Swarming behaviour in predator-prey model

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Collective behaviour course research seminar report

Collective animal behaviour, especially swarming in predator-prey dynamics, offers insights into survival strategies that emerge under evolutionary pressures. This report outlines the initial objectives and foundational concepts for simulating predator-prey. Inspired by previous work, we examine how survival pressures can drive emergent group behaviours in prey through reinforcement learning. We begin with an overview of related work, from classic rule-based models to more recent reinforcement learning approaches, highlighting advances that allow agents to adapt to changing environments. Our primary objective is to recreate a reinforcement learning-based model where predator-prey interactions lead to swarming and evasion behaviours. The model will then extend to include environmental obstacles and an additional species, enabling us to investigate the interplay between interspecies interactions and survival strategies.

Simulation | swarming behaviour | predator | prey

The sudden emergence of swarming behaviours in animals is one of the most striking examples of collective animal behaviour. These behaviours have been extensively studied for their implications for the evolution of cooperation, social cognition and predator–prey dynamics[1]. Swarming, which appears in many different species like starlings, herrings, and locusts, has been linked to several benefits including enhanced foraging efficiency, improved mating success, and distributed problem-solving abilities. Furthermore, they are hypothesized to help with improving group vigilance, reducing the chance of being encountered by predators, diluting an individual's risk of being attacked, enabling an active defence against predators and reducing predator attack efficiency by confusing the predator. [2].

In this project we will be taking inspiration from the work of Li et al. (2023) and Olson et al. (2013) to explore how survival pressures can drive the emergence of swarming behaviour. The first goal will be to create a realistic simulation where both prey and predators learn to adapt through reinforcement learning based on their drive to survive. Modelling these interactions, we will observe how simple survival pressures can lead to evolution of more complex behaviours like flocking, swirling and edge predation.

Then, we will extend our research by evolving out existing model by introducing new environmental obstacles and new species to observe how interspecies interactions lead to new survival strategies.

Related work

The modelling of swarming behaviour has evolved from foundational rule-based frameworks to more sophisticated reinforcement learning (RL) approaches, with intermediate advances in topological and vision-based models that add realism to agent interactions.

Rule-Based models. Early models of swarming relied on static interaction rules to simulate basic group dynamics. Aoki's Zone Model (1982) introduced three interaction zones-repulsion, alignment, and attraction-where agents adjust their behaviour based on proximity to neighbours [3]. Later, Vicsek's Model (1995) and Reynolds' Boids Model (1987) introduced basic alignment rules (and in Reynolds' case, also cohesion and separation) to generate coordinated group movement [4][5]. Although effective in modelling simple swarming behaviours, these models rely on fixed rules that limit agents' ability to adapt dynamically to changing environments or threats.

Topological and Vision-Based Extensions. Topological and vision-based models improved realism by adding sensory and neighbour-based constraints. Hemelrijk & Hildenbrandt (2008) introduced a perception model where agents respond only to neighbours that are visible within a variable radius, adjusted by local density, stabilizing cohesion across varied densities [6]. Kunz & Hemelrijk (2012) further refined this approach by incorporating visual occlusion, where agents respond only to visible neighbours, simulating real-world sensory limitations [7]. While these models increase biological realism, they remain rule-based and lack the flexibility of adaptive RL models.

Advances in RL-Based Models. Reinforcement learning has enabled a significant leap in modelling swarming behaviours by allowing agents to learn and adapt based on environmental feedback rather than relying on fixed rules. RL models produce dynamic, emergent behaviours like flocking and evasion, closely mimicking natural adaptive responses to survival pressures.

- Li et al. (2023): In this RL-based predator-prey model, prey agents develop swarming behaviours by maximizing survival rewards and minimizing capture penalties [2]. Prey adaptively form cohesive groups and evade predators, learning these behaviours through experience rather than pre-set alignment rules.

- Olson et al. (2013): Olson and colleagues focused on predator confusion, where prey learn to cluster, reducing individual predation risk by confusing predators [1]. This model highlights RL's capability to foster adaptive, emergent behaviours in predator-prey dynamics.

- Lowe et al. (2017): The Multi-Agent Deep Deterministic Policy Gradient (MAD-DPG) algorithm enables agents to learn in mixed cooperative and competitive environments, making it ideal for systems with multiple interacting species [8]. MADDPG supports complex, dynamic environments by allowing agents to optimize strategies in both cooperative and adversarial contexts, such as predators and prey with differing objectives.

Objective. Building on the RL framework of Li et al. (2023), this project introduces a third species and environmental obstacles to explore their effects on swarming and predation [2]. By adding these complexities, we aim to investigate how prey adapt to both predator pressure and environmental challenges, and how interactions with an additional species influence swarm dynamics and survival strategies.

Methods

For our project we will be using python and modelling the predator-prey model in a two dimensional space without any edge constrains.

TODO - agent modeling, reinformcnt learning, new spieces and obstacle, evaluation metric?

Results

Even though we currently don't have any results, we can outline what we anticipate to achieve. One of the results will be a simple model that is a recreation of Li et al. (2023) model in python. It is expected to model the development of swarming behaviours. We have already extracted their code and have successful ran it. We intend to compare our results with the article.

After that, we will build upon our existing model by adding new obstacles and interspecies interactions.

Discussion

Though we just started working on the project, we have already encountered some issues when trying to run the code of our main article. We managed to contact the original authors and they were quick and happy to help so as of right now, we are happy to report we got the code working and running.

We acknowledge that we have set ambitious goals, especially by introducing a new species into the mix. We anticipate a lot of new issues will arise through the semester, however we are excited to challenge ourselves and we are determined to learn from the process no matter the outcome.

Initially this project began with just two people working on it, but due to the complex nature of the project, we have joined forces with another group of just one member. This will enable us to work on the assignment more efficiently and have easier time achieving our goals.

CONTRIBUTIONS. AK worked on introduction, expected results and discussion, TB worked on related work, VL worked on abstract and getting original model to work.

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