Replication of Adaptive Growth Processes: A Model Inspired by Pask's Ear

Serkan Kocairi

School of Engineering and Informatics
University of Sussex, UK
sk857@sussex.ac.uk

Abstract

In this paper, we replicate and extend a model presented by Nathaniel Virgo and Inman Harvey inspired by the system that can distinguish two sounds from a homogeneous chemical solution originally introduced by Pask (1950). We examined whether the model adapts by moving the target area suddenly, and we tried to find its hyperparameters.

keywords: self-organisation, reward, reinforcement learning

Introduction

Gordon Pask created a device discriminating between two different sound frequencies from a homogeneous chemical solution in the late 1950s. This device was called Pask's Ear, and it has inspired research in various models, including self-organization, reward mechanism and artificial life. A model inspired by Pask's Ear, which is about ants leaving a chemical called pheromones to reach the food target, was created by Nathaniel Virgo and Inman Harvey. Virgo and Harvey reinforced the entire system according to whether an ant arrived at the target area in this model.

During adaptive growth, ants compete for a target range in this model, and successful ants build much more pheromone trails that attract other ants to follow the same path as unsuccessful trails decay over time. This mechanism resembles the reinforcement learning process in which actions that lead to a reward are reinforced while those leading to undesired outcomes are diminished over time.

The main difference between the model we reproduced and the typical ant-based model is that while individual agents are often rewarded based on their behaviour in an ant-based model, the model is rewarded as a whole in Virgo & Harvey model.

In our reproducing, we experiment to increase the complexity of the model by changing the target range suddenly, and we try to figure out which parameter best optimizes the model. But before we dive into the details of our model, we first review some related research that highlights some of the reasons we find this system interesting.

Related Research

Researchers from different areas, such as engineering and biology, have been interested in adaptive growth processes. In the last years, several studies have looked at the use of the self-organizing system to regulate the growth processes inspired by biological systems such as ant colonies.

A paper that suggests a model for adaptive growth based on self-organization and stochastic processes is "A noise-driven mechanism for adaptive growth rate regulation" by Frusawa et al. (2010). Using the bacterium Escherichia coli, the authors of this work experimentally test their theoretical model to determine how noise in gene expression may induce adaptive growth rate control in bacteria.

Another investigation on the self-organization of speech sounds in young children is "The self-organization of speech sounds" by Oudeyer (2006). According to the study, infants categorize speech by self-organizing their vocalizations and perceiving input from the surrounding environment.

Finally, "Steering the Growth of Adaptive Self-Preserving Dissipative Structures" by Egbert et al. (2018) presents a model for self-organizing structures based on the principles of dissipative structures and nonlinear dynamics. The model suggests that structures can adapt and evolve in response to environmental changes by self-organizing and preserving their dissipative structure.

Method

We present a system of pheromone trails dropped by ant agents which move from the beginning to the end of a grid. The grid occurs 50 columns and 500 rows without borders on each side; exemplarily, we can imagine the grid as a massive paper roll. In every cell of the grid, a number exists to represent the amount of the pheromone. These numbers are initialised to zero.

An ant randomly enters the grid from one of the top cells and moves through the grid until reaching the bottom by stepping once each time. It can move to the cell right below or to one of the cells on either side of that cell (i.e. one of three cells). It decides which cell to go to according to the probability distributions of the pheromones in these cells, and it lays down the pheromone of itself to the cell in which it exists before leaving. These steps are followed until the ant reaches the bottom of the grid, and the next ant repeats the same steps. To show the algorithm step by step:

"1. Look at the amount of pheromone in the cell directly below and the cells to either side of it, three cells in total (the edges wrap around).

2. Add the value $\delta = 0.1$ to each of these three numbers (this is to prevent very weak trails from having a strong effect) and normalise them to get a probability distribution.

3. Move to one of the three cells below according to the computed probability distribution

4. Add the value 1.0 to the amount of pheromone in the previously occupied cell" (Virgo and Harvey, 2008)

When an ant reaches the bottom, the decay function appears for a while, and the pheromones exponentially decay in each cell in the grid. The reward function determines the length of this time and the amounts of the decay. If the decay time is too short, the pheromone trails left by the ants will disappear quickly, and the ants will be more likely to explore new areas of the surface. However, if the decay time is too long, the pheromone trails may persist for too long, leading the ants to continue following outdated paths even after they are no longer the most rewarding. Besides that, a value of $d = 0.01$ is subtracted from every cell before the next ant enters the model. (If the result is less than zero, then it is equalised to zero)

The Reward Function

In this model, we want the ant arrives at the target range determined. If the ant hits the target, the score will be equal to 1, and 0 if it misses. To show the reward function altogether:

"1. Let the score for iteration i be $S_i = 1$ if the ant arrives at the bottom of the grid within the target interval, 0 if it misses.

2. This value is smoothed out in time slightly using a leaky integrator: Let the reward value $R_i = R_{i-1} + (S_i - R_{i-1})/\lambda$. We give the parameter λ the value 2.0 and let $R_0 = 0$.

3. Ants are assumed to arrive at a rate $99R + 1$. This is represented by multiplying each pheromone value by $1 - 1/(495R_i + 5)$ (an approximation to $e^{-5(99R_i-1)}$) to represent a constant decay of pheromone during the variable time period between ants arriving." (Virgo and Harvey, 2008)

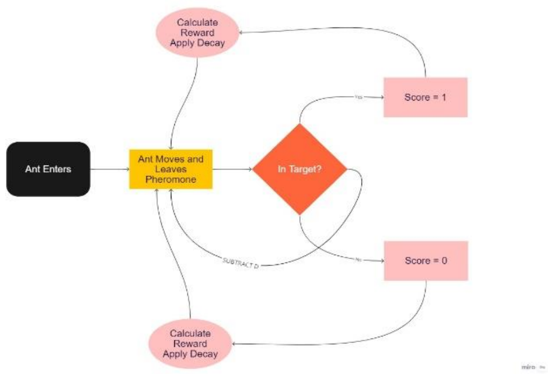

Figure 1: The flowchart represents the ant's entry into the grid and the actions taken according to whether it is in the target range. This process is repeated as many as the number of iterations.

Extension

Virgo and Harvey experimented with the self-organization of pheromone-releasing ants to find a target range. In this experiment, we will suddenly change the target range after a certain point in the iteration and examine the adaptation of the ants to the new target range. Apart from this, we will be optimizing the parameters that are effective in the success of the model, using a kind of GridSearch algorithm. (The GridSearch algorithm is used to optimize the hyperparameters of a model.)

While trying this experiment, we change the number of iterations of the model and the time of releasing the new range.

Result

We will first examine the results where we change our target range at different iteration moments without optimizing the hyperparameters.

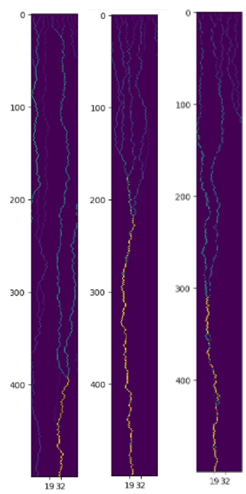

Figure 2: This graph represents the path followed by the ants as a result of changing the target range to (0,13) in the 1000th, 3000th and 5000th iterations of the model with a target range (19,32) and iteration number of 15000 without hyperparameter optimization.

As seen in figure 2, regardless of which iteration the target range changes, it is observed that ants are found more in the first specified range, even if it keeps up with the change in the 1000th iteration.

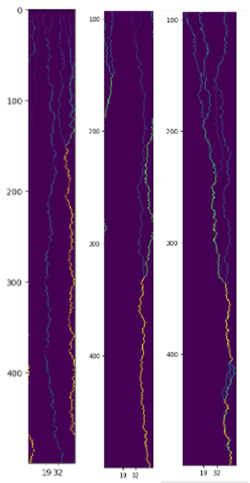

Figure 3: This graph represents the path followed by the ants as a result of changing the target range to (0,13) in the 1000th, 3000th and 5000th iterations of the model with a target range (19,32) and iteration number of 15000 with hyperparameter optimization.

The final model is built using the Lambda, Subtract, and Score hyperparameters that produced the best results among the models built using various combinations of these parameters. As a result of our last model, when the target range changed in the 1000th iteration, the ants turned to the new target. In other examples, they slightly tend to the new target range but could not hit there.

Discussion

As a replication and extension of Nathaniel Virgo and Inman Harvey's model inspired by Pask's Ear, we aimed to change the target range of the model at some point and examine the model's response with its initial hyperparameters and optimized hyperparameters to these changes.

Figure 2 shows that ants follow the main route with initial parameters even if we change the target range suddenly. Starting from here, we can analyze the parameters selected by us. We chose the subtraction parameter applied to every cell before the next cell entered the grid. When you examine closely subtraction, you can see that it obstructs the cells, which have fewer pheromones inside to increase.

On the other hand, Lambda and Score affect the reward and indirectly affect the decay function. A bigger score will affect the larger reward, and an increase in the reward will make the decay larger, thus helping the pheromone in the cells to disappear quickly. The larger the lambda, the smaller the reward, causing the decay to be smaller.

After hyperparameter optimization, we can observe that the ants tend to adapt to new sources, but this adaptation depends on the time and how big the grid size is. Lastly, for future works on adaptive growth processes, we can add some obstacles to the grid and make it much more complex.

References

Egbert, M. and Kolezhitskiy Y. and Virgo, N. (2019) Steering the Growth of Adaptive Self-Preserving Dissipative Structures ALIFE 2019: The 2019 Conference on Artificial Life

Chikara, F. and Kuhiniko K. and Hiroshi S. (2010). A noise-driven mechanism for adaptive growth rate regulation

Oudeyer, P.-Y. (2014). The self-organization of speech sounds. Journal of The Royal Society Interface

Virgo, N. and Harvey I. (2008) Adaptive growth processes: a model inspired by Pask's ear. In: Proceedings of the Eleventh International Conference on the Simulation and Synthesis of Living Systems, Winchester, UK.