How do different communication strategies in prey affect their population curves?

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Abstract

Populations of predator prey relationships have been monitored for hundreds of years, helping humans understand their behaviours and interactions. With the increased computing capabilities, professionals can create simulations of the environments and creatures to capture similar data on a much larger scale. We can use the findings from these simulations to investigate real world ecosystems to reason about their stability.

For this project, I will be creating 2-creature simulations, a prey and predator, and monitoring how the changes in the prey's communication with one another impact their global population. The predators and environment will remain consistent across the experiments as we are only investigating how the changes to the communications between the prey impact our findings.

All creatures have vision of their local environment, and based on what they see, and inputs from any communication received will act towards their primary goals. The decision-making processes for the creatures will also remain consistent, with the only change being the parameters of the prey changes depending on the current communication strategy.

Questions

1. How do different communication strategies[1] in prey affect their population curves[2]?
2. How do different communication strategies in prey affect the chances of forming a stable ecosystem[3]?

Communication Strategies – Methods of knowledge sharing between our agents to allow increasing understanding of the environment.

Population Curves – A mapping of the global populations over time of the different types of agents.

Stable Ecosystems – An ecosystem containing both types of agents for an extended duration.

Background research

Similar Systems

Lots of existing publicly available systems exist showing the standard population curves found in predator/prey environments (Learning Link, 2020). A subset of these work using mathematical models for probabilistic action selection to simulate behaviour (Shodor, 2006). In simulations like these, creatures are independent and acting based purely on their probabilities. Even the slightest changes in these probabilities can massively change the resultant population graphs, ending in collapsing populations. For these simulations, the environment is set into grid regions, and the creatures move between these. This is unrealistic, especially in combination with the lack of perception. We could however extend this decision making to include what information is perceived and communicated between our prey and conduct our experiments from there.

Alternatively, there are existing simulations that are built up in continuous space in which agents move freely. These are more accurate simulations of creature movements, where agents have direction, sight, etc. Systems like this typically have much more stable populations but require heavier computation to detect collisions and perform decision making (Prezzza's Work, 2022). They also require massive amounts of training to determine the decision making, which would be particularly problematic with us having multiple different models.

Regardless of which environment we use, the population curves of our control group (the standard model with no communication) should mimic the properties of a Lotka-Volterra equation (Wikipedia, 2023). Once we have found such an environmental equilibrium, we can investigate how communication strategies impact it.

Knowledge Sharing / Communication

To form the experiments, we have different models of communication for our prey. Sharing knowledge between AI systems can allow the agents to learn information about much larger areas of their environment even when individually they have limited sight. It's important that we consider the physical limitations of animal communication, but we can still investigate the impacts of those which are unrealistic.

One method that can be used for the communication is the creation of tuples to map directional relationships using Ontologies. Tuples like this are used to efficiently map the relationships between sets of agents. This knowledge representation is often used in chatbots and question answering systems but can be adapted to give rough directional information between prey in our environment. The main advantage of tuples is that once enough are collected, knowledge graphs emerge which can link together distance agents (Chowdhury, 2019). The emergent behaviour from this could potentially result in agents having primitive communication across the entire environment, provided there are enough agents present. The actual Ontology will be defined within our agents to form a procedural language (Genesereth, M, 1994).

Design & Implementation

When it comes to the internal architecture of agents, there are many possibilities. But for this simulation, we will be following the notions of agency (Wooldridge, M & Jennings, N, 1995). These define the basic components to form an agent, 3 of which are especially important to our experiment:

1. Reactivity. Agents perceive their environment and respond in a timely fashion.
2. Pro-Activeness. Agents do not simply act in response to their environment, they are able to exhibit goal-directed behaviour.
3. Social Ability. Agents interact with other agents via some kind of agent-communication language.

To run the experiments and model our system, I have used Python 3.9. The libraries available allow me to run the simulations and export our findings for investigation. A full list of used libraries can be found in [Python Libraries].

Environment

The environment is a blank canvas for our experiments, allowing all the emergent behaviours to be entirely based on the agent interactions. Because of this, we assume that the environment provides enough resources for the prey to live and reproduce, assuming they survive long enough. This is appropriate for our model since we want our prey to collaborate to survive instead of competing for food or other resources in the environment.

This oversimplification does reduce the realism to some extent, so to counteract this without changing the emergent behaviour in our agents, we slightly tweak their internal variables based on the global populations of the agents in the system. The justifications for which are explained in the individual agent descriptions below.

To implement the environment, we use the Tkinter library to create a 1000px wide space for our agents to exist within. The edges of which wrap around, to give a pseudo-continuous space. Tkinter is great for visualising our simulations and observing the emergent behaviour of our communications, although it is computationally expensive when it comes to running hundreds of moving agents in hundreds of experiments. Once we have observed the emergent behaviour for our agent types, we will be running the masses of the experiments without rendering.

Predators

In our system, Predators will be built as purely reactive agents (Wooldridge M, 2002) using a state-based model. They will have a limited amount of energy, which is drained over time and replenished upon eating a prey. This fits into the notions of agency, with the goal being to *survive* by eating prey and eventually *reproduce*. This pro-activeness relies on the agents perceiving their environment and reacting in kind to eat the nearby prey.

Since the focus of this experiment is on the social abilities of the prey, the predator agents have no social ability and will independently hunt the prey. The communication strategies we are investigating could be applied to the predators, but since they inherently compete for the food (prey) in this model, it wouldn't benefit the individual agents.

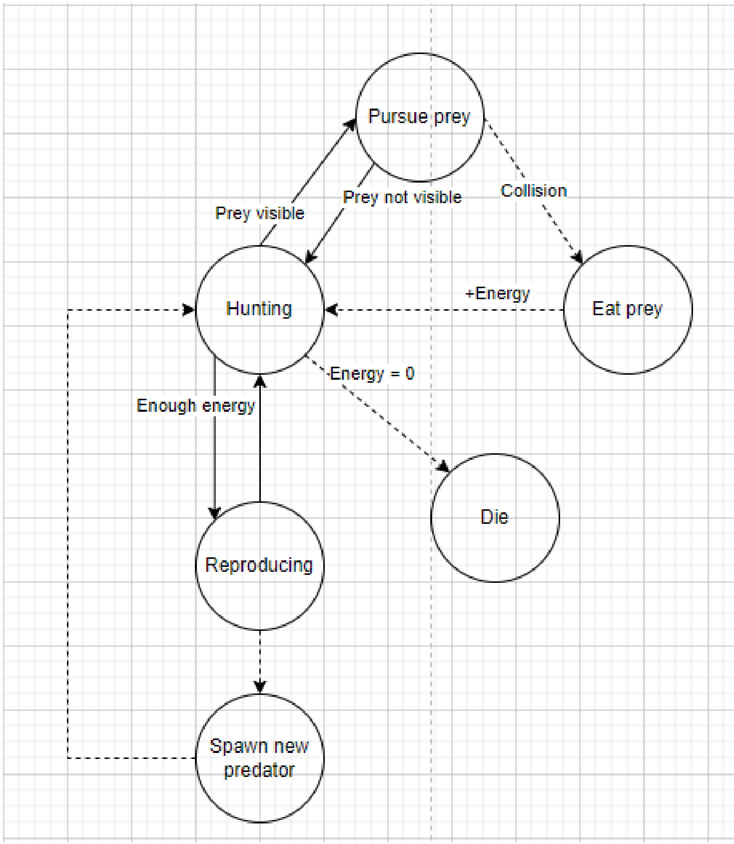

Figure 1 - Predator state behaviour

Finding the balance for all the internal parameters of the predators was a difficult challenge when developing the system. It's important for the predators to be as realistic as possible, whilst also being fair, in the sense that they aren't too easy to evade and aren't too oppressive. To account for this, predators have slightly less perception that the prey, but move faster. In addition, the amount of energy predators have when they initially spawn in, as well as the amount regained when they consume a prey are adjusted based on global populations and a slight random deviation. The global adjustment is to account for the changes in other resource we aren't considering within our environment, such as shelter and water. Whereas the random deviation is to add agent variety, such as size of the prey, how healthy either creature is, etc, which we are also omitting from our simulation to focus on communications.

Prey

Prey are also modelled as purely reactive state-based agents with their reactivity and pro-activeness working towards the same goals as the predators: *survive* and *reproduce*. Although these goals are achieved differently. Predators are actively trying to consume the prey, so their survival is dependent on their ability to evade the predators. Their reproduction occurs if they survive for a long enough duration, because of the prey food assumptions we spoke about in [Environment]. This model means prey are entirely collaborative, guaranteeing the communication will try to benefit others, avoiding advanced behaviour such as lying about predators so they have less competition for food.

The Prey also have some slight variation in their internal variables, such as reproduction time to account for the omission of the food and water in the environment.

Zero communication

Firstly, we want to evaluate a baseline for the prey agents with no communication. Consequently, the only parameters for decision making being it's immediate perception of the local environment. We will then build the other prey models on this basic structure with different communication strategies.

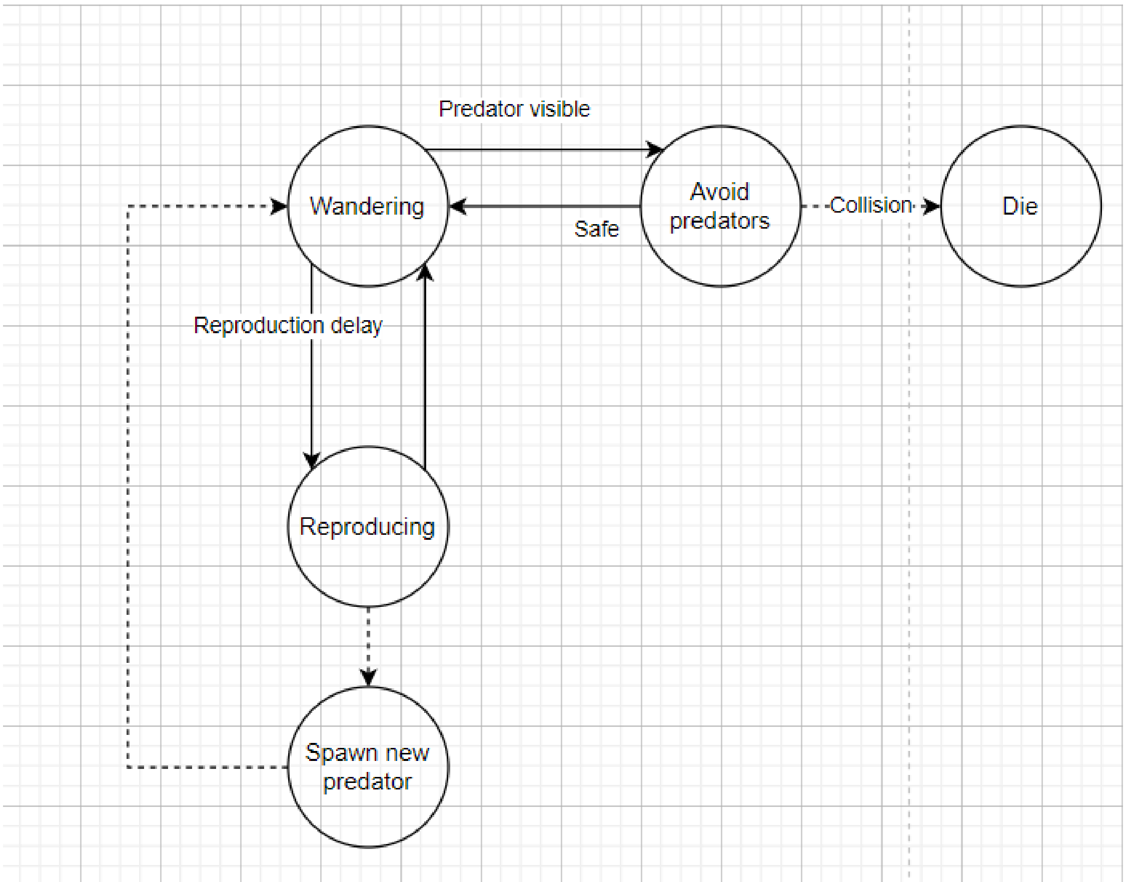

Figure 2 - State behaviour in non-communicative Prey

There are 3 states for prey: wandering, avoiding, and reproducing.

When wandering, the agents simply move around randomly, waiting until they can reproduce when they switch into the reproducing state. Alternatively, if the agent sees a predator, it will switch into the avoiding state.

While avoiding, the agents will be actively moving away from the visible predators. This will be simply moving in the opposite direction to the predators perceived.

While reproducing, agents must remain stationary. This is only for a short period of time, after which the prey will spawn another agent. Both of which live independently, returning to the wandering state.

Like the predators, choosing the internal parameters of the prey was a tough and important decision. They must be specifically chosen to ensure that the prey are realistic and fair. Therefore, the design chosen gives prey slightly higher perception ranges than the predators but move slower. Consequently, prey have the opportunity to avoid predators before being actively hunted but will likely be eaten if spotted.

Local communication

Adjacent alerts

Like bird songs, auditory communications are common in the animal kingdom (Khan Academy, 2023). It was therefore a logical first step to simulate this communication strategy and investigate any emergent behaviour. This simply builds upon the existing structure of our prey, adding in an additional movement clause to those prey who both "wandering" and receive communication from an adjacent prey.

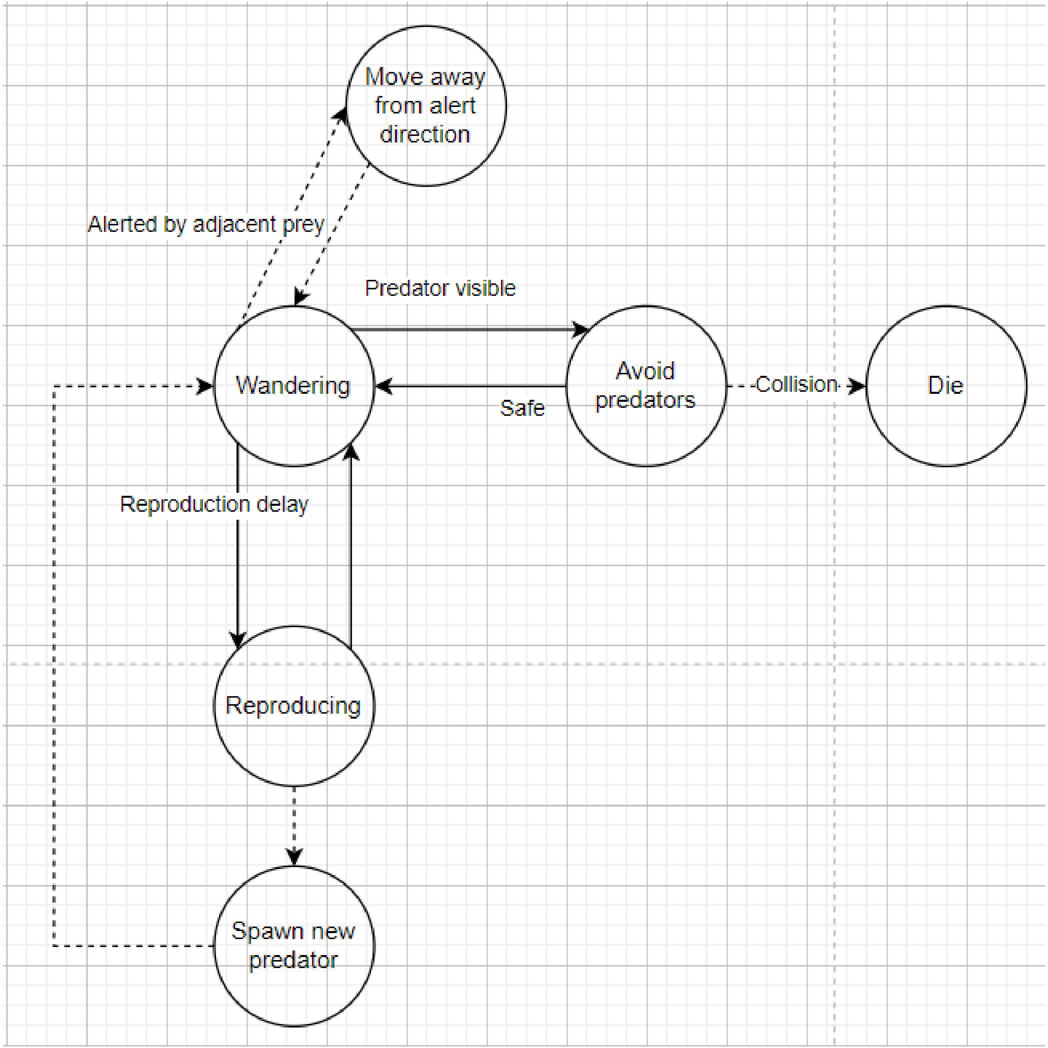

Figure 3 - Local communication prey

The logic behind this design is based on the urgency of different states. If a prey can see a predator, then it ignores alerts from other prey since the predator it can actively see is likely more of a threat. Therefore, only prey who are wandering will move away from alerts produced by those actively fleeing.

The most important part of this is the alert itself. To implement this, we use a design reminiscent of the tuples discussed earlier [Knowledge Sharing / Communication]. Although because we are only sending these alerts to directly adjacent agents, this doesn't use a blackboard system and we simply pass our communications between individual agents.

❖ **[Source Prey, Direction of alert, Target Prey]**

Prey receiving these alerts then move in the opposite direction to the source prey. To account for things noise in our system and the inaccuracy in which sound travels, the direction of alerts is only based on a {*North; East; South; West*} basis relative to the target prey.

Echoing Alerts

To take the idea of adjacent warning sounds further, next we implement the idea of prey repeating a sound they hear to increase the perceivable range. This collaborative behaviour causes a single alert to move through groups of adjacent prey.

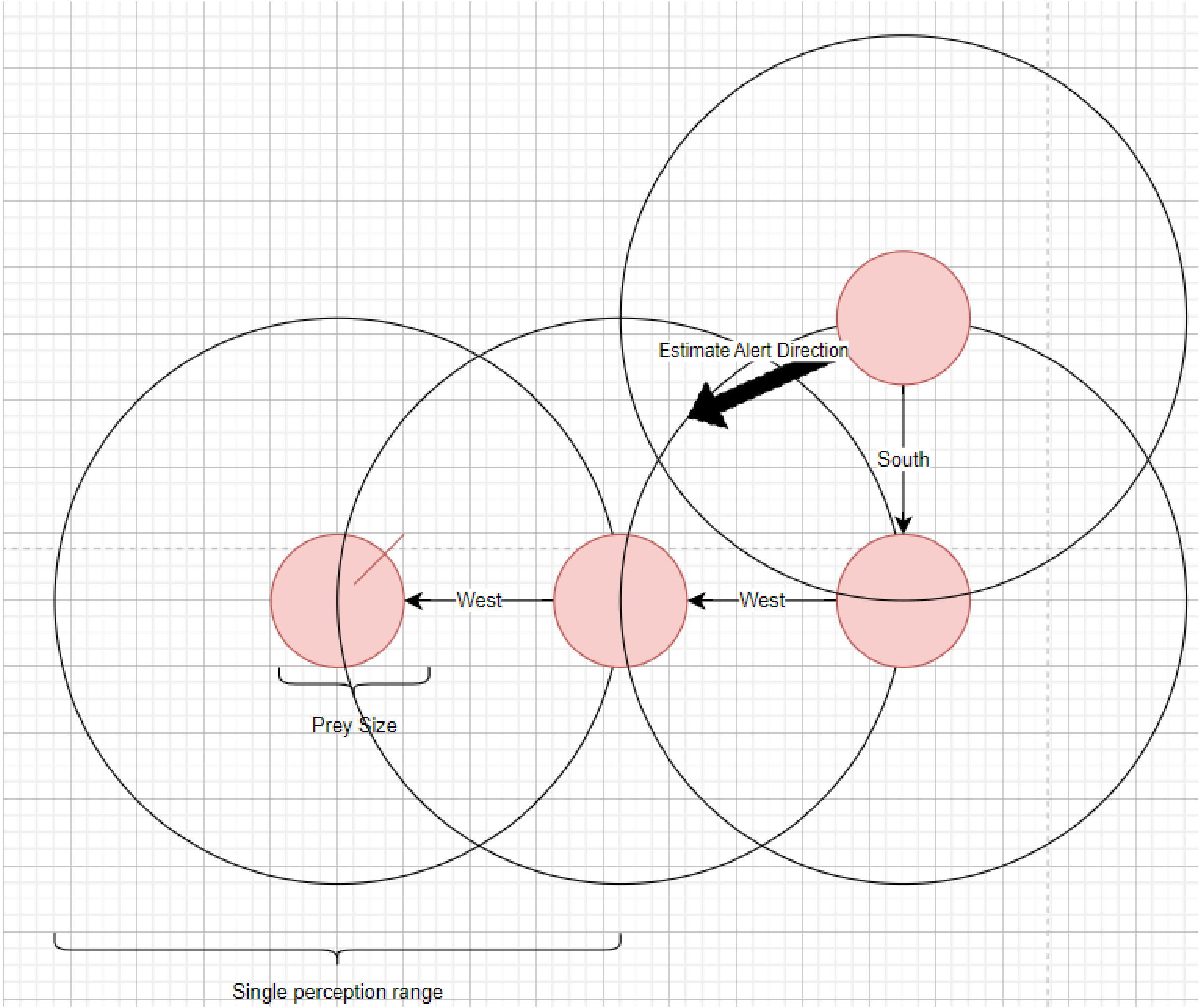

Figure 4 - Echoing alert system in Prey

Using the same alert structure as before, we can then build up chains of alerts through a group of prey to form a knowledge graph. Using the combined directions of the warning sounds, any prey who receive the alert can build up an estimated direction to the source of the alert, and therefore a relative direction to the potentially dangerous predator [Figure 4]. Prey then use a state-based behaviour like before to move away from this direction if they are wandering.

When it comes to implementing this, we build up estimated relative directions as the alert spreads through the prey, removing the need to trace the knowledge graphs and giving us the same outcome. This does require some difficult trigonometry when it comes to implementation. Having the environment developed using a coordinate system and using compass directions to communicate makes relative turns and directions take a lot more overhead, which is reflected in the code. Although this is more efficient then tracing the shortest path through a knowledge graph.

Global communication

The final communication strategy we want to investigate is the idea of a shared global brain between all the prey in an ecosystem. This is implemented using a blackboard system in which prey post the location of predators they perceive. All the subscribed prey then access this information and actively avoid getting close to known predators.

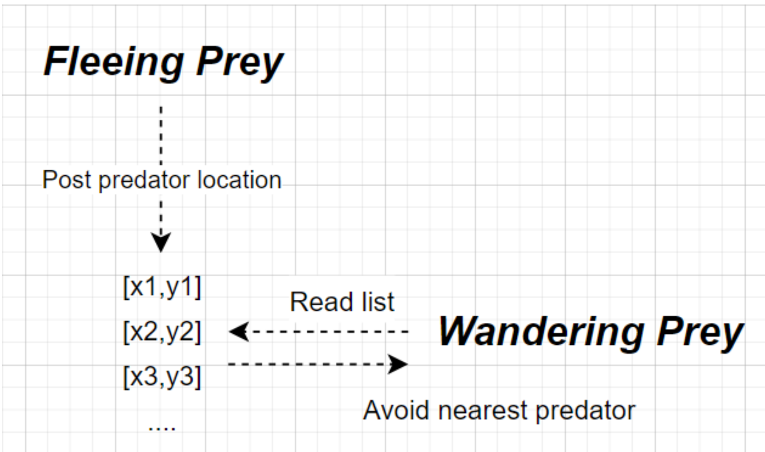

Figure 5 - Global blackboard communication in Prey

An interesting point about the global communication is that it works using the coordinate system, which would require the prey agents to know their relative location in the world. This is of course unrealistic in terms of knowing exact positions in a world space, although animals do know their relative position in the world so it's not completely impossible. The alerts could instead be changed to give the location using descriptions of the local environment, but since the environment is the same in this model, we rely on the coordinates.

These agents are also unrealistic with their use of a shared knowledge base. This isn't a technique that is biologically possible in any creatures, although it is reminiscent of the type of communication that could arise from a use of technology like mobile communications in human.

Overall, the global communication is too extreme for something we would expect to see in a predator-prey ecosystem, but it will still be interesting to see if they can form stable environments and have differing population curves than the other strategies.

Experiments & Findings

We want to ensure that the experiments we are running are measuring the changes in behaviour based on the communication and not other factors, such as spawn locations. To counter this, we seed the spawn locations each time we run the system. A "run" consists of simulating this seeded spawn layout with each of our 4 communication strategies. When simulating hundreds of runs, this then ensures that our findings are in fact due to the communication behaviours, and not the randomness of the spawn locations.

Stability

For our experiments, an environment will be classified as *stable* if it lasts at least 3000 ticks without at any point running out of agents. Since the global populations of each agent type is constantly monitored, if we have 0 predators or prey at any point, we know the ecosystem has collapsed. We then complete 300 runs of the simulation and find the percentage change of the environments becoming stable.

Table 1 - Stable ecosystems

Communication Strategy	Zero	Local	Local Echo	Global
Percentage of ecosystems classified as "stable"	1%	6%	10%	0%

In these 300 runs, you can see that the chances of stable ecosystems forming is still rather low. This is not totally surprising based off what we already know about the fragility of ecosystems, but these numbers alone don't tell us much about how the behaviour impacts the stability. Instead, we want to look at more specific information. Importantly, we want to look at the reasons environments collapse, by monitoring the populations of predators and prey at the moment it collapses and use this to understand how the stability changes with our communication techniques.

Table 2 - Collapsing ecosystem data

Communication Strategy		Zero	Local	Local Echo	Global
Percentage of ecosystems that collapse from over predation	%	5%	2%	5%	6%
Average Prey population without over predation	μ	9.5	14.3	16.0	11.4
Standard Deviation of Prey populations without over predation	σ	6.3	8.9	9.9	8.1

Looking at the this, we can clearly see that over-predation is uncommon within our current simulation. We can then infer that the largest threat to the ecosystems collapsing is a lack of prey for the predators to consume. We can then look at the populations of the prey in these collapsed ecosystems. Despite most of the failing systems being from predators not eating enough prey to sustain themselves, the average amount of prey in more advanced communication strategies is far greater than those without.

As expected, the Local communication makes the prey more elusive, increasing the average population at the point of predator extinction by 51%. Even more impressive is the echoing communication having a 68% increase in prey populations, which is without a doubt because of the increased knowledge they have about their environment.

What is interesting to look at is the Global communication strategy. While it does show an increase in the populations of the prey (+20%), it has an even more likely chance to collapse due to rampant predation and didn't provide any stable environments. When watching the simulations run, you can see the Prey end up flocking in the directions of unknown predators, resulting in them having lots of easy hunting and causing the system to become wildly unstable. This isn't a behaviour that affects the other communication strategies since the alerting system only deterring prey from high-risk predators.

This knowledge can then be used to understand the probabilities of the stable environments [Table 1]. Local and Local Echo communications consistently sustain higher populations of prey, which then means that predators have more available food. When a predator randomly wanders into a prey, it almost always consumes it, although that prey sends out the alert which causes nearby prey to avoid the predator. This stops entire groups being consumed by a single predator, which ultimately results in these higher populations. Although the higher population then increases the chance for the predators wandering into another group of prey. Emergent behaviour like this can be seen in the rendered runs of the system.

This proves that the Local and Local Echo communications do increase the stability of the environments by giving an abundance of prey for the predators to randomly consume, definitively answering question 2.

Population Curves

For those ecosystems that became "stable", we can then look at the population curves over time and reflect on our original question. We can clearly see that stable environments produce Lotka-Volterra equations, showing the relationships are realistic reflections of an ecosystem. Although the shapes of these varies between each stable environment, meaning when we look at averages, we no longer get the interesting shapes and instead flattened averages [Figure 6, Figure 7, Figure 8].

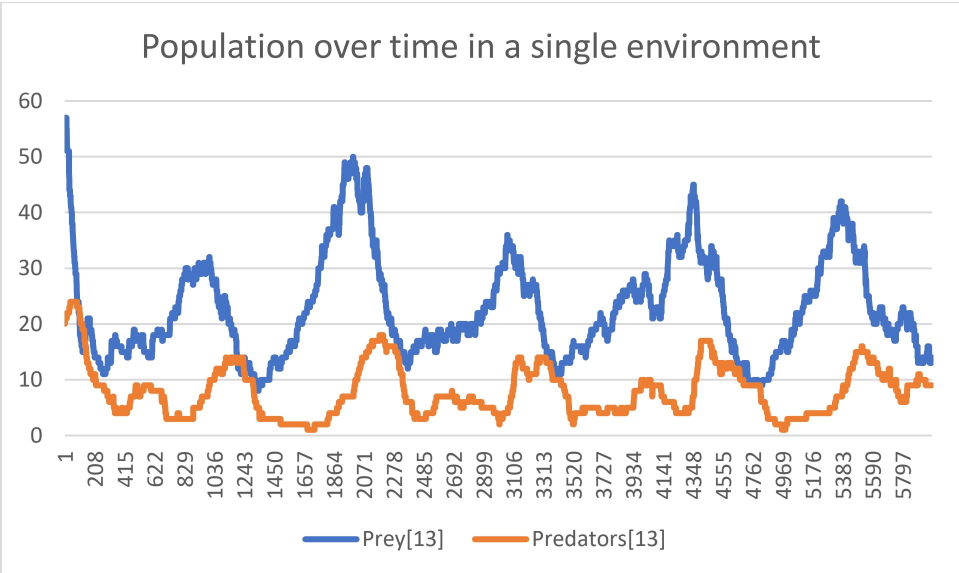

Figure 6 - Population curve of a single Local Echo Communication Prey ecosystem

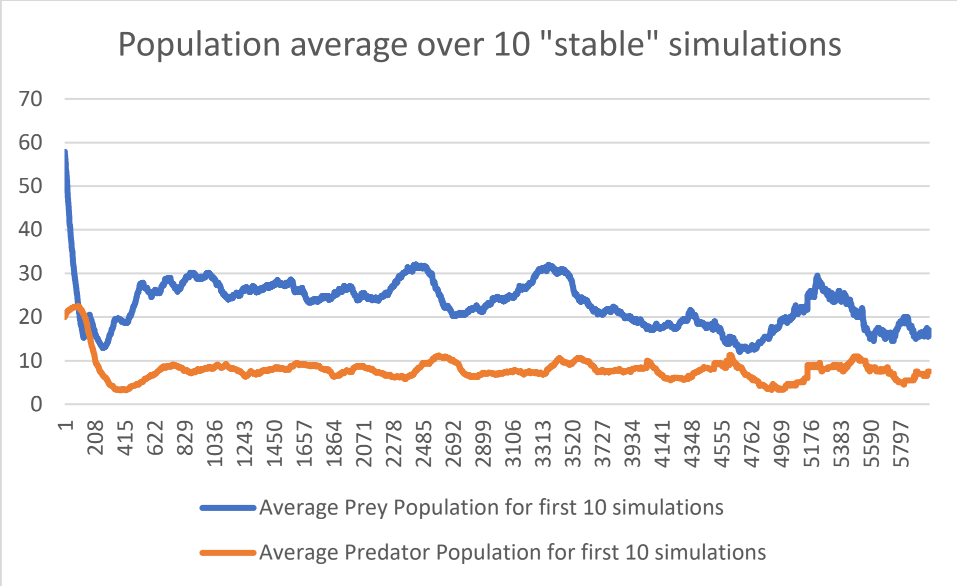

Figure 7 - Population curve over 10 ecosystems

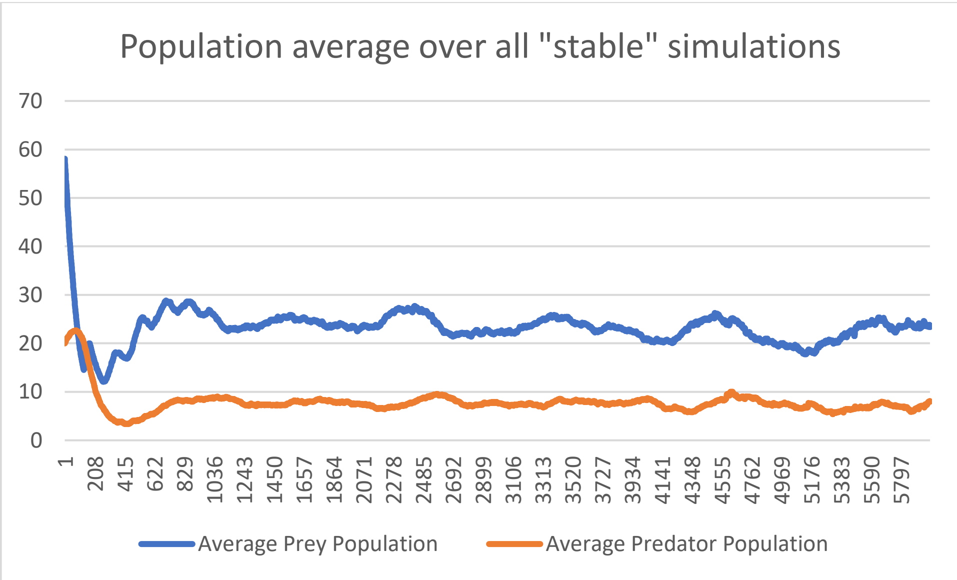

Figure 8 - Population curve over all ecosystems

Having the averages over so many stable ecosystems still shows some interesting findings [Figure 9]. Most importantly, we can look at the average populations for each communication strategy and see that the populations of Prey are consistently much higher in Local and Local Echo communication. This is due to the prey being able to collaborate, keeping one another safer. Despite the increase in the prey populations, the predators remain fairly constant throughout all the communication strategies. This clearly shows that even when all other conditions are the same, the average prey populations are significantly higher when given more capable communication strategies, further supporting our conclusion about environmental stability.

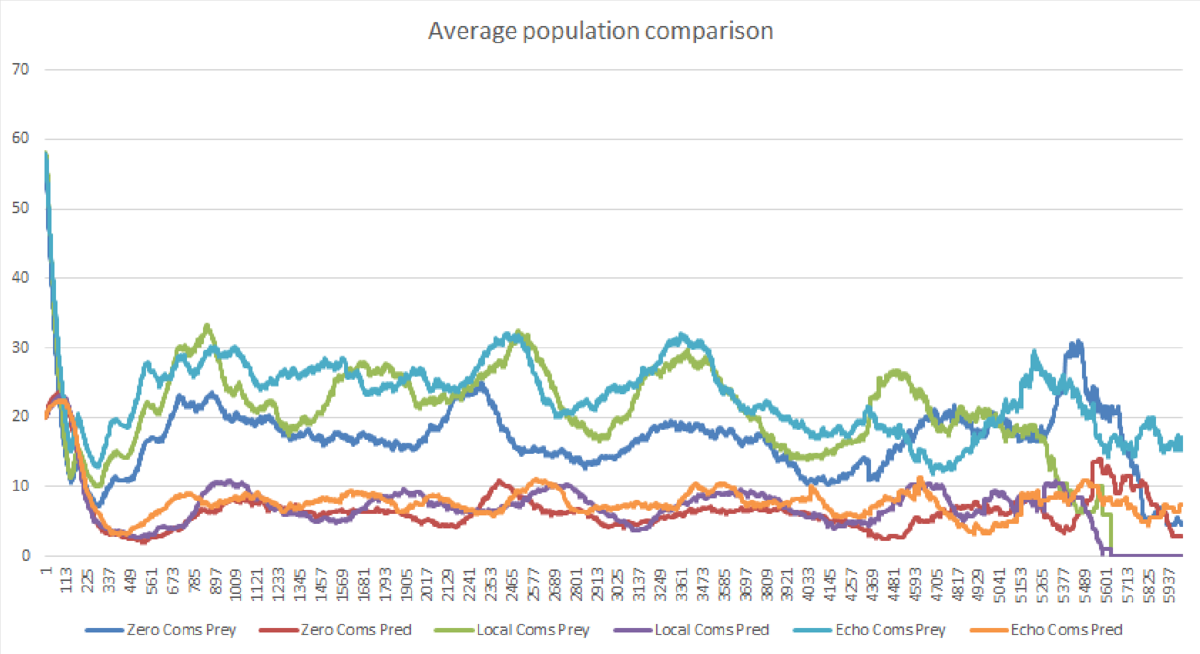

Figure 9 - Average of 10 Populations for each Communication strategy

Other than the overall population of prey being consistently higher, there are no other significant changes in the population curves between the communication strategies. Looking at individual populations, there is no correlation between the number of peaks, the distance between them or even their heights among the communication strategies implemented.

Based on these findings, we can only really conclude that the prey populations are consistently higher in the Local and Local Echo communication strategies. Besides this, the population curves are so wildly different between each ecosystem, we can't observe any other changes. Therefore, different communication strategies have little effect on prey population curves.

Limitations

While these experiments successfully answer our questions and show some correlations between communication strategies and environmental stability, there are a few shortcomings that need addressing to confirm the legitimacy of the findings before we apply them to a real-world ecosystem.

First off, the system only shows interactions between two types of agents. This is great for demonstrating their specific relationship, but ecosystems contain hierarchical chains of hundreds of different creatures all preying on one another which can lead to some very different behaviour then what we have observed.

Secondly, in our experiments the predator agents are modelled with zero communication. This is again useful for answering our questions in relation to prey communication, but in the wild, predators communicate as well to hunt in packs and share larger bounties of food. This is a very difficult thing to consider within our model, since predators naturally compete with one another for food, and the decision making behind this would be incredibly complex, requiring deep coordination, negotiation over yields of food, and so on.

Finally, I would consider changing the perception of the agents. In our current model, agents have an equal perception in all directions based on their location, knowing simply if another agent is within a certain radius. More realistic models of animals do exist, with directional based perception simulating the actual visions of predators and prey, although these require massive amounts of training using genetic algorithms to perform the decision making for movements. In combination with sharing the alerts from other agents, this would result in 4 huge neural networks which need training.

Next Steps

Each of these limitations should be addressed if the project is to continue, particularly the application of the communication strategies to the predators, and the increased number of agent types. This would make the simulations much more representative of a real ecosystem, giving our findings much more validity. Although with more possible interactions, we would have to collect more data to understand the behaviour since it would be far more complex. For example, you could collect data about number of agents perceived by our prey, life expectancy, volumes of communications, etc.

Other than these, the Global communication prey should be adapted to include better decision making to determine when predators should be avoided based on distance. This could be done using a state-based reactive agent like the one currently implemented, but a genetic algorithm would be far better for training all the internal variables and decision making. This would also require some level of memory, using complex knowledge such as recently consumed prey means a healthy predator near to that location. While this is a much more considerable piece of work, and potentially a research project in it's own right, it would make a far more successful and representative model for a global communication method than that we investigate.

Conclusion

Overall, the change in the communication has direct influence on the stability of the environment. However, other than the small population increase, the shape and structure of the population curves remain consistent with Lotka-Volterra equations. This research fills an important gap in predator-prey simulations and sheds light on the massive impact the inter-agent communications have on the stability of the environments. In addition, these successful strategies are also found in nature, which lends more authenticity to the individual agents and the findings. This shows the important implications of knowledge sharing agents in the creation of realistic and sustainable predator-prey relationships, and its consistency with the natural flows of the ecosystem.

References

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Python Libraries

- Tkinter - https://docs.python.org/3/library/tkinter.html
- Time - https://docs.python.org/3/library/time.html
- Pandas - https://pandas.pydata.org/
- Random - https://docs.python.org/3/library/random.html
- Math - https://docs.python.org/3/library/math.html