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Flock behaviour in a prey-predator model
Modeling Complex Systems 1MA256

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1 Introduction

In nature collective behaviour is an astonishing phenomena that can be seen in numerous of species including for instance the flocking of bird, and ants forming ”highways” to travel and bugs flying in swarms. Thanks to this behaviour, the individuals of the population can benefit in several ways. For example, it can keep energy and heat within the population, increase food gathering or protect against attacking predator. The latter was studied and modelled with self propelled particles in a prey-predator model by Yuan Lin and Nicole Abaid in their report ”Collective behavior and predation success in a predator-prey model inspired by hunting bats” [1]. A similar approach to their modeling is done in this paper with some interesting modifications and extensions.

2 Model description

The model studied in this report is a self propelling particle prey-predator model consisting of particles living along the surface of a torus. The torus is modelled by unfolding it into a 2D square with side length L and with periodic boundary conditions. On this 2D plane two types of particles live: prey and predators. All the particles are initially spawned with uniformly distributed random probability position and angle (direction). In total there are $N_{prey}+N_{predator}$ particles on the torus which will interact with each other in discrete time. The movement and interaction of the particles are described in the following two subsections.

2.1 Prey

The prey move and interact with other prey according to the Vicsek model. This model's idea is that at every discrete time step, the particles moves according to the average direction of its neighbors within a certain circle with radius r_{prey} and with a certain amount of added noise η. That is, the particles follows its neighbors, aligns with them and moves in a flock where the noise represents a wrongly evaluated direction of its neighbors. The angle in which a particle align itself can be described mathematically by:

$$\theta_i(t+1) = \tan^{-1}\frac{\sum_{j\in r_{prey}}\sin(\theta_j(t))}{\sum_{i\in r_{prey}}\cos(\theta_j(t))} + \phi_i(t) \tag{1}$$

where $\theta_i(t+1)$ is the angle of particle i at time step $t+1$ and ϕ is a random angle from a range $[-\pi,\, \pi]$ multiplied with noise factor η_{prey}.

The calculated angle θ is then used to update the X and Y position of particle i according to:

$$\begin{aligned} X_i(t+1) &= X_i(t) + S_{prey}\cdot\cos(\theta_i(t)) \\ Y_i(t+1) &= Y_i(t) + S_{prey}\cdot\sin(\theta_i(t)) \end{aligned} \tag{2}$$

where S_{prey} is the speed of the prey.

2.2 Predator

The predator movement is split into three different scenarios. The first is when no prey is within a circle of radius $r_{predator}$ and the predator can not sense any neighboring prey to hunt. In that case the predator moves as random walker around the torus and updates its position according to:

$$\begin{aligned} X_i(t+1) &= X_i(t) + S_{predator} \cdot \phi_i(t) \\ Y_i(t+1) &= Y_i(t) + S_{predator} \cdot \phi_i(t) \end{aligned} \tag{3}$$

where S_{prey} is the speed of the predator and ϕ is a random angle from a range $[-\pi, \pi]$ multiplied with noise factor η_{prey}..

When the predator can sense prey, i.e there is prey within a circle of radius $r_{predator}$, the predator starts hunting. The predator evaluates the distance to all neighboring prey, finds the closest one and updates it angle to head towards that prey. The update angle is determined by simply finding the angle between the position of the closest prey and the predator itself. In order to not give the predator a perfect behaviour in its hunt for prey, a random angle $\phi(i,t)$ is added to the update angle. Using the update angle, the position of the predator is updated as:

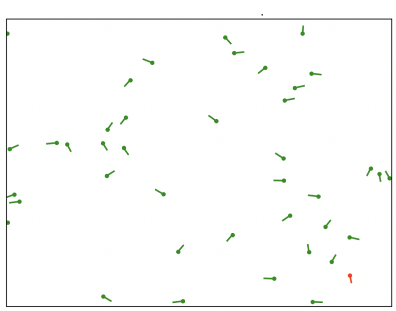
$$\begin{aligned} X_i(t+1) &= X_i(t) + S_{predator} \cdot \cos(\Phi_i(t)) \\ Y_i(t+1) &= Y_i(t) + S_{predator} \cdot \sin(\Phi_i(t)) \end{aligned} \tag{4}$$

where $S_{predator}$ is the speed of the predator and Φ is the angle heading towards the closest prey with a random angle from a range $[-\pi, \pi]$ multiplied with noise factor $\eta_{predator}$ added to it.

If the closest prey is at a maximum range of r_{eat}, the prey is considered to be eaten by the predator. In such case, the prey is moved to a random position on the torus with a random angle in order to keep the size of the prey population constant and the predator continues moving randomly.

2.3 Comparison to the model in the original paper

The model presented by Yuan Lin and Nicole Abaid in their paper [1] is to a large extent very similar to our model presented in Section 2. One of the main difference, and maybe the most obvious one, between the models is the world the particles live in. Lin and Abaid model their world as a three dimensional cube of side length L with periodic boundary conditions whereas in our model the world is a 2D torus. The representations of both worlds is shown in Figure 1 below.



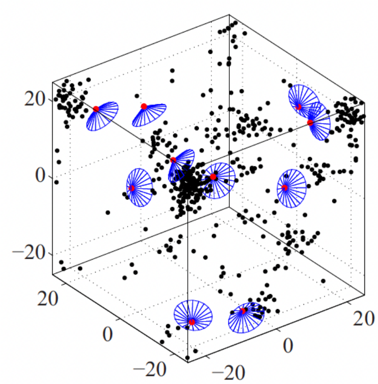


Figure 1: Plots of our world (left) and Lin and Abaid's world (right) [1].

In addition to the world representation, the predators "sight" is different in our model. Lin and Abaid uses conical sensing space for the predator, as seen as the blue cones in Figure 2, which is done to replicate the physical parameters of a big brown bat. However, in our model the predators sensing space is circular resulting in a possibility to sense prey behind them and making the hunting easier. This modeling can for example represent that predators sense their prey with their hearing (spherical/circular sensing) rather than sight (conical sensing).

Another difference between the models is how the position of the particles is updated. Lin and Abaid's model uses velocity vectors to update position whereas in our model angles are used. However, these angles are converted to vectors when the position is updated, making the difference not that large.

3 Simulation result

In this section, results of sample runs for different parameter values will be presented to give the reader an overall understanding of the behaviour of the model. Videos of the sample runs are available at: `https://drive.google.com/drive/folders/1JQqekZyVZgz2KKuROS8YdbGTxKgEePCr?usp=sharing`.

The first interesting behaviour that the model presents is when η_{prey} is low or even zero. In this case, all the prey align themselves after a certain time, creating a large flock that moves together in a certain direction. If the predator starts following a prey moving with the flock and can't catch it because for example it has the same or less speed, the predator will catch and eat very few prey. Although, if the predator moves in the opposite or perpendicular direction of the moving flock, the hunt will be more successful. This behaviour of the model is shown in the video SampleRun1.

On the other hand, if the η_{prey} and $\eta_{predator}$ is high, i.e the movement of the particles is very noisy, the simulation looks like a simulation of a Brownian motion. Very few hunting attempts is successful by the predator since it moves basically randomly when it is hunting and the prey doesn't alignment themselves with neighboring prey. This behaviour of the model is shown in the video SampleRun2.

Varying the speed of the prey and predator also presents some interesting behaviour. When the prey is much faster than the predator, the predator can not keep up when chasing a prey but randomly catches prey because they simply sometimes are close enough for the predator to eat them. Contrarily, when the predator is faster than they prey, they catch every prey they sense, making the hunt much more successful. These behaviours of the model is shown in video SampleRun3 and SampleRun4.

A successful behaviour for the prey seems to be aligning themselves with each other. When they align with each other, it can be hard for the predator to find the flocks of prey and the predator simply becomes a random walker. This behaviour can be seen in SampleRun5 and be compared to SampleRun4 where the prey actually align.

However, when prey interact with each other and create flocks, the entire flock can be eaten by the predator if the predator is fast enough. This creates a behaviour of the predator eating a lot of prey in small amount of time rather than a continuous eating over the duration of the simulation. If one wants a more continuous eating for the predator, the sensing radius $r_{predator}$ can be increased and predator finds single prey more often. This behaviour is shown in SampleRun6.

3.1 Choosing measurement of interest

There are a lot of interesting measurements one can use to study self propelling particles and a prey-predator model. For instance, one can use polarisation to measure alignment or use cell coverage to see how the particles is distributed over the world. However, in our case every single parameter of the model will more or less determine how successful the predator is at hunting prey, or vice versa how many prey survive. This is clearly seen in the sample runs provided above. As a result, it seems natural to use number of prey eaten as the main measurement when analysing how modifying parameters affect the behaviour of the model.

4 Modifying a parameter

In this section, an investigation on how systematically changing certain parameters leads to a change in how many prey is eaten. As there are a lot of parameters of the model, not all will be able to be tested and when a certain parameter is not explicitly given a value or being tested, it will take the standard value of that parameter provided in Table 1 below. All the simulations will be run for 100 time steps.

$L = 1$	$N_{prey} = 50$	$N_{predators} = 1$
$\eta_{prey} = 0.2$	$\eta_{predator} = 0.2$	$r_{eat} = 0.05$
$r_{prey} = 0.2$	$r_{predator} = 0.2$	$\frac{S_{predator}}{S_{prey}} = 1.5$

Table 1: A table providing the standard values for the parameters of the model.

4.1 $r_{predator}$ impact on amount of eaten prey

By changing the predator's radius of interaction $r_{predator}$, one can measure how the number of eaten prey changes. In Figure 2 below a phase transition plot of how the number of eaten prey versus $r_{predator}$ is displayed which was created by simulating the model 50 times for 20 values of $r_{predator}$ between 0.01 to $\sqrt{\frac{L}{2}}$.

Analyzing Figure 2, one notices some interesting behaviour of the model. If $r_{predator}$ is small the predator barely interact with prey and therefore don't hunt for them which explains why the number eaten prey is small. When $r_{predator}$ increases, the predator can find prey and can successfully eat prey during its hunting. However, in the $0.2 - 0.7$ for $r_{predator}$ there is barely any difference in number of eaten prey. This can be explain by the fact that predator seek the closest prey and therefore a predator won't seek a prey far away from itself even if it can see it.

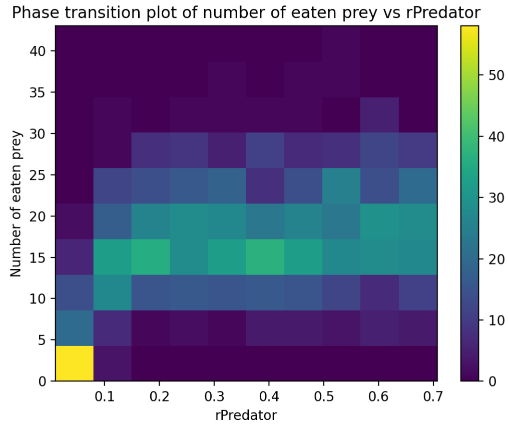


Figure 2: Phase transition plot of how the number of eaten prey versus $r_{predator}$.

4.2 $S_{predator}$ impact on amount of eaten prey

In Figure 3 below a phase transition plot is displayed, showing how the number of eaten prey is affected with by change of parameter $S_{predator}$. This plot was created by simulating the model 50 times for 20 values of $S_{predator}$ between 0.1 to 10. Note that $S_{predator} = 0.1$ results in the prey being 10 times faster than predator whilst $S_{predator} = 10$ means that the predator is 10 times faster than the prey.

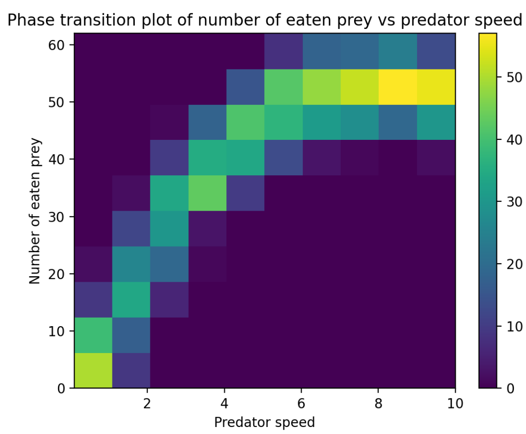


Figure 3: Phase transition plot of how the number of eaten prey versus $S_{predator}$.

From Figure 3 it is clearly displayed that an increase in predator speed results in a more successful hunt for the predator. However, when the speed reaches about 6, i.e the predator is 6 times faster than the prey, the increase in number of prey eaten stops. The reason for this phenomena is that the predator becomes so fast that it moves past the prey during its hunt and either have to turn back to catch the prey or finds another prey to hunt. As a result, the predator have a harder time to catch prey and therefore the number of eaten prey doesn't increase.

4.3 η_{prey} and $\eta_{predator}$'s impact on amount of eaten prey

In Figure 4 and 5 below, phase transition plots of how the number of eaten prey versus η_{prey} and $\eta_{predator}$ respectively is displayed. They were created by simulating the model 50 times for 20 values of respective η between 0 and 1 where 0 minimizes the randomness in particle movement and 1 maximizes it.

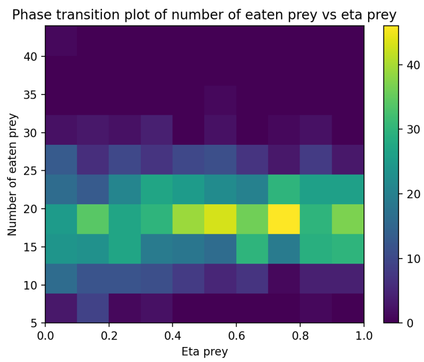


Figure 4: Phase transition plot of the number of eaten prey versus η_{prey}.

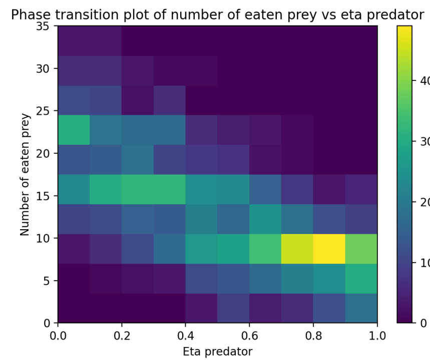


Figure 5: Phase transition plot of the number of eaten prey versus $\eta_{predator}$.

First and foremost, the results in Figure 4 were quite surprising. We expected that the alignment of the particles (low η_{prey}) would help the prey avoid the predator (as discussed in Section 3) in a larger extent which does not seem to be the case. Although there are more cases where there are more number of eaten prey for higher value of η_{prey}, it was expected that the difference for low and high η_{prey} would be bigger. However, in Figure 5 the results looks like more our expectations. When $\eta_{predator}$ is low, the predation is high since the predator is not interfered by noise in its hunt for prey. A high value for $\eta_{predator}$ on the other hand, leads to the predator having a hard time to evaluate were to move to catch prey which in turn results in less predation.

4.4 Conclusion from the modification of parameters

From the results that was presented in previous sections, one can conclude that the parameters definitely affect the predation of the model. If we seek a high predation, the predator should be significantly faster than the prey, have a radius of interaction $r_{predator} = 0.2$ or higher and the perturbation for the predator $\eta_{predator}$ should be low. Contrarily, if low predation is sought the prey speed should be high, $r_{predator}$ should be lower than 0.2 and $\eta_{predator}$ should be high.

5 Extension

In this section, two extensions to model is introduced, analyzed and discussed. The extensions are focused on changing the rules for the particles, i.e how the move and interact with each other.

5.1 Extension 1: Prey can detect and avoid predators

As discussed in the future work section in Yuan Lin and Nicole Abaid's paper [1], it would be interesting to study the behaviour of the model if the prey is able to detect and evade predators. In this section, the evasion of prey work by the principle that if one or several predators are within the prey's sense range r_{prey}, the prey will avoid the closest predator by moving in the opposite direction of the predator. In Figure 6 a phase transition plot of number of eaten prey versus r_{prey} is displayed, showing how the extension adds a new interesting dynamic for the model. When r_{prey} is low, the prey do not have enough time to sense the predator, resulting in easy hunting for the predator. However when r_{prey} increases, the hunting becomes harder rapidly and when $r_{prey} > 0.3$ the predator manages to eat only a few prey.

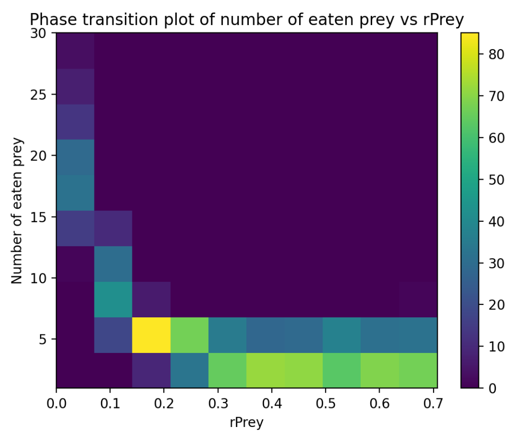


Figure 6: Phase transition plot of how the number of eaten prey versus r_{prey} using the extension of the model.

This extension does not only affect the number of eaten prey, but also how the prey and predators move and interact with each other. Firstly, when prey is trapped between two predators or group of predators, they barely move but instead end up changing direction back and forth. As a result, the predators can catch up with the prey and most cases eat it since the prey doesn't know where to go to evade the incoming hunt. In general, this technique of trapping prey seems to be a very successful strategy for the predators. Moreover, the avoidance rule seems to group the prey much more close to each other than before. Consequently, the predators have a hard time to find and hunt prey since they are not distributed as evenly over the torus. However, when these dense groups get caught when for example two predators trap them, the predators have more prey to eat. In the same Google Drive provided in Section 3, there is an example run using this new rule, displaying the interesting behaviours of the model.

6 Extension 2: Flock behaviour

To create a more realistic and dynamic type of behaviour of the particles, flock behaviour is introduced. This was inspired by the flock behaviour introduced by C.Reynolds in his paper "Flocks, herds and schools: A distributed behavioral model" [2] and it consists of three steering behaviour describing how an individual particle maneuvers based on the direction and position of nearby flock mates. The first steering behaviour is alignment which will be handled by the Vicsek model introduced in Section 2.1. The second is cohesion which make sure each individual steer toward the average position of nearby neighbors. Lastly, separation steering is added to maintain prudent separation within each flock, i.e each individual to steer avoid collision with local flock mates. All in all, these three steering behaviours creates an interesting dynamical flock behaviour where the population can consist of solitary particles and flock of particles with different sizes. To make sure this behaviour works more realistic and smoothly, momentum is added to the movement of the particles. This means that the prey and predator does not instantly move to/away from the other species when they are within the sight radius. This is achieved by adding the difference between the current angle and the optimal angle pointing to the other species, multiply it with a factor we refer to as turning speed and add the result to the current angle. As a result, the movement of the particles is not as jagged as before and since the momentum is added to both species, the success rate of hunting should approximately stay the same. In the same Google Drive provided in Section 3, there is an example run using this new extension, displaying the momentum of the particles and the flocking behaviour of the prey.

In Figure 7 below, a phase transition plot of how different type of flocking and steering behaviour affect the number of eaten prey. From the plot, it is displayed that no flocking favours the predators while the survival rate of prey increases when the prey flock. However, it was expected to be a larger difference between flocking and no flocking. The reason for the difference being small could the fact that prey naturally flocks when they evade predators, as discussed in Section 5.1, and hence adding an advanced flocking behaviour does not affect as much.

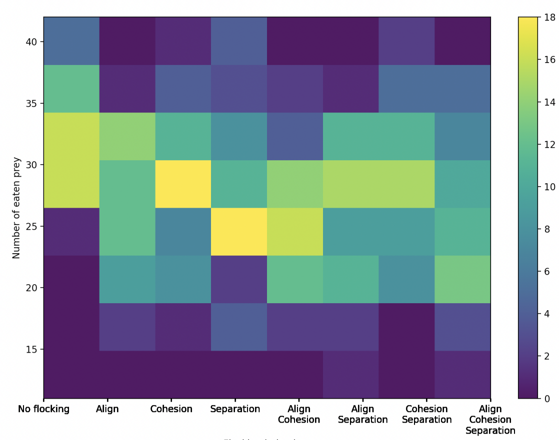


Figure 7: Phase transition plot of how the number of eaten prey versus flocking behaviour.

7 Conclusion

To begin with, it can be concluded that a prey-predator hunt model using the Vicsek model can be implemented in an easy manner and still provide some really interesting results. As seen in Section 4, modifying parameters of the model changes the behaviour of particles as well as interesting metrics of model.

Moreover, the possibility for prey to detect and avoid predators adds another dimension to the complexity of the model. This attribute does not only increase the survivability of the prey, but comes with interesting behaviour such as natural flocking due to evasion. With this extension, some interesting starting points for further works appears. As discussed in Section 5.1, there are several obvious behaviour of the predator such as trapping flocks of prey that would increase the eating for the predators. For example, one can use a similar approach to what Wang et al. did in their paper "Deep-Reinforcement Learning-Based Co-Evolution in a Predator–Prey System" [3] where deep-reinforcement learning was used to represent the adaptation and evolution of predators and prey, to find new and improve the behavior of the particles.

From the analysis of the second extension, it can be concluded that flocking behaviour favours the survivability of the prey. This result goes hand in hand with what has been seen in research and what we see in nature every single day where animals group and flock to reduce risk of predation [4] [5] [6]. This reduced risk is in our case most probably a result of earlier detection of incoming threats [4] but in more realistic environments there can be several different influential mechanisms, including for example "confusion effect" experienced by predators [7]. In addition to the risk of being predated is decreased, flocking can come with other benefits, including energy and warmth keeping storage within the population [8].

All in all, the majority of the results were interesting but not that surprising. Similar results are seen in both nature and research which fortifies our results and proves that our model is displaying a realistic behaviour. In addition, our results reinforces the knowledge we have of behaviour in nature, in particular prey and predator relationships were flocking is present.

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