end{aligned}$$

2.3 Agent Strategies

During the implementation of the system, we developed three major agent strategies: Random Agents, Greedy Agents, and BDI Agents.

2.3.1 Random Agents. As the name suggests, these agents select their next action without considering the state of the environment or their own observations. They randomly choose their next action with an equal probability among the Action Space and do not assess the feasibility of their chosen actions based on their observations. If an action is impossible, the environment treats it as if they have chosen to stay still. Consequently, they do not employ any strategies to optimize their survivability, acting purely on randomness.

$$RandomAgentAction \sim \text{Uniform}(ActionSpace) \quad (6)$$

2.3.2 Greedy Agents. These agents follow a straightforward strategy based on the Manhattan distance between their position and the closest opposing agent's position. Tigers' goal is to minimize this distance, while Deer aim to maximize it. Each agent acts solely based on the position of the closest opposing agent, without considering the positions of other opposing agents. However, they take into account their current position in the environment and choose only from the possible actions that align with their goal of either minimizing or maximizing the distance.

$$PossibleMoves = \{a \in ActionSpace \mid \text{CellInDirection}(a) \text{ isn't wall}\} \tag{7}$$

$$Action = \underset{a \in PossibleMoves}{\arg\max} \; \text{Goal}(a) \tag{8}$$

$$\text{Goal}(a) = \begin{cases} \text{distance}(deer, tiger + a), & \text{if agent is a Tiger} \\ -\text{distance}(deer + a, tiger), & \text{if agent is a Deer} \end{cases} \tag{9}$$

In case the agent is unable to observe any opposing agent, they will move randomly in that time step:

$$RandomAction \sim \text{Uniform}(PossibleMoves) \tag{10}$$

2.3.3 BDI Agents. These agents are modeled as Intentional Systems, which means they adopt intentional stances that develop agent behaviors in terms of mental states: beliefs, desires, and intentions. At the beginning of each step, every agent updates their beliefs based on the observed state of the environment. They then update their desires using the information contained in their beliefs and choose their intentions based on these desires. BDI agents aim to maximize their survivability by considering both their own observations of the world and the information received from members of their species or family. They account for their current position in the environment and select actions that align with their goal of survival, choosing only from the possible actions that best fulfill this objective.

In our system, only BDI Tigers possess the capability to collaborate and synchronize their efforts for more efficient hunting. At each time step, tigers update their positions and assess the locations of visible deer. More specifically, tigers receive the observations of each tiger within a continuous chain of tigers, meaning the sharing is transitive. For example, if tiger A directly sees tiger B and tiger B also sees tiger C, the 3 tigers are connected via B and thus all share the same absolute observations, which are the union of all 3 individual observations. Additionally, each tiger also receives the relative observations of tigers outside its chains, which includes their position, deer counts and cooperation status. Armed with this information, tigers establish partnerships conducive to more effective deer hunting, adhering to social norms and conventions. The process of selecting a cooperative partner (t_2) and deer (d) to hunt for a Tiger (t_1) unfolds as follows at each time step:

$$\underset{t_1,t_2 \in \text{AvailableTigers},\; t_1 \neq t_2,\; d \in \text{Deer}}{\arg\min} \; \text{distance}\,(d, \text{AveragePosition}(t_1, t_2)) \tag{11}$$

AvailableTigers	Alive tigers that don't have a partner
Deer	Alive deer
AveragePosition	Calculates the average of two points

In case, t_1 successfully finds t_2 but doesn't find d, the tigers will form a cooperation pair, and will use their relative observations to move in direction of the closest tiger that sees deer. In case, t_1 doesn't find t_2, it will ignore all deer found, and focus on finding a cooperative pair. To do so, it will utilize its relative observations to move in the direction of the closest tiger that also doesn't have a cooperative pair.

When a cooperation is formed and a deer is selected, the tigers will define the side of the deer they will approach to initiate their hunt by positioning themselves according to:

$$PossibleMoves = \{a \in ActionSpace \mid \text{CellInDirection}(a) \text{ is vacant}\} \tag{12}$$

$$Action(t_1) = \underset{a \in \text{PossibleMoves}}{\arg\min} \; \text{distance}(\text{CloserSide}(deer, t_1, t_2), t_1) \tag{13}$$

$$\text{CloserSide}(deer, t_1, t_2) = \underset{(s_1,s_2) \in \text{Sides},\; s_1 \neq s_2}{\arg\min} \; (\text{distance}(s_1, t_1) + \text{distance}(s_2, t_2)) \tag{14}$$

In case, no deer was observed by the tiger or the members of its species, it will move randomly like described in (10).

Meanwhile, at each time step, deer also update their positions and assess the locations of visible tigers. They receive absolute observations from directly visible family members (we remove the chain sharing), including their positions and the positions of any tigers they observe, as well as relative observations from unseen family members, detailing their positions and the number of tigers they observe. Deer use this comprehensive information to select their next action, aiming to maximize the distance between themselves and the weighted average positions of the perceivable tigers, as follows:

$$DeerAction = \underset{a \in PossibleMoves}{\arg\max} \; \text{WA}(deer) \tag{15}$$

$$\text{WA}(d) = \begin{cases} WAdistance(d, SeenTigers + CloseDeerSeenTigers), & \text{if } \neq \emptyset \\ WAdistance(d, UnseenTigers), & \text{otherwise} \end{cases} \tag{16}$$

In case, no tiger was observed by the deer or the members of its family, it will move randomly like described in (10).

3 EMPIRICAL EVALUATION

In order to empirically evaluate our multi-agent system, we primarily focused on analyzing the deer and tiger strategies that resulted in a higher number of family survivors and tiger survivors, respectively. To accomplish this, we separated our analysis into several teams, each with different combinations of tiger and deer behavior:

- All agents following Random strategy
- All agents following Greedy strategy
- All agents following BDI strategy
- 50% Greedy agents and 50% Random agents
- BDI Tigers with 50% BDI Deer and 50% Greedy Deer

The following metrics were proposed for our analysis:

(1) Tiger's average number of time steps to capture deer per episode

(2) Average number of deer consumed/captured per episode
(3) Average time steps per episode
(4) Average number of deer alive for each family per episode
(5) Average number of Random deer and Greedy deer alive for each family per episode
(6) Average number of BDI deer and Greedy deer alive for each family per episode
(7) Success rate of tigers Given the combinations and metrics above, we ran simulations on 30 different environments, ensuring a relevant sample size to minimize the randomness of the environment generation.

3.0.1 Average Number of Steps to Capture Deer. This metric assesses the efficiency of deer capture by calculating the average number of time steps each tiger takes to capture a deer successfully, signaled by the regeneration of the tiger's HP. This allows us to compare the performance of random tigers, greedy tigers and BDI tigers, and determine which strategy is faster at capturing deer.

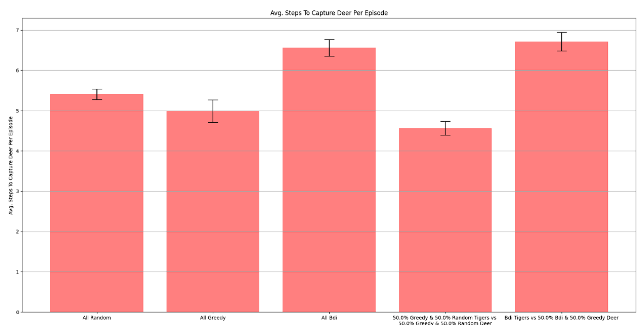

Figure 2: Average Number of Steps to Capture Deer per Episode

3.0.2 Average Number of Steps per episode. This metric helps us understand how different combinations of tigers and deer affect the duration of the simulation. By measuring the average number of time steps until the environment ends, we can determine if certain combinations lead to quicker or longer simulations.

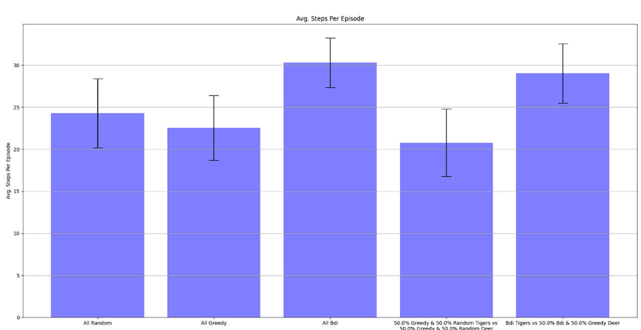

Figure 3: Average Number of Steps per Episode

3.0.3 Average number of deer captured per tiger per episode. This metric allows us to compare the effectiveness of different tiger strategies by measuring which type of tiger captures the most deer. This helps us determine which tiger strategy is the most successful in capturing deer. This also allows us to conclude if some combinations lead to more captures per tiger. This is calculated by measuring the deer that died in each episode and averaging all episodes.

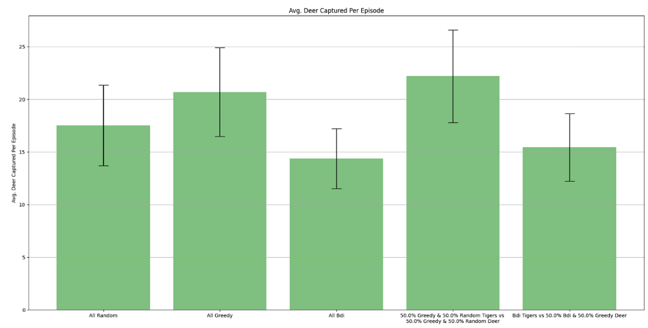

Figure 4: Average number of deer captured per episode

3.0.4 Average number of different families of deer alive per episode. This metric helps us understand which combination of tigers and deer leads to the highest number of surviving deer and which family of deer is most likely to survive. This information is useful in determining which family attributes are most effective in preserving the deer population. This is calculated by measuring the deer of each family alive at the end of an episode and averaging all episodes.

3.0.5 Average number of Random deer and Greedy deer alive for each family per episode. The fifth and sixth metrics are designed to evaluate the performance of mixed cases, where both random and greedy tigers and deer are present. These metrics allow us to determine which family of deer is more likely to survive in mixed environments and evaluate the overall performance of the system in handling different combinations of deer behavior. They are calculated as above, but taking into consideration the strategy of each agent.

3.0.6 Average number of BDI deer and Greedy deer alive for each family per episode. These metrics also evaluate a mixed case, but with BDI and greedy deer instead, while also keeping the tigers as BDI. This is crucial, offering a direct comparison of the different strategies used in the deer. It also helps us understand which combination of tigers and deer leads to the highest number of surviving deer and which family of deer is most likely to survive. They are also calculated as above, taking into consideration the strategy of each agent.

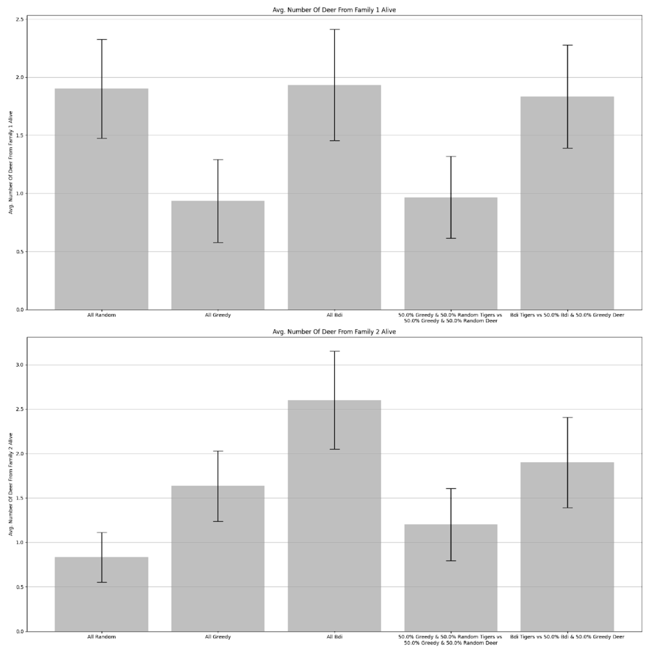

Figure 5: Average number of different families of deer alive per episode

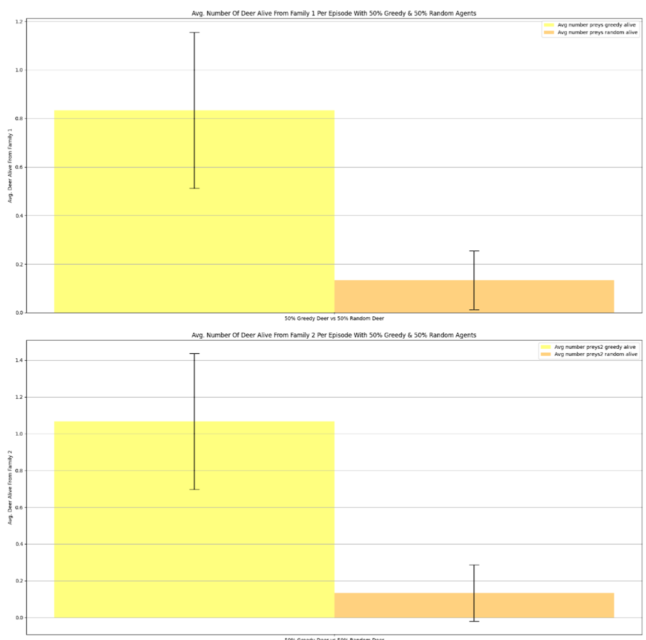

Figure 6: Average number of Random deer and Greedy deer alive for each family per episode

3.0.7 Success rate of tigers. This metric is a crucial metric because it directly measures the primary objective of the predators: capturing deer. This metric provides a clear, quantifiable indicator of

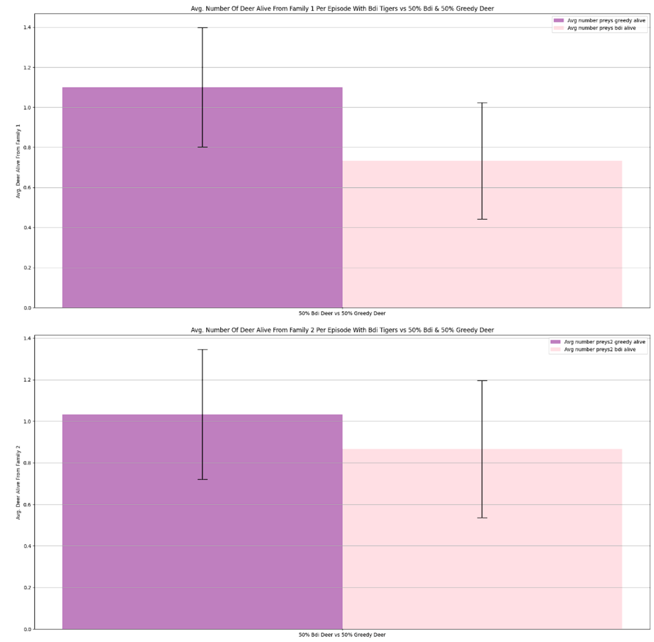

Figure 7: Average number of BDI deer and Greedy deer alive for each family per episode

performance, allowing us to compare different strategies objectively. By analyzing the success rate, we can determine how well the tigers' tactics work in achieving their goal and understand the impact of various factors such as agent intelligence, coordination, and adaptability. It is calculated by taking the amount of deer of the family with more casualties and dividing it by the initial value of deer of that family, which allows us to obtain the fraction of population captured, with 1 being the ideal value.

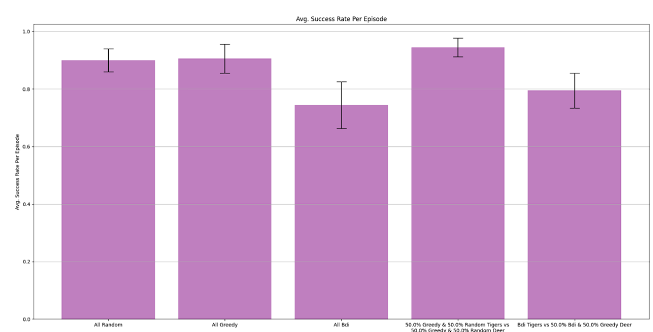

Figure 8: Success Rate of Tigers with different strategies

By analyzing the number of steps required to capture deer (Figure 2), the number of deer captured by the tigers (Figure 4/Figure 5), and the success rate of tigers (Figure 8), we can infer that the BDI strategy, while technically making the system more intelligent, from the direct comparison between BDI and Greedy deer (Figure 7), we can see the superiority of the Greedy deer. This can most likely be explained by the usage of weighted averages when deciding the BDI deer's movement, which turned out to be detrimental, or requiring finer tuning. As for the BDI tiger, since it's a cooperation strategy, we enforced the necessity of hunting deer as a pair of tigers. We're lacking the evaluation of this strategy without this requirement to be certain, but, since this strategy is an upgrade over the Greedy tiger, we can infer that this requirement was the main reason for the gap between both tiger strategies. From Figure 8, we observe that the strategies that optimize the efficiency of deer capture are Greedy and Random, especially when used together. This efficiency can be attributed to the nature of those strategies: Random agents, which do not consider the state of the environment in their decision-making process, leading to deer being captured by chance. Additionally, the Greedy strategy does not account for scenarios where a deer is being pursued by two tigers, as it only attempts to flee from the closest predator. This undermines the intelligence of deer using these strategies. Conversely, BDI deer, which employ more complex decision-making processes, substantially increase the difficulty for tigers, who must hunt cooperatively to capture them efficiently, making their success rate lower and creating the illusion that Random and Greedy tigers are better.

Furthermore, Figure 5 suggests that family structures and their attributes influence survival rates differently depending on the strategy employed. For Random agents, deer from Family 1 exhibit almost double the survival rate compared to those from Family 2. This discrepancy may be due to the fact that Random agents do not observe the environment in their decision-making process, leading to a situation where deer from Family 2 were consistently unlucky with their movements and ended up moving closer to predators by chance.

Conversely, strategies such as Greedy, BDI, and the mix of Random and Greedy yield better survivability outcomes for deer from Family 2. This could be hypothesized that Family 2's movement advantage aligns better with the predictable, yet straightforward, nature of the Greedy strategy and the sophisticated decision-making of BDI agents. Since these strategies use observations from the environment, Family 2's ability to move 2 units at a time enhances their capacity to exploit the environment or react more effectively under the pressure of targeted pursuits and intelligent evasion. This movement advantage is more impactful than Family 1's better vision range, as the increased mobility provides a significant edge in escaping predators and maneuvering through the environment efficiently.

Interestingly, the mixed team of BDI and Greedy deer shows negligible differences in survivability between the two families, achieving almost identical results. This indicates that the combined strengths of intelligent decision-making and straightforward tactics create a balanced dynamic that neutralizes the differences in family attributes. This balance might level the playing field, suggesting that such a hybrid strategy effectively mitigates the inherent disadvantages one family might have over the other in more polarized strategy scenarios.

Greedy agents demonstrate a significant improvement over random agents, as shown by the reduction in the average number of steps needed to capture deer. This improvement highlights the benefits of a straightforward, though short-sighted, approach. The greedy strategy, focused on immediate gains, proves to be more effective than random movement in terms of achieving the primary objective of capturing deer. Overall, these findings underscore the complexities and trade-offs involved in employing different strategies within a multi-agent system, providing valuable insights into optimizing predator-prey interactions.

4 FUTURE WORK

Due to the time constraints, we were not able to implement all the desired features for the system. In future iterations of this project, we would aim to expand and enhance the capabilities of our agents and the overall system through several key areas of development:

- **Reinforcement Learning:** A significant advancement in the capacities of our system would be to integrate learning, specifically Reinforcement Learning. By employing reinforcement learning, agents can learn optimal strategies over time based on rewards and penalties received from their actions. This would enable them to adapt to the environment more effectively, improving their hunting or evasion strategies dynamically as they gather more experience.
- **Divide and Conquer Strategy:** Currently, tigers tend to cluster around the closest deer, which often leads to inefficient hunting patterns with many tigers crowding one area while deer in other zones remain untouched. This approach would allow agents to spread out across the grid, systematically dividing the area into sections to ensure comprehensive coverage and reduce deer survivability by avoiding unnecessary agglomerations.
- **Memory System:** By incorporating a simple memory system for the agents, they could remember previous locations of tigers or deer and use this information to make more informed decisions. This would prevent them from repeatedly checking the same locations and help them identify patterns in deer movement or tiger behavior, thereby optimizing their survival strategies.
- **Loyal Cooperation:** Instead of reassigning their cooperation partners every iteration based on immediate benefits, tigers would maintain consistent partnerships until death. This loyalty could lead to more stable and effective hunting groups, potentially improving overall hunting success by fostering stronger cooperative bonds and reducing the overhead of constantly re-evaluating partnerships.
- **Move Prediction:** Tiger's strategy would benefit from being able to infer the most likely moves of deer and preemptively position themselves if beneficial. By predicting the possible escape routes and behaviors of deer, tigers can optimize their movements to intercept and capture deer more effectively. This predictive capability would enhance the strategic depth of the game, providing a more challenging and realistic simulation of predator-prey dynamics.