Using Genetic Algorithm to Optimize Social Behaviors in the Pattern-of-Life Simulation

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
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Abstract

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Social networks play a crucial role in individual well-being and social dynamics. This thesis explores the feasibility of using an evolutionary algorithm to study the optimal human attributes for maintaining strong social networks, through an agent- based simulation framework called Patterns-of-Life simulation (POL). We implemented a custom Genetic Algorithm within POL that allows agents to reproduce or exit the simulation based on the strength of their social connections. Six key attributes—age, education level, financial status, interest, joviality, and food need—were analyzed. We ran two sets of experiments: one with only survival pressure caused by social networks, and the other with an additional financial pressure introduced through rising housing prices. Our results show that agents with high education level and financial status are more likely to maintain a strong social network and financial sustainability. Agents with moderate food needs and balanced joviality also had better outcomes. The simulation framework also functions as an evolutionary toolbox to study how populations respond to external changes and selection pressure over time. This demonstrates the utility of evolutionary agent-based modeling in studying complex social systems like social networks.

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Chapter 1

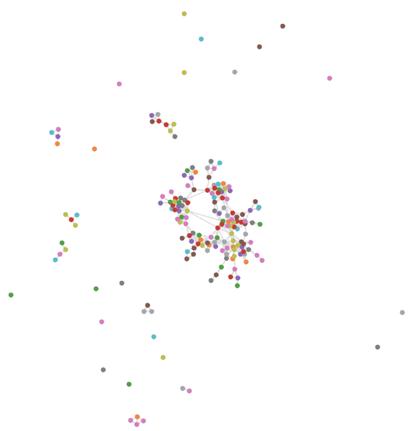
Background

1.1 Social Network and Agent-Based Modeling (ABM)

A social network is a graph-based structure representing social entities—such as individuals, groups, or organizations—and the relationships or interactions connecting them, such as friendship [1]. Social networks play a crucial role in human well-being, influencing mental health and survival. To better understand the formation and evolution of social networks, researchers use methods of simulation and modeling to observe patterns of interactions among individuals in society. One powerful tool is Agent-Based Modeling (ABM), a method used to simulate the behaviors and interactions of individuals ("agent") to help understand how an overall system operates. For example, it can be used to simulate human behavior and interactions in a society. Agent-Based Modeling (ABM) can be used to simulate complex interactions in social systems (e.g. [2, 3, 4]). Particularly, previous studies have used ABM to explore social networks (e.g. [5, 6, 7]). However, there is a lack of research that investigates social networks from an evolutionary perspective using ABM. In this study, we aim to use an ABM framework to optimize people's social network by exploring what kind of people could maintain strong social networks throughout an evolution process.

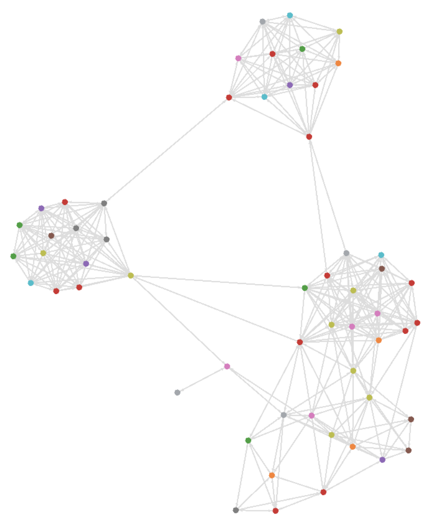
1.2 Agent-Based Patterns-of-Life Simulation (POL)

The ABM framework we use in this study is the Agent-Based Patterns-of-Life Simulation (POL) [8, 6, 9], which is developed in JAVA and based on MASON framework [10]. POL works as a simulator, simulating the realistic patterns of life and dynamic social networks of humans. The simulator creates a virtual environment constructed from real maps. In the simulator, agents behave as people in the real world. They have daily activities, such as working, eating, and visiting recreational sites. They travel and make decisions based on their internal needs (e.g. income, education, preferences, needs, etc.) and the external world. The agents' needs are designed based on Maslow's hierarchy of needs [11]. In this study, we primarily focus on the third level—the need for love and belonging—to explore the formation and evolution of social networks.



(a) Time Step 1

(b) Time Step 2



(c) Time Step 3

Figure 1.1: Visualization of social networks generated by the POL simulator. Colored dots represent agents, where different colors mean that agents have different interests. Edges indicate social connections (friendships) between them. The three subplots show the evolution of the same group of agents' social network structure at different time steps.

Several studies have been done based on POL simulation. One benefit of using POL is its ability to compensate for missing or hard-to-obtain data in real life. For example, POL has been used to simulate human mobility and generate datasets of human trajectories [12, 13]. It has also been combined with genetic algorithms to expand and mimic real but sparse datasets [14]. In addition, POL has contributed to fields such as medicine and immunology. For instance, it has became a foundation of a disease simulation model to study infectious disease in population and data bias control [15, 16].

1.3 Evolution and Genetic Algorithm

Researchers incorporate the concepts of natural selection and evolution into ABM. This incorporation allows ABM system to simulate adaptive agents' behavior and attributes over time. Natural selection gradually filters out agents with less advantageous attributes while selecting for those with more beneficial attributes. Several previous studies have applied natural selection and evolution to ABM to investigate research questions across various fields, such as biology, ecology, linguistics, sociology, etc. (e.g. [17, 18, 19, 20, 21]). Several research adopt Genetic Algorithm [22], an optimization technique inspired by natural selection, in ABM to solve complex modeling and optimization problems across broad fields (e.g. [23, 21, 24, 25, 26]). Genetic algorithm simulates the process of biological evolution, where candidate solutions evolve over generations through selection, crossover (recombination), and mutation. Individuals with better performance are more likely to pass their traits to the next generation, gradually leading the population toward an optimal solution.

There exist several toolkits for implementing genetic algorithms. One widely used toolkit is ECJ, a Java-based evolutionary computation system developed by Sean Luke [27]. However, using ECJ in our simulator POL requires a relatively long runtime for each simulation loop. Therefore, due to time constraints and incompatibility with the evaluation structure of POL, we did not adopt ECJ, and instead implemented a genetic algorithm more suitable for our environment.

Chapter 2

Analyze Social Network in Evolutionary Perspective

2.1 Approach

In this section, our purpose is to address two key questions:

(1) What kinds of individuals are more likely to maintain better social networks. In other word, what attributes of agents (such as education level, age, physiological need, etc.) are more important to maintain a better social connection. We employed the Agent-Based Patterns-of-Life Simulation (POL) [6] to simulate agents' behavior and generate data of their social connection. We included evolution dynamics into the simulation to select the agents with optimal attributes throughout the evolution.

(2) How to incorporate evolution dynamics into this simulation, allowing it to serve as a tool to observe how people adapt and evolve over time.

2.1.1 The logic of social network in simulator

In the simulator, agents form friendships when they meet others at recreational or social areas, such as restaurants, pubs, etc. If agents meet at the same place at the same time, there is a chance they will become friends. Friendships are strengthened when friends meet again, increasing the tie's strength based on how frequently they interact. Meanwhile, there is a logic of decreasing friendship strength. Each day, the strength of every friendship gradually weakens, simulating the fading of social connections over time. Once a friendship becomes too weak (under a threshold), it is removed from the social network. That is, if two agents don't meet for a while, their connection will become loose and this friendship will eventually disappear. Consequently, the social network evolves as agents continue to meet, build, or lose connections.

2.1.2 Agents in simulator

Agents' attributes

The simulator records each agent's agentID as their name. Each agent has their own attributes, which are listed in table 2.1, reflecting distinct people in the real world.

Choice of Agents' attributes

In our simulator, not every attribute is suitable for inclusion in the genetic algorithm to research its impact on social networks. For example, the simulation does not have a penalty mechanism for not sleeping, so manipulating the *Sleep Need* attribute might lead agents to stay awake consistently. Therefore, we decided to let the attribute *Sleep Need* follow its natural pattern.

As a result, we extracted six attributes (*Age, Food need, Education level, Interest, Joviality, Finance*) that influence the social network to be used in the following genetic algorithm part. *Interest* influences which pubs an agent chooses to visit, as agents prefer pubs with visitors who share similar interests, which increases the likelihood of forming new friendships. *Age* contributes similarly by affecting the similarity score in pub selection since agents tend to visit places with people of similar age. *Education level* impacts social network through employment: agents with higher education levels are more likely to secure jobs, enabling connections via the work network. Also,

Attribute	Definition
Shelter Need	Indicates whether the agent has adequate housing or needs to find shelter.
Age	Represents the agent's age in years, affecting behavior and decisions.
Food Need	Tracks the agent's hunger level and appetite, influencing eating behavior.
Has Family	Indicates whether the agent lives with family members such as a partner or kids.
Sleep Need	Describes how tired the agent is and when they plan to sleep.
Joviality	Measures how likely the agent is to prioritize socializing over working. The more the Joviality is, the more the agents focus on socializing.
Financial Safety Need	Describes agent's wealth, job status, and ability to afford basic needs.
Education Level	Captures the agent's highest level of completed formal education.
Love Need	Refers to the agent's friendship network size and social connection strength.
Interest	The agent's personal preferences, used to choose recreational sites.

Table 2.1: Definitions of agent attributes

Education level influences the income level, which subsequently affects the agent's social site selection and friendship formation opportunities. *Food need* influences the frequency of restaurant visits, which serve as a recreational place where agents can interact and strengthen social ties. *Joviality*, representing how likely the agent is to prioritize socializing over working. Agents with high joviality are more likely to seek new social interactions when their current social happiness is insufficient. Lastly, *Finance* decides whether an agent can afford recreational activities such as visiting pubs and influences the chance of friendship formation. To be specific, we used agents' hourly salary rates to represent the financial status of each agent.

Agents' attributes Initialization

At the beginning of the simulation, these six agents' attributes are initialized as shown in table 2.2.

Attribute	**Initial Distribution**
Age	Uniform integer between 18 and 60
Food Need	Uniform real value between 0.2 and 0.8
Education level	4 discrete values: Low (10%), High School/College (54%), Bachelors (23%), Graduate (13%)
Interest	Uniform discrete choice from 10 interest categories
Joviality	Uniform real value between 0.0 and 1.0
Finance	Initial hourly salary varies by education level, and is bounded between \$10.00 and \$100.00

Table 2.2: Summary of agent attribute distributions at initialization

These attribute values change over time as the simulation runs and the genetic algorithm in 2.1.3 progresses. We record the attribute values daily to observe how agents evolve.

2.1.3 Agents evolution with Genetic Algorithm

In this part, we introduced evolutionary dynamics into the social simulation by integrating a Genetic Algorithm into the simulator. We did this to observe which kind of agents survive longer in the simulation, and thereby identify which and what attributes are more important for sustaining a strong social network and long-term well-being.

Algorithm Design

Originally, in this simulator, agents live in the world and only exit the world (which, in real life, correspond to moving to another city) due to financial reasons. For instance, when they can no longer afford rent or food and thus fail to meet their shelter need or food need.

We extended this logic by introducing two behavior of the agents: (1)Another cause of agent departure: agents can now also exit the world due to poor social networks, specifically if they lack enough friends and do not meet their need for social happiness. (2)Reproducing: Agents who have good social networks could reproduce.

In the simulator, there exists the logic below: After initializing the population with agents of the initial attributes, the simulation world starts running. Every day, agents conduct daily routines, including working, eating, socializing, etc. Every night, agents update their needs, including financial status and food consumption. Meanwhile, social ties decay and friendships falling below a threshold are removed from the network. Based on this foundation, we designed an algorithm as shown in figure 2.1. We added a component called "Agent Assessment" to the nightly routine, which checks the strength of each agent's social network. Agents with strong social networks are selected to reproduce. Reproduce means that the agent creates a child agent who inherits his attributes, with a certain probability of mutation. Meanwhile, agents with weak social networks are removed from the world. Remove means the agent quits his job and is removed from any network (friend network, working network, etc.) in this world, and the house the agent living in is vacated. Agents with regular social networks remain unchanged.

After experimenting with different parameter settings, we identified relatively balanced conditions of agents reproduction and departure (shown in 2.3) that prevent the population from growing or declining extremely over time.

Category	**Condition / Value**
Strong Social Network	≥ 20 friends for 10 consecutive days
Weak Social Network	< 5 friends for 20 consecutive days
Regular Social Network	Other agents
Mutation Probability	0.08 (8%)

Table 2.3: Agent Assessment Standard and Mutation Settings

In this case, if an agent has more than 20 friends and maintains this status for

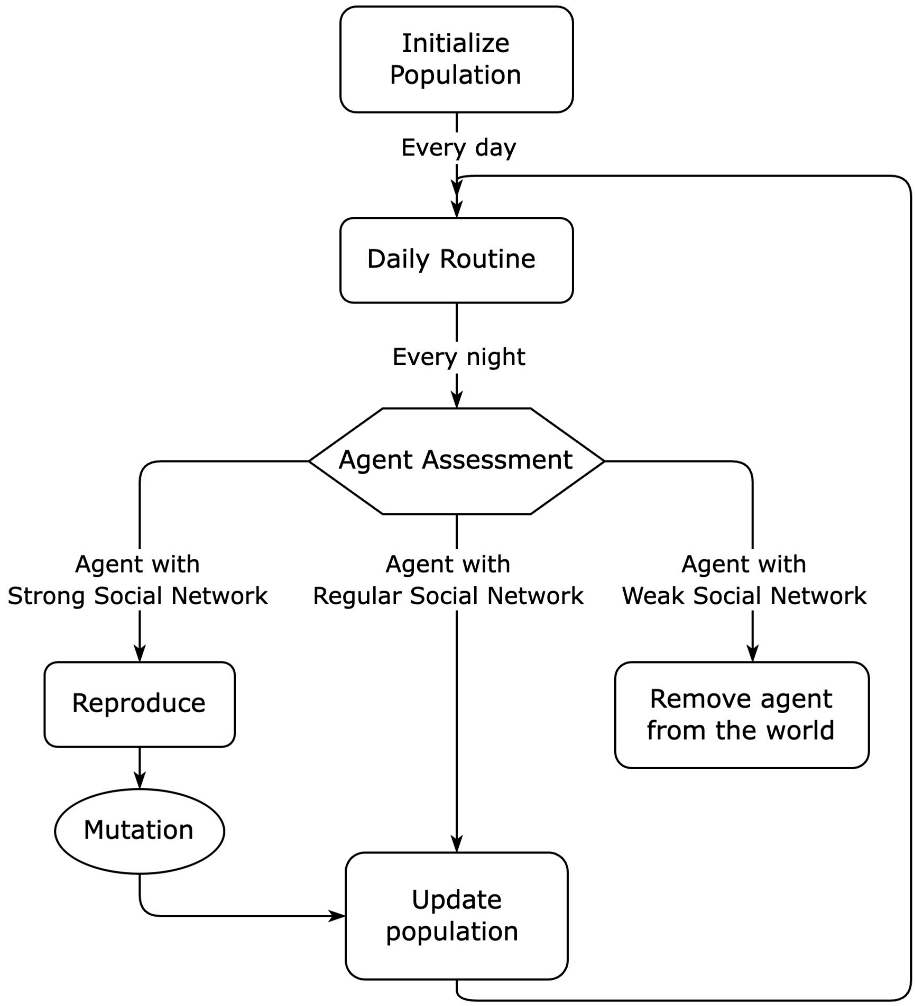


Figure 2.1: The flow chart of the genetic algorithm in the simulator.

10 days, this agent is considered as having a good social network and are capable of sustaining stronger and longer friendships effectively. The agent will reproduce and create a child. The child inherits every value of the attribute from his parent, but each attribute has probability of 8% to be mutated, that is, to be initialized with a random value. As a result, for example, the child may share the same education level, joviality, finance, and food need, but the child might have a different interest from the parent.

If an agent has less than friends and maintains this status for 10 days, this agent is considered as having a poor social network, and will removed from the world on the 10th day.

Threshold of Attributes

As evolution continues, agents gradually become "elites", which means that they achieve the best possible values in all attributes. However, this is unrealistic —— in the real world, no individual can be perfect in every aspect. Therefore, we designed an algorithm that sets a "threshold" for each attribute to address this problem.

First, we aimed to analyze the evolved population distribution to identify which attribute values are more likely to result in a strong social network. Based on the distribution, we aimed to assign scores to attribute ranges. For example, by the end of the evolution, if there is a higher proportion of agents who are younger, it indicates that younger people are more likely to maintain long-term friendships and develop stronger social networks. Then, agents aged 20–30 receive 3 points, agents aged 30–50 receive 2 points, and agents aged 50–70 receive 1 point. Similarly, if agents with higher education levels are more prevalent, it suggests that higher education contributes to stronger social networks. Graduate-level agents get 3 points, undergraduate-level agents get 2 points, high school level get 1 point, and low education level get 0 points.

Then, the total score across all attributes for each agent cannot exceed a certain threshold, such as 15 points. This allows us to observe how evolution prioritizes and balances different attributes under resource constraints, helping us identify which traits are truly more critical for long-term survival and social success.

However, due to the result in figure 2.6-2.10, we couldn't observe obvious trends for each attribute (due to high noise), so it is hard to assign clear scores. Therefore, this part was not included in the following result.

2.1.4 Dataset Generation, Processing and Visualization

Now, after adding the logic, we started to set up a dataset from the simulator. To trace the social networks, the simulator itself counted the number of friends for each agent each day. It also recorded the attributes value for each agent.

Based on this, in the "Agent Assessment" section of Figure 2.1, we calculated the averages of each attribute across all agents each day. We also calculated the number of living agents each day. With these data, we constructed two structured tables: one recorded which agents live in the world over time (agentID vs. date), and one recorded the attributes of each agent (attributes vs. agentID). By mapping these two tables, we generated frequency histograms agents' attributes. To study attribute evolution, we selected multiple dates and used ridge plots (via kernel density estimates $\hat{f}_h(x)$ explained in formula 2.1) to visualize how distributions shifted over time.

$$\hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{2.1}$$

where: n is the number of agents currently alive, h is the bandwidth parameter that controls the smoothness of the density estimate we use 0.17 based on the standard deviation and sample size, x_i is the i-th agent's attribute value, x is the position at which the density is estimate and depends on the range of the attribute's values, K is the kernel function and we used the Gaussian kernel. By using this equation, we could observe the proportion of each attribute value and how these distributions change over time.

2.2 Experiments, Results and Analysis

2.2.1 Parameters

Parameter	Value
Initial Agent Number	500
Time	1 year
Map	Atlanta downtown

Table 2.4: Parameters used in simulation.

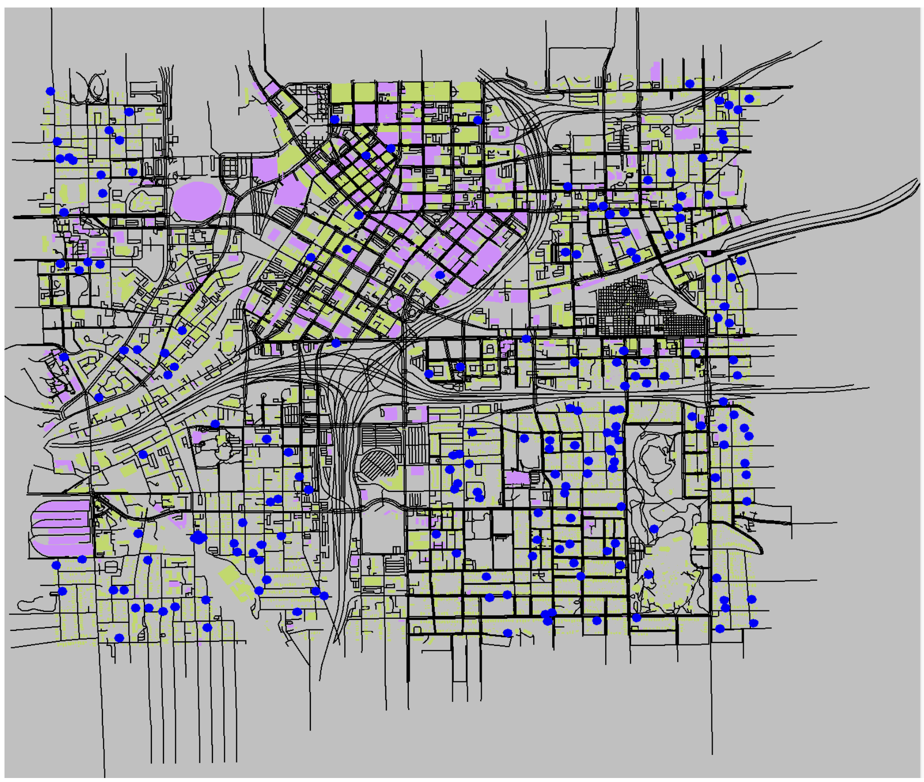


Figure 2.2: The map of Atlanta downtown.

We run the simulator in one year with 500 initial agents using the map of Atlanta downtown.

2.2.2 Results and Analysis

The change of Agents Population Size

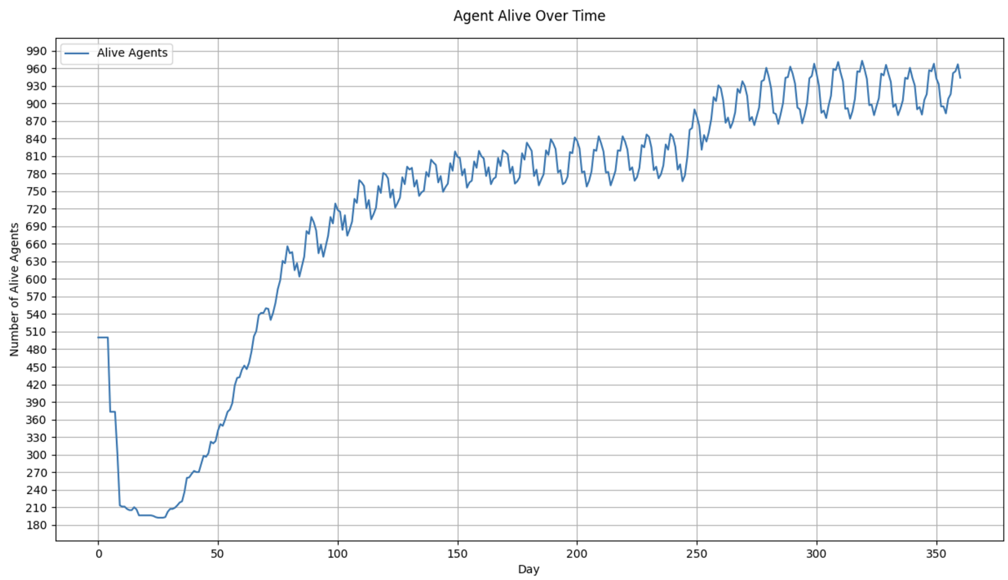


Figure 2.3: The change of agent size over time.

From the figure 2.3, we can observe that the population size drops sharply at the beginning, then gradually increases and stabilizes with periodic fluctuations. The drop at first is because of the simulator has a warm-up stage: at the beginning of the simulation, the 500 agents are initialized with different financial savings. Part of them cannot afford the house rental, so they will be soon removed from the world.

The following periodic fluctuations show the cycle of reproduction and removal based on social network conditions. The duration of a cycle is about 10 days. This duration implies there are some synchronized or coupled mechanisms inside the simulation that contribute to the 10-day fluctuation cycle. We suggested two potential reasons: (1) A weekly cycle of social network: agents tend to have more time for social activities during weekends, allowing them to make more friends and trigger the reproduction condition. (2) The thresholds we set for reproduction and removal both rely on 10 consecutive days (≥ 20 friends to reproduce, < 10 friends to be removed), which is a multiple of 10. These synchronized settings may cause agents to react at roughly the same times, leading to the observed 10-day fluctuation cycle.

We can also observe that around the 250th day, the population entered a higher stage. This may be because after the first 250 days of mutation and selection, the population had gradually evolved a group of well-adapted agents who were more likely to meet the reproduction condition.

The change of the average values of attribute

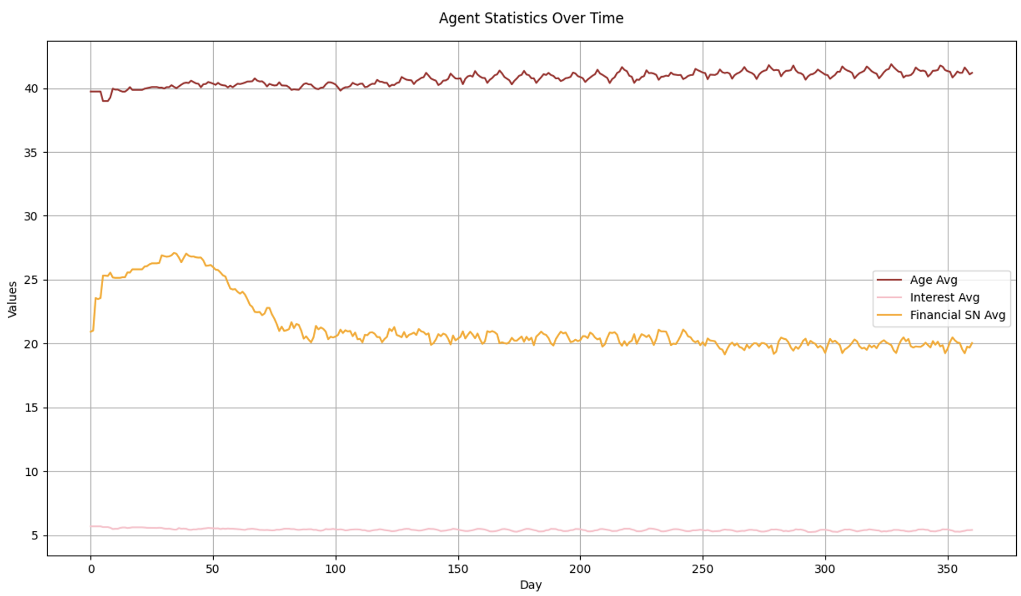


Figure 2.4: The average values of Age, Interests, and Finance of agents over time.

This figure shows the trends of agents' average Age, Interest, and Financial Safety Need over time. All three attributes gradually stabilize. The average Age increases slightly, and Financial Safety (represented by hourly salary) increases initially and then remains stable. Interest remains consistently stable around a value of 5. Since Interest is initialized randomly and uniformly for each agent within the range of 1 to 10, it is reasonable that its average stays around 5. Therefore, we will not further explore the distributional change of Interest in the following analysis.

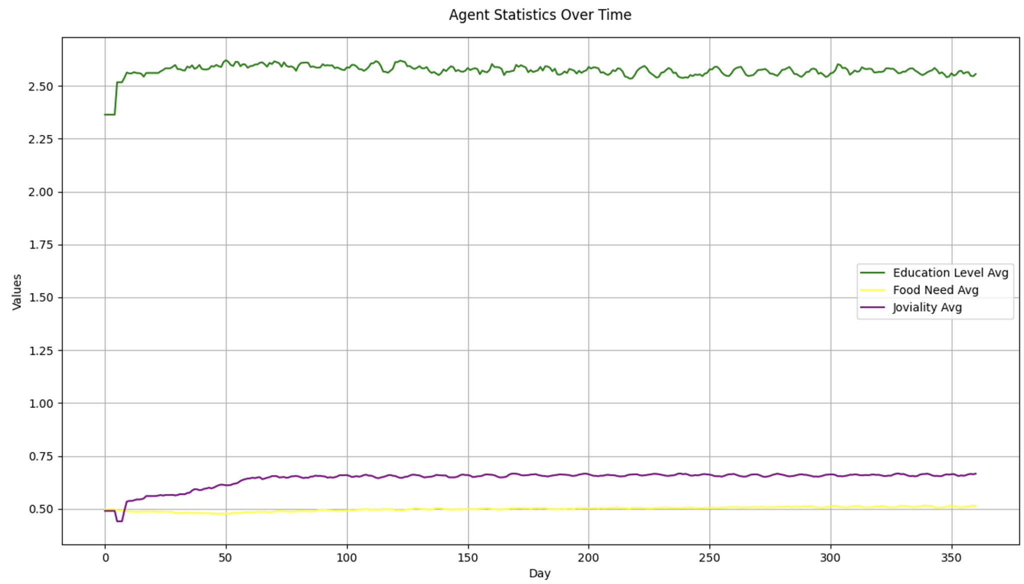


Figure 2.5: The average values of Education, Food, and Joviality of agents over time.

From this figure, we can see that the Education Level increases rapidly at the beginning and stabilizes around 2.6, which is explainable: since during the warm up stage, agents who can't afford the house rentals are removed from the world, and agents with the higher education are initialized have higher financial saving so they can afford the rentals and survive. Joviality increases gradually and stabilizes around 0.7, while Food Need remains relatively constant.

However, although the figures of averages show stable trends, they cannot represent the changes in distribution and therefore may not provide an accurate representation. Therefore, we analyze each attribute's affect on social networks together with Figures 2.6 to 2.10.

The evolution process of each attribute's distribution

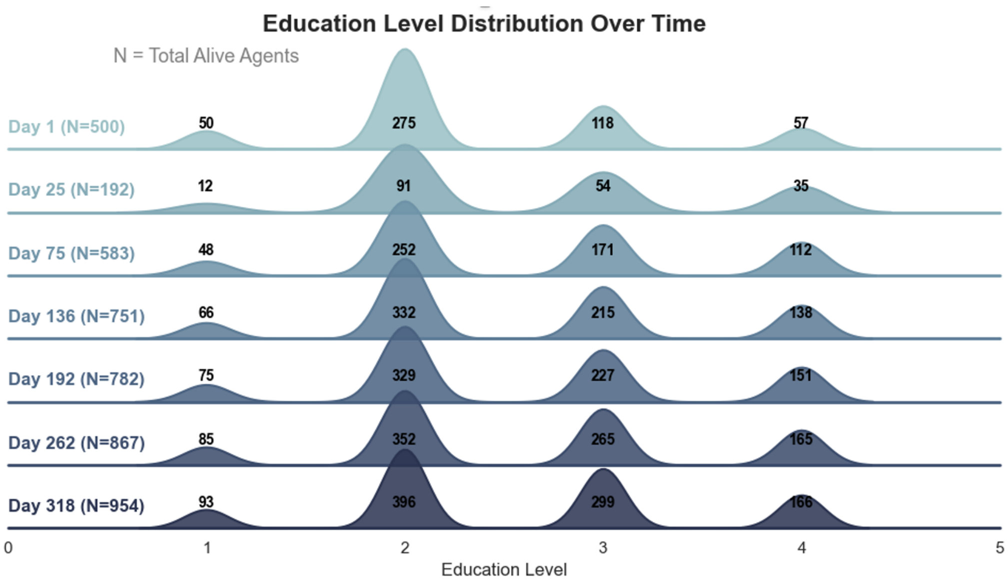


Figure 2.6: The change of the distribution of education over time.

The population initially centers around Education Level 2 (High School), as it is initialized with the highest proportion of agents at this level, reflecting real-world social patterns. Over time, more agents accumulate at levels 3 and 4, indicating an overall improvement in education across the population.

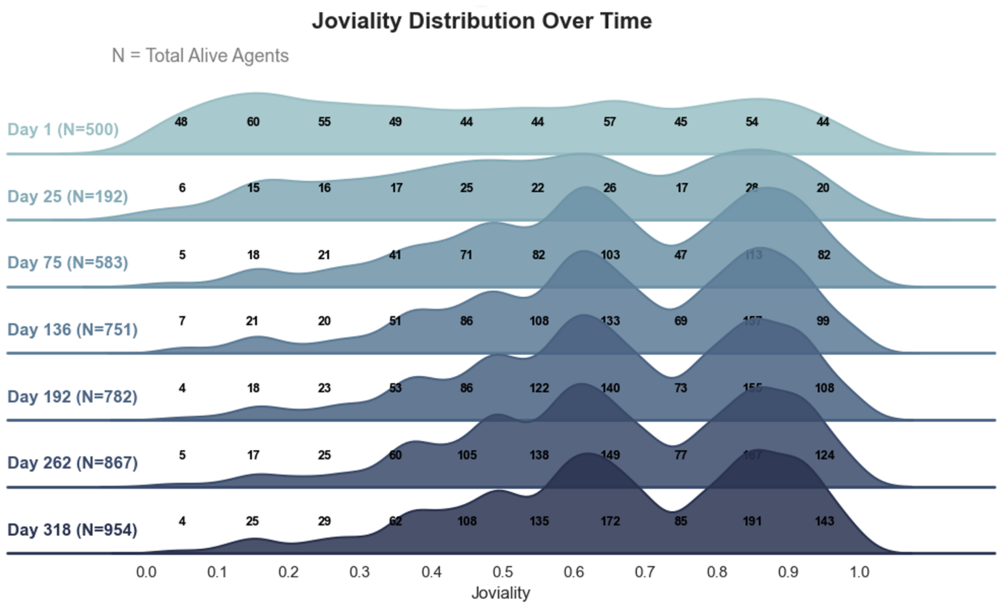


Figure 2.7: The change of the distribution of joviality over time.

The figure shows the joviality distribution gradually shifts rightward, with many agents eventually clustering around 0.6 to 0.9. There is a dip in 0.7-0.8, possibly due to a slight difference during initialization, which can be regarded as noise. Overall, the trend follows our expectation, since the more people prioritize on social over money, the more and longer friendship they can sustain. Through evolution, more and more agents are with high joviality.

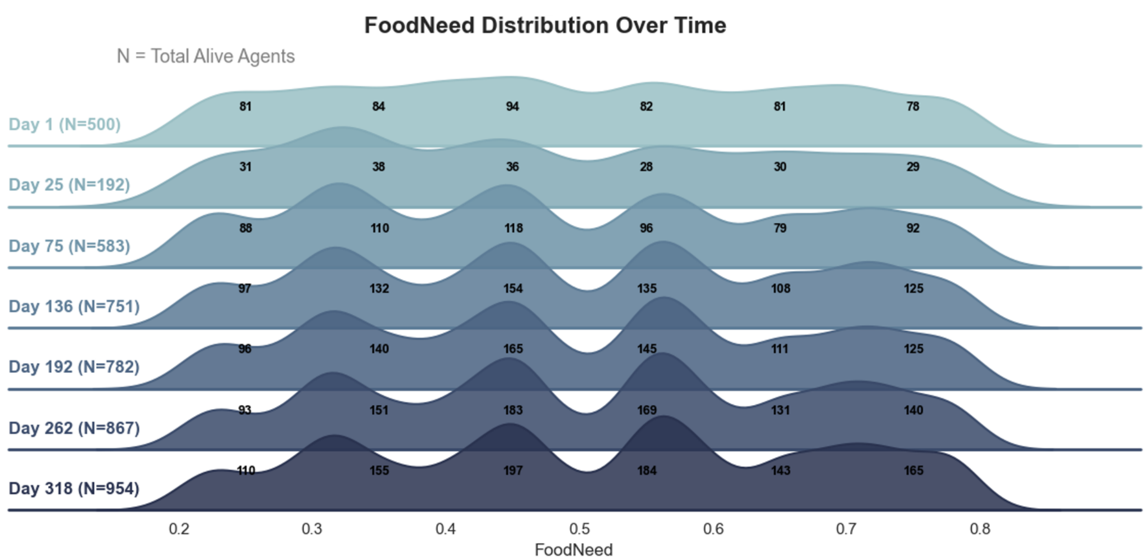


Figure 2.8: The change of the distribution of Food Need over time.

This figure shows that the distribution of Food Need gradually concentrates in the range of 0.3 to 0.6 over time. This suggests that agents with a moderate level of food need are more likely to survive in the world. Agents with excessively high food need may deplete their financial savings quickly due to higher spending on food, while those with very low food need may miss opportunities to socially connect with others. Both cases may lead to elimination in the evolutionary process. Therefore, having a moderate level of food need appears to support the development of a strong social network.

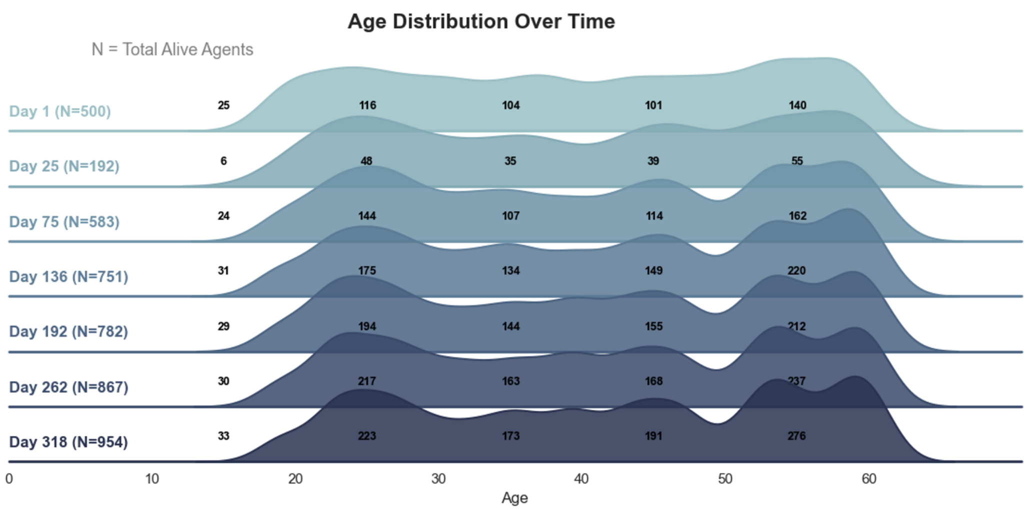


Figure 2.9: The change of the distribution of age over time.

This figure depicts the trend in the Age distribution of agents. The number of agents aged between 20–30 and 50–60 increases over time. This is a questionable result, since on day 1, there is an uneven distribution initialization that more agents aged between 20–30 and 50–60. This may result in noise in the evolution process.

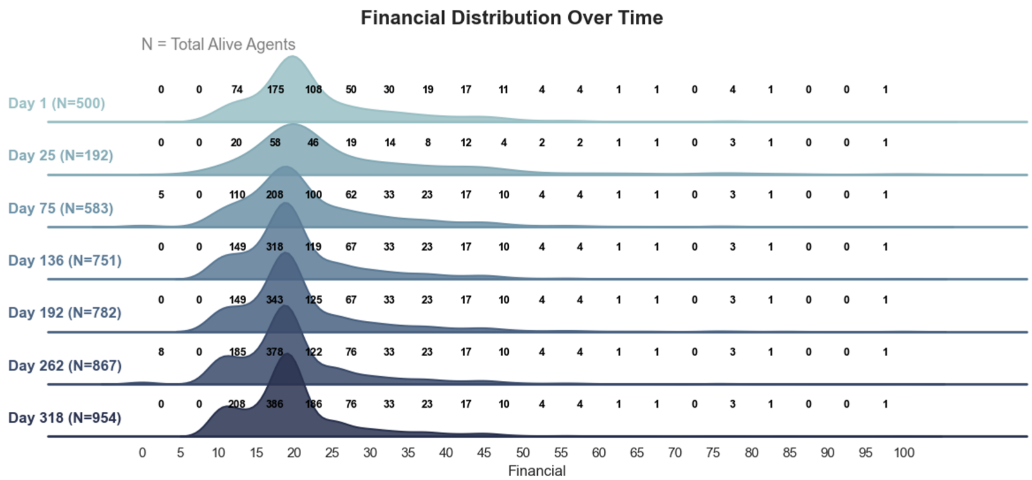


Figure 2.10: The change of the distribution of finance (hourly salary rate) over time.

This figure shows the distribution of agents' financial attribute (hourly salary), which initially concentrates between 15 and 25 and stabilizes over time with no obvious shift. Since the population was already relatively concentrated on day 1, agent reproduction and departure may not significantly result in an overall shift of distribution. However, we could see that since agents' joviality became higher over time in 2.5, agents focused more on socializing instead of making money, so there is a slight trend that agents with 10-15 hourly rate increases.

Noise and Limitation

From the distributions of joviality, age, and finance, we observe that the initialization phase could have a significant impact on the evolution process, introducing noise into the early stages of the simulation.

Meanwhile, the result of Joviality and Financial distribution reveals a potential survival issue: if agents evolve solely to have better social networks, they tend to increasingly prioritize socializing over working. While this strengthens their friendship, it may come at the cost of reduced time and energy for work and getting income. This imbalance implies a risk — agents might become socially fulfilled but financially unsustainable, eventually leading to a population with low economic viability.

Based on these two considerations, we suggested a solution in the next chapter.

Chapter 3

Analyze Social Network in Evolutionary Perspective with Financial Survival Pressure

3.1 Approach (The Change of House Rental Price)

In this chapter, we introduced an additional financial survival pressure in the simulator to select the final winner throughout the evolution.

We introduced a social environment where the house price increase periodically to add more survival pressure. Our goal was to create an extremely selective environment to"kill" the agents gradually. Thus, those who survive until the end are not only with better ability to have strong social networks, but also financially capable of living in the world. We would like to observe how the population adapts to a more competitive environment. Also, we would also focus on the small number of agents who survive until the end, rather than the entire population, the results are less affected by the noise produced by initial distribution.

To be specific, every once in a while, the rental cost increases. If agents cannot afford it, they will leave the world because their shelter needs are no longer satisfied.

Due to the computational time limitation of the simulator, we only ran the simulator for 1 year. We aimed to find an appropriate rental change parameter that fits within this one-year simulation period. The rental cost should not increase too quickly, as it would cause the population to decline rapidly and the evolution wouldn't have enough time to take place; nor should the rental increase too slowly, as it would be difficult to observe meaningful evolutionary trends within 1 year. As a result, we experimented with various parameter combinations. Eventually, we decided to make rental cost increase by 20% every 10 days, as shown in equation 3.1.

$$\text{rentalCost}_{day+10} = 1.2 \times \text{rentalCost}_{day} \tag{3.1}$$

3.2 Experiments, Results and Analysis

After implementing the logic of periodically increasing house prices, we ran the simulator using the same parameters: a one-year simulation period, the Atlanta downtown map, 500 initial agents, and a mutation chance of 0.08.

The change of Agents Population Size

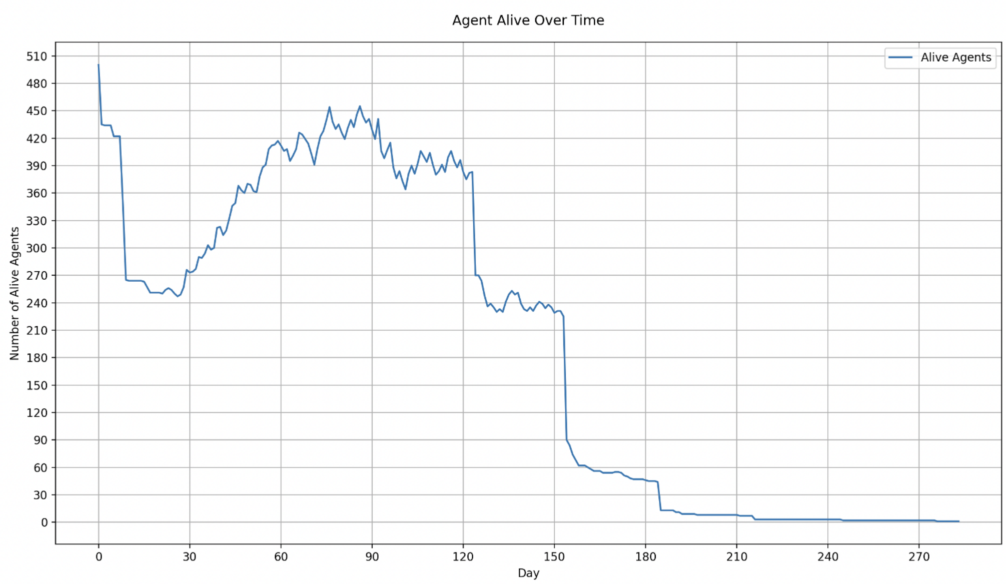


Figure 3.1: The change of agent size over time.

This figure shows how the number of alive agents changes over time after the house price increase. A significant drop in population is observed in multiple stages, indicating that more and more agents are unable to afford the rising prices. By the end of the simulation, only a small portion of agents remains, which aligns with our expectations.

The change of the averages value of attribute

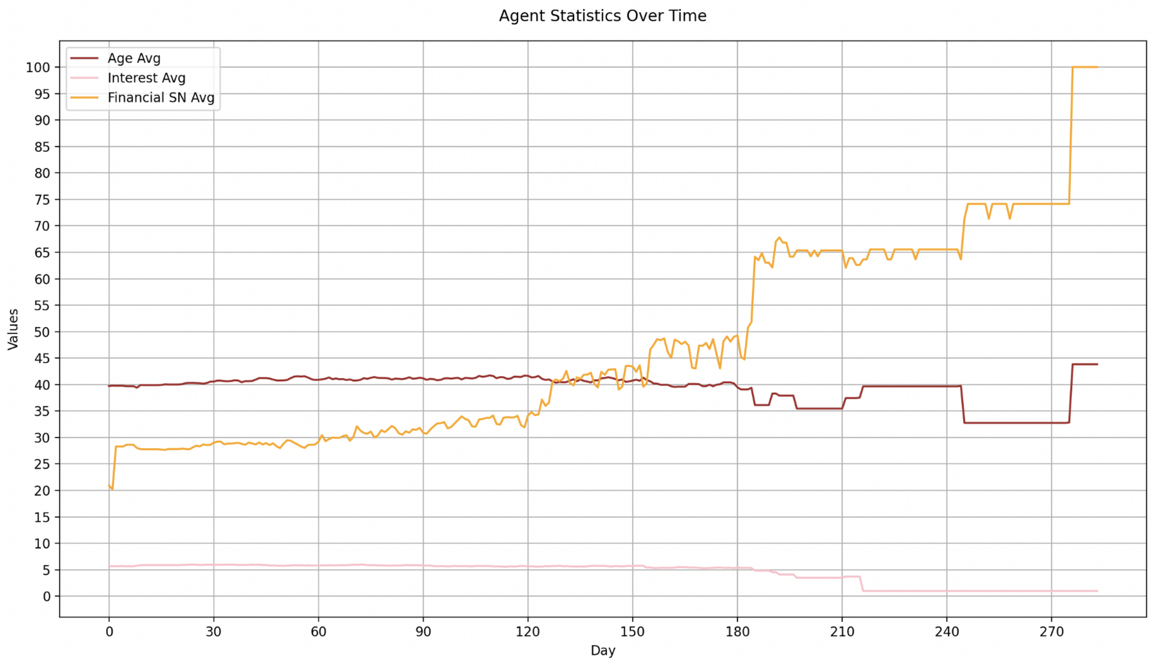


Figure 3.2: The average values of Age, Interests, and Finance of agents over time.

This figure illustrates the evolution of the average Age, Interest, and Financial Safety Need of agents after house price change. After about the 280th day, three attributes remain straight lines, showing there is only one agent alive. Within 20 days, the last survivor exit the world, validating the influence of our departure condition - because if he existed alone, he would have no friends and leave the world within 20 days. The Interest remains relatively stable, which shows its value is random so is independent of both agents' social network and the financial pressure. The average Age decreases slightly over time. Financial Safety Need shows a sharp increase after the house price change, reflecting the greater financial pressure faced by surviving agents.

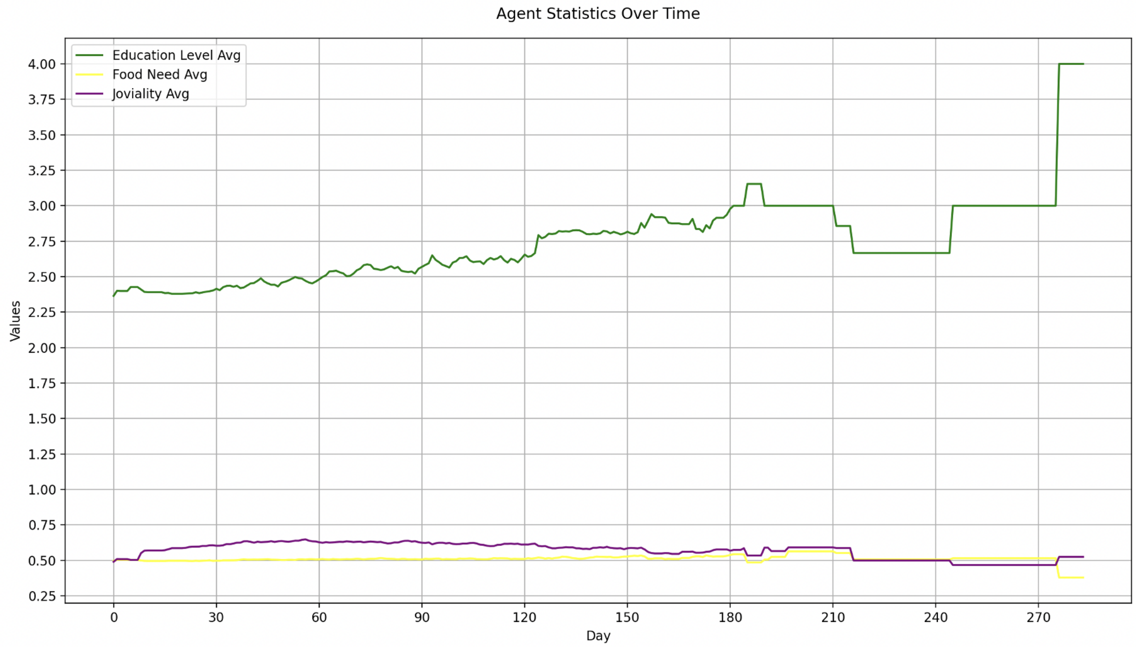


Figure 3.3: The average values of Education, Food, and Joviality of agents over time.

This figure shows the evolution trends of the average Education Level, Food Need, and Joviality of agents after the house price change. Education Level steadily increases and then jumps sharply near the end of the simulation, indicating agents of high education level survive at the end. Food Need remains relatively stable around 0.5, indicating that agents maintain this attribute at a moderate level. Joviality shows an initial upward trend, followed by a gradual decline toward the end of the simulation. This suggests that agents initially prioritized social interactions, but as housing prices increased, they had to shift more of their time and energy toward work.

The evolution process of each attribute's distribution

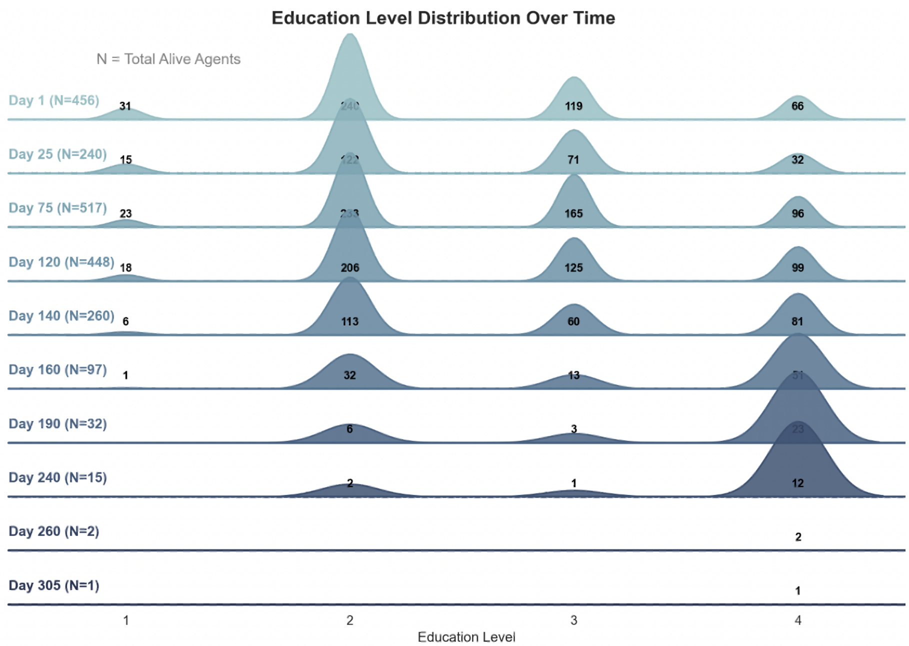
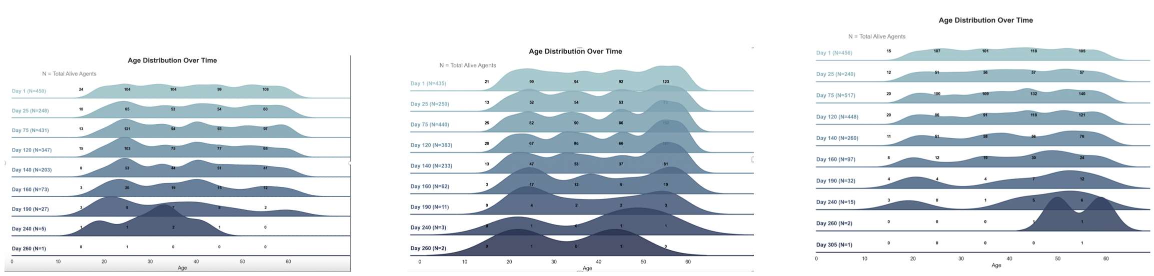


Figure 3.4: The change of the distribution of education over time.

From this figure, in the early stages, most agents are concentrated at level 2 (High School). As the simulation progresses and survival pressure intensifies, agents with lower education levels gradually disappear, and the distribution shifts toward higher levels. By the end, only a few highly educated agents remain in the population. This shows that agents with higher education levels are more likely to maintain both a strong social network and financial sustainability.



(a) Seed 1 (b) Seed 2 (c) Seed 3

Figure 3.5: The change of the distribution of age over time under different random seeds.

From the age distribution figures, we observe that although the final surviving agents tend to cluster within a certain range, there is no significant overall shift in the distribution throughout the evolutionary process. To reduce the influence of noise, we ran multiple simulations with different random seeds, which determine the initialization. We selected three representative results for comparison, and the outcomes suggest that the age of surviving agents appears to vary randomly across seeds. Combined with Figure 2.9, we suggest that age may not play a significant role in determining an agent's ability to maintain strong social connections and economic stability.

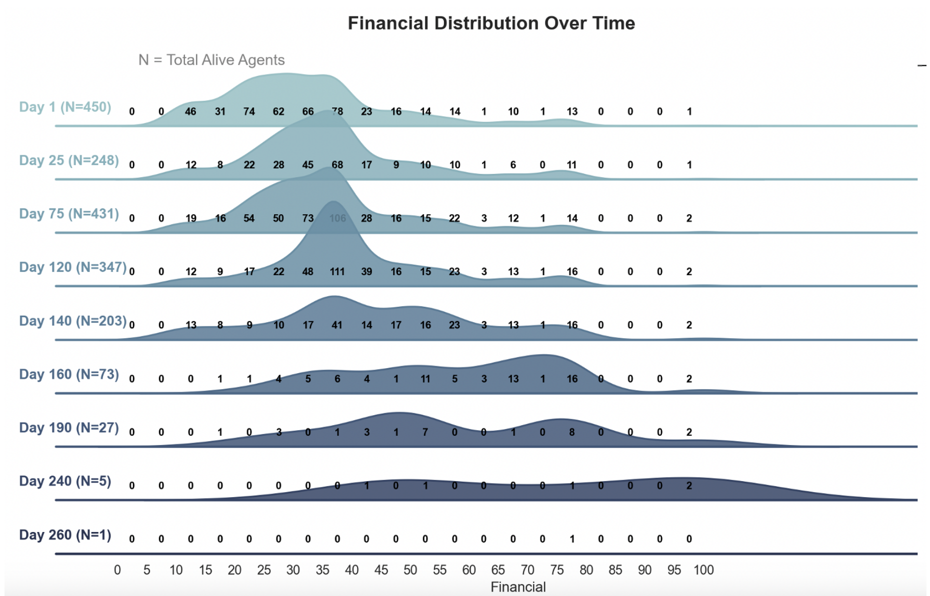


Figure 3.6: The change of the distribution of finance (hourly salary rate) over time.

From this figure, we observe a rightward shift in the population distribution over time. As the simulation progresses and selection pressure increases, agents with lower financial values are gradually eliminated.

It is worth noting that two agents with salaries in the 40–55 range still survive, which is not considered a high salary compared to the overall distribution. This is because the simulation includes a budgeting mechanism: agents with certain personality types, such as Croesus or Balancus, intentionally reduce their weekly spending when their finances are tight.

However, the overall rightward trend still suggests that agents with lower salaries are less likely to sustain strong social connections and economic stability.

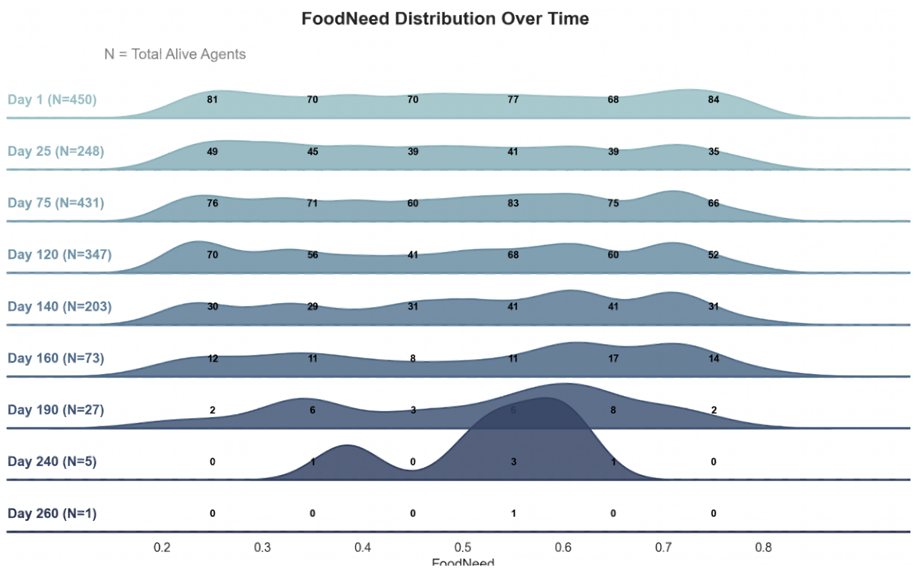
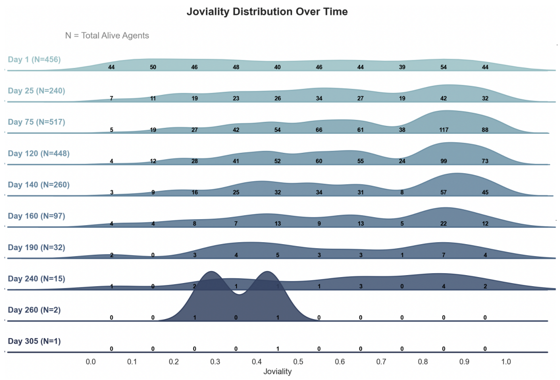
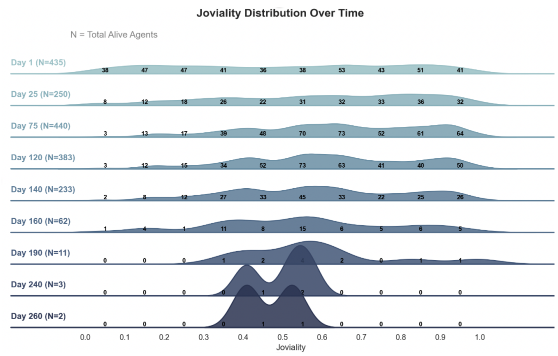


Figure 3.7: The change of the distribution of Food Need over time.

This figure shows that, over time, the distribution of food need narrows and converges around the mid-range value of 0.5. Agents with extremely high or low food needs are gradually eliminated from the simulation. This trend is consistent with the one observed in Figure 2.8, which supports the idea that agents with moderate food needs are better able to balance their spending on food with the opportunity to build social connections in restaurants.



(a) Random Seed 1



(b) Random Seed 2

Figure 3.8: The change of the distribution of Joviality over time under different random seeds.

From the two figures showing the distribution of Joviality over time, we observe that Joviality values gradually concentrate around the mid-range (0.4–0.6). Agents with extremely low or high Joviality are less adaptable under increasing survival pressure. This trend addresses the concern raised in the previous chapter—namely, that if agents evolve solely to improve their social networks, they may increasingly prioritize socializing over working, leaving limited time to earn money. The results suggest that agents with balanced social tendencies are more likely to survive in the long term.

Chapter 4

Discussion

4.1 Summary of Analysis

In this work, we successfully applied a genetic algorithm-based approach to an agent-based social simulator to explore how individual attributes affect long-term survival under evolving economic and social pressures. By simulating multiple generations of agents with varied characteristics, we were able to analyze which attributes contribute to maintaining strong social connections and financial sustainability over time. In addition, we introduced a house price increase mechanism to impose greater survival pressure, which (1) effectively counteracts the noise introduced by initialization, (2) accelerates natural selection by eliminating agents with weaker attributes and selecting advantageous attributes, and (3) incorporates financial pressure into the system, making the simulation environment more realistic.

The simulation results reveal that education level plays a crucial role—agents with higher education levels tend to survive longer due to their initial financial advantage and better adaptability. Financial Safety Need (measured as hourly salary) also shows strong impact, with higher-income agents being more resilient under rising house prices. Agents with a moderate level of Food Need and Joviality are selected, balancing cost, working and social connections. Age appears to have minimal influence, as the distribution of surviving agents remains random across seeds.

4.2 Limitation and Future Direction

While the simulation provides valuable insights, there are several limitations to consider.

First, the algorithm relies on several assumptions. For example, the condition for defining a “strong” or “weak” social network. These thresholds were determined experimentally for balanced evolution performance in our simulator, but they may not directly reflect real-world social dynamics. In future work, we aim to replace manually tuned conditions with empirical social data or adaptive methods for defining strong and weak social networks. Meanwhile, we will experiment with more mutation numbers, to research on how mutation would affect on the evolution of the attributes.

Second, the agents are not able to fully simulate real humans, as they do not capture the full complexity of human behavior and characteristics. For instance, agents are not assigned gender, which prevents realistic modeling of biological reproduction through genetic inheritance from two parents. In the future, we plan to enrich agent design by introducing gender, age dynamics, and more realistic genetic inheritance mechanisms. This would allow for more biologically plausible reproduction processes, including child agents starting from age zero and inheriting combined traits from both parents.

Lastly, the rate of house price change in the simulation may not accurately reflect real-world patterns. For example, our simulator is based on the urban structure, and our algorithm may tend to remove agents with insufficient financial resources from the city. This behavior does not necessarily align with how population distribution and migration occur in reality. Based on this limitation, we intend to study how to include policy and economic change in AGM [3], house price market dynamics [28, 29], and people preference on rural-urban migration [30]. We plan to incorporate economic models of policy and housing market dynamics and agent migration behavior. This would make the simulated urban environment more aligned with real-world dynamics and economic trends.

Chapter 5

Conclusion

In this study, we proposed an evolutionary agent-based modeling approach to investigate the formation and sustainability of social networks. By embedding a Genetic Algorithm into the POL simulator, we enabled agents to evolve over time based on their ability to maintain strong social ties. Through multiple simulation runs, we identified education level and financial stability as key factors contributing to agents' long-term survival. Agents with moderate food needs and joviality were also more successful in maintaining their social network. In contrast, age appeared to have limited influence.

To address the noise introduced during initialization and to simulate a more competitive environment, we introduced a housing price increase mechanism. This added financial survival pressure helped filter out less-adapted agents and accelerated natural selection. The enhanced setting more accurately reflected real-world dynamics and highlighted the trade-offs between strong social networks and economic sustainability.

Our findings underscore the potential of combining agent-based modeling and evolutionary computation to explore complex social networks. Future directions include incorporating more realistic agent designs and condition designs, integrating economic policy and urban migration models for broader applicability.

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