An Agent-Based Model of Classroom Seating Behaviour

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***Abstract*—An agent-based model is developed aimed at capturing core dynamics in classroom seating behaviour. The model comprises the social network of the students, an individual's sociability, a seat's desirability based on its position in relation to important attributes in the environment, and seat accessibility. Results of one-factor-at-a-time and Sobol sensitivity analysis on the model are discussed in detail. Model parameters are estimated by using real data on seating behaviour gathered during lectures. The discussion of the model is presented in terms of several simulation experiments.**

I. Introduction

SUPPORT has been found for the assertion that auditorium seating and equivalent social processes are not random, but guided by both strategic reasoning and individual preferences [1]. In this report an agent-based model (ABM) for classroom seating behaviour is developed. A generic framework, which to our knowledge is completely new, is built. It enables incorporation of individual preferences and general seating behaviour tendencies as well as an underlying social network. The proposed ABM is conceptually based on Schelling's famous segregation model, which has been successfully applied and adjusted to the low-cost setting of seating decisions in classrooms [1]. However, existing models omit the fact that individuals are connected by diverse social ties. We expect the introduction of a friendship network to have an impact on final seating arrangements as it is generally considered desirable to be around friends.

The model description follows the ODD (Overview, Design concepts, Details) protocol [2]. The model is fitted to (a limited amount of) real data gathered from lectures at the University of Amsterdam in order to accurately develop and verify the framework. Finally, model simulations are analysed and discussed in detail.

II. Model Description

A. Purpose

The first objective of this project is to provide a generic framework that describes classroom seating behaviour and other equivalent social processes that are driven by aggregate social choice. It should be easy to elaborate on the proposed model and tweak parameter settings such that they better fit observations.

Secondly, the model may provide insight into the process of seat selection; what kind of strategic reasoning is applied, and what individual preferences are important? The focus is on generating certain characteristic phenomena and core dynamics. More specifically, it is not the goal to reconstruct any particular seating arrangement in detail.

Lastly, the model may serve as an additional tool in classroom design. Different design concepts can be simulated and tested, with an aim of maximizing satisfaction of students.

B. Entities, state variables, and scales

The first important entity is the environment: the classroom. The environment is characterized by a (non-toroidal) grid, which is static. Positions in this grid are labelled with coordinates $x = 1, ..., X$ (indicating columns) and $y = 1, ..., Y$ (indicating rows). Each position $\vec{x} = (x, y)$ corresponds to either a seat or part of an aisle – or, depending on the desired complexity of the room, the positions can also be labelled as pillars, doors, windows, computer desks, etc. This, however, is not necessary in the model which is presently developed.

Secondly, seats are located at a number of positions on the grid. Aisles separate the seating into blocks and enable access to the seating. Accessibility is an important component to the model, as limited access to available seats will hinder the students' prospective seat choice.

A seat is either empty or taken. Initially all seats are empty; if an agent chooses to sit at position $\vec{x}_i$ then the corresponding seat is taken.

Seats have an attribute called 'position utility' $p(\vec{x})$, which takes values from the continuous closed interval $[0, 1]$ where zero indicates an unattractive position and one indicates desirable. This attribute is a function of the seat's location in the room, since factors such as door vicinity and lecturer's position are expected to affect the 'value' of a seat. The greater the desirability of a seat, the larger the probability someone will choose to sit there.

Finally, the agents/individuals. The agents pick a seat based on the positional desirability and accessibility of all available seats together with the personal preference, which includes their sociability and social network. An agent's 'sociability' trait is a measure for how likely they are to sit next to people they do not know. This can take any value from the closed interval $[-1, 1]$, where -1 indicates aversion towards sitting next to others, zero indicates indifference and one indicates a preference. Next, the social network is represented as a connectivity matrix that characterizes the friendship for all pairs of agents.

Further agent attributes may include (for instance) eyesight, which is likely to add a personal preference to sitting at the front. Additional attributes like these require corresponding attributes of seats. Currently, however, this is not modelled, but additional data may provide sufficient basis for adding these kind of factors to the model.

The temporal scale is simply defined as a sequence of decision-making events. In general, classrooms are filled within 15 minutes, however we do not consider time (hours, minutes, etc) in this model.

C. *Process overview and scheduling*

The scheduling for every agent is depicted in Algorithm 1. First, the environment and social parameters are initialized. Agents then enter the classroom one at the time and pick a seat based on which seat fits their desires best. After the first agent has picked his/her seat, the environment is updated. Only then the next agent enters the room, picks a seat, and so on. Thus, the number of iterations is the same as the number of agents seated in the classroom. There is no need to assume an arrival rate, since time is modelled as a series of discrete events, and not in a continuous manner.

Algorithm 1 Pseudo-code for scheduling

```
init classroom
init social network
init sociability
while true do
    agent = create_agent(social network, sociability)
    utility = calculate_utility_seats(classroom, agent)
    seat = choose_seat(classroom, utility)
    classroom = sit(agent, seat)
end while
```

D. *Design Concepts*

1) Basic Principles: The model is a discrete choice model; the agents are presented with a choice set of discrete options (all available seats). The choices are mutually exclusive (one cannot occupy several seats at once), the choice set is exhaustive (it is inherent to the model that you pick a seat in the room) and the number of alternatives is finite (the classroom has finite dimensions). In picking their seat, the agents determine a utility corresponding to each seat and then choose the one with highest utility. Hence, utility theory is applicable [3]. However, for simplicity error terms are discarded.

2) Emergence: The interplay of the different utility components yields complex seating patterns emerging from individual characteristics and preferences. With the underlying social network we expect a tendency of friends being clumped together. Similarly, by adding sociability to the model it is to be assumed that sociable people will seek each other's company while socially anxious people will try to avoid others. Hence, a clustering of friends or sociable students and a spread of socially anxious people is expected to emerge in final seating arrangements.

Furthermore, the preferred seat or seats of the classroom will attract more students in the early stages of the run. Thus, depending on the location of these seats, we will see clustering around this preferable section.

Finally, limited accessibility to seats in the centre of a block is expected to yield the frequently observed phenomenon of accumulation of taken seats close to the aisles which in turn inhibits further filling of central seats at later stages of the seating process.

3) Objectives: Agents try to find the seat with highest utility, they do this at the time they come into the classroom. The exact utility function which they try to maximize will be discussed in section II-G. It is important to note that their utility may still change after they have chosen a seat due to seating behaviour of other agents, but in the current model the agents cannot change their seat once chosen.

4) Prediction: The agents do not consider seating choices of future agents. For example, social agents will not favour rows with empty seats even if their friends will join later.

5) Sensing: It is assumed that when agents enter the classroom they have full knowledge of their environment; they know exactly which seats are taken and who is sitting in which seat.

6) Interaction: There is no communication between agents and the only interaction is indirect. Agents will change the expected utility of a seat from the perspective of another individual by sitting close to it, this is the only way in which agents interact.

7) Stochasticity: The social network and sociability characteristics are initialized randomly based on the collected data. Furthermore, agents are assumed to be rational and thus always choose the seat location with maximum utility. However, in the case of multiple, equally attractive options, a random choice among them is made.

8) Observation: The most important data collected from the model simulations are the final 2D seating arrangements. These seating arrangements may reveal characteristic phenomena and core dynamics by analysing and describing them by (for instance) textural features for pattern classification. More details about output measures are discussed in sections IV and V.

It is important to mention that in the current model the agents do not adapt to changes in their environment after they have selected a seat. Furthermore, agents do not learn (despite being in a classroom); agents do not have memory of previous visits to the same lecture room. Prediction is also not modelled. However, it might be worthwhile to add this to the model and allow agents to consider whether their (best) friends are already in the room and if not, pick a seat alone if they are likely to show up later. Finally, there is no collective behaviour of agents, because they are handled one at the time. Seating behaviour of groups of individuals coming in together is another interesting possible elaboration on the current model.

E. Initialization

At initialization an empty classroom with a specified design (see section II-F) is created. All seats are available and differ only in their inherent positional utility.

Inspired by [4], the social network is generated by a custom algorithm which grows a random graph iteratively based on a given degree sequence. It determines the number of friends each student has. For sake of comparability, we generate the data-based sequence only once per class size. Then, initialization simply comprises random permutation and subsequent construction of a fitting social graph. Likewise, the pool of sociability traits is generated by sampling from the real-data distribution. The order in which sociability values are assigned to agents is again obtained by random permutation.

Agents are initialized following the order of nodes in the social network and the order of sociabilities respectively. The next corresponding characteristics, that have not been used yet, are assigned to the new student.

F. Input Data

The classroom design to be specified comprises the following features: number of horizontally aligned seating blocks, number of seats per row in each block, number of rows, positions of horizontal and vertical aisles, and entrances. Within this project the classroom layout is fixed to two blocks with 6 and 14 seats per row, and 13 rows respectively. Two vertical aisles exist, one between the blocks and one at the margin of the larger block. This design corresponds to the classroom used for data collection (see section III). Position utilities are taken from 6 discrete bins ($\{0, 0.05, 0.2, 0.5, 0.7, 1\}$) with values and arrangement derived from the questionnaire as shown in Appendix A.

Both input sequences for the social network and sociability are sampled randomly from the respective real-data distribution (see Appendix A). Due to limitations during data collection, sociability values had to be restricted from the interval $[-1, 1]$ to $[0, 1]$, discarding social aversion. Numbers of friends range from 0 to class size N. The length of friendship degree sequence and sociability sequence determines the class size of the model instance, meaning the maximal number of students entering the room, which can range from 1 to 260 for the considered classroom layout.

In general model experiments, 0 is used as random seed. For repetitive simulations this value is successively increased by one.

G. Sub-models

Now the utility function that the agents try to maximize will be discussed in detail. Each individual i, with $i = 1, ..., N$ (where N is the total number of individuals, which must be less than or equal to the total number of available seats), assigns some utility $u_i(\vec{x})$ to a seat at position $\vec{x}$. Next, the individual sits down on the seat which is assigned the highest utility. The total utility U is the sum over all individual utilities once everyone has found a seat.

The seats' utility an individual assigns is influenced by the relation of the individual to the people in neighbouring seats. Thus, a 'friendship' term depends on the social network connections to neighbours and is denoted $f(\vec{x}_i, \vec{x}_j)$ where $\vec{x}_i$ is the position of the seat the individual is evaluating and $\vec{x}_j$ the position of other agents' seats. As mentioned before, the utility function is also influenced by the sociability term $s_i(\vec{x})$ which depends on the agent's sociability trait λ_i and of course also on the people in neighbouring seats.

Remaining terms in the utility function are the positional desirability of the seat denoted $p_i(\vec{x})$, and an accessibility term denoted $a_i(\vec{x}_i, n)$ which reflects how convenient it is for an agent to reach the seat. Agent i's utility rating of seat $\vec{x}$ is a linear combination of these four terms:

$$u_i(\vec{x}_i) = \beta_1 f_i + \beta_2 s_i + \beta_3 p_i + \beta_4 a_i, \tag{1}$$

in which the coefficients $\beta_j \in [0, 1]$, with $\sum \beta_j = 1$, represent the relative importance of each component. They are determined by fitting the model to real data. Each utility term is scaled to values between zero and one, resulting in a total utility with the same range, $u_i \in [0, 1]$.

The friendship term: The social network of the agents is a graph represented by a connectivity matrix C of size $N \times N$. This connectivity matrix can be constructed in several ways:

- *Do I know my neighbour?* In this option it is only relevant whether the individual knows the other people in the room. If individual i knows the person j then this is indicated by setting C_{ij} to one, or to zero when they do not know each other. In this case it is assumed friendships are mutual, resulting in an unweighted, undirected graph with binary and symmetric connectivity matrix C.
- *Do I like my neighbour?* In this option the relationship between individual i and person j is rated by some number C_{ij} on the interval $[-1, 1]$, where -1 implies full aversion towards the other individual and 1 indicates a close friendship. In this system zero implies indifference towards the other. A reasonable assumption is that people feel the same way about each other, meaning the network is undirected. In other words: person A cannot feel differently about person B than person B feels about person A. In this case the connectivity matrix C is also symmetrical. This assumption need not be the case however.

The strength of the friendship C_{ij} introduces a bias in choosing a seat; you want to stay away from people you do not like (C_{ij} is negative) and stick around people you do like (C_{ij} is positive). If C_{ij} is set zero for all relationships (for example, at the start of a new course) then relations to other people do not influence the decision where to sit and the seating arrangement is random (or fully dependent on other terms in u_i). In the case everyone knows everyone else (the connectivity matrix consists of ones only) it is expected that everyone will group together in the classrooms, because they are biased towards sitting with people they know.

For simplicity the base model that is analysed is of the type '*Do I know my neighbour?*'.

Connecting with the neighbours: The value of the friendship and sociability terms in the utility function u_i are determined by looking at the people in neighbouring seats. One can choose to include second neighbours or, for instance, exclude people in front or behind by specifying the interaction strength matrix α. When only considering direct neighbours, the matrix has size 3×3, when including second neighbours it has size 5×5, and so on. For now, assume only nearest neighbour interaction. The currently applied interaction strength matrix α for nearest neighbour interaction is:

$$\alpha = \frac{1}{2} \begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix}, \tag{2}$$

where the only relevant seats are the seats directly to the left and right of the agent, the row in front and to the back do not matter. The friendship term f_i is determined as follows:

$$f_i = \sum_j \alpha_j \cdot C(\vec{x}_i, \vec{x}_j), \tag{3}$$

where the sum runs over all neighbouring seats j and $C(\vec{x}_i, \vec{x}_j)$ returns a one if the agents at positions $\vec{x}_i$ and $\vec{x}_j$ know each other and zero otherwise.

For the sociability term s_i a similar strength of interaction matrix can be defined. However, at this point there is no reason to assume it to be different from α. The sociability term is determined as follows:

$$s_i = \lambda_i \sum_j \alpha_j \cdot h(\vec{x}_i, \vec{x}_j), \tag{4}$$

where λ_i is the agent's characteristic sociability value. Negative values imply aversion towards sitting next to other people, zero means indifference and one indicates desire to sit next to others. $h(\vec{x}_i, \vec{x}_j)$ is defined in the following way:

$$h(\vec{x}_i, \vec{x}_j) = \begin{cases} 1, & \text{if seat } \vec{x}_j \text{ taken and } C_{ij} = 0 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

With this, the student's sociability only comes into effect for seats being occupied by students the decision-maker does not have a social relationship to. The final sociability component s_i is obtained by shifting and scaling the value such that $s_i \in [0, 1]$ for all possible s_i.

The seat position term: Some seats in a classroom are more desirable than others. This may, of course, depend on strictly personal preference. However, it is not unreasonable to expect some general tendency of people

low-level entities	explanation	type	scale
D	classroom design (shape, seat count n_{seats}, positions of aisles and entrances, etc.)		
N	class size	integer	[0,n_{seats}]
β_1	friendship coefficient	float	[0,1]
β_2	sociability coefficient	float	[0,1]
β_3	position coefficient	float	[0,1]
β_4	accessibility coefficient	float	[0,1]
α	interaction strengths	matrix of floats	$\sum \alpha_{i,j} = 1$
λ_i	student i's sociability	float	[-1,1]
C	social network	connectivity matrix	binary
$p(\vec{x})$	seat $\vec{x}$'s position utility	float	[0,1]
high-level entities			
$f_i(\vec{x})$	friendship term of seat $\vec{x}$ evaluated by agent i	float	[0,1]
$s_i(\vec{x})$	sociability term of seat $\vec{x}$ evaluated by agent i	float	[0,1]
$a_i(\vec{x})$	accessibility of seat $\vec{x}$	float	[0,1]
$u_i(\vec{x})$	total utility of seat $\vec{x}$ evaluated by agent i	float	[0,1]

TABLE I: Overview of all variables.

picking a seat in a classroom. Only modelling the general tendency is straightforward, then each seat is assigned some utility value which reflects the general desirability of that seat and

$$p_i(\vec{x}_i) = a, \qquad a \in [0, 1]. \tag{6}$$

In the model analysed, each seating block is split into three sections, front middle and back, and a value is assigned to each section of each block, where all seats in a section take the same desirability. For example, the front three rows may get a rating of zero, and the middle section gets a rating of one, and sections to the side of the room receive some value in between. These ratings are estimated on observed behaviour.

Implementing unique personal preference is more difficult. The agents will need additional characteristics that reflect where they want to sit (close to the door, close to the window, close to the teacher, etc.) and the seats need corresponding characteristics to be able to compare the persons preference to the seat. A survey could be conducted to gather data on this. However, as a first implementation, it seems best to only consider a general tendency in seat desirability.

The accessibility term: Having to ask people to move to get to a specific seat is cumbersome and often avoided. Hence, a utility penalty to this action can be introduced. It is reasonable to assume that n, the number of people you must ask to move to get to a seat, has an influence on this penalty; the more people you have to ask, the higher the penalty. Hence, the "getting to your seat"-penalty is some function of n and the position of the seat you want to get to $\vec{x}_i$. For now it is assumed that g_i increases linearly as a function of n:

$$g_i = \begin{cases} 0, & \text{if } n = 0 \\ b \cdot n, & \text{if } n \geq 1 \end{cases} \tag{7}$$

The factor b need not be determined, because it can be absorbed into coefficient β_4. It is, however, needed to estimate $g_i(n = 1)$. For simplicity, the implemented model uses $b = 1$.

In order to maintain equal scales for all utility components, this penalty is scaled by the maximal possible number of people to ask n_{max} and subsequently inverted to model a reward for seats with good accessibility. The final accessibility term becomes:

$$a_i = 1 - \frac{g_i}{n_{\text{max}}}. \tag{8}$$

It is not claimed that the framework presented above provides a perfect description of the mechanics underlying classroom seating behaviour. The framework is meant to provide a basis for describing classroom seating and equivalent social processes. In the following sections the unknown parameters are estimated by comparing the framework to real data, and simulations with an exemplary model implementation are analysed and discussed.

III. Data Collection

To create representative attributes for the agents and to fit the decision-making process to real-world behaviour, we collected data in one specific lecture room at Science Park, University of Amsterdam. Via an online questionnaire, we gathered information about sociability, number of friends, influence of people sitting next to you, preferred seats and more. The most relevant results are given in Appendix A. Furthermore, we captured the seating distribution at the moment the lecture started, which we consider to be final seating arrangements. These are used for parameter estimation.

Our model only considers agents entering one at a time, hence we only collected data from lectures starting at 9 and 11am. We did this to increase the likelihood that students would enter the room alone instead of in a group, which is more likely when students had not spent time together earlier in the day. To this end we also excluded lectures that were not the first of the day for students in that course.

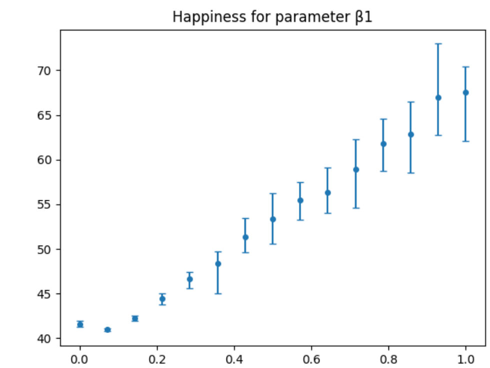
This resulted in a selection of three lectures with 8, 25 and 79 students attending.

IV. Sensitivity Analysis

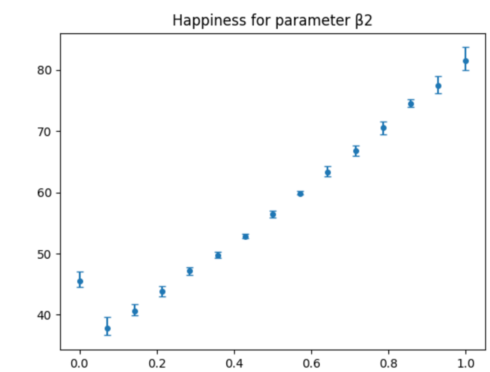
One-factor-at-a-time (OFAT) and the Sobol method are two useful sensitivity analysis (SA) techniques applicable to ABMs [5]. Sobol analysis, being a global SA method, samples the entire search space of parameters and provides measures of a model's sensitivity of the output parameters to the input parameters while taking interaction effects between parameters into account. OFAT on the other hand is a local SA method, where a base parameter setting is chosen and each parameter is varied individually while maintaining the base setting for the remaining parameters. OFAT analysis can reveal whether the response of a model to input parameters is linear or non-linear and whether tipping points occur, and it is not as expensive to run as the Sobol method.

Sensitivity of the classroom model is examined with respect to five input parameters, namely the four coefficients of the utility function, β_1, β_2, β_3, β_4, and class size N. The coefficients β_i are limited to any real value in $[0, 1]$ and class size is limited to an integer in $[1, 260]$, with 260 being the maximum amount of seats in the classroom model.

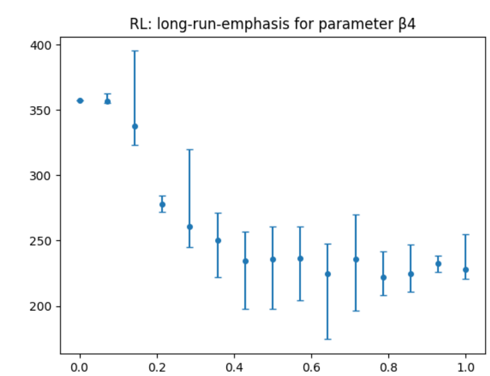
We examine the sensitivities of a number of output parameters of our model with respect to changes in the input parameters defined above. A simple output measure we can use to quantify changes is one we shall call "happiness", which we define as the total sum of utilities of all students in the final state of the model, discarding the accessibility term. This restriction to only use p_i, s_i, and f_i is based on the assumption that once a student is seated it is not relevant any more if the seat is easy to reach or not. We also measure sensitivity in the output measures of "homogeneity" and "correlation", which are features derived from the grey-level co-occurrence matrix (GLCM) [6], [7]; and in "RL non-uniformity" and "RL long-run-emphasis" which are features derived



(a) The effect of varying β_1 on happiness.

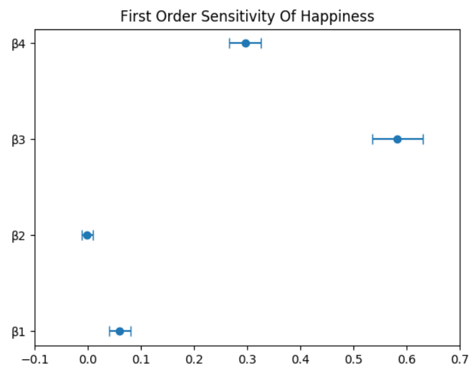


(b) The effect of varying β_2 on happiness.

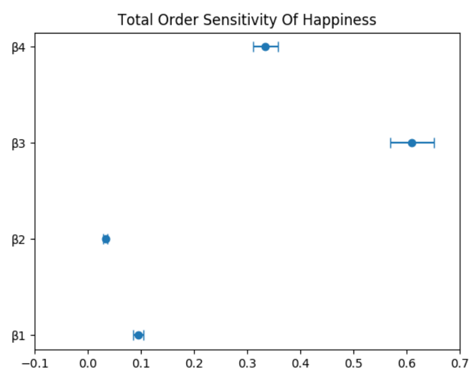


(c) The effect of varying β_4 on long-run-emphasis.

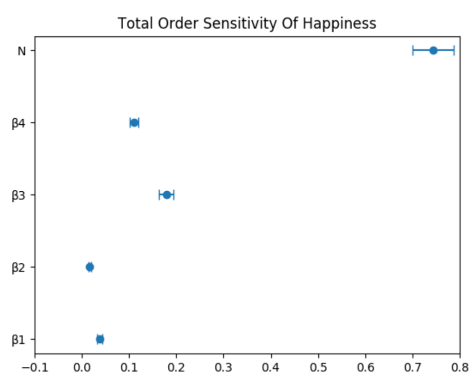
Fig. 1: OFAT analysis showing the effect on "happiness" of varying the coefficients β_1 and β_2, and the effect of varying β_4 on the run-length based measure, long-run-emphasis. The horizontal axes show the input parameter value and the vertical axes show the happiness measure.



(a) First order indices for the happiness measure.



(b) Total order indices for the happiness measure.



(c) Total order indices for the happiness measure, including class size N.

Fig. 2: The first-order and total-order indices of the coefficients β_i to the happiness measure of the model's final state, with class size fixed at 130. Also the total-order sensitivity indices with class size N included as a parameter. The horizontal bars show the 95% confidence intervals.

from the vector of run-lengths [8], meaning the counts of consecutively filled seats in a row, determined for all possible cluster lengths respectively. These four measures are higher-order image statistics which are commonly used in texture classification. For our purposes, they seem to be appropriate measures for capturing qualitative changes in emerging seating patterns. Definitions can be found in Appendix B.

For OFAT, the coefficients β_i are assigned a base setting of 0.25, respectively, and class size N is assigned a base setting of 130, half of the classroom's maximum capacity. The standard behaviour of the model is to scale the given coefficients β_i such that they sum to one. However for the OFAT analysis to give us meaningful results we require that a modification of an input parameter is independent of the other parameters. To that end we have turned off this scaling behaviour when running the OFAT analysis such that we can observe the independent affect of an input parameter on an output parameter. To apply OFAT we take 15 equidistant samples for each of the five parameters and for each of these samples we perform ten replicate runs, thus performing a total of $5 \cdot 15 \cdot 10 = 750$ runs.

As can be seen in Figures 1a and 1b, the coefficients β_1 and β_2 cause an approximately linear increase in happiness. We also note that when β_3 or N, the number of students in the classroom, is increased the happiness measure increases linearly. These linear relationships make obvious sense: as any one of the coefficients β_i increase, the respective component of the utility equation, f_i, s_i or p_i, contributes more greatly to the overall happiness; as N is increased the happiness measure increases simply due to the fact that there are more students. The only non-linearities we witness for the coefficients are for the initial increases in β_1 and β_2. It is difficult to ascertain the exact cause for these, except that as the respective coefficient, β_1 or β_2, moves from having no influence at value 0, to a positive value, it is causing students to pick seats that are somehow resulting in lower values from the remaining components of the utility equation. We surmise that the most likely case for this is that, as the friendship f_i or sociability s_i components of the utility equation carry more weight, students choose seats closer to other students, and this is causing the accessibility to the preferred seats of the students coming in later to drop below the threshold they will consider to get to that seat. In the case of the coefficient β_4, we observe in Figure 1c how as the accessibility of a seat becomes more important when choosing a seat, that the long-run-emphasis (which is loosely-speaking a measure of the length of students sitting in a row) decreases. We also note the tipping point at approximately $\beta_4 = 0.1$

which is when students seriously start considering sitting in more accessible seats.

For the Sobol analysis we take the standard approach of sampling as many points as possible in the parameter space in order to accurately estimate sensitivity measures [12], to this end we use Saltelli sampling to sample 24000 points from the parameter space, performing a single run of the model per sample. For the Sobol analysis since we are taking into account interactions between parameters we consider the model in its standard form where the inputs β_i are scaled at runtime. In Figures 2a and 2b we see the results of a Sobol analysis considering only the four coefficients β_i as parameters. In these plots we see that the model's happiness measure in its final state is considerably more sensitive to changes in β_4 and β_3, than in β_1 or β_2. Overall β_3, the positional factor has greatest effect on the system, and β_2 the social factor has almost no effect on the model. We also note the slight jump in first-order to total-order indices for each parameter, indicating there are some higher-order interactions between parameters but these are overshadowed by the first-order effects. We also include the total-order indices from a Sobol analysis where class size N is also included as a parameter (Figure 2c), this shows how the happiness measure of the model in its final state is much more sensitive to N than to any of the coefficients β_i.

V. Parameter estimation

The four utility coefficients β_i are determined by fitting the model to the collected data. On the one hand, this is a required step to find realistic values for these parameters, which can then be applied in further experiments. On the other hand, the procedure of matching model output and real-world observations is a form of replicative model validation. All simulations are performed within the experimental frame that we faced during data collection, including classroom layout, sociability distribution, and friendship degree distribution. Thereby, the model behaviour is validated by evaluating the similarity of seating patterns, without insisting on exact locational accordance.

The main principle we use for parameter estimation is to generate various sets of coefficients and run repetitive simulations for each of these sets. For each parameter set and each of the three observed seating arrangements, 10 repetitive simulations are performed, and the respective similarity between the model output and the observation is computed. The objective function f to be minimized in order to fit the model to the data can then be expressed as the mean error over all repetitions and datasets:

$$f(\beta_1, \beta_2, \beta_3, \beta_4) = \sum_{d=1}^{3} \sum_{i=1}^{n_{\text{rep}}} \frac{e_{d,i}}{3 \cdot n_{\text{rep}}}, \tag{9}$$

with n_{rep} the number of replicative runs and $e_{d,i}$ the error between model output and dataset d. For this comparison, two different methods are applied. In both cases a characteristic 1-dimensional distribution is derived from the binary seating pattern, which can then be compared by calculating the mean-squared error between model distribution and the target pattern distribution. The first method is based on counting occurrence of clusters with specific run-lengths (RL), as it is used in section IV. The second method searches for predefined local binary patterns (LBP) of size 3×3 and counts how often each of these patterns occurs in the seating arrangement [11]. Parameter estimation is performed independently for these two methods.

Since the mapping from model inputs to the final seating pattern implies non-linearities and stochasticity, it is not possible to apply a simple gradient descent to minimize the objective function. Instead, we use the simultaneous perturbation stochastic approximation (SPSA) algorithm [9], [10], which enables gradient approximation relying only on a small number of measurements per iteration. Further, it is claimed to be useful for multivariate problems and noisy objective functions. Considering the run-time of our model, its parameter dependencies, and the inherent randomness, the SPSA seems to be an appropriate approach that gives a fair trade-off between finding optimal parameters and minimizing computational costs.

The output of the SPSA algorithm is the best performing of all tested parameter sets. For statistical confidence, we perform a series of t-tests on the sets of repetitive mean-squared error measurements to identify and remove parameter sets that differ significantly ($p < 0.1$) from the best performing set. All remaining sets are considered successful in replicating the real-world seating process. Taking their average for each of the four coefficients yields the final results, which are summarized in Table II. Table III captures some statistics about the distribution of mean errors over the successful parameter sets. For both methods, the small variance in mean errors compared to their average supports the assumption that the remaining parameter sets are all comparably successful.

Regarding the emerging coefficients, we observe that β_2 is zero for both comparison methods and all successful parameter combinations. Apparently, sociability is not relevant at all for the observed seating process, which reinforces the result found during sensitivity analysis. We hypothesize that this irrelevance arises mainly due to missing information about social aversion. During data collection only social indifference or tendency to sit next to unknown people have been enquired. Supposedly, only the introduction of social aversion is able to produce different seating dynamics. We will address this in the course of model experimentation (section VI).

Apart from the sociability issue, it is striking that with the LBP-method none of the social components f_i and s_i plays a role for seating choices. Position utility and accessibility are the only influential components. However, this needs to be interpreted carefully: Visual examination (see Fig. 3 reveals that especially for the last lecture with 79 students the LBP-model is able to reproduce the two main clusters, but instead of emerging around the centre of the right block the clusters are rather attached to the two aisles. This is comprehensible considering the fact that accessibility is the most important component in this model, forcing the agents to prefer seats being easily accessible from the aisles. Nevertheless, from the real-world arrangement we assume this to have less impact. The model resulting from RL-parameter-estimation yields a somewhat more appropriate spatial distribution regarding the positioning of clusters. However, it generates a less realistic scattering around the clusters. Regarding the two smaller lectures, it is questionable if the comparison of patterns is of any value, since the number of agents is apparently too small to identify characteristic behaviours.

Based on the facial evaluation together with everyday experience, we opt for the parameter set obtained by the RL-method, where friendship is respected.

In sum, we could verify that our model is capable of generating diverse aggregate seating dynamics, but the reproduction of specific characteristic patterns is limited by the small amount of available data to fit the model to, as well as by the output measures being used to compare two arrangements. We observe that the currently applied measures are able to capture general local properties of seating patterns but they do not include global features such as positioning of clusters in the room. To improve results, more elaborated output measures or combinations of measures working on multiple scales need to be defined.

VI. Simulation Experiments & Discussion

In this report, we described an agent-based model for classroom seating determination. The choice for a seat is based on the agent's sociability, friendship, preferred seating location and accessibility of the seat. Only one classroom is considered during this research.

comparison method	β_1	β_2	β_3	β_4
RL	0.3681	0.0000	0.2490	0.3829
LBP	0.0000	0.0000	0.4606	0.5394

TABLE II: The coefficients emerging from the parameter estimation using the two different methods 'run-lengths' (RL) and 'local binary patterns' (LBP) to compare model output with observed seating patterns. The final coefficients are obtained by taking the mean of both methods.

comparison method	avg(mean errors)	var(mean errors)
RL	1.1394	2.35×10^{-2}
LBP	1.4376	2.56×10^{-2}

TABLE III: The average and variance over all mean errors of successful parameter combinations.

In order to assess the attributes of our agents, we collected data in a lecture room. Through this, we obtained information on seating distribution, sociability, friendships and preferred seats. We were unable to asses the accessibility term due to the complexity of the measurement. Unfortunately due to time constrictions and the lack of usable lectures for our model, we could not obtain a reasonable amount of data. Furthermore, we encountered lectures with (much) less students than expected, which gave us biased seating distributions.

Our data collection provided information about social affection to unknown people, but did not include questions about aversion to sitting beside strangers. This directly influenced the parameter estimation, where we

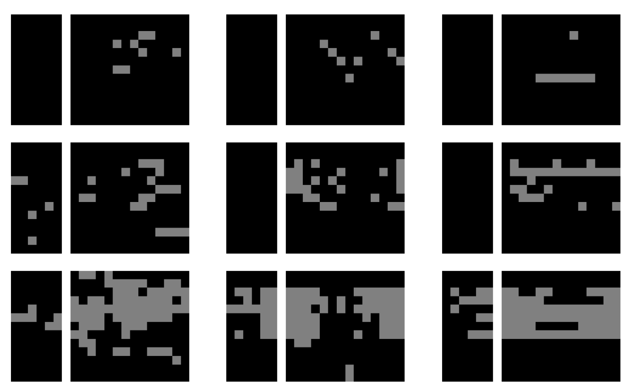


Fig. 3: Seating patterns observed during visited lectures (left) compared to simulation results (with random seed = 123) using the coefficients emerging from the estimation with LBP (centre) and RL (right). The rows refer to the three different lectures included in the data collection.

estimated the factor for sociability to be zero. The current implementation is out of balance, because it only increases clusters, but has no counterforce; there is little scattering of students in the classroom, they just prefer to sit together. The data collection could be improved by adding the option to indicate that you do not like to sit next to an unknown person.

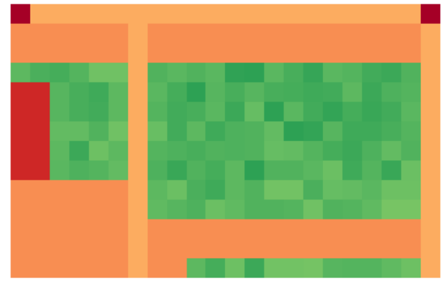
However, to assess the influence of negative sociability we compared two model simulations. The first uses a uniform sociability distribution in the interval [0,1], while the second extends the interval to [-1,1]. In figure 4, the final seating distribution of the simulations are depicted. When the interval [0,1] is used, we observe a strong clustering of students in (a), while the interval [-1,1] experiences a more scattered result in (b). Consequently, this social aversion has great impact on our model and should be included in further experimentation.

On the other hand, the social graph could be improved on two things. Firstly, as we stated earlier, the available data set was small and therefore probably unreliable regarding the extracted friendship degrees (figure 6a). Secondly, we assumed the answers to be correct, while misinterpretation of questions and uncertainty in student's answers could have a major impact on the data. We did not perform any statistics on the dataset.

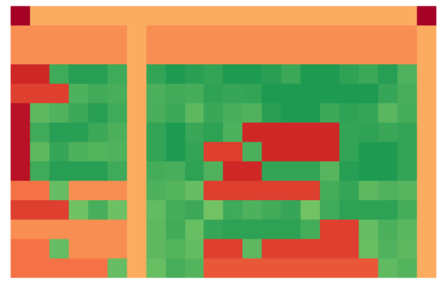
To this end, we ran simulations with a scale-free [14], a random [13] and our own data-generated social network to weigh the effects of the degree distribution. The parameters were set based on the estimation using RL. The final result does not show significant differences, but our customly created social network depicts more scatter (figure 5). Furthermore, we observe a tendency of stronger clusters of 'happy' agents emerging from the two artificial networks. We should note that both scale-free and random networks are created with arbitrarily estimated parameters. With regard to the surprisingly small effects of the underlying friendship network, further research should be conducted to work out the causes and to experiment with networks having more extreme friendship clusters.

In our model environment, agents will enter the classroom one at a time and decide without interference of other agents. Yet in real-life, we do not encounter this, but see a mix of individuals and groups entering the room and make choices while some people still decide, others are moving and some have taken their seat. Further modelling could consider movement, decision making and even future friend prediction. The latter consists of an agent's attempt to predict whether friends will join the agent and thus considering a seat with enough available space next to it.

The simulations were assessed and compared via univariate variable outputs. More sophisticated measures of the structure and distribution may be used that could validate our model parameters. An analysis of the time-series nature of the room as it fills up is another dynamic that we did not study in detail. We assumed that the final arrangement captures this behaviour in a meaningful way. An attempt to capture larger structural information using entropy at various kernel sizes yielded unsatisfactory and statistically insignificant results.



(a) Social affection with sociability trait $s_i \in [0, 1]$.



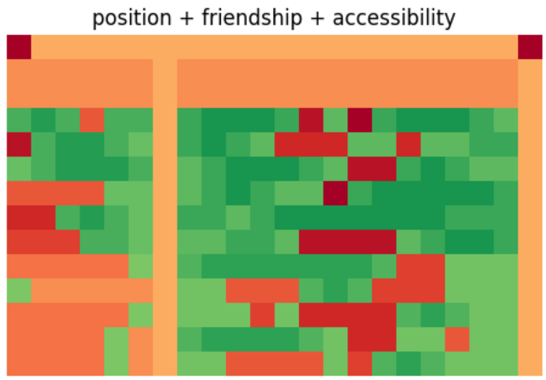
(b) Social affection & aversion with sociability trait $s_i \in [-1, 1]$.

Fig. 4: The simulation results when changing the sociability term. The class size is 150 and $\beta_1, \beta_2, \beta_3$ and β_4 are $\{0.37, 0.5, 0.25, 0.38\}$, being rescaled automatically by the model implementation.

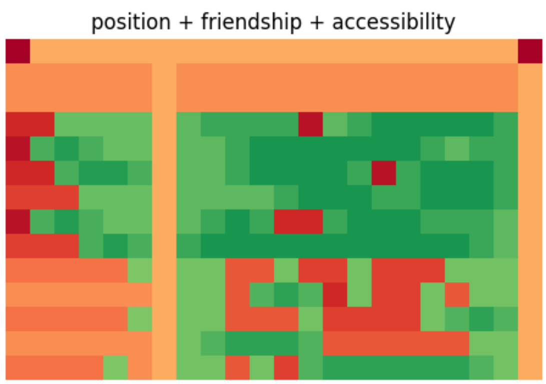
VII. Conclusion

In this paper, we lay the ground rules and principles for modelling classroom seating behaviour. A simple model is able to illuminate core dynamics of seating distributions, yet some aspects proved to be more difficult than expected. Setting up and collecting data about agents attributes and seating distribution, as well as providing the justified sub-models to mimic the agents decision making process were a major challenge of this research.

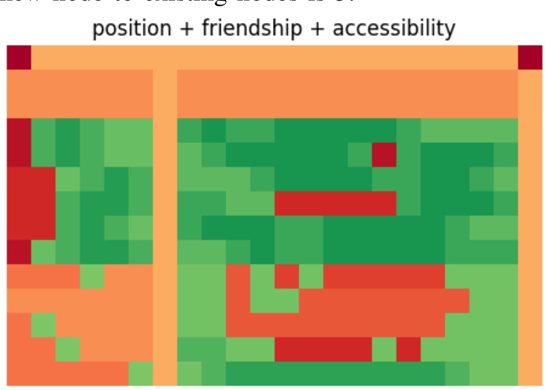
We identified and addressed some fundamental limitations of our model as we defined it to be. We outlined areas of further analysis given a larger and richer data set that future studies may provide.



(a) Custom social network generated from the data.



(b) Social graph is based on Barabasi-Albert random graph. The number of edges to attach from a new node to existing nodes is 5.

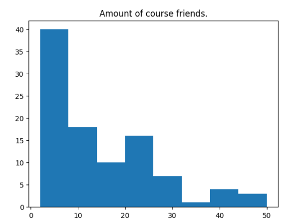


(c) Social graph is based on Erdos-Renyi random graph. The probability of edge creation is set to 0.2.

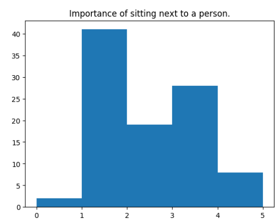
Fig. 5: The simulation results when changing the friendship network. The class size is 150 and $\beta_1, \beta_2, \beta_3$ and β_4 are $\{0.37, 0, 0.25, 0.38\}$.

Appendix A
Input Distributions

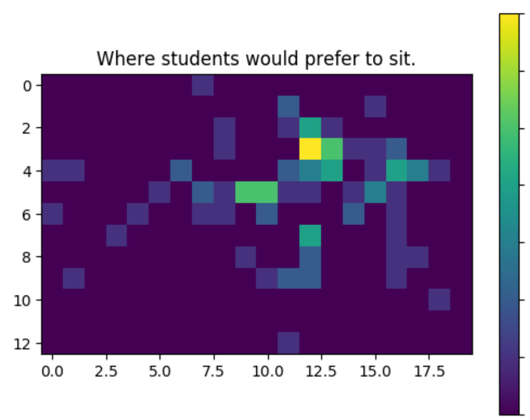
The most relevant results from the data collection are given in Figure 6. The distribution of friendship degrees is used to make a social network in the simulations. Sociability traits for agents are drawn from the sociability distribution. The data on preferred seat locations was used to define and assign utility values to the bins for position utility shown in Figure 7.



(a) Friendship degrees



(b) Sociability (5 bins)



(c) Preferred seat locations

Fig. 6: The observed distributions used to generate the inputs (a) ‘friendship degree sequence’ , (b) ‘sociability sequence’, (c) ‘position utilities’. All distributions are derived from the entire set of collected data, no differences between the lectures are made in order to compensate the limited amount of available data.

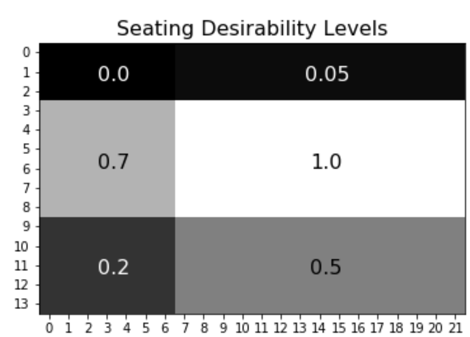


Fig. 7: Levels of desirability of the seating sections.

APPENDIX B
OUTPUT MEASURES

A. GLCM Features

We compute the GLCM $P(i,j)$ for distance $d = 1$ and angle $\theta = 0$, meaning that only horizontally adjacent pairs of pixels are considered. The analyzed seating distribution is binary, resulting in a 2×2 matrix with $i, j \in \{0, 1\}$.

$$\text{homogeneity} = \sum_i \sum_j \frac{P(i,j)}{1 + (i-j)^2} \tag{10}$$

$$\text{correlation} = \sum_i \sum_j P(i,j) \frac{(i-\mu_i)(j-\mu_j)}{\sigma_i \sigma_j} \tag{11}$$

with means μ_i and μ_j, and standard deviations σ_i and σ_j.

B. Run-Length Features

The run-length features are computed based on the run-length vector p_r, where $p_r(j)$ is the number of consecutive horizontal runs with length j.

$$\text{run-length-nonuniformity (RLN)} = \frac{1}{n_r} \sum_j p_r(j)^2 \tag{12}$$

$$\text{long-run-emphasis (LRE)} = \frac{1}{n_r} \sum_j p_r(j) j^2 \tag{13}$$

APPENDIX C
MODEL REPOSITORY

Our code is available on Github: https://github.com/WavyV/ABM_RocketMan. We added an interactive Jupyter Notebook for ease of use.

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