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Agent Based Modeling

A wealth based gentrification model using agent-based modelling

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1 Introduction

> "If there is any agreement in academic circles about gentrification, it is that there is no simple definition of the term, though as the word suggests, any definition must have some emphasis on the class dimensions of urban change."
>
> *Tom Slater*

1.1 Gentrification

A lot of people were forced to leave their houses as result of what has been called 'gentrification' (London et al., 1986; Davidson and Lees, 2005; Holm and Schulz, 2018). Gentrification could be described as the phenomenon in which low income (usually minority) groups are displaced from their original neighborhood as middle or high income groups start moving into the neighborhood. The reason for displacement is the increase in rent as a result of the increase in the physical appearance of the neighborhood through the renovations of the new inhabitants (O'Sullivan, 2002; Holm and Schulz, 2018).
Many attempts have been made to give a more concise definition of gentrification (Davidson and Lees, 2005; Holm and Schulz, 2018). In this report, we will use the definition of gentrification as described by London et al. (1986): "Gentrification is a type of neighborhood change taking place within many inner city areas (within two or three miles of the central business district). It is characterized by middle class people moving into poor or working class residential areas, renovating the homes, and eventually coming to equal or outnumber the original residents. The result is often a dramatic change in the overall socio-economic status of the inhabitants and in the physical appearance of the area." In general, gentrification is defined by Davidson and Lees (2005) as "the coincidence of (1) the reinvestment of capital; (2) the social upgrading of locale by incoming high-income groups; and (3) direct or indirect displacement of low-income groups". The focus of this report is how this social upgrading of houses causes the displacement of low-income groups.

Due to the increasing intensity of gentrification in cities worldwide such as London, Berlin and Amsterdam in the last few years (Davidson and Lees, 2005; Glatter, 2007; Gent, 2013), the topic of gentrification has recently been studied more extensively across a variety of disciplines. Gentrification models and analyses on how and why gentrification happens have become especially prevalent, because of the negative effects of gentrification ranging from increasing income inequality to segregation. London et al. (1986) emphasizes that this change is brought about through predominantly private market activity (but not exclusively).
The concept of segregation is related to the idea of distance or isolation among different social groups (Feitosa, 2010). In other words, gentrification can be viewed as a special case of segregation. In this report gentrification is studied in the framework of Schelling (1971) on segregation.

1.1.1 Measuring

An important question is how to determine whether a district is in the gentrification process and how the intensity of gentrification can be quantified. Although this discussion has been conducted for years, it has not come to a consensus. As an example, Hedin et al. (2012) compared the data on income in different cities in Sweden during five year periods. They then defined 'gentrified' as an end state by establishing a threshold for the average income increase in the five time period. Other articles, e.g. Smith (1996) and Torrens and Nara (2007), cover gentrification as a more complex process where speed and dynamics of change define gentrification.
In this report the term 'gentrified' will be used as an end state for a neighborhood that meets the criteria stated in section 2.3.3. As the model will be described in more detail in section 2.3, the motives for choosing 'gentrified' as a discrete state will be explained.
The underlying motives for the rest of our model are based on an article by Holm and Schulz (2018) where the GentriMap model is introduced that describes the gentrification index as a combination of the

real-estate and the *social index*. The *real-estate index* is measuring real-estate value increases, while the reduction of poorer or lower-status households is measured with the *social index* (i.e. in other words it measures the social upgrading of the houses).

1.1.2 Aim

In this report a simple agent-based gentrification model is described in order to understand the dynamics of gentrification. This model will be used to capture the dynamics of gentrification based only on property conditions and income using the rent-gap theory, while the effect of attractiveness of houses based on their location from a certain important site (like a city centre) was assessed. In addition, further analysis will be done on the speed of gentrification of a low-income neighborhood and on the emergence of segregation based on wealth. Finally, sensitivity analysis will be done on the model.
Understanding the dynamics of gentrification will enable policymakers to influence the process in critical neighborhoods.

The report will be structured as follows. First the model will be described and validated using the Overview, Design Concepts and Details (ODD) Protocol, which is described by (Grimm et al., 2010). Afterwards the results of the analysis of gentrification will be discussed along with the results of the sensitivity analysis of the model. Lastly, the conclusions drawn from the results will be discussed.

1.2 Model

The model used for the investigation is a modification of the model as described in O'Sullivan (2002). This model is closely related to the Schelling model. (Schelling, 1971)

2 Gentrification model

2.1 Overview

2.1.1 Purpose

Our gentrification model tries to capture the dynamics of the emergent behaviour of gentrification in an isolated neighborhood. This is done using rules that are as simple as possible, which are inspired by the rules proposed by O'Sullivan (2002). With the output of the model we can analyze how quickly a neighborhood can gentrify based only on economic and spatial properties and the status changes associated with them.

2.1.2 Entities, state variables, and scales

The model contains two types of entities: properties and the neighborhood. The properties function as the agents in the model. Because the agents do not move and each grid cell contains an agent, they can also be regarded as the spacial units of the model. The agents are arranged on a square grid, which makes the space of the model discrete. Due to a dependency on distance from a set point, the edges of the grid do not interact with each other. The state variables of the properties are given in Table 1. The agents do not move from their position, but instead interact with the neighbors in their direct Moore neighborhood (cardinal and diagonal directions) using the income of their occupants I_i and their property conditions C_i to determine their next state. When in an EMPTY state, a property calculates its price P_i with which it tries to attract an occupant with a higher income in order to go back to an OCCUPIED state.
The neighborhood functions as the environment of the model. It contains the state variables which affect the behaviour of all agents. The state variables of the neighborhood are given in Table 2. The neighborhood status S represents the quality of the neighborhood based on the condition of its properties, which deteriorate at the depreciation rate r_D, and the income of the occupants, while the status variability S_δ represents stochastic effects and the error in the status calculation. The distance factor d determines how far a property is from a location of interest, and the agent's mobility p_m represents how influential the economical difference between him and his neighbors, as well as the status neighborhood are as factors for him to leave the neighborhood.

Table 1: State variables of the properties in the model.

State variable	Description	Range
i	Agent index	$0, 1, 2, ...$
I_i	Income	$[0.0, 1.0]$
C_i	Property condition	$[0.0, 1.0]$
(x_i, y_i)	Position	Indices of the cells
P_i	Property price	$[0.0, 1.0]$
STATE	State of occupation of the property	OCCUPIED or EMPTY

Table 2: State variables of the neighborhood.

State variable	Description	Default value	Range
S	neighborhood status	-	$[0.0, 1.0]$
S_δ	Status variability	0.01	$[0.0, 0.1]$
d	Distance factor	0.0	$[0.0, 2.0]$
p_m	Agent mobility	0.02	$[0.0, 0.1]$
r_D	Depreciation rate	0.0015	$[0.0, 0.1]$

A single time step of the model represents 1 month, while the spatial scale is in undetermined units, somewhere between a household and a house block. The time units of the model are mainly relevant for the default values of the state variables of the environment.

2.1.3 Process overview and scheduling

For each time step, the processes were scheduled in the following manner:

Algorithm 1 The model's pseudocode

```
while neighborhood is not gentrified do
  for all properties do
    if property is OCCUPIED then
      Emigration
    else
      Immigration
    end if
  end for
  Update properties
  Update status
  Check if gentrified
  if neighborhood gentrified then
    return time difference in years
  end if
end while
```

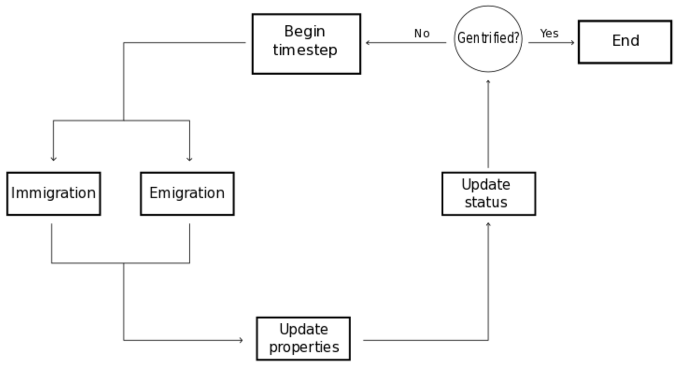


Figure 1: Process scheduling.

2.2 Design Concepts

2.2.1 Basic principles

The model is partially built on the principles of the Schelling model. Each cell of the grid (the neighborhood) represents a housing property (i.e. a household) and can possibly be occupied. Instead of using homophily as with the Schelling model, the occupants make their decisions based on the incomes and property conditions of the neighboring properties. These decisions influence the probability of occupants abandoning their property and the improvement of the properties by new property owners.
The rules for the improvement of properties by new occupants are based on the rent-gap theory. The rent-gap theory, which states that investment in the value of a residential property is largely dependent on the difference between the rental income and the potentially achievable rental income (Smith, 1987), has been proposed as a purely economic explanation for gentrification. Since the rent-gap theory is based only on economic properties, it makes for a good fit with the model.
The model includes a neighborhood status which represents the attractiveness of the neighborhood for potential occupants with higher incomes. The change in neighborhood status is based on the changes in the average income and the average conditions of the properties, but it also includes a normally distributed variability term, which represents the changes of the unknown variables which are not based on the economic properties of the neighborhood.
The model also includes a distance factor which represents the intensity of the effect of the distance of a property from a distant city centre on the attractiveness of a property to potential higher income occupants when it is abandoned by its current occupants.
This model was designed to explore the time it would take for a neighborhood to be considered gentrified. The number of time steps, representing months, that it takes for the neighborhood to go from a low status and low income neighborhood to a neighborhood with high status higher income neighborhood is taken as the time it takes for a neighborhood to be considered gentrified.

2.2.2 Emergence

It is expected that a distance factor will cause the neighborhood to gentrify only locally, but will cause the whole grid to be less likely to gentrify. In the local neighborhood (i.e. the 3x3 grid around each house) the increases in physical conditions will reinforce each other. In the original setup (with a distance factor of 0) this local behaviour is expected to spread through all of the grid. However, in the case that there is a non-zero distance factor, this process will be of different importance or will have a different speed at different distances from the city centre. This will result in partial gentrification, only parts of the city close to the centre will reach a certain average income and difference parts of the grid will have their own dynamics (more or less, depending on the value of the distance factor). Because of the stochasticity of the model it can still happen that the whole district gentrifies, but this will be less likely.

2.2.3 Adaptation

In our implementation, adaptation is not modeled. The behaviour of occupants does not change through time. Instead of trying to find a more suitable property for them in the neighborhood in case they are unsatisfied, they are thrown out of the grid. However, adaptation can be found in many different implementations of the model in which the occupants do not leave the neighborhood.

2.2.4 Fitness

An occupant's fitness is measured by whether he stays on the neighborhood or not. The factors that influence the duration of his stay is the property's condition, as well as his income, which must be higher than the mean of his closest neighbors. Nonetheless, his existence is utterly determined by a random sample of a Gaussian distribution whose probability of being chosen reduces as the previously mentioned factors obtain higher values.

2.2.5 Learning

As it was pointed out in the 'Adaptation' section, the occupants do not adapt to changes and thus they do not have traits that change through this learning process.

2.2.6 Prediction

The occupants behaviour is not based on prediction. Predictive techniques could be used for an occupant in order to move to a better property, but in the model this is not the case. There is no fixed number of occupants that move around, because as soon as an occupant is unsatisfied he moves out of the neighborhood entirely and a new one might take his place; if he can afford the unoccupied property. Hence, there is no need for the occupants to develop a predictive behaviour whatsoever.

2.2.7 Sensing

Each occupant is assumed to know his income and property's condition, as well as the incomes of his closest neighbors. His decision to move out is based on the income gap and the neighborhood status; thus, he has a picture of the status of the whole neighborhood, too. On the other hand, he's not aware of the average income of the whole neighborhood and the condition of each property since these are not determinant factors for his decision to stay or not.

2.2.8 Interaction

There is an indirect interaction between the occupants. An occupant's decision to move out is determined by two factors; the neighborhood's status and the income gap between him and his neighbors. Therefore, an occupant's presence can be determined by up to 8 other occupants which surround him each step.

2.2.9 Stochasticity

Stochasticity has a major role in this model. At first, the neighborhood is initialized with occupants of three different wealth classes and properties whose conditions are chosen based on a random sample from a Gaussian distribution. Another case where stochasticity is straightforward is the occupant's decision of moving out. For this decision, he primarily takes into consideration the mobility, neighborhood status and the income gap between his neighbors. However, we didn't want to leave out of the model the random everyday life occurrences that may lead someone to change his residence; job offer, personal issues etc. In this model, this is represented by a random sample from a Gaussian distribution.

2.2.10 Collectives

There are generally no collectives in the model. Although collectives can emerge as a property of the model, these collectives do not have any state variables of their own.

2.2.11 Observation

The neighborhood status S, average income I_μ and average condition C_μ are collected after each time step of the model. I_μ is used to decide when the neighborhood is considered to be gentrified. If the neighborhood is gentrified within 3000 time steps (which is equivalent to 250 years), the time until gentrification T_g is collected for analysis when the model is stopped.

2.3 Details

2.3.1 Initialization

In its initial state, every property of the neighborhood is occupied. Our intention was to examine the gentrification of a not extremely poor neighborhood in order to capture its initial downfall, too. Thus, the vast majority of occupants have an income of $\frac{1}{3}$ to $\frac{2}{3}$ with a few exceptions of both of the other ends. The default values for the state variables of the neighborhood are given in Table 2.

2.3.2 Input data

This model does not use real data, but rather relies on the libraries that were used in the implementation. The use of real data could not be compatible, since - for example - unusual for an occupant to leave his residence within the first month after moving in. It is obvious that this is a simplified model which tries to analyze the extremely complex topic of gentrification.

2.3.3 Submodels

The rules in each submodel are (modifications of) the rules proposed by O'Sullivan (2002).

Immigration
When a property is empty, a new occupant can move in. In order to decide if an occupant moves in, a possible buyer is proposed which gets an income assigned that is randomly drawn from a normal distribution with $\mu = \frac{1}{2}(S + P_i)$ and $\sigma = 0.1$, bounded by the range $[\frac{1}{4}(S + P_i),\ \min(1,\ \frac{3}{4}(S + P_i)]$. If this income is higher than the price, the agent is accepted as the new property owner.

$$I_{i,new} = \begin{cases} I_{i,potential} & \text{if} \quad I_{i,potential} > P_i \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

If the potential buyer fails to become the new property owner, the price is adjusted for the next time step.

$$P_i(t+1) = \frac{P_i(t) + I_{i,potential}}{2} \tag{2}$$

If the local rent gap of the property, given by

$$G_i^{(C)}(t) = \bar{C}_N(t) - C_i(t) \tag{3}$$

is greater than zero and the income of the new owner is greater than the condition of its property, the new owner is considered to improve its property condition. This home improvement loan is then randomly drawn from a normal distribution, bounded by [0, 0.5] and added to the physical condition:

$$C_{i,new} = C_{i,old} + \mathcal{N}(\mu = S - C_i(t), \sigma = 0.1) \tag{4}$$

If the income of the proposed buyer is not higher than the price of the property, the property remains empty and the property condition experiences a decrease due to vacancy.

$$C_{i,new} = C_{i,old} - 0.2\ r_D \tag{5}$$

Emigration
For every occupied cell in the grid, the local income gap is calculated, given by

$$G_i^{(I)}(t) = \begin{cases} I_i(t) - \bar{I}_N(t) & \text{if} \quad I_i(t) - \bar{I}_N(t) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where I_i is the income of the owner of that property. Each property owner then decides whether he wants to move based on this income gap. The probability of an owner moving out of the neighborhood is given by the formula

$$p_{move} = p_m(1.5 - S - C_i) \tag{7}$$

A random number is then drawn from a uniform distribution, and when this is lower than p_{move}, the occupant moves out of the neighborhood and leaves an empty property, which sets the income of the property to

$$I_{i,new} = 0 \tag{8}$$

If the random number is bigger than the probability of moving, the agent stays in his property. The price of each property that is sold is given by the formula

$$P_i = \frac{1}{2}(C_i + \bar{I}_N)(1 + d_i) \tag{9}$$

where C_i is the property condition of the cell that is sold, $\bar{I}_N$ the average income of its neighbors and d_i the distance factor, given by

$$d_i = d\left(\frac{1}{2} - \frac{y_i}{H}\right) \tag{10}$$

with y_i the y-coordinate of the cell and H the height of the grid.

Update properties
After the Emigration and Immigration submodels are completed, all the properties experience decay of size r_D.

$$C_i(t+1) = C_{i,new} - r_D \tag{11}$$

The property incomes are also updated.

$$I_i(t+1) = I_{i,new} \tag{12}$$

Update status
After the properties are updated the status of the neighborhood S is updated using

$$S(t+1) = S(t) + \frac{1}{n}\left(\sum_i^n C_i(t+1) - C_i(t) + I_i(t+1) - I_i(t)\right) + \mathcal{N}(\mu = 0, \sigma = S_\delta), \tag{13}$$

where n is the number of agents in the model. Because S is bounded on the interval $[0, 1]$, the value of S is not allowed to exceed these bounds. This is guaranteed after calculating $S(t+1)$ by clipping the value between 0 and 1.

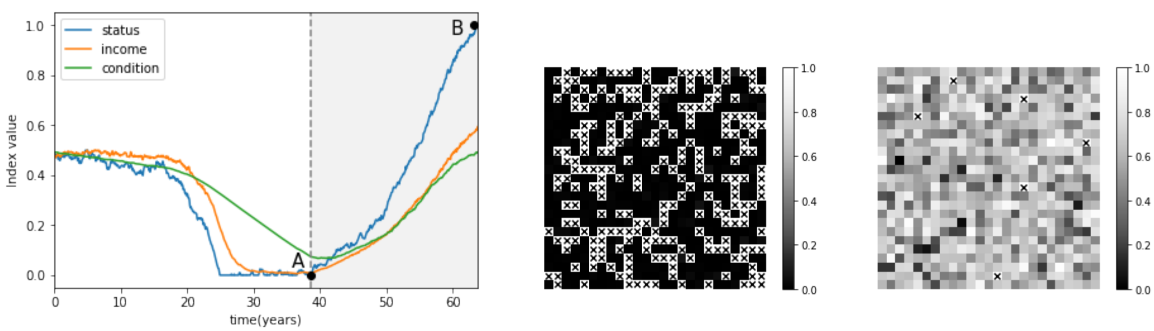
Gentrification check
At the end of each time step the model checks if the neighborhood is gentrified. As stated above, a precise definition of gentrification does not exist. When a definition for gentrification is chosen based on speed, this implicitly states that slower changes of state variables during the process can be caused by factors that are not (purely) part of the global concept of gentrification. Since in our model these factors are excluded, the change in state variables can be accounted to gentrification as long as the change of the state variables are big enough to minimize the role of stochasticity. In our model, this means that when measuring the duration of gentrification, the timer begins to measure when the status of the neighborhood is 0 and

stops when it becomes 1. This requirement is backed by the observation that gentrification happens primarily in low income neighborhoods and thus gentrification starts when the neighborhood is in a bad state.

The definition of gentrification that we use is a discrete state in which low income occupants are displaced as middle and higher income occupants moved into the neighborhood. For the sake of simplicity, this means that we consider the neighborhood gentrified when $S = 1$ and $\frac{C_\mu + I_\mu}{2} > 0.5$. When the neighborhood is considered gentrified, the gentrification time T_g is collected as the number of time steps between the last time steps of the model and the last time step when $S = 0$.

3 Results

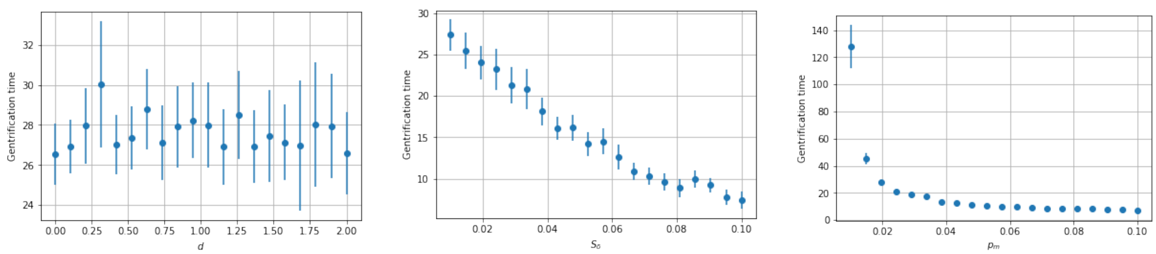
First of all, a typical run is presented to show the general dynamics and the general idea what is considered as gentrification. In Figure 2 gentrification occurs between time step A and time step B, according to the definition given in the previous section. The corresponding neighborhood situations are shown in Figure 2b and 2c At time step A (see Figure 2a) the status is 0 and is nonzero at the time steps after A. In Figure 2b we see that all households have low income at this point of time. The end of the gentrification process is characterized by a status of 1 and the average of the mean income and physical condition of the houses to be at least 0.5, which is attained at time step B, at which point most of the household are of high income, see Figure 2c.



(a) Dynamics (b) Situation A (c) Situation B

Figure 2: (a) Typical output dynamics of the model. The time between situations A and B is considered the gentrification process. (b) Corresponding neighborhod situations, where the color scale represents income. Empty properties are marked with an X.

For all runs of the model the parameters were set to the default values given in Table 2 unless stated otherwise. The model was initialized by setting all agents in an OCCUPIED state with conditions $C_i \sim \mathcal{N}(\mu = 0.5, \sigma = 0.1)$ and incomes $I_i = C_i + \mathcal{N}(\mu = 0, \sigma = 0.025)$ bounded on $[0.0, 1.0]$ and by setting the neighborhood status to $S = 0.5$. In order to analyze the model, two forms of sensitivity analysis were done using the gentrification time as the model output, namely a local sensitivity analysis using One-Factor-At-a-Time (OFAT) analysis and a global sensitivity analysis using the Sobol method.
The OFAT analysis was done by varying one of three model parameters: the status variability S_δ, the agent mobility p_m or the distance factor d. The depreciation rate r_D was not analyzed, because this parameter represents the time needed for a property to go from the best possible condition to the worst possible condition, which we assume to be between 55 and 56 years. Due to the stochasticity of the model, 50 iterations per parameter value were used. Since the neighborhood can fail to gentrify within a run of the model, runs without a model output were discarded from the analysis. The results of the OFAT analysis are presented in Figure 3. The error bars on the data points are the 95% confidence intervals. These error bars are valid under the assumption that the Central Limit Theorem holds for the relatively low amount of iterations per parameter value.
The global sensitivity analysis was done by running the model using parameter values for S_δ, p_m and d sampled using Saltelli's sampling scheme and analyzing the variance decomposition of the model outputs



(a) (b) (c)

Figure 3: Graphs of the gentrification time as a function of the (a) distance factor (b) status variability (c) agent mobility for OFAT analysis.

Table 3: First order and total variances obtained from global sensitivity analysis

	S_1	S_1 confidence	S_T	S_T confidence
p_m	0.640	0.243	0.909	0.148
S_δ	0.162	0.103	0.515	0.127
d	0.022	0.051	0.224	0.093

using Sobol's method. The Sobol analysis was done using two independently sampled Saltelli samplings with 200 samples corresponding to 8 model runs per sample (since second order variances were also calculated). As with the OFAT analysis, any sample containing a failed model run was discarded from the analysis. The results of the Sobol analysis are presented in Table 3, where the first order variances and total variances are tabulated along with their confidence intervals.

4 Discussion

In this topic, we discuss how the distance factor, the status variability and the mobility of agents influence the gentrification time, as well as how sensitive each one of those factors are in the implementation.

4.1 Gentrification time and distance factor

The distance between each property of the neighborhood and a specific location does not intervene with the time that is needed for the neighborhood to be gentrified. Taking the graph of Figure 3a into consideration, there is no clear correlation between these two factors - there is neither an increase nor a decrease of the time as the distance widens. An explanation of this behaviour could be that even though it is more possible for properties close to a location of interest to find occupants who will improve the overall neighborhood status, properties that are distant will have proportionally less chances to find such occupants; thus the total time would not be affected. Furthermore, one could claim that the social status of the occupant seems to have a greater impact to a decision of immigration in comparison to the convenience of the property's location. There is reason behind such allegation, since there is no need for somebody to move entirely out of a neighborhood if she is well content with his surroundings (house and neighbors). On the other hand, judging by how sensitive the distance factor is, not completely safe conclusions could be derived from the graph.

4.2 Gentrification time and status variability

From both the analysis of the status variability in Figure 3b and the Sobol analysis we can see that the model seems to be moderately sensitive to the value of the status variability. There even seems to be a somewhat linear dependence of the gentrification time with the status variability. It seems that the diffusion of the Gaussian random walk added to the neighborhood status reinforces the speed of gentrification when the state of the neighborhood is brought in a convenient position to gentrify. The status variability only seems to influence the dynamics meaningfully when the neighborhood status is close to both the average income and the average property condition as is demonstrated in the typical run in Figure 2. Since the status variability represents the unknowns of the model which are not based on economic properties, but rather the social factors, we can see that the economic properties start leading the dynamics only when the non-economic properties decide on the course of the dynamics. This demonstrates that the status variability is crucial to the dynamics of the model and that it may prove useful to model the non-economic properties into the agents themselves instead of relying on the assumption of a normally distributed error term.

4.3 Gentrification time and agent's mobility

As the agent's mobility increases, the gentrification time decreases at an almost inversely proportional rate. The agent's mobility represents how influential the rental gap and the status neighborhood are as factors for an agent to leave the neighborhood. The higher the value, the higher the chance is for an agent to not be satisfied with his stay. This leads to a state of an almost empty neighborhood. In this state, the possibility of an agent finding and remaining at a property increases since there won't be many neighbors that are economically superior and the only determinant factor of the stay is the property's condition. Hence, the gentrification time shortens.

4.4 Future work

We recommend the following analyses and extensions for future work. First of all, the effect of a distance gradient may be more relevant if the topology of the gradient is different. The distance gradient could for example decrease property prices as the distance to the center of the neighborhood grows larger. The model could also be extended by adding distinctions between rented and bought property similar to the model described by O'Sullivan (2002). Another effective extension could be to replace the Gaussian error term used to model the uncertainty in the change of neighborhood status with a term governed by non-economic properties modelled into the agents themselves, such as social factors like occupant ethnicity and an individual agent status to try and capture similar dynamics. Lastly, different types of properties such as shops, markets and other facilities could be introduced to the model which could affect the probability of occupants moving due to changes in quality of life and living expenses within the neighborhood.

5 Conclusion

We have analyzed our gentrification model using both an OFAT local sensitivity analysis and a global sensitivity analysis, which uses the Sobol method.
From the OFAT analysis we can conclude that the gentrification time is most sensitive to a change in the agent mobility, followed by a moderate sensitivity to changes in the status variability. The gentrification time seems to be inversely correlated with the agent mobility and linearly correlated with the status variability. We can also conclude that the gentrification time does not meaningfully change as the distance factor is varied.
The results from the Sobol sensitivity analysis seem to corroborate the conclusions drawn from the OFAT analysis as the largest explained variance is again from the agent mobility followed by the status variability. The distance factor also does not seem to be a relevant variable from the Sobol analysis due to its low explained variance.
For further research we recommend an analysis to see if the distance factor is more relevant when using the distance from the middle of the grid and we recommend that the model will be extended by adding a distinction between renting and buying of properties, replacing the Gaussian error term in the neighborhood status with a term based non-economic properties of the agents or by adding other types of agents which represent facilities which influence quality of life and living expenses.

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A Model code

In this section, the reader can find the code we used and have written.

```
import random
import numpy as np

from mesa import Model, Agent
from mesa.time import SimultaneousActivation
from mesa.space import SingleGrid
from mesa.datacollection import DataCollector

def bounded_normal(mu,sigma,minimum,maximum):
    '''
    Draw repeated samples for
    bounded normal distribution
    '''
    mu = np.clip(mu,minimum,maximum)
    i = 0
    while True:
        X = np.random.normal(mu,sigma)
        if X >= minimum and X <= maximum:
            return X
        if i > 100 or mu < 1e-4:
            return minimum

class PropertyAgent(Agent):
    '''
    Property Agent
    '''
    def __init__(self, pos, model, income):
        '''
        Create a new agent (property).
        '''
        super().__init__(pos, model)
        self.pos = pos
        self.income = income
        self.empty = False
        self.move_out = False

    def step(self):

        # shortened references
        model = self.model
        conditions = model.conditions

        neighbors = model.grid.get_neighbors(self.pos,True)
        neighborhood = model.grid.get_neighborhood(self.pos,True)

        # Calculate income gap
        neighbor_incomes = [neighbor.income for neighbor in neighbors]
        mean_income = sum(neighbor_incomes) / len(neighbor_incomes)
        income_gap = max(0.0, self.income - mean_income)

        x,y = self.pos

        # Decide if occupant moves out
        d_factor = self.model.d_factor
        U = np.random.uniform()
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        if not self.empty and U < model.mobility*(1.5 - model.status + income_gap):
            self.move_out = True
            self.empty = True
            value = 0.5*(conditions[x,y]+mean_income)
            self.price = np.clip(value*(1+d_factor*(0.5 - y/self.model.height)),0,1)

        if self.empty:
            # Prepare list with neighboring property conditions
            neighborhood_conditions = []
            for cell in neighborhood:
                if cell[0] != None:
                    neighborhood_conditions.append(conditions[cell[0],cell[1]])

            # Calculate rent gap
            mean_condition = sum(neighborhood_conditions) / len(neighborhood_conditions)
            self.rent_gap = max(0.0, mean_condition - conditions[x,y])

    def advance(self):

        # shortened references
        model = self.model
        conditions = model.conditions
        x,y = self.pos

        if self.move_out:
            model.income_change -= self.income
            self.income = 0
            self.move_out = False

        elif self.empty:
            bound = model.status+self.price
            income = bounded_normal(0.5*bound,0.1,0.25*bound,min(1.0,0.75*bound))

            if income > self.price:
                model.income_change += income - self.income
                self.income = income

                # Decide if new owners improve the property
                if self.rent_gap > 0 and income > conditions[x,y]:
                    improvement = bounded_normal(model.status-conditions[x,y],0.1,0.0,0.5)
                    conditions[x,y] = np.clip(conditions[x,y]+improvement,0,1)

                self.empty = False

            else:
                # decrease price and condition if property stays empty
                conditions[x,y] = np.clip(conditions[x,y]
                                          - 0.2*self.model.depreciation_rate,0,1)
                self.price = 0.5*(self.price + income)

class GentrificationModel(Model):
    '''
    Model class for the Gentrification model.
    '''

    def __init__(self, height, width, depreciation_rate, mobility, status,
                 stat_var, d_factor):
        # Set model parameters
        self.depreciation_rate = depreciation_rate
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```
        self.mobility = mobility
        self.status = status
        self.stat_var = stat_var
        self.d_factor = d_factor
        self.height = height

        # Global tracking variables
        self.mean_income = 0.0

        self.schedule = SimultaneousActivation(self)
        self.grid = SingleGrid(height, width, torus=False)

        self.datacollector = DataCollector(
            model_reporters={"status": lambda m : m.status,
                             "income": lambda m : m.mean_income,
                             "condition": lambda m: m.mean_condition},
            agent_reporters={"x": lambda a: a.pos[0], "y": lambda a: a.pos[1]})

        self.running = True
        self.hit_bottom = False
        self.last_bottom = 0
        self.gent_time = None


        self.conditions = np.zeros((width,height))

        # Set up agents
        # We use a grid iterator that returns
        # the coordinates of a cell as well as
        # its contents. (coord_iter)
        for cell in self.grid.coord_iter():
            x,y = cell[1], cell[2]

            self.conditions[x,y] = bounded_normal(0.50,0.1,0.0,1.0)

            # Income initially differs little from property conditions
            while True:
                income = self.conditions[x,y] + np.random.normal(0.0,0.025)
                if income >= 0.0 and income <= 1.0:
                    self.mean_income += income
                    break

            agent = PropertyAgent((x, y), self, income)
            self.grid.position_agent(agent, (x, y))
            self.schedule.add(agent)

        self.mean_condition = np.sum(self.conditions) / self.conditions.size
        self.mean_income /= self.conditions.size


    def step(self):
        '''
        Run one step of the model.
        '''

        # For tracking change
        old_conditions = np.copy(self.conditions)

        # Initialize change tracking variables
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```
self.income_change = 0.0

self.schedule.step()

# Update property conditions
self.conditions -= self.depreciation_rate
self.conditions = np.clip(self.conditions,0,1)

conditions_change = self.conditions - old_conditions

# Update neighborhood status
self.status += ((self.income_change + np.sum(conditions_change))
                / (conditions_change.size))
self.status += np.random.normal(0.0, self.stat_var)
self.status = np.clip(self.status,0,1)

# Update datacollector variables
self.mean_income += self.income_change / self.conditions.size
self.mean_condition = np.sum(self.conditions) / self.conditions.size

self.datacollector.collect(self)

if self.status == 0.0:
    self.hit_bottom = True
    self.last_bottom = self.schedule.steps

if self.schedule.steps > 2999:
#    self.gent_time = None
    self.running = False


if (self.status == 1.0 and
0.5*(self.mean_condition + self.mean_income) > 0.5 and
self.hit_bottom == True):
    self.running = False
    self.gent_time = (self.schedule.steps - self.last_bottom)/12
```