Modeling Gentrification Process Final Report

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Github Repository: https://github.gatech.edu/ssamal31/Modeling-Gentrification

1 Abstract

Our team has chosen to focus our project on modeling the rate of gentrification in urban areas. Gentrification is the process of neighborhood transformation that involves an influx of wealthier individuals into a lower-income area, often leading to the displacement of long-term residents. In Atlanta, this phenomenon has been widespread and continues to affect many neighborhoods.

The motivation for our project stems from a desire to understand how long it takes for gentrification to reach a point where the process is considered "complete." To support our research, each team member has reviewed scholarly papers on the concept of gentrification, examining various techniques and models used to simulate the process. We aim to adopt the methods we find most effective for our project.

2 Project Description

The goal of our project is to develop a simulation model that captures the dynamic processes and patterns of gentrification in urban areas. Specifically, we aim to explore how socioeconomic and spatial factors interact over time to drive changes in neighborhood demographics, property values, and displacement rates.

Key aspects of gentrification captured in our model include:

- **Income Dynamics:** The transition from low-income to high-income residency within neighborhoods, driven by changes in affordability and desirability.
- **Property Prices:** The evolution of housing costs as an indicator of gentrification progress and a factor influencing resident displacement.
- **Neighborhood Desirability:** The appeal of a neighborhood to new residents based on local amenities and social factors.
- **Spatial Influence:** The cascading effect of changes in one neighborhood influencing surrounding areas.
- **Vacancy Trends:** How rising property prices increase vacancies, leading to opportunities for redevelopment or displacement.

Gentrification occurs when wealthier individuals move into historically lower-income neighborhoods, often due to proximity to city centers or improved amenities. This process raises property prices and transforms neighborhood characteristics, such as the opening of new businesses or upgrades in infrastructure. However, these changes often lead to the displacement of long-term residents who can no longer afford to live in the area. Over time, the neighborhood undergoes significant economic and cultural shifts.

Our model uses a cellular automata approach to simulate gentrification within a large urban city. Each cell represents a neighborhood block with attributes such as income level, property price, and desirability. These attributes evolve over time based on interactions with adjacent blocks. The initial simulation begins with a 10x10 grid to represent neighborhoods and their interconnected dynamics.

3 Literature Review

A paper from the University of Colorado Boulder describes two simple dynamical systems to model gentrification. The systems are based on three assumptions: a subpopulation that increases the desirability of a neighborhood, the desirability of a neighborhood, and the average price of real estate in a neighborhood. They investigate the linear stability of equilibria and numerically determine the characteristics of oscillatory solutions as a function of system parameters.

The first model uses three variables: the fraction of the artist population living in the neighborhood, A, average real estate price, P, and desirability, D. It is also assumed that an influx of artists increases the desirability of the neighborhood. These dynamics lead to the following model:

$$\begin{aligned}
\tau_A \frac{dA_n}{dt} &= \sum_{m=1}^{N} \left[h(P_m - P_n)A_m - h(P_n - P_m)A_n \right], \\
\tau_D \frac{dD_n}{dt} &= \sigma(A_n) - D_n, \\
\tau_P \frac{dP_n}{dt} &= D_n - P_n,
\end{aligned}$$

The first equation describes the flow of artists between different neighborhoods, the second equation describes how the desirability of neighborhood n evolves given the fraction of artists in A_n. The third equation specifies that the real estate price of neighborhood n relaxes to the current desirability with timescale τ_P.

However, this model makes several simplifications, such as ignoring spatial organization, heterogeneity, and considering only one social group. Despite these limitations, the model nicely depicts the interplay between real estate prices and the movement of subgroups.

In another paper titled "Gentrification and displacement: Modeling a complex urban process," researchers from IUPUI, Arizona State University, and Claremont Graduate University used an agent-based model (ABM) to simulate gentrification in an urban environment. The ABM begins with a basic grid of plots, each with attributes such as price and quality. These plots change over time based on factors such as proximity to amenities and resident preferences or constraints.
The residents in the model are categorized by their wealth and make location decisions based on a utility function that considers variables including price, plot quality, proximity to amenities, transportation, and population density. Additionally, residents move if they find a better location or if they are displaced due to increased costs (i.e., when the price of their current plot exceeds twice their wealth).

If the price of plots in the bottom price quartile increases into the upper quartiles, those plots become classified as gentrified. This process is tracked along with resident movements to determine the prevalence and impact of gentrification and displacement.

The model also experiments with different scenarios by adjusting the following variables:

- Density preferences,
- Segregation preferences,
- Disamenity removal.

After analyzing the results, the researchers concluded that higher density and lower segregation preferences led to higher rates of gentrification and displacement, particularly among poorer and minority residents.

Overall, the model effectively demonstrates the significant effects of gentrification in urban areas. However, it is important to note that this model simplifies a complex process, and there may be other factors worth considering for our project.

In the paper titled "Modeling Gentrification Dynamics: A Hybrid Approach," cellular automata (CA) are used to model fixed entities like properties and their spatial relationships within a regular grid. Each cell represents a property and is assigned attributes such as property value, size, and accessibility to amenities. These automata interact with mobile agents (households) to simulate real estate dynamics. The CA captures the spatial structure of neighborhoods and allows for localized interactions, such as property value changes based on neighborhood desirability, which drive the overall gentrification process.

The CA grid is essential for representing fixed infrastructure (e.g., roads, buildings) and allows properties to influence one another spatially, mimicking real-world gentrification where changes in one area often affect neighboring properties. The transition rules govern how properties (cellular automata) evolve over time based on interactions with households (agents). Some key rules include:

3.1 Property Price Update

Property prices are adjusted based on vacancy rates and demand:

$$P_{t+1} = P_t \times (1 + \beta \times (V_{norm} - V_{current})),$$

3.2 Resident Mobility

Households decide whether to move based on property prices, preferences, and accessibility. The propensity to move is modeled as:

$$P_{move} = 1 - \frac{S_{current}}{S_{ideal}},$$

3.3 Hedonic Valuation

Property values are calculated using a hedonic pricing model:

$$P_j = C + \sum_{k=1}^{n} V_k \times Q_k,$$

These rules allow the model to simulate how neighborhood gentrification evolves as residents interact with the urban environment and property markets.

In the abstract model discussed by Liu and O'Sullivan in their paper titled "An Abstract Model Of Gentrification as a Spatially Contiguous Succession Process," gentrification is simulated through a combination of supply and demand-side factors using theories such as Rent Gap, Filtering, and Household Life Cycle. The model integrates a cellular automaton (CA) and an agent-based model (ABM) to simulate how housing and households interact over time.

The CA framework represents housing units, with each cell reflecting a housing unit, while the ABM represents households. The model aims to capture how spatial dynamics evolve over time, including how rent gaps (the difference between actual rent and potential rent) drive gentrification through renovation events. Initially, rents are randomized, and households are assigned to housing units based on life-cycle stages (young, middle-aged, old). Younger households cause faster deterioration, while middle-aged households contribute more to renovation, reflecting their economic capacity.

The model reveals that gentrification often starts in run-down areas near wealthier regions, aligning with observed patterns. As rent gap thresholds increase, renovation becomes concentrated, forming waves of gentrification, where spatial segregation of rent levels occurs. The model's strength lies in its ability to depict gentrification as a contagious spatial process, where the renovation of one unit influences neighboring areas. This framework illustrates how localized housing market dynamics can lead to broader neighborhood-wide changes.

These formulas work together to simulate the spread of gentrification as households move in and out, and as housing units are renovated based on the calculated rent gap. The model dynamically adjusts based on spatial relationships and economic conditions, driving localized changes that can lead to broader gentrification patterns over time through the use of cellular automata combined with agent-based modeling.

3.4 Rent Gap Calculation

$$r_g = \frac{r_n - r}{8r_n}$$

3.5 Renovation Probability

$$P_r = \frac{1}{1 + e^{-\beta(r_g - g)}}$$

3.6 Rent Dynamics

$$r_{t+1} = r_n + N\left(\frac{r_m - r_n}{2}, \alpha\right)$$

The paper titled "Modelling urban change with cellular automata: Contemporary issues and future research directions," authored by researchers from the University of Queensland and the University of London, is a meta-analysis that discusses various challenges faced by the urban change modeling community, particularly with respect to the use of Cellular Automata (CA) methods.

The authors identified four major issues with modern descriptions of urban change:

- The limitations of CA modeling to urban expansion, rather than addressing the multi-dimensional processes of urban change such as regeneration, densification, gentrification, in-fill development, sprawl, urban shrinkage, and vertical growth.
- The absence of factors representing individual human decision behaviors and their collective implications for urban change.
- Minimal effort in utilizing emerging sources of big data to calibrate and validate CA models, as well as capturing the role of human actors in urban dynamics.
- A lack of comprehensive theories in CA modeling to explain urban change mechanisms and dynamics.

In each section of the paper, the researchers review relevant literature that highlights these issues. They explain how these challenges cause models to inaccurately describe complex phenomena such as urban shrinkage, vertical densification, gentrification, and stochastic human decision-making. The article also suggests solutions, such as leveraging big data to calibrate and validate models and incorporating modern theories that address economic and social decision-making processes.

4 Conceptual Model

As described above, we initially start with a 10x10 cellular grid, with the following state variables for each cell:

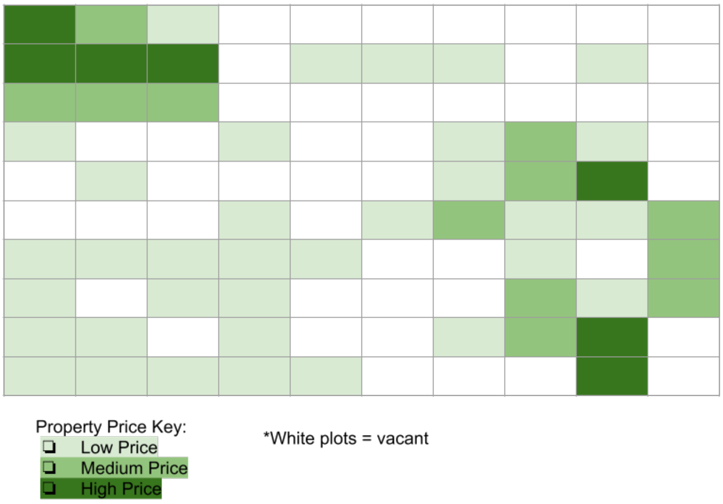
- Household income (HI): This represents the primary income for the area. By tracking the transition from low-income to high-income states, we can model how various factors displace low-income residents. These states are represented as:
  - 0: low income
  - 1: high income
- Property Price (PP): Represents the average price of housing within the area, categorized as:
  - 0: low price
  - 1: medium price
  - 2: high price
- Desirability (D): The desirability of a resident to move into a specific area, on a scale from 0 to 3.
- Vacancy Status (VS): Reflects the proportion of vacant housing within the area, represented as a continuous value between 0.0 and 1.0. A vacancy level of 0.0 indicates full occupancy, while 1.0 indicates total vacancy.

Based on these states we make the following assumptions:

- Cells defined as high income increase the property price of surrounding cells up to a certain threshold.
- Higher income residents generally increase the property value of surrounding housing.
- Low income cells with high desirability will have their property price increase.

- Vacancy is a gradual measure rather than binary. If the property price exceeds what low-income households can afford, the vacancy level of a cell increases continuously from 0.0 to 1.0. Higher vacancy values indicate greater levels of displacement or unaffordability, providing a nuanced understanding of how affordability constraints contribute to partial vacancies before complete displacement occurs.
- After a certain property price threshold increase, if the cell is low income it will become vacant.
  - If a neighborhood has desirable amenities, it will attract investment effectively increasing the price even if the area is low-income, pushing out low-income residents.

We first intend to have the initial state of the model be set randomly, with at least a few empty cells and arbitrary incomes, prices and desirability. In the future we will set the initial state to model an urban area (such as Atlanta), in order to verify the accuracy of the model. We use a time step of 1 year since gentrification typically unfolds over a long period of time with most socioeconomic market reports being collected on a multi-year basis. Example Grid:



We define this model with the following equations:

Property Price Update Rule:
Property prices increase based on desirability and income level. Since middle income is removed, formula simplifies:

$$P_{t+1} = P_t * (1 + \alpha * (\text{Income Factor} + \beta * D_t))$$

Where:

- α is a base multiplier for price increases.
- **Income Factor** is:
  - 0 for low income
  - 0.3 for high income
- D_t is the desirability score (0-3).

Desirability Update Rule:

Desirability increases when nearby blocks have higher property prices.

$$D_{t+1} = D_t + \gamma * (\frac{\text{Avg Nearby Property Price}}{P_t} - 1)$$

Where:

- D_t is the current desirability.
- γ is a factor controlling how much neighboring property prices affect desirability.
- **Avg Nearby Property Price** is the average property price of adjacent blocks.

Vacancy Rule:
Low-income households will vacate if the property price becomes too high for them to afford. The vacancy level is represented as a continuous measure, allowing for partial vacancies based on affordability constraints:

$$\text{Vacancy} = \max\left(0, \min\left(1, \frac{P_{t+1} - (\text{Income Threshold} \times I)}{\text{Income Threshold} \times I}\right)\right)$$

Where:

- **Income Threshold** is the percentage of income that households can spend on housing (e.g., 30%).
- I is the household income.

If the property price exceeds what low-income residents can afford, the vacancy level of a cell will increase continuously from 0.0 to 1.0. Higher vacancy values indicate greater levels of displacement or unaffordability, providing a nuanced understanding of how affordability constraints contribute to partial vacancies before complete displacement occurs.

5 Model Refinement and Improvements

During the development of our gentrification simulation, we made several adjustments to refine the model and better capture the dynamics of urban change. Below, we outline the key changes: 7

5.1 Float Representation for PP and D

We updated the *PP* (Property Price) and *D* (Desirability) variables from discrete values to floats. This change slowed the progression toward a steady state, enabling more gradual and realistic transitions in the simulation. The refined model better reflects the incremental nature of urban property value and desirability changes.

5.2 Revised Income Update Logic

The household income (H) update logic was modified to simulate the displacement of low-income residents more effectively:

- If vacancy (VS) > 0.5 and desirability (D) ≥ 2.0, the cell is updated to high income ($H = 1$).
- If vacancy (VS) > 0.5 and desirability (D) < 1.0, the cell is updated to low income ($H = 0$).

This approach models the dynamics between desirability and affordability in urban areas, where rising desirability often correlates with displacement pressures.

5.3 Revised Vacancy Logic

The vacancy logic in our simulation was refined to better capture the relationship between property prices, income, and vacancy status.

5.3.1 Previous Logic

Vacancy and income were updated based on strict conditions:

- High income ($H = 1$) was set if vacancy_status $= 0$, desirability ≥ 2, and property_price ≥ 1.
- Low income ($H = 0$) was set if vacancy_status $= 0$ and desirability < 1.
- Vacancy status became 1 if $H = 0$ and property_price $\geq$ threshold; otherwise, it was 0.

Revised Logic

Vacancy status now uses a dynamic formula: where threshold = 2 ensures affordability. The result is bounded between 0 and 1:

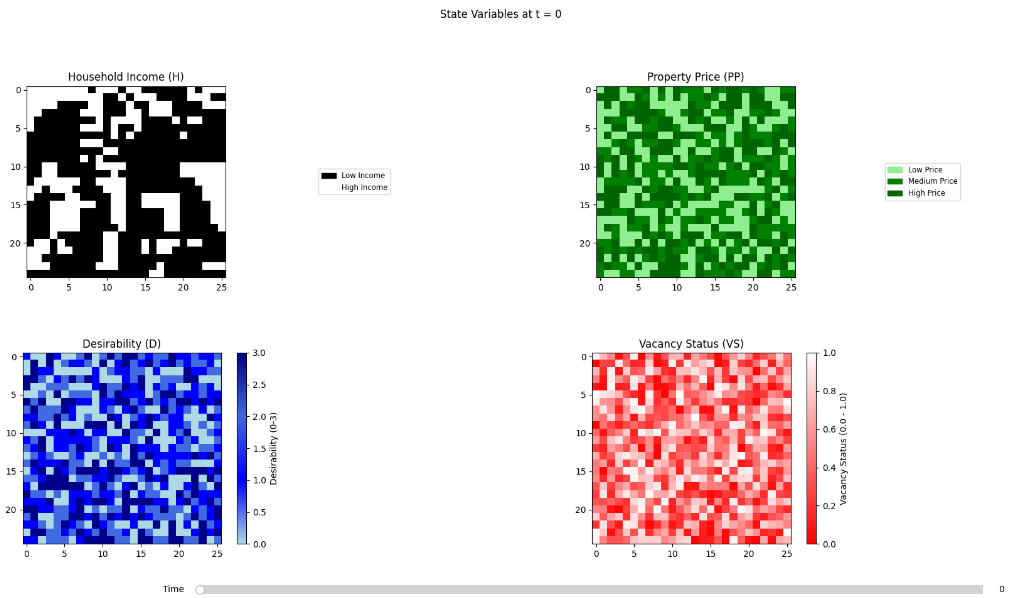
$$\text{new\_vacancy\_status} = \max(0, \min(1, \left(\frac{\text{property\_price}}{\text{threshold}}\right) - \text{income}))$$

This new approach allows for smoother transitions, better reflecting economic pressures in the simulation. A low income household will struggle to hold on to moderately or high-income housing, eventually being forced to vacate the house.

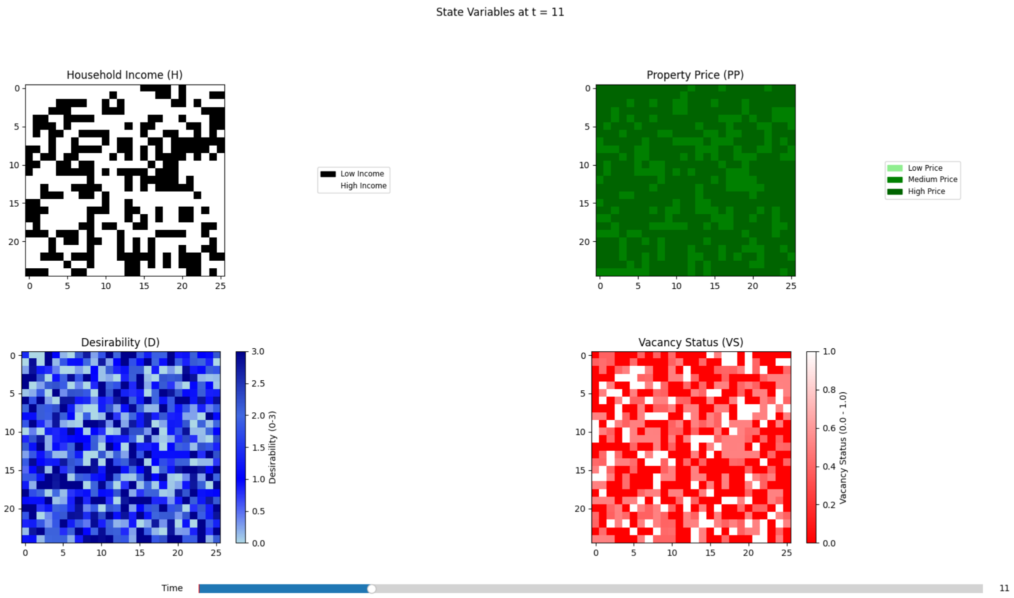
6 Simulation Model

Our simulations model visualizes all 4 interconnected layers of the CA model. In the following model, we initialized the housing income to be similar to that of various counties in Atlanta from the 2020 Census, with other variables initialized randomly: Property price on a scale of 0-2, desirability on a scale of 0-3, and vacancy on a scale of 0-1.

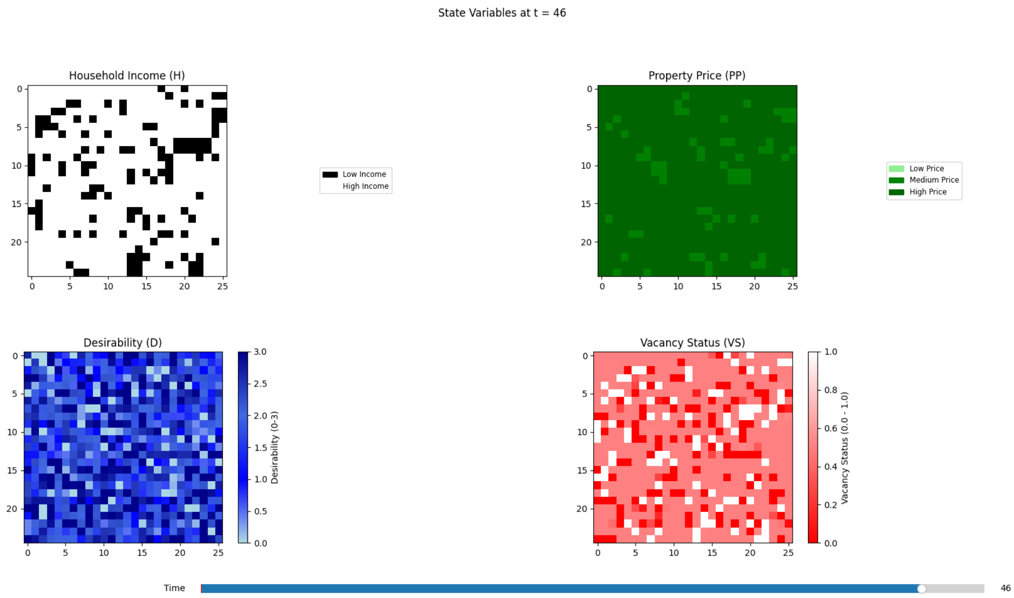
Below the model is a timeline that can be dragged left or right to observe behavior and interplay between the variables as time progresses.



In the following diagram, after just 11 timesteps, we see that low-income households are being replaced by high-income households, and the only people capable of surviving in the market for pricey housing are those with that kind of income. This further exacerbates pricing by driving it up even more.



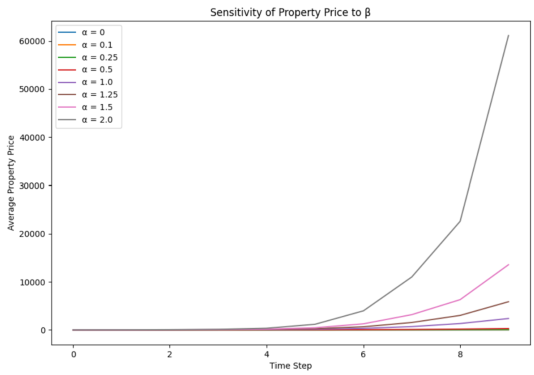
By the end we see that low-income households are incapable of holding onto housing, given that vacancy status looks like almost an inverse of the housing income model. Prices for housing are soaring (in the Property Price model), and only the most wealthy maintain stable housing while the rest, though still with high income, hold a tenuous grip on their property.



7 Experimental Results & Validation

We conduct a sensitivity analysis to evaluate the degree of sensitivity of the model's output to changes in alpha, beta, and gamma. This helps us identify the most influential parameters and ensures that the model is stable under different conditions. We initialize the model in each scenario with the same seed to ensure the same initial conditions while varying the weight values.

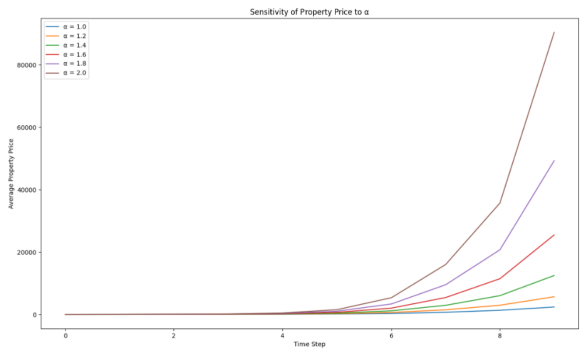
Beta modifies the strength of the relationship between desirability and property price, where a higher β makes the property price more sensitive to changes in desirability and a lower β reduces the effect of desirability on the property price.



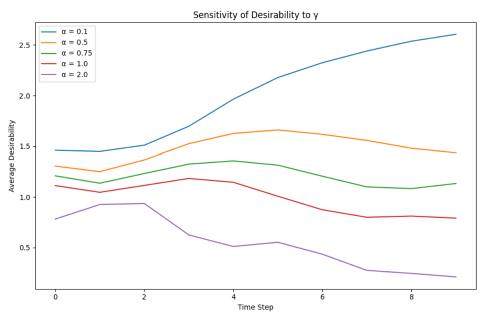
$$P_{t+1} = P_t * (1 + \alpha * (\text{Income Factor} + \beta * D_t))$$

Comparing weights of [0, 0.1, 0.25, 0.5, 1.0, 1.25, 1.5, 2.0] for β and standardizing alpha as 1.0 we can observe that the average property price of the area increases exponentially as we increase β. This is expected as the initial board has mostly positive desirability values and only positive gamma and alpha values. We also expect to see a sharper increase in property value as we increase β as the sensitivity to change increases with a larger β.

The alpha parameter (α) represents how sensitive the price is to changes in the income factor and desirability. A higher value of α means that the price should increase more dramatically for a given change in income and desirability. A lower value can mean that the price increases or decreases in a slower manner.



Revisiting the property price equation we would expect to see α have a greater effect on average property price since this weight influences both income factor and desirability. We can see that with a large α value leads to a sharper increase in average property price which is to be expected.



$$D_{t+1} = D_t + \gamma * (\frac{\text{Avg Nearby Property Price}}{P_t} - 1)$$

Gamma is a parameter that controls the nearby property price's influence on the desirability. The term inside the parenthesis measures relative difference between the average nearby price and current price, decreasing or increasing the desirability based on whether nearby properties are more or less expensive than the current one. We expect that with a larger gamma value that the desirability will change more dramatically in response to nearby property prices. In the graph we can observe that high gamma values decrease average desirability while smaller gamma values increase average desirability. Gamma values of 0.1 and 2.0 also influence our average desirability more dramatically.

Since our cellular automata model is inherently spatial, averaging out property prices and desirability might obscure critical spatial patterns of heterogeneities, and fail to consider clusters of high or low property prices. In order to have some spatial measurements we measure Moran's I to find some spatial autocorrelation between variables, more specifically the distributions of desirability and property price. A value closer to +1 indicates clustering of similar values, 0 indicates little clustering or random distribution, and a value closer to -1 indicates dissimilar values cluster.

$$I = \frac{n}{W} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{X})(x_j - \bar{X})}{\sum_{i=1}^{n}(x_i - \bar{X})^2}$$

```
CA_moran = Board(50, 50, cell_features_weight, alpha=1.0, beta=1.0, gamma=1.0)
CA_moran.initialize_cells()
d_vals = np.array([[CA_moran.cells[x, y]["D"] for y in range(CA_moran.dimY)] for x in range(CA_moran.dimX)])
p_vals = np.array([[CA_moran.cells[x, y]["PP"] for y in range(CA_moran.dimY)] for x in range(CA_moran.dimX)])
print("Initial Moran I for Desirability: ", moran_check(d_vals))
print("Initial Moran I for Property Price: ", moran_check(p_vals))

for t in range(5):
    CA_moran.update()

d_vals = np.array([[CA_moran.cells[x, y]["D"] for y in range(CA_moran.dimY)] for x in range(CA_moran.dimX)])
p_vals = np.array([[CA_moran.cells[x, y]["PP"] for y in range(CA_moran.dimY)] for x in range(CA_moran.dimX)])
print(f"Moran I for Desirability after {t} steps: {moran_check(d_vals)}")
print(f"Moran I for Property Price after {t} steps: {moran_check(p_vals)}")
```

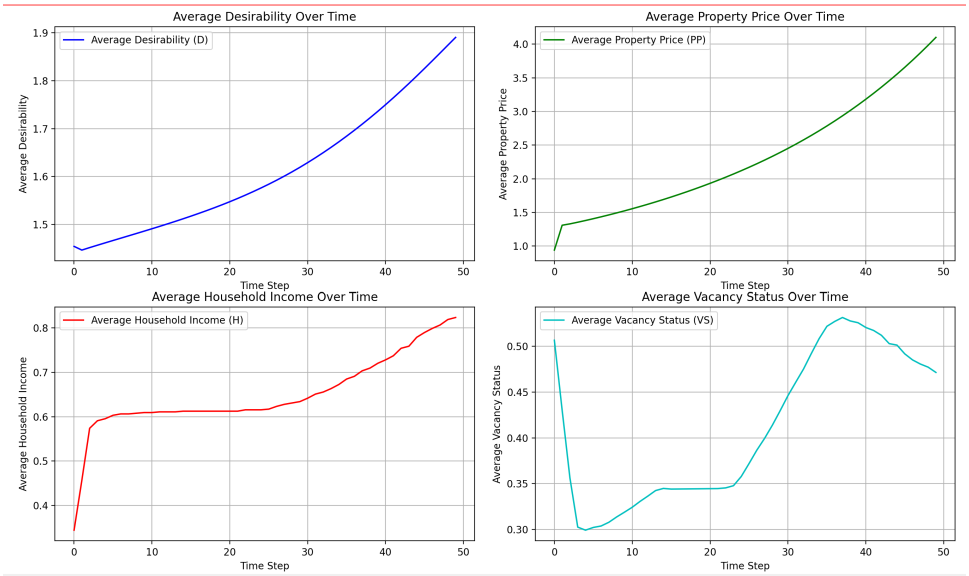
```
Initial Moran I for Desirability:  0.002819205624898964
Initial Moran I for Property Price:  0.004660727826753227
Moran I for Desirability after 4 steps: -0.001667974882260826
Moran I for Property Price after 4 steps: -0.007273273365982366
```

Initializing a random board with weights standardized at [1.0, 1.0, 1.0] we find that the initial board has a Moran I of -0.009435 for desirability and -0.002403 for property price. After 10 timesteps we find the desirability at -0.0041382 and property price at 0.3223. We find that desirability has little or unrelated clustering, and after stepping through it tends to get slightly more unclustered. Property price initially starts randomized or unclustered, but then similar property price values cluster together as the Moran 1 value increases. If we increase this to 50 time steps, we find that the desirability increases to 0.4909 and property price increases to 0.5458, indicating that in these initial states similar values will start to cluster.

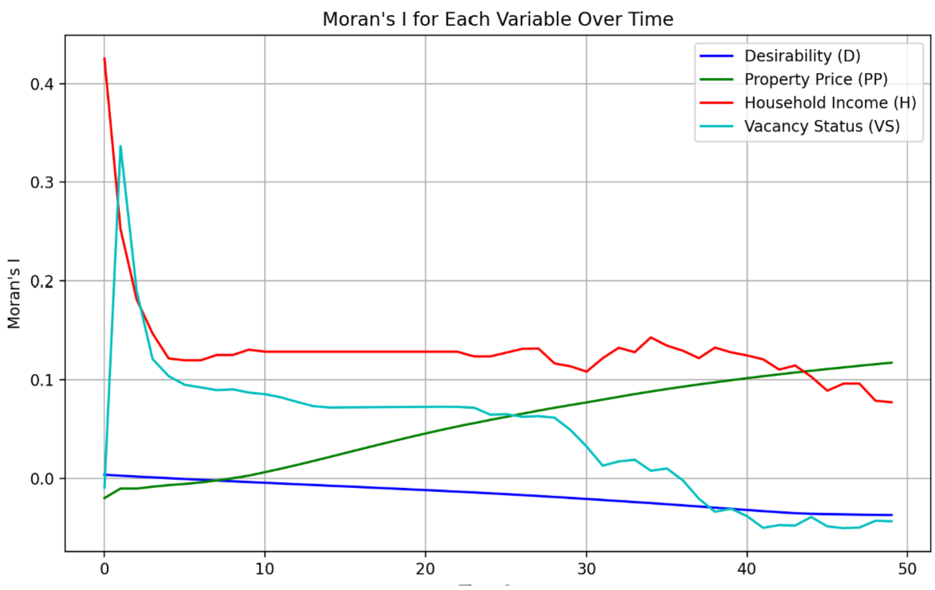
We attempt to accelerate the model by changing alpha, beta and gamma to [2.0, 2.0, 0.1] since we expect larger alpha and beta values to accelerate the change in property price, and lower gamma values to increase desriability. In this case after 10 time steps we get a desirability of -0.01102 and property price value of 0.000925. Although this clusters similar desirability values slightly better than the previous weights, it clusters property price at a slower rate.

Large time steps also cause the Moran I calculation to error when dividing the denominator when it is 0. This may be because when all the values in the board are identical, the deviation from the mean will be 0 for every cell causing a division by 0. This also indicates that there are certain weight combinations where property price and desirability reach a steady state very quickly, or changes do not occur fast enough. This can also be observed in the previous weight sensitivity graphs where we see property prices stuck at a steady state for the first initial states in the alpha and beta graphs. Potential ways to mitigate this rapid change is by introducing some noise or randomness to updates for each time step to maintain variability.

We perform a similar analysis to our 2020 Atlanta model and get the following average Vacancies, Household incomes, Desirability and Property Prices:



We can observe that Average household income increases sharply, then at a slower rate, which represents higher income residents starting to move into cheaper properties. This in turn increases the average property price over time, as higher income residents are able to afford an increase in rent. The influx of higher income residents can also be explained by an increased average desirability, in which only higher income residents can occupy popular spaces. We monitor the average movement of all residents, showing that the most movement occurs in the initial time steps, then slows down at around 40 time steps.



We expect a high Moran I value for household income since these are the initial conditions modeled after Atlanta. Over time we see income steady out at a positive value, indicating that those with similar incomes will remain together. Interestingly vacancy status becomes more randomized and tend to cluster dissimilar values together over time, perhaps indicating that gentrification in this case doesn't continuously spread from one region, but requires multiple origins to effectively spread.

8 Discussion, Conclusions, & Summary

8.1 What We Learned About the System

Throughout this project, we learned a lot about gentrification and the use of cellular automata as a tool for modeling complex systems. Initially, gentrification felt like a difficult topic to model because it involves so many interconnected factors—economic, social, and spatial. However, cellular automata provided a structured way to break this complexity into manageable pieces. By representing neighborhoods as grid cells and defining rules for how their states change, we were able to simulate the gradual transformations that occur in urban areas.

One of the biggest takeaways for us was seeing how local interactions—such as the impact of a high-income neighborhood on its neighbors—can lead to larger patterns of change across a city. This really drove home how gentrification is not just about isolated events but about ripple effects that spread over time. It was fascinating to watch how clusters of high desirability and rising property prices emerged in our model, echoing real-world patterns we've seen in cities like Atlanta.

We also learned a lot about the limits of our model. For example, while cellular automata capture spatial relationships well, they struggle to incorporate broader influences like government policies or economic shocks. These limitations made us realize that models are never perfect but can still provide valuable insights. We also encountered challenges with our equations—some parameters caused the model to reach a steady state too quickly, which made us rethink how to introduce randomness or variability to reflect real-world dynamics better.

8.2 Suggestions for Future Work

If someone were to build on this project, we'd suggest a few key directions:

- **Incorporate External Influences:** Add factors like policy changes or infrastructure development to observe their effects on gentrification patterns.
- **Introduce More Nuanced Behaviors:** Implement features such as cultural factors influencing neighborhood desirability.
- **Expand the Scale:** Simulate interactions between multiple cities or regions to explore broader spatial dynamics.

8.3 Closing Thoughts

This project allowed us to gain valuable insights into both the phenomenon of gentrification and the application of cellular automata for modeling complex systems. Our model highlights the importance of local interactions and ripple effects in driving large-scale urban changes. We hope this work serves as a foundation for future explorations into urban development.

9 References

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10 Appendix - Division of Labor

Documentation, Code Integration, and Final Project Submission - All Members

Team Member	**Task Descriptions**
Henry	Desirability Update Function & Time-Step Visualization
Soham	Cellular Automata Structure Setup & Unit Testing of Update Functions
Desirae	Property Price Update Function & Whole-Run Testing
Nicole	Simulation Visualization & Visualization Cleanup
Aishi	Vacancy Calculation & Graph Implementation