Agent-Based Modelling of an Ant Colony
Emergent Foraging Behavior and Shortest Path Discovery

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In this simulation I build a model of a colony of ants. Each ant is an autonomous agent acting based on a few locally and individually minded goals. Together the colony of ants can form trails between food sources and its nest and can find the shortest path through obstacles. The ants do not directly communicate with each other, but leave traces of pheromones in the background grid that serve has a history of ants that have passed through a given location and what their results were. In my fairly simple simulation I was able to discover basic emergent foraging behavior, and basic path optimization.

INTRODUCTION

Collective Behavior

A collective behavior is a complex behavior arising from the actions of generally simple autonomous actors or agents. Each agent follows its own set of rules and acts individually minded, but through the interactions of the individuals, there arises more complicated behavior or emergent behavior. The prime example of a real life agent-based system with collective behavior is an ant colony. Individual ants perform simple behaviors such randomly foraging and following other ants, yet ant colonies are known to have complicated behaviors. Ants can harvest and store food without any central control or intelligent direction [1]. Ant trails built by the passage of millions of ants can extend many miles through jungles connecting distant food sources. Such trails are emergent phenomenon, since no single ant could build such a trail network, yet these trails arise without purposeful design through the individual actions of a colony. Many other examples of collective behaviors can be found in nature, for instance the motion of a flock of starlings. In that case each bird is acting based on the actions of adjacent birds yet as a whole the flock of thousands of birds can turn in seeming unison.

The emergent foraging behavior of ants relies on their indirect communication via pheromones, which forms the center of this work. In nature ants secrete a chemical compound as they move which leaves bits of information that other ants are sensitive to. For instance if a foraging ant has found a food source (as happens in this work), it will leave a chemical trail that indicates food was found. Real ant pheromones are quite detailed and can share information such as distance to food, quality of food, and amount of food, not to mention other necessary things like danger [2].

Agent-Based Modelling

Agent-based modelling is developing a computer simulation that mimics collective behaviors. Just like natural collective behaviors, agent-based modelling is using a group of generally simple autonomous actors or agents to simulate a complex phenomenon. It is useful in many fields ranging from biology to economics to robotics, and is a technique that is often used to discover insight into the simple behaviors of the individuals based on trying to replicate the emergent behaviors.

This study designs an agent-based model for an ant colony to gain insight into the creation and application of an agent-based model and also to discover the behaviors of ant colonies. By trying to replicate the foraging abilities of an entire colony of ants, I try to discover the rules governing individual ants. More specifically this work attempts to discover the trail building emergent phenomenon of foraging ants through the use of simulated pheromones. Once creating the model the goal was to see how well the simulated colony could find a food source and build a trail from the nest to the food source. Then once initial trail building phenomenon had been observed, the second goal of this work was to use a colony's food finding capabilities to find the shortest path through obstacles. Ant Colony Optimization, as this is sometimes referred to, uses the simulated ant colony and their pheromones to find shortest paths. The idea is that if the ants are faced with multiple paths they will explore all probability proportional to the strength of the pheromone path. Shorter paths can be traversed faster so the strength in those paths is reinforced more [3].

ANT COLONY MODEL

The ant colony of this work's model is composed of 20 ant objects within a greater world of food, obstacles, and pheromones. Each ant is an object of a class *Ant* (refer to Figure 2) that contains parameters and methods defining the probabilistic behavior of the ant within the

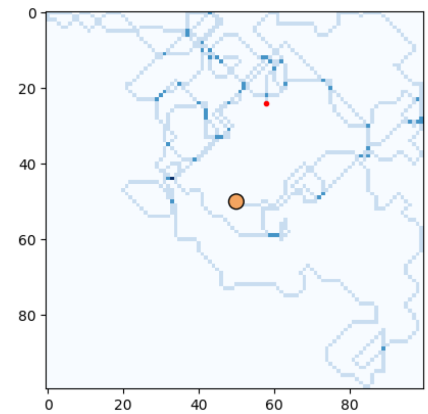

FIG. 1: One-thousand steps of a single ant's foraging. As the ants walks it leave a very faint pheromone trail, which is below the threshold of sensitivity to other ants, unless it is carrying food.

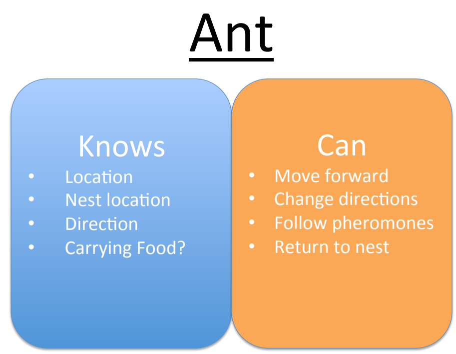

FIG. 2: The basic attributes of an individual ant. An ant object has a direction and a location. It also knows the location of its home nest and whether or not it is carrying food. The ant has methods that define its behaviors with associated probabilities. It has a probability of changing directions, probability of following pheromones, and probability of returning to nest (given that it has food).

environment. Each ant has information about its location, direction of travel, and whether or not it is carrying food. It also has methods that define its behavior such as randomly changing direction, following pheromones, and returning to its nest. Each ant has access to information about the world regarding the presence of food, obstacles, and pheromones which are stored in separate *numpy* arrays. However, each ant can only access local information, that which is stored in locations at or adjacent to the ant's own location, and has little memory of the past. In other words at any instant each ant "sees" only a grid of size 9 with itself in the center, and this is all the information it uses to act. One caveat is that each ant also knows the location of its nest, although it does not know what is in between it and the nest. Ants have two primary behaviors governed by different methods (with some cross over): foraging for food, and bringing food back to the nest.

Foraging Behavior

During foraging the ant is randomly wandering through the world until it collides with a food source. Initially the ants were programmed to take unit length steps in random directions simulating a random walk, though this resulted in brownian-like motion which was unrealistic. On a later iteration ants were given a direction and chance of changing directions since real ants often walk relatively straight for periods of time. On every step the ant had a probability of ~ 0.9 of moving froward in its original direction and probability ~ 0.1 of changing directions. If it chooses a new direction, directions closer to the original direction are more likely.

In order to discover if this behavior was realistic, I placed real ants on pieces of paper and traced out their paths. What I found was that the motion was more fluid and weaving. As a result the last version gave ants a 0.5 chance of changing directions (unless faced with an obstacle), and if so then the probability of choosing a new velocity vector was weighted by the cosine distance between the current direction and the new velocity vector. The exact weighting was done using a Gaussian with mean zero and standard deviation $\pi/4$, so that directions farther away from the original direction are significantly less likely. See Figure 1 to visualize an ant's foraging path.

If an ant crosses a trail of pheromones it has a probability of following the trail, typically set to be between ~ 0.75 to ~ 1. If it decides to follow the trail then at every step the ant will step towards pheromone with probability proportional to the strength of the pheromone, or with some low probability not follow the pheromone. Ties between locations with the same amount of pheromones are broken by weighting in the ant's original direction. If instead ties are broken randomly then an ant on a single pheromone trail will move randomly back and forth on it, staying roughly in the same location. Ants will sometimes get stuck in patches with a lot of pheromones or criss-crossing pheromone paths and walk in circles, but this also a phenomenon observed in real ants, albeit less frequently observed [4].

Tuning the parameters regarding pheromone following was quite difficult. On the one hand I wanted ants to follow trails closely to capitalize on found food, but on the other hand I wanted them to be able to break away from the trail sometimes to discover new food sources or new paths. When following a trail I wanted ants to continue in a relatively straight path (instead of circling without direction), but I also wanted the ants to follow the strongest pheromones. These balancing factors resulted in fine (and often frustrating) parameter tuning.

Returning to Nest with Food

Once an ant has bumped into a food source either through chance or by following a pheromone trail, it switches a Boolean variable to indicate it is now carrying food. Its goal now is to deliver this food to the nest and as it moves it leaves a pheromone trail which indicates that an ant carrying food passed through that location. Since an ant intrinsically knows the location of the nest and its own location, the ant will head straight for the home nest (all the while leaving pheromones), and will continue straight unless it faces any obstacles.

If an ant encounters an obstacle on its way back to the nest it must proceed through a balance of exploration and heading toward the nest. Too much exploration and the path may be a long one, but not enough exploration and ant may never find a path around or out of the obstacle.

One strain of ants avoids obstacles through use of a variable named p_{nest} indicating the probability of choosing a path directly back to the nest. Initially upon finding food, p_{nest} is set to 1, indicating that the ant should try to head directly back to the nest. If along this path an obstacle is encountered then a new path is chosen which is as close to the original path as possible and p_{nest} is decreased by a little. If more obstacles are encountered then p_{nest} is decreased further still. The reasoning of the ant is that if a direct route is not working (i.e. it is running into obstacles), then it should explore more. After exploring a bit more, if from the new location a direct route seems to be working then p_{nest} is increased. p_{nest} is the variable which allows the ant to balance exploring and capitalizing on a direct route to the nest. This exploration is shown in figure 6, and resulted in ants unable to simply move around obstacles.

The next strain of ants upon encountering an obstacle would pick a direction closest to the direction of the nest and stick to it until there was a direction available that was close to the direction of the nest and also close to the original direction. If the original direction was not taken into account in choosing the new direction then an ant would pace back and forth along an obstacle going above and below the level of the nest without getting very far.

The most recent version of ants goes one step farther and also responds to pheromones. If faced with an obstacle and there are pheromones present they will with probability ~ 0.75 follow pheromones as the foragers did: move toward stronger pheromone with probability proportional to the strength of the pheromone. The reason their probability of following pheromone is lower is to encourage more exploration.

RESULTS/DISCUSSION

The colony of ants in this model are able to create pheromone paths between food sources and the nest and are able to go around obstacles. Through communication via pheromones, ants are able find food and bring back food to the nest more efficiently than any ant individually would be able to. Figures 4 and Figure 5 give examples of pheromone trails between an ant nest and food sources. Pheromone trails allow ants to find the food more quickly than if each could only randomly search for it. In the case that the food source and nest are spread far apart (e.g. Figure 5) it takes the ants a long time to randomly bump into it, but once a trail has formed the ants much more often bump into the trail and can follow it to the food source.

Additionally ants can find the shortest path to an obstacle, but not always. In one set of tests I set up a block in-between nest and food where one way around was twice as long as the more direct route (Figure 7). My goal was to have ants randomly discover the paths and eventually converge on the shorter one. Initially I believed that simply because the path was shorter ants would be able to move back and forth along it faster. Therefore at the two junctions I gave each ant a 50% chance of going left or right along pheromone paths that were of equal strength and which were fixed. Remarkably, after many such experiments the paths were used almost exactly the same amount. Likely this was due to the fact that I had only a finite number of ants so at every turn fewer ants were available to march back and forth along the path. This initial experiment convinced me that pheromones were necessary.

In order to get ants to follow the shortest path I used evaporation of the pheromone trail and having ants follow pheromone trails with probability proportional to the strength of the trail as well as with some probability of leaving the trail. Evaporation meant that pheromone trails left by ants that took the longer route were weaker by the time the ants had reached the nest, and with the right strength of evaporation the trail might be gone entirely. Additionally, giving ants a higher probability of leaving the trail meant that ants were "impatient" and would more often break from the long trail before reaching the destination. Getting the exact right balance of evaporation and leaving trail probability while still allowing ants to reach the destinations was quite difficult.

I broke down shortest path finding into 2 separate categories. The first category was whether ants could forage and find a food source, create the path and then converge on the shortest path. The second category was that if I started the experiment with two different length paths to a food source, would the ants converge on the shortest. In the former case I found that the path the ants chose was heavily dependent on which path was found first. If the longer path was found first it was difficult for ants to change paths. Over 20 such experiments, 11 out of 20 converged on the shortest path, due primarily to the short path being discovered first.

For the second category, ants could more easily converge on the shortest path if multiple paths were present for them since the shortest path would be reinforced first and afterwards the other ants would follow it. Out of 20 experiments where two paths were created ahead of time with equal strength, the ants converged on the shortest path in 15. In the cases that ants didn't converge on the short path it seemed ants randomly chose the longer path and then reinforced it.

I was never fully able to get ants to change paths once a strong ant trail had been established. The positive feedback of following an established trail and reinforcing it was difficult to break even with negative forcings like evaporation. Additionally the longer trail benefited in that if ants were evenly distributed then they would bump into the longer trail more often since it had more surface area.

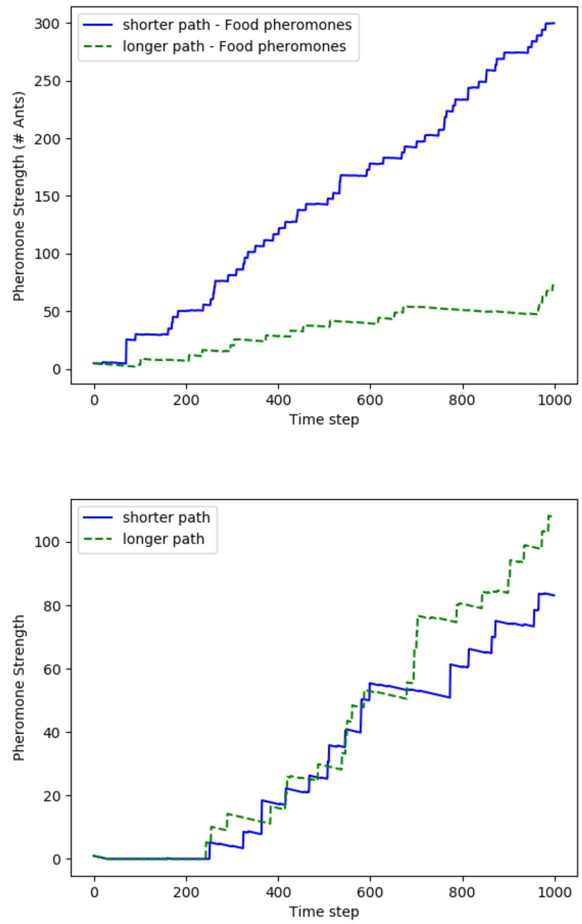

FIG. 3: The pheromone trail strength on two different trials for the longer path and shorter path of the L-shaped block (Figure 7). Sometimes the shorter trail would diverge and sometimes the longer trail diverged. It often depended on which trail was discovered first, since once a trail was discovered the pheromones on that trail became very strong and were hard to break away from. Notice the evaporation of trails in between ants.

CONCLUSION

In conclusion, the ants of this study were able to form and follow pheromone trails to and from food sources. Although the ants were sometimes able to converge to the shortest path, more tweaking of hyperparemters and experimenting with ant methods (like pheromone following algorithms) might be needed to allow convergence more often. I have a new appreciation for the complexities of the algorithms controlling real ant behaviors which have evolved over the last several hundred million years.

FUTURE WORK

This model of an ant colony has about 10-15 hyperparemeters that were tuned manually in order to discover emergent behavior. Future work could tune these hyperparameters more effectively, which might be all that is needed for better shortest path discovery. For instance the number of ants, evaporation strength, the probabilities of following a trail, probability of breaking from a trail, the weights governing balancing direction and pheromones all can be tuned. Larger changes to the model might include rewriting the method which dictates how ants return to the hive. There are many edge cases that were difficult to address and for lack of time I often hard-coded patches to fix them. For instance in returning to the hive ants often want to move in the direction that is closest to the hive, but also stick to a direction. I would like to have each objective be given a certain probability weight, but the weights were hard to balance so instead I had the ants pick a direction if if that direction was behind them then I forced them to keep walking straight. Unfortunately, sometimes the ants do need to move backward (see Figure 8).

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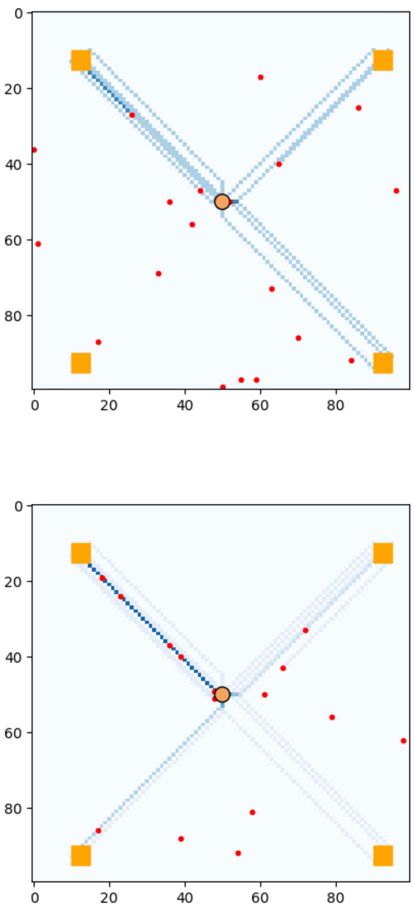

FIG. 4: Pheromone trails from the same world at two different times. The top plot depicts an earlier time and the bottom plot depicts a later time. Ants are the red dots, the orange squares are food, the middle circle is the nest, and pheromones are the background blueish shading. As some paths are used more, the pheromones along those paths are strengthened and appear brighter than the pheromone paths of the other trails. As a result more ants travel along the brighter path and reinforce it further.

my complaints about the ants not moving where I wanted them to. Thank you to the teaching team especially Professor Blas Cabrera and Fellow Ryan Hazelton for this class.

[1] D. M. Gordon, Cell Systems Review , 514 (2016).
[2] E. Wilson and M. Pavan, Psyche **65**, 41 (1959).
[3] S. S. Jayadeva, R. K. Amit Bhaya, and S. Chandra, Swarm Intelligence (2013).
[4] T. Schneirla, American Museum Novitates **1253**, 126 (1944).

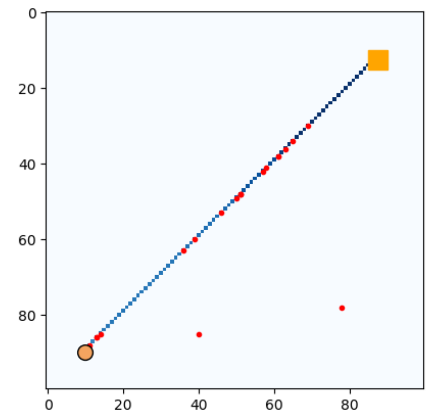

FIG. 5: Pheromone trails from nest (circle) to food source (square). Ants are able to follow the trails to the distant food source and so can find the food more quickly than if each could only randomly search for it. When the probability of following the pheromone trail is set to 1, then within not too much time all of the ants are running back and forth along the pheromone trail from nest to food and back.

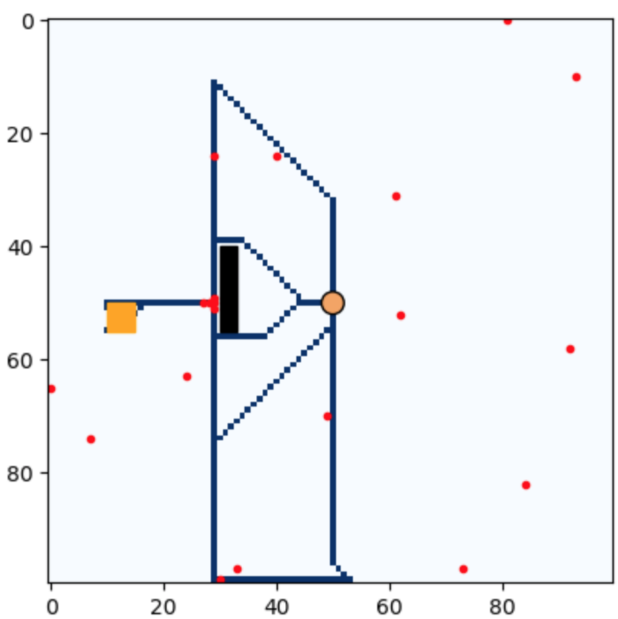

FIG. 6: Pheromone trails from food around an obstacle and back to the nest. The orange box is the food, the black box is the obstacle, the brown circle is the nest, and the red dots are the ants. There are five unique paths back to the nest, with some longer than others. If this simulation were continued for a long time, it is expected that the shorter paths would allow ants to more quickly go back and forth along them, strengthening their pheromones over the longer paths. In this way the ant colony would learn the fastest way around an obstacle.

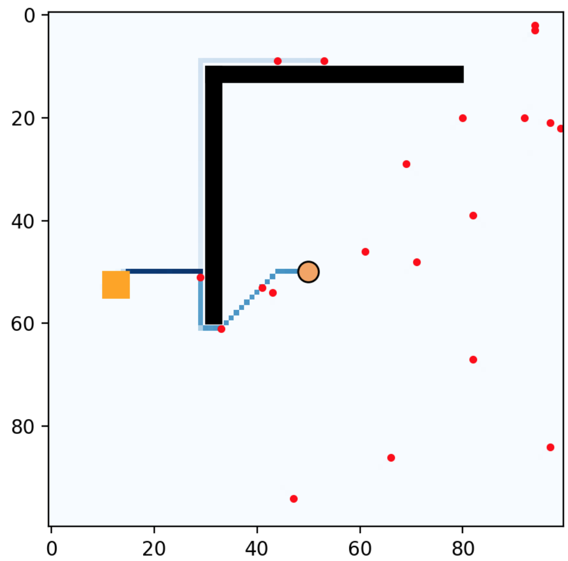

FIG. 7: Most ants are using the shorter path around the block but several more adventurous ants diverged from the established trail and are exploring around the scenic route. Due to evaporation their trail will disappear unless another ant follows, however their pheromone trail makes it more likely that another ant will break from the more established path and follow suit.

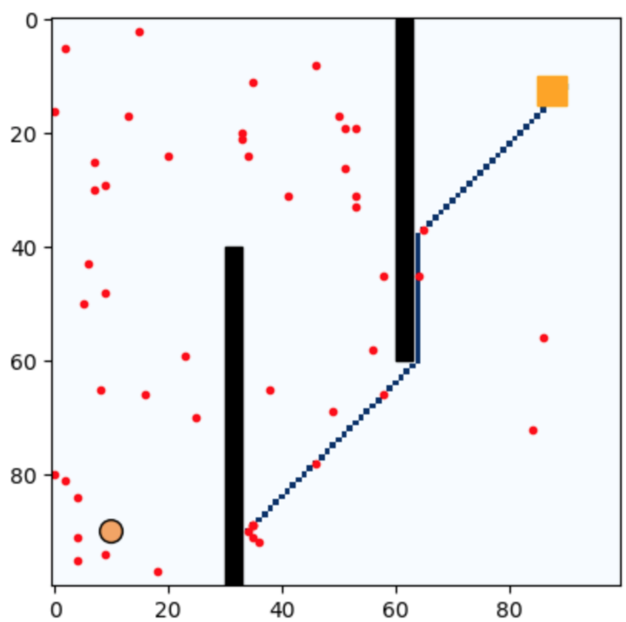

FIG. 8: On a new random maze, ants get stuck by their own pheromones and don't get back to the nest. More imporvements need to be made to the returning to nest method.