The Role of Relocation Policies in Urban Segregation Dynamics

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Abstract

This study addresses a gap in the existing literature on the Schelling segregation model by conducting a comprehensive qualitative assessment of various relocation policies. We introduce novel Schelling models driven by different relocation policies and analyse their impact on the convergence time and final segregation levels. Our findings demonstrate that all policies result in segregation levels within bounds established by policies where agents relocate to maximize their happiness. Notably, a policy ensuring the minimum improvement in agent segregation significantly reduces the model's convergence time. These results underscore the potential influence of relocation policies, such as those employed by online recommenders in real estate platforms, on societal segregation dynamics. The study provides valuable insights into potential strategies for mitigating and decelerating segregation through tailored recommendations.

Keywords

Segregation, Schelling, Agent-Based Models

1. Introduction

In 1971, Thomas Schelling proposed the very first agent-based model to explain how individual actions could result in a global phenomena like segregation [1, 2, 3, 4]. In Schelling's simple spatial proximity model, a division between the two groups of the population emerged as a result of a homophily tendency of the agents that, he claimed, in real life can happen along many dimensions such as ethnicity, language, income, and class affiliation [4]. Agents of two types are placed randomly on a two-dimensional grid (city), with each agent having a preference for living next to people of his type. When an agent is surrounded by too many agents of a different kind it becomes unhappy and moves to an empty cell that satisfies its preferences. Schelling observed that even when agents are tolerant (low homophily threshold), the city gets segregated in a few simulation steps.

Several variants and enhancements of the Schelling model have been proposed so far. Some of them modify the agents' behaviour, for example associating to each agent an income status [5] or treating the problem with a reinforcement learning approach [6]. Other works analyse what happens to the model if the environmental configuration, like city size or shape change [7, 8, 9, 10, 11], or if the dynamics take place on a network-like structure [12, 13]. In two of these works [12, 9], the agent picks the cell that maximizes its happiness. Other works included real-world segregation data along with strategies to validate simulated behaviour with observations [14, 15, 16] or implement agent behaviours based on psychological and sociological theories [17, 18, 19, 20]. A recent empirical study suggests a link between experienced income segregation and an individual's tendency to explore new places and visitors from different income groups [21]. Gambetta et al. [22] show that imposing mobility constraints to agents in the Schelling model strongly affects convergence time and the final segregation level.

While previous research has explored various aspects of urban segregation using models like the Schelling model, there is still a gap in understanding how different strategies or guidelines, known as "relocation policies," directly influence the dynamics of urban segregation. These policies could include government initiatives, algorithms employed by real estate platforms like Idealista, Booking, or Airbnb [1], or other mechanisms that shape the distribution of people across neighbourhoods.

These online real estate platforms are more and more actively suggesting housing options to users, playing a pivotal role in influencing urban development [23]. The choices individuals make, guided by these platforms or

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other relocation policies, can contribute to scenarios of either increased or decreased segregation within the city, or the emergence of other phenomena like *gentrification* [24, 25]. Furthermore, these platforms have been proven to have a crucial impact on the urban scenario. For example, in areas with a high AirBnB presence, rents and transactions substantially rise [26] and racial biases appear to be reinforced [27].

This work aims to fill the literature gap, underscoring the need to systematically measure and understand the numerical impact of different relocation policies on urban dynamics. It does so by offering relocation suggestions to a portion of Schelling model-like agents and scrutinizing how these recommendations affect both convergence time and observed levels of segregation. Our findings reveal that policies focused on income (dis)similarity notably increase segregation times, while strategies encouraging agents to relocate where they would experience minimal or maximal happiness expedite segregation times. Notably, these latter policies establish both lower and upper bounds for the observed segregation levels of all the analysed policies.

2. Policy-driven segregation model

Schelling's classical model illustrates how urban segregation may emerge due to individual preferences for similar neighbours. The city is represented as a grid where agents of two types (initially placed randomly) inhabit cells or leave them unoccupied (approximately 20% remain empty). The parameter h controls agents' homophily tendencies. At each simulation step, an agent in position K evaluates its Moore neighbourhood [28] Γ_K – the surrounding eight adjacent cells in a square formation. If an agent has fewer than h neighbours of its type, it becomes unhappy and relocates to a random, empty cell. Figure 1 schematizes the Moore neighbourhood of a happy cell (left) and unhappy cell (right). The simulation terminates when all agents are happy.

Schelling's analysis reveals striking outcomes: even with a low h value (e.g., $h = 3$, indicating agents are happy with only 3/8 of their neighbours sharing their type), the city segregates rapidly, maintaining an average segregation level higher than the agents' minimum requirement.

This paper aims to evaluate the impact of diverse relocation policies within the classical Schelling model in terms of convergence time and final segregation level. In our model, each simulation takes place on a 50×50 grid where 75% of its cells are randomly populated with M agents. The agents are categorised into two groups: majority agents (60%) and minority agents (40%). At the beginning of the simulation, each agent is associated with a fixed income w. To this purpose, as in [5], we

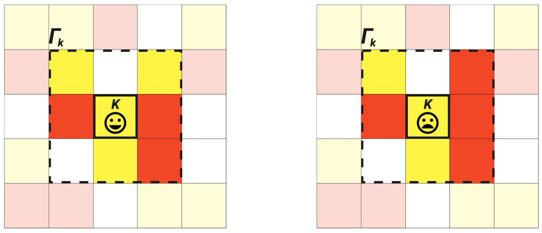

Figure 1: Example of a happy agent (left) and an unhappy agent (right) with a homophily threshold $h = 3$. The dashed square represents the Moore neighbourhood Γ_K of cell K. On the left, three yellow agents are in the neighbourhood of a yellow agent, so the agent is happy. On the right side, only two agents share the type of the agent in cell K, making the agent unhappy.

use income data from the 2022 USA Social Security Administration report,[2] which delineates the US worker population percentages within specific income intervals. Every agent is assigned an income interval b with a probability proportional to the US population within b, and the assigned income w is picked uniformly at random within b. The majority agents are the richest 40% ones; the minority agents are the poorest 60% ones. Note that the income assignment changes at each simulation, enhancing the robustness of our results. Figure 2 shows the income distribution: as expected, a few agents have a high income, while a heavy tail of agents have a low income.

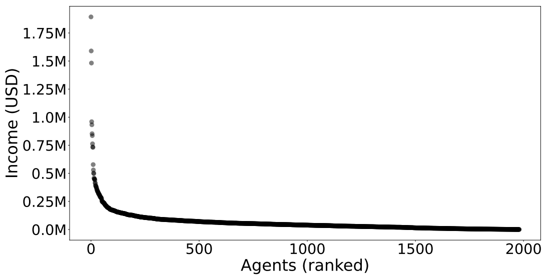

Figure 2: Income distribution of the agents in the model. On the x-axis, the agents are ranked by associated income. The y-axis represents the income. A few agents have a high income (around 1 million dollars), and the majority of the agents have a low income.

Simulation starts with agents randomly spread on the grid (see Figure 3, left). Each cell can either be occupied by only one majority agent (yellow), occupied by a minority agent (red) or be empty (white). At the end of the simulation, the grid appears spatially clustered as in Figure 3. Even if agents are tolerant (e.g., they are happy

[2] www.ssa.gov/cgi-bin/netcomp.cgi?year=2022

when just 3/8 of neighbours are similar to them), the city ends up segregated.

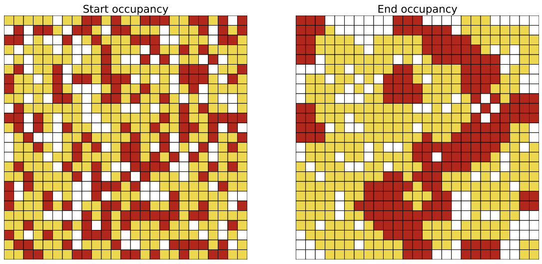

Figure 3: Example of a Starting (left) and final (right) distribution of the agents when our model terminates. White cells are empty; the majority type agents occupy yellow cells, and the minority type agents occupy red cells. The grid dimension is 25×25 for visualisation purposes.

In contrast with the original Schelling model, and following the idea proposed by Gambetta et al. [22], each cell A is associated with a relevance score r, representing the cell attractiveness. We assume a core-periphery structure to model the distribution of relevance across the grid cells [29] (see Figure 4) and use a radial distribution where the relevance value of each cell decreases with its distance from the grid centre C:

$$r(A) \propto \frac{1}{\sqrt{d(A,C)}} \tag{1}$$

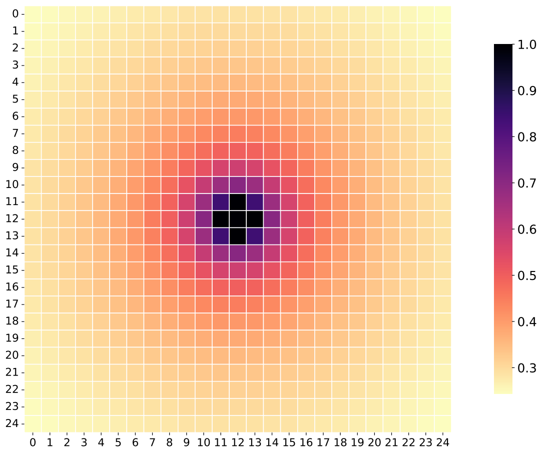

Figure 4: Cell's relevance distribution. Central cells have a higher relevance than peripheral ones. The visualized grid (25×25) is smaller than the actual one for visualisation.

The distance between any two cells K and J on the grid, represented by coordinates (x_K, y_K) and (x_J, y_J), is computed as their Euclidean distance:

$$d(K,J) = \sqrt{(x_K - x_J)^2 + (y_K - y_J)^2} \tag{2}$$

The Moore [28] neighbourhood centered at a cell $K = (x_K, y_K)$ is defined as:

$$\Gamma_K = \{(x,y) : |x - x_K| \leq 1, |y - y_K| \leq 1\} \tag{3}$$

We compute the number of agents in the Moore neighbourhood of cell E that are of the same type of agent in cell J as:

$$\Sigma(J,E) = \sum_{E' \in \Gamma_E} C(J,E') \tag{4}$$

where $C(J,E')$ denotes the equality of agents between cell J and cell E':

$$C(J,E') = \begin{cases} 1 & \text{if } type(J) = type(E') \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where $type(K)$ returns the type of the agent in cell K. For each agent, a, its segregation score indicates the number of agents of the same type of a in its Moore neighbourhood divided by 8 (the maximum number of Moore neighbours):

$$s(a) = \frac{\Sigma(K,K)}{8} \tag{6}$$

The average segregation score of the grid, $\langle S \rangle$, is the average of the segregation score of all the agents:

$$\langle S \rangle = \frac{\sum_{a \in M} s(a)}{|M|} \tag{7}$$

The richness W_K of a Moore neighbourhood Γ_K with m agents is the average income of the agents in the cells within Γ_K:

$$W_K = \frac{1}{m} \cdot \sum_{X \in \Gamma_K} w_X \tag{8}$$

where w_X denotes the income of the agent in cell X.

The similarity between two Moore neighbourhoods is assessed in terms of average income similarity, i.e. the square root of the absolute difference between the average incomes of the two neighbourhoods.

$$sim(\Gamma_K, \Gamma_J) = \sqrt{|W_K - W_J|} \tag{9}$$

Finally, $tau(K)$ represents the consecutive time steps during which a cell K has been empty, starting from the last step and moving backwards.

2.1. Relocation policies

An agent moves to an empty cell when it is unhappy, i.e., the number of neighbours of its type is smaller than a homophily threshold $h = 3$. In the original Schelling model, when unhappy, an agent moves to a random empty cell (*random* policy). In our model, we introduce more sophisticated relocation policies.

When an agent leaves its cell A because unhappy, our model assigns to an empty cell B a score proportional to a policy $\mathscr{P}$, sorts the cells in decreasing order, and selects the top k cells. The unhappy agent uniformly randomly picks one of these k cells. We set $k = 30$ to emulate real-world practices in online real estate platforms, typically suggesting 30 results per page. [3]

We investigate six main policies:

- **Similar neighbourhood**: the score of a cell B is calculated as:

$$p(B) \propto sim(\Gamma_A, \Gamma_B) \tag{10}$$

  The more the neighbourhood of a cell B is similar to the neighbourhood of the original cell A, in terms of average income of the agents, the higher the score of cell B.

- **Different neighbourhood**: the score of a cell B is computed as

$$p(B) \propto \frac{1}{sim(\Gamma_A, \Gamma_B)} \tag{11}$$

  The score of the cell B is inversely proportional to the economic similarity between the starting and ending neighbourhoods.

- **Minimum improvement**: the agents may move only to cells it would be happy. Among these cells, the score of each cell B is inversely proportional to the number of agents of the same class of the agent in the starting cell A:

$$p(B) \propto \frac{1}{\Sigma(A, B)}, \text{ if } \Sigma(A, B) \geq h \tag{12}$$

- **Maximum improvement**: the agents may move only to cells it would be happy. Among these cells, the score of each cell B is directly proportional to the number of agents of the same class of the agent in the starting cell A

$$p(B) \propto \Sigma(A, B), \text{ if } \Sigma(A, B) \geq h \tag{13}$$

- **Recently emptied**: we assign a higher score to the empty cells that have been emptied for the lower amount of time in the last steps:

$$p(B) \propto \frac{1}{\tau(B)} \tag{14}$$

  The rationale behind this policy is to assume that a reasonable choice for an RS, is to suggest users occupy locations that were already in conditions of being inhabited and that were recently free.

- **Distance-relevance**: the score of a cell is directly proportional to the cell's relevance and inversely proportional to the distance between the starting and arriving cell [22]:

$$p(B) \propto \frac{r(B)^2}{d(A, B)^2} \tag{15}$$

  This policy encapsulates a fundamental principle of human mobility, as postulated by the Gravity model, wherein individuals seek to minimize travel time while being drawn toward significant locations [30].

In Figure 3, we presented the initial (left) and final (right) configurations resulting from the execution of the model, where all agents follow the baseline *random* policy. Starting from the same initial configuration, Figure A1 reports the final configurations of simulations in which all agents follow the other six policies

2.2. Experimental settings

In our experiments, we vary the adoption rate $p \in [0, 100]$, a parameter representing the percentage of agents following the suggested policy. At the beginning of the simulation, each agent has a probability p to follow the policy during all steps of the simulation, and thus a probability $1 - p$ to follow the random policy. Each agent will be categorised as policy-follower or not at the beginning of the simulation based on probability p. The baseline of our experiments is the classical Schelling model, where all agents follow the random policy (this, $p = 0$).

We perform 100 simulations for each configuration of the model. Each configuration combines the values of two parameters: the policy $\mathscr{P}$ and the adoption rate p. Each simulation uses a different random spatial distribution of agents on the grid and a different random income assignment taken from the income distribution. Each simulation terminates when all agents are happy or after a maximum of 300 simulation steps. For each simulation, we calculate the convergence time, n, the number of steps needed to reach an equilibrium state, and the final segregation level, $\langle S \rangle$, at the end of the simulation.

3. Results

The analysis of convergence time as p varies uncovers intriguing patterns (see Figure 5).

The baseline *random* model typically converges in around 27 steps. In accordance with the suggestion of Gambetta et al. [22] the more the users follow a *distance relevance* policy, the more the segregation process is slowed down (hence, the higher n). The two policies

[3] see idealista.com

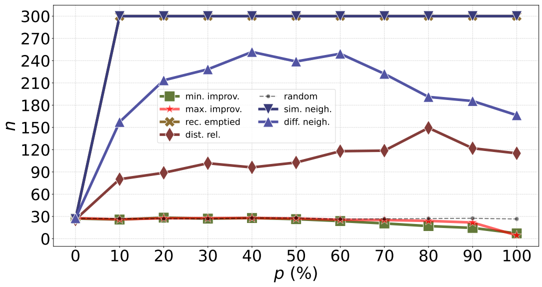

Figure 5: Average convergence time n across 100 simulations of models with a growing percentage p of users accepting the suggestion of the RS.

rooted in the neighbourhood income similarity, *similar neighbourhood* and *different neighbourhood* substantially increase convergence time. In particular, the model is not able to reach a stable equilibrium if 10% (or more) agents relocate to a similar neighbourhood. A similar result holds for the *recently emptied* policy.

Remarkably, the only two policies that effectively expedite segregation, reducing the value of n as their adoption rate p increase, are the policies that suggest agents to relocate in places where they would be happy: *minimum improvement* and *maximum improvement*.

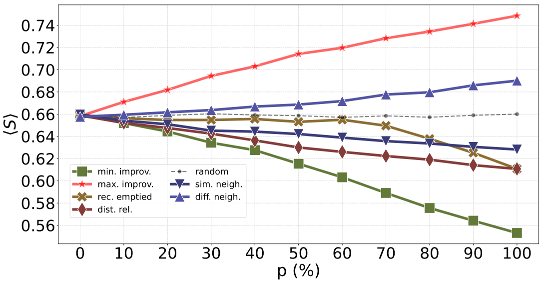

Figure 6: Average final segregation levels $\langle S \rangle$ across 100 simulations of models with a growing percentage p of users accepting the suggestion of the RS.

Even more intriguing insights emerge from analysing the final segregation level varying the adoption rate p (Figure 6). The final segregation level $\langle S \rangle$ for the baseline *random* model stabilises around 0.66. Notably, for all policies, the more users adhere to a policy, the greater the change in $\langle S \rangle$, indicating that suggesting relocation policies other than the random one significantly impacts urban segregation.

Only two policies, *different neighbourhood* and *maximum improvement* amplify final segregation levels as adoption rate p increases. In particular, the former leads to the most substantial rise, while even the policy suggesting an unhappy user move to a neighbourhood with a different economic composition significantly amplifies segregation, especially when influencing the majority of the population.

Conversely, four policies lead to a reduction in $\langle S \rangle$: *recently emptied*, *distance-relevance*, *similar neighbourhood* and especially *minimum improvement*. The *recently emptied* policy shows a negligible reduction until only 60% of the population adopts it but becomes increasingly effective with an increased adoption. The *distance-relevance* policy substantially decreases $\langle S \rangle$. However, the policy that most effectively reduces final observed segregation levels is *minimum improvement*: even with a small percentage of agents following this policy, the average $\langle S \rangle$ reduction is substantial.

4. Discussion

Our study explores the intricate relationship between relocation policies and the dynamics of urban segregation. Through a series of simulations, we unveil the impact of these policies on both convergence time and the final level of segregation.

The implications of policies grounded in neighbourhood composition, such as the *similar neighbourhood* and *different neighbourhood*, reveal intriguing trends. On the one hand, as one can expct, suggesting agents to relocate to a neighbourhood with a similar income, thereby maintaining a comparable average income distribution among neighbours, increases convergence times. In fact, if agents adhere strictly to this policy, the model fails to converge. On the other hand, it is noteworthy that even suggesting agents to relocate to a socioeconomically *different neighbourhood* slows down segregation times. This deceleration is most pronounced when between 40% and 60% of users relocate according to this policy. Interestingly, having 100% of agents follow this policy produces a similar effect, in terms of convergence time, as only 10% of agents following it. This dichotomy can also be appreciated in the segregation levels $\langle S \rangle$ analysis.

Counterintuitively, a policy that suggests agents relocate to a socioeconomically *different neighbourhood*, thus suggesting a mixing, increases the average observed segregation levels as its adoption increases. Surprisingly, suggesting agents relocate to neighbourhoods with a similar average income distribution reduces the final observed segregation levels.

The analysis of the observed final segregation level seems bounded by the outcomes of two extreme policies: the *maximum improvement* policy drives the final segregation level to its maximum, and the *minimum improvement* policy minimizes it. This distinction becomes particularly pronounced when the relocation policies are adopted by many agents (high adoption rate p). Indeed, *minimum improvement* for $p = 100\%$ reduces the final segregation level by 16.67% compared to the baseline model. Conversely, *maximum neighbourhood* significantly increases the final segregation level by 13.64%. From a sociological perspective, this observation emphasizes how policy choices significantly mould societal structures. The extremes represented by the accentuated segregation of the *similar neighbourhood* or *maximum improvement* policies and the minimized segregation of the *minimum improvement* policy delineate the wide spectrum of potential societal outcomes based on policy implementations. Recognizing these boundaries provides crucial insights into the intricate connection between policy decisions and the resultant societal dynamics. It clarifies how different policies can influence segregation levels, thereby guiding more informed and balanced interventions.

5. Conclusion

This paper investigates the effects of different relocation policies within the Schelling model on convergence time and final segregation levels. It sheds light on how these policies influence urban segregation dynamics, paving the way for future research and the development of more equitable urban strategies, particularly in understanding the impact of online real estate platforms on neighbourhood demographics.

This work can be improved and extended in several directions. Inspired by Moro et al. [31], designing a policy that exploits the time series of empty cells could offer valuable insights. This approach might uncover historical occupancy patterns, revealing which cells have predominantly housed similar agents or which tend to retain happy occupants for longer durations. Similarly, there is room to expand the model by training a Machine Learning (ML) model across multiple model iterations. This approach could empower algorithms to predict optimal cell choices for ensuring an agent's maximal happiness probability. Moreover, by considering broader global factors, these models might suggest strategies that maintain a stable or reduced average segregation level within the city.

Appendix

In Figure A1, we present examples of final configurations produced by the execution of the model in which the 100% of agents follow one of the six policies. All the simulations starts from the same initial configuration reported in Figure 3 (left).

It is noticeable that the *different neighbourhood* and *maximum improvement* policies, depicted in the last row, result in a visually less mixed scenario compared to the other policies, particularly the *minimum improvement* one (top right), which appears to be more mixed.

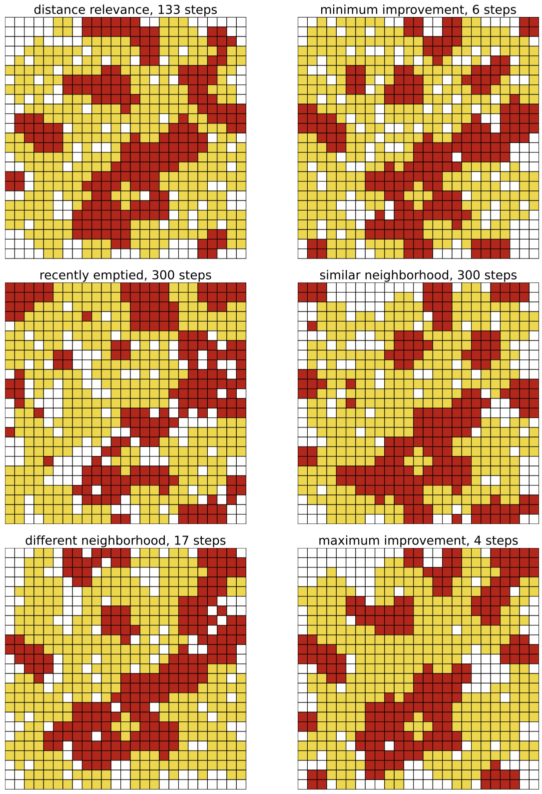

Figure A1: Examples of final configurations produced by each policy on a 25×25 grid.

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A. Online Resources

The code for replicating and reproducing our model and experiments is available at https://github.com/mauruscz/RS-chelling. The simulation has been performed using the Python module MESA [32].