How Do Ants Maintain Consensus in the Context of Changing Decisions?

: Investigating Ants' Sharp Turn During Collective Transport Using Simulation

Jooseok Lee and Sitong Lu

Abstract

Paratrechina longicornis ants can form consensus quickly during collective transport and make a sharp turn without stalling. We plan to investigate the mechanism behind this phenomenon where ants change their collective direction and form consensus quickly by extending an existing approach on collective decision-making. In order to explain this phenomena, we extended an existing decision-making model with two additional factors; decaying preference and short-term memory. We conducted a simulation to verify that expected behaviors such as sharp turns emerge with the extended model. Although the extended model showed the expected behaviors, we also found that sharp turns could emerge with the base model, which was in contrast to our assumption. We conducted in-depth analysis to understand how the base model's parameters indirectly influence the number of sharp turns occurred. Finally, we built a visualization tool to show how our proposed model governs the collective movement of a group of ants using Qt Framework. The proposed model would broaden our understanding of the collective decision-making process among animals especially in the context of changing decisions. It could also be used in diverse domains including cooperative robotics to help agents deal with dynamic environments where they need to frequently change their original decision.

1. Introduction

According to [1], Paratrechina longicornis ants sometimes made sharp turns without hesitation during collective transport when they were faced with bar-shape obstacles. These sharp turns enable ants to traverse unknown lengths of obstacles even though it is not an optimal route. For example, it would have been an optimal route for ants to continue moving after they made their initial choice to the left and turned to the other direction (i.e., sharp turn 1) as shown in Figure 1. Nevertheless, making sharp turns is a good strategy for ants when their earlier decisions are not effective.

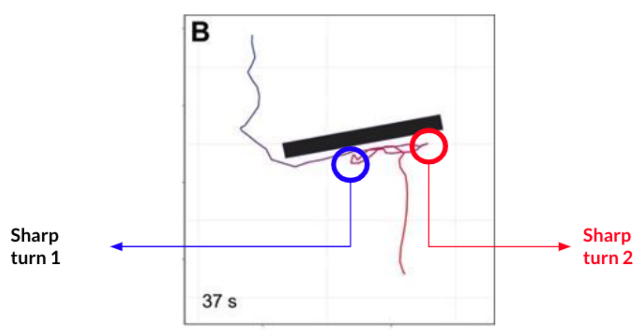


Figure 1. Sharp turns during collective transport

How a group of animals comes up with consensus is an active research area. [2] proposed a unified model of decision-making based on the Bayesian framework to consolidate various previous studies. According to the authors, the probability of choosing a certain option gets higher as the number of other individuals who chose the same option increases (i.e., Figure 2). n_x indicates the number of individuals who chose option x while n_y indicates the number of individuals who chose the other option or option y. k is a parameter that determines the strength of others who chose the opposite option. Parameter a and s indicate the strength of external and social information, respectively. Figure 3 is a probability map showing the probability of choosing an option (i.e., option x) based on the number of other individuals who chose option x and the other (i.e., option y). This model, however, could not effectively explain how a group of ants maintains a consensus when they make a sharp turn during collective transport. In particular, if ants get stuck into an absorbing area, where every ant chooses one option over the other indicated by the circled region in Figure 3, it is likely that they will keep moving to the chosen direction forever.

$$P_x = \left(1 + \frac{1 + as^{-\left(n_x - k\, n_y\right)}}{1 + as^{-\left(n_y - k\, n_x\right)}}\right)^{-1}$$

Figure 2. Each individual's probability of choosing option x

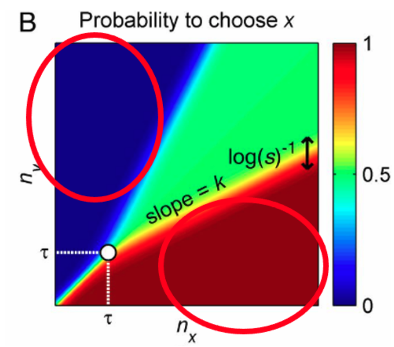


Figure 3. Probability of choosing option x

To address this issue, we proposed an extended decision-making model in the context of two choices. Specifically, we introduced two concepts, namely decaying rate of preference and short-term memory, into the model. In our extended model, the preference of choosing one option exponentially decreases as ants have chosen that option without any rewards (e.g., getting closer to the colony in the context of collective transport). At the same time, the elapsed time without any rewards is stored in ants' short-term memory. We tested the effectiveness of the newly introduced components using simulation. Several metrics such as number of sharp turns and magnitude of speed changes were used to analyze the emerging collective behavior based on the extended model. In addition, we compared our model with the reference model proposed by [2] to gain in-depth insight into the relationship between the number of sharp turns and parameters in the models. Finally, we built a visualization prototype to show how our model works during collective transport using Qt Framework.

2. Related Work

Forming a consensus during collective decision-making is one of the most important aspects for group survival. Various studies were conducted to explain how different kinds of animal groups come up with a consensus, resulting in numerous decision-making models. A unified decision-making rule, where each individual makes a decision with Bayesian estimations based on the number of others with the same choice, was proposed in [2] to consolidate the previous efforts.

The collective movement of Paratrechina longicornis ants were analyzed in [2]. It was observed that Paratrechina longicornis ants can maintain a consensus not only when they are collectively transporting but also making a sharp turn in the presence of obstacles [1], which could not be effectively explained with the decision-making rule proposed in [2].

Various synchronization mechanisms were studied to understand how a group of animals shows a collective and coordinated behavior. Mathematical analysis of synchronization between oscillators was conducted in [3]. The information transferring mechanism proposed in [4] showed that a school of fish can achieve a highly accurate collective movement and make consensus decisions even with conflicting information. It was also shown that introducing a variable refractory period enabled social spiders to effectively synchronize their hunting strategy in noisy environments [5].

3. Extended Model Formula

We came up with the extended model formula based on the assumption that the preference of moving to one direction would decrease if ants move along it without making any progress. In other words, as the elapsed time without reward increases, the positive effect of either n_x (i.e., the number of individuals who chose direction x) or n_y (i.e., the number of individuals who chose direction y) decreases depending on the direction of moving ants. Figure 4 shows the extended formula.

$$P_x = \left(1 + \frac{1 + as^{-(n_x * Decay(t_x) - k*n_y)}}{1 + as^{-(n_y * Decay(t_y) - k*n_x)}}\right)^{-1}$$

$$Decay(t_x) = e^{\frac{-t_x^2}{\lambda^2}}$$

$$Decay(t_y) = e^{\frac{-t_y^2}{\lambda^2}}$$

Figure 3. Extended formula

Here, t_x or t_y represent the elapsed time without rewards on moving to either direction x or y. They could be interpreted as the short-term memory of ants. The movement of ants are determined by the collective decisions of every ant, which will be detailed in the next section. When a group of ants makes a turn or changes its moving direction, the elapsed time related to the previous direction is set back to zero. For example, if ants group changed their moving direction from x to y, t_x is set back to zero. That is, $t_x \times t_y \geq 0$ for all time. Implementing long-term memory concept or setting back t_x or t_y to positive value could be an interesting future work. Decaying functions or $Decay(t_x)$ (or $Decay(t_y)$) are designed to exponentially decrease the impact of n_x (or n_y, respectively).

Figure 4 shows probability maps of choosing direction x with regards to different values of t_x. As the value of t_x increases, the regions with high probability or red regions get smaller, which indicates that the newly introduced concepts have the expected effect. However, we also found that the probability map stops changing after a certain point. This is mainly due to the fact that P_x converges to $(1 + \frac{1+as^{k*n_y}}{1+as^{-(n_y - k*n_x)}})^{-1}$ if t_x becomes ∞. This is the limitation of the current version of the formula and possible solutions to this issue will be discussed in the discussion section.

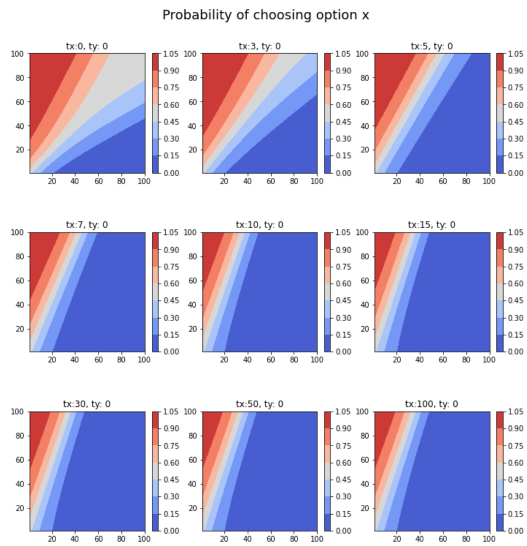


Figure 4. Probability maps depending on the value of t_x

4. Simulation

4.1. Simulation setting

With the extended model, we conducted a simulation to verify that the expected collective behaviors such as sharp turns emerge. We simulated the decision-making process of a group of ants when it is faced with bar-shaped obstacles during collective transport. Figure 5 illustrates the simulation setting. When an ant group encounters an obstacle, each individual ant decides to go left (i.e., direction x) or right (i.e., direction y) randomly at first. Then, in each following step, each ant decides to go left or right based on the extended formula we previously proposed. The speed of collective movement for each step is calculated by the net force of ants. For example, the speed of going left will be higher when 80% of ants decide to go left than when 60% of ants decide to go right. In this project, the speed follows a tanh function that takes the difference between numbers of ants who chose direction x and y. So, the speed ranges from -1 and 1 where minus value means going left and plus value means going right. The higher the difference between numbers of ants for each direction, the higher the absolute value of speed is. There were 100 decision-making steps in each simulation run. Total number of ants in the process was 36 and we ran 1,000 simulation runs to get results. Python and Jupyter Notebook were used to conduct the simulation.

Figure 5. Decision-making process when ants are faced with bar-shape obstacle

4.2. Results

We used two custom-made metrics to determine whether the expected behavior (i.e., sharp turn) occurred during simulation. First, we counted the number of turns that occurred in the simulation. That is, we counted how many times the group of ants changed their moving direction. On average, the group of ants made 9.52 turns out of 100 decision-making steps in each simulation run. The standard deviation of turns was 2.20. Figure 6 is the histogram that shows the distribution of the number of turns that occurred in the simulation.

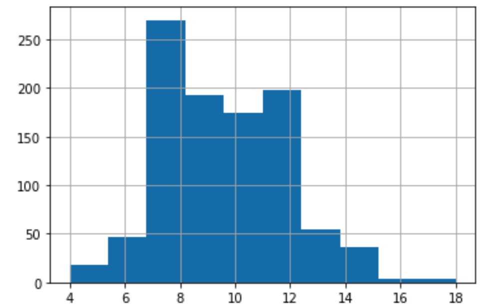


Figure 6. Distribution of the number of turns

We also compared the speed changes in turns and normal movements to show that sharp turns occurred in the simulation. It was observed that speed changes when turns happened were much higher than when ants were moving to one direction, indicating that the turns were sharp. The average speed changes when turns happened was 1.01 with standard deviation 0.12, while an average of 0.13 with standard deviation 0.02 in case of normal movements (i.e., when ants were moving to one direction). We also conducted a t-test and found that p-value is 0.0 meaning that there was a statistically significant difference between turning and normal situation. Figure 7 shows the box-plot of comparison.

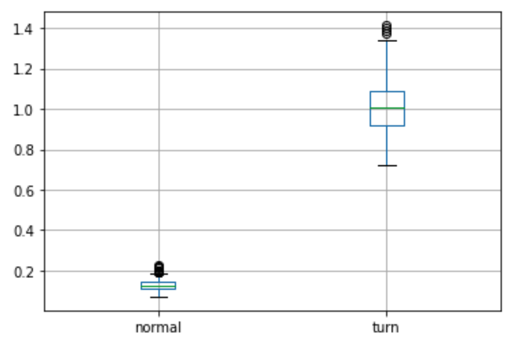
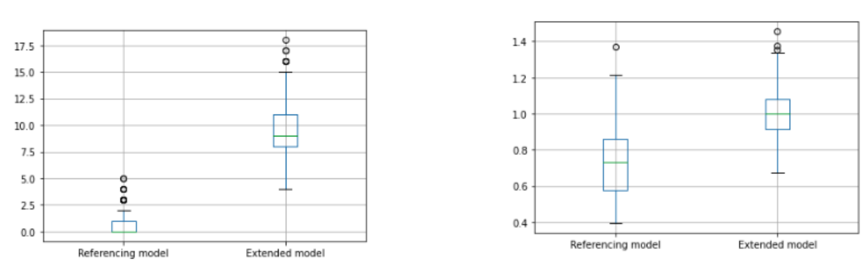


Figure 7. Box-plot of comparison between turning and normal situation

For further analysis, we conducted a comparison between the reference model (i.e., the decision-making model in Figure 2) and our proposed model using the two metrics; number of turns and speed changes. Our model showed a higher number of turns and speed changes when turns happened than the reference model, indicating that our extension had the expected outcomes. On average, 9.52 ± 2.20 turns occurred with our extended model while 0.38 ± 0.73 turns occurred with the reference model. The average of speed changes when turns happen was 1.01 ± 0.12 with the extended model while 0.71 ± 0.21 with the reference model. We checked that both differences were statistically significant using t-test. Figure 8 shows two box-plots comparing two models with respect to two metrics.



Comparison between two models (number of turns)

Comparison between two models (Speed changes)

Figure 8. Box-plots comparing the reference model and the proposed model

However, we also found sharp turns did occur with the reference model in contrast to our assumption. We did in-depth analysis of the reference model to see why this phenomenon happened and the results will be discussed in the next section.

5. Discussion

5.1. In-depth analysis of the reference model

As mentioned before, we found that sharp turns occurred with the reference model, which was in contrast to our assumption. To understand this phenomenon, we further analyzed the behavior of the reference model. We conducted a parameter sweep and found that the interplay between parameter a, which denotes the strength of external reasons, and s, which denotes the strength of social information or other ants' decisions, could indirectly influence the number of sharp turns that occurred during the simulation when the total number of ants are relatively small. Figure 9 shows the probability of choosing option x when $s = 1.07$, $a = 2.5$, and $n = 36$. The minimum value is 10.7% and the maximum value is 89.2% meaning that there is some randomness even though n_x or n_y reach to extremes. That is, parameter s and a could determine the behavior of the model in extreme points. Figure 10 shows the minimum probability of the reference model depending on varying values of parameter s and a. The impact of parameter s was much higher than parameter s in controlling the degree of randomness in extreme points. Although sharp turns could occur with the reference model, we think that our approach has an advantage that we could explicitly control the occurrence of sharp turns.

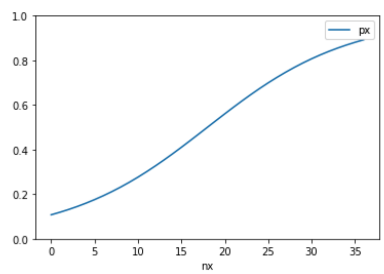


Figure 9. Probability of choosing option x ($s = 1.07$, $a = 2.5$, and $n = 36$)

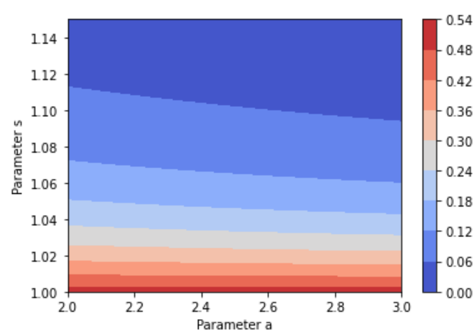


Figure 10. Minimum probability of choosing option x depending on two parameters

5.2. Limitation of the existing extended model

As mentioned in section 3, the probability map of the extended model stops changing after a certain point. This is because the probability of choosing option x converges to $(1 + \frac{1+as^{k*n_y}}{1+as^{-(n_y-k*n_x)}})^{-1}$, which corresponds to the linear line in Figure 11, if t_x becomes ∞. So, there is still the possibility of getting stuck in an absorbing state where every ant chooses one side when the total number of ants are relatively large.

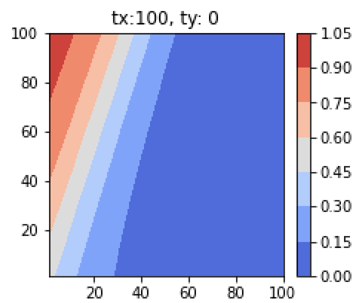


Figure 11. Probability map when $t_x = 100$

To overcome this limitation, we tried a different formula to come up with an extended model version 2. Figure 12 shows the newly derived formula. In this new formula, we applied the decaying factor to the probability directly (i.e., P_x and P_y) instead of applying the decaying factor to the number of ants who chose certain option (i.e., n_x and n_y). As shown in Figure 13, the problem of getting stuck in an absorbing state was solved with the new formula. Conducting simulations with the newly derived formula could be a future work.

$$\left(1+\frac{Decay(t_y) * (1+as^{-(n_x-kn_y)})}{Decay(t_x) * (1+as^{-(n_y-kn_x)})}\right)^{-1}$$

Figure 12. Newly derived formula

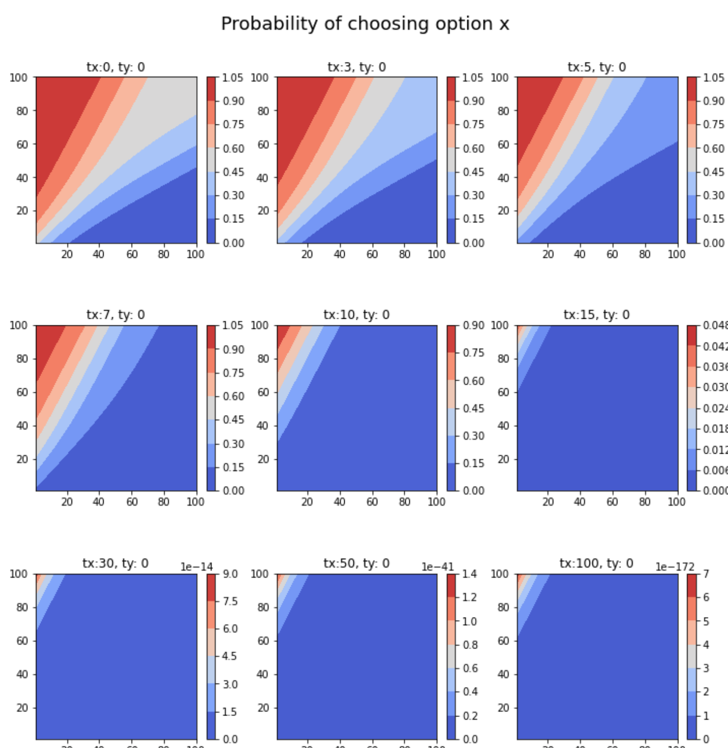


Figure 13. Probability map with newly derived formula

6. Visualization Tool

To visualize the results obtained from our simulation, we utilized Qt to create a simulator consisting of two boards composed of cells. The first board, referred to as the "decision board" later in this section, contains cells that signify the directional decision made by individual ants.

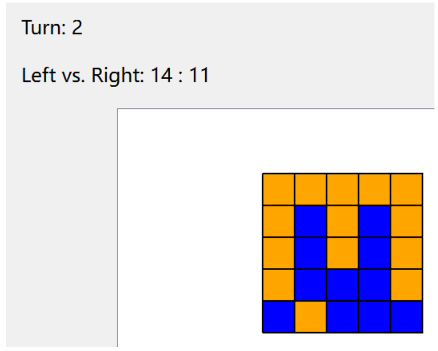


Figure 6. Example of possible outcome of the decision board

The second board, known as the "map" later in this section, contains cells that represent the ant army, the desired food source, or any obstacles hindering the ant army's progress. Each type of cell is distinguished by a specific color, and a color indicator table on the left side of the boards indicates the meaning of each color. Initially, the ant army and food will be located at the middle points of the first and last rows of the map, respectively.

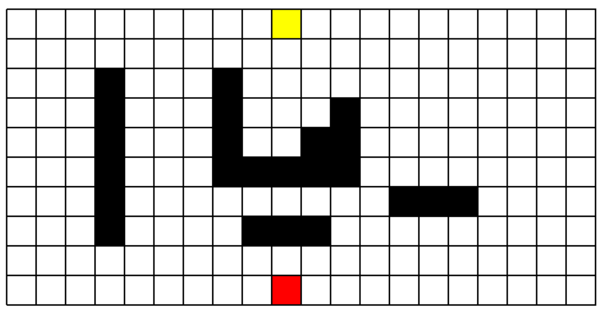


Figure 7. Example of the map

The simulation's life cycle is divided into turns. In each turn, the ant army on the map aims to move forward and eventually reach the food. If there is no obstacle directly in front of them, the ant army will move one cell up. However, if an obstacle obstructs their path, the decision board will generate directional decisions for each individual ant using the extended model formula we developed in the previous section. The formula considers various factors, such as the ant's previous decision, the ant army's previous group decision, the number of ants that turned left/right in the previous turn, the strength of nonsocial information, the strength of social information from others, and the relative impacts of opposite options. After generating each ant's direction, the system sums them up and decides the group decision based on the highest vote between left and right directions. At the end of each turn, the ant army will update its location on the map based on the group decision for the current turn generated by the system.

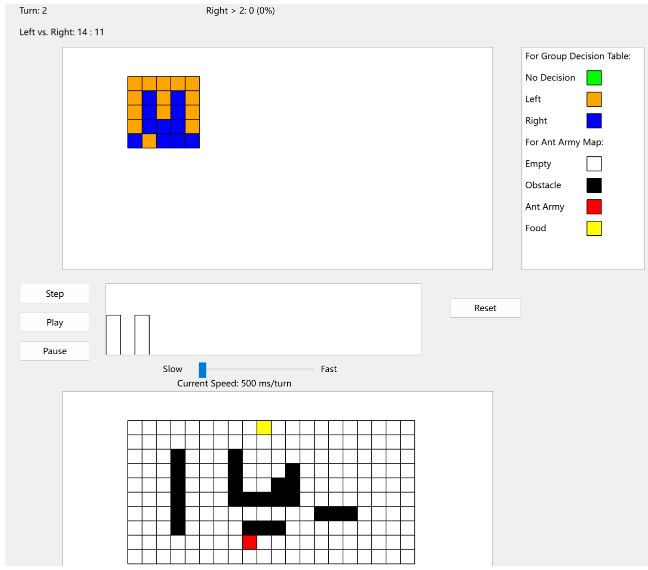


Figure 8. Screenshot of the entire simulator

The user can place obstacles on the map by left-clicking on cells. To begin the simulation, the user can press the "Step" or "Play" button to either play a turn or run the turns automatically. The speed for running each turn automatically can be adjusted by a sliding bar. The statistical bar between the two boards will keep updating the bar chart, representing the percentage of right direction chosen by individuals compared to the left direction as the turns iterate. When the ant army reaches the food, all buttons except "Reset" will be unclickable, and the simulation will stop.

7. Conclusion

In this project, we extended a decision-making model proposed by [2] in which the probability of choosing an option is determined by the number of others who chose the same option in order to explain sharp turns that occurred during collective transport of Paratrechina longicornis ants. We introduced two new concepts, namely decaying preference and short-term memory, into the model. Then, we conducted similar experiments to check whether the expected collective behaviors such as sharp turns emerge with the proposed model. We used two metrics, namely the number of turns and the magnitude of speed changes, to check whether sharp turns occurred during the simulation. Higher number of turns and magnitude of speed changes were observed with the proposed model, indicating that our model had the expected results. However, we also found that sharp turns could occur with the reference model, which was in contrast with our assumption. With in-depth analysis, we found that an interplay between parameter a and s could indirectly influence the number of sharp turns occurred during simulation. Finally, we developed a visualization tool to show how our proposed model governs the collective movement of a group of ants.

Conducting a field experiment to understand how a group of ants moves along a bar-shape obstacle during collective transport is a possible future research direction. Since all of our works were solely based on several assumptions, it should be compared with field experiment results. Similar to the simulation setting, we could analyze the movement of ants when they are faced with varying lengths of obstacles. In particular, it would be interesting to check whether ants change direction randomly or systematically. If the possibility of changing direction increases with the length of travel to one direction, it indicates that an explicit and systematic mechanism, such as our approach, for changing direction is necessary. In addition, other concepts such as long-term memory would be needed if the length of travel to one direction increases over time.

The proposed model would broaden our understanding of the collective decision-making process among animals especially in the context of changing decisions. If it is proven to be effective, the model could also be used in diverse domains including cooperative robotics to help agents deal with dynamic environments where they need to frequently change their original decision.

8. Contribution

Idea generation - Jooseok Lee, Sitong Lu
Proposal - Jooseok Lee, Sitong Lu
Formula formation - Jooseok Lee
Simulation - Jooseok Lee
Data analysis - Jooseok Lee, Sitong Lu
Visualization tool - Sitong Lu
Presentation - Sitong Lu, Jooseok Lee
Report - Jooseok Lee, Sitong Lu

9. Bibliography

Jooseok Lee is a first year professional master's student in the department of Computer Science at CU Boulder, specializing in data science and engineering. He previously worked as a data scientist at Netmarble for 3.5 years. He also majored in Industrial and Management Engineering at POSTECH. His main interest is in applying machine learning and data analysis techniques to various domains.

Sitong Lu is a second year professional master's student majoring in Computer Science at CU Boulder, with a subplan in Software Systems and Cloud Computing. He also majored in Computer Science and minored in both Writing and Mathematics at CU Boulder during his undergraduate studies. He is currently working as a backend database engineer at QI Path. He does not have a main interest in any specific area/direction and is currently treating himself as a full stack developer.

Reference

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GitHub

https://github.com/akitomoya616/Ants-Movement-Tracker