***Paths to Diversity*. A simulation of conformity in environments with different geometry**

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Abstract The geometry of the environment can affect numerous psychological, social, and ecological processes. But its roles in social learning and the dynamics of descriptive norms remain unclear. Here we use agent-based modeling to explore how environments with different geometric shapes can constrain social learning to produce universally shared descriptive norms. Our simulations show that an environment with an irregular layout facilitates the emergence of multiple descriptive norms in a population, whereas an environment with a regular grid plan constrains social learning to produce a behaviorally homogeneous population.

1. Introduction

All agents live, forage, and interact in environments with different geometric shapes and layouts, determined by different distributions of physical borders, paths, roads, buildings, walls, and barriers. Some living spaces have a circular shape, some a grid plan, and some are star-shaped or with an irregular layout. Some spaces have one center, while others are polycentric; some have well-delineated, self-contained neighborhoods, others do not have distinct neighborhoods. Some spaces are larger than others; and some have shorter, less curvy, or better-connected paths.

In philosophy (Rietveld & Brouwers 2017), psychology (Gibson 1979), ecology (Dale & Fortin 2014), and urban planning (Batty 2008), geometrical features of the environment have been shown to shape dwellers' behavior at multiple spatial and temporal scales, which is consistent with the *spatial determinism* hypothesis that "people's agency and subjectivity are shaped and determined by the spaces they are in" (Kukla 2021: 13).

Urban planners, architects, geographers, economists, and philosophers have often supported or assumed some version of spatial determinism. For example, Le Corbusier assumed that the regular grid with its straight paths and right angles is the ideal geometry for a well-functioning, modern, urban space, while the zigzagging curve is "ruinous, difficult and dangerous… a paralyzing thing" (1987: 10). Similar assumptions that the grid is the ideal urban plan, as it would facilitate orderly settlement, more efficient transit, and even "represent an egalitarian system of land distribution, [have been] expressed in the context of modern democracies, principally the United States" (Kostof 2018, 59). Spatial determinism is also assumed in philosophical utopias, where a grid plan is supposed to promote conformity to a desired moral and political order (Meyerson 1961; Lynch 1981; Hall 1998; Baldacchino 2018).

Studying a broader range of urban plans than the grid, and leveraging diverse bodies of empirical data, proponents of *space syntax* have supported spatial determinism by showing that geometric features of a city can predict dwellers' patterns of movement, the duration of their commutes, and the frequency of their encounters with random people (Hillier et al. 1986; Penn 2003). Similarly, studying the size of cities, economic geographers have demonstrated that it can robustly predict outcomes such as population density, commuting dynamics, quality of public service delivery, transit accessibility, economic growth, and environmental footprint (Batty & Longley 1994; Bettencourt & West 2010; Harari 2020).

Despite increased theoretical and empirical attention to how geometric features of the environment can affect socially significant outcomes, an underexplored question concerns the relationship between environmental layout and social learning. Specifically, we know little about possible roles of different environmental plans in conformity-biased social learning and the emergence of descriptive norms. Here, we use agent-based modeling to study how variation in the distribution of paths and barriers in an environment can constrain conformity-biased social learning to produce one, universally shared, descriptive norm in a population.

We define social learning as "learning that is facilitated by observation of, or interaction with, another individual (or its products)" (Heyes 1994: 207; Kendal et al. 2018), and conformity as a species of social learning consisting in an exaggerated propensity to modify one's behavior to align with the behavior of others (Cialdini & Goldstein 2004). Conformity-biased social learning can lead to the emergence of *descriptive norms*, which are typical or normal behaviors that individuals follow when they expect enough other individuals to do the same (Bicchieri 2006: 31-32). In particular, conformity can produce behaviorally homogeneous populations where only one, universally shared, descriptive norm emerges (Efferson et al. 2008).

Muldoon et al. (2014) studied the emergence of descriptive norms with an agent-based model of a standing ovation. Their model includes agents with a certain propensity to stand up (or stay seated), which can change over time based on their intrinsic preference for standing up, observation of other agents, and bias to conformity. But Muldoon et al.'s (2014) model does not consider possible variation in the geometric structure of the learning environment. Similarly, Weatherall & O'Connor (2021) and Fazelpour & Steel (2022), who used network modeling to respectively study how variation in the communication structure and in the demographic diversity of a population can limit the negative effects of conformity on the ability to reach accurate beliefs, also neglect potential roles of the geometric layout of the learning environment on agents' belief dynamics.

Thus, by clarifying the relationship between the geometry of an environment and conformity's tendency to produce behaviorally homogeneous populations, our study complements and extends existing work on social learning and the emergence of descriptive norms. Specifically, after describing the setup of our simulations (Section 2), we explain how variation in the geometric layout of an environment (Section 3), its density (Section 4), and agents' status quo bias (Section 5), can bear on conformity's likelihood of producing behaviorally homogeneous groups. We conclude by discussing the significance of our findings for spatial determinism, the epistemology of conformity, and the emergence of descriptive norms (Section 6).

2. Modeling setup

We used NetLogo 6.3 to develop four agent-based simulations of M agents (i.e., "the population") over N time steps. In each simulation, we varied the layout of the environment by changing the distribution of paths and barriers; we fixed the number of time steps to 50, and the size of the population to 500 agents, who could move through the available paths, observe others' behavior, and modify their own behavior based on social learning.

In the modeling setup of our simulations, the real-valued variable P_n^i represented the *effective propensity* of agent *i* at time step *n* to pick a number between 0 and 1. We assumed that this number represented a type of behavior that the agents could display. For a concrete, suggestive example, imagine that the possible types of behaviors of our simulated agents are percentages of their income (whatever that is) that they want to donate to a charity.

Following Muldoon et al. (2014), we defined agents' effective propensity to display a certain type of behavior as the convex combination of an *intrinsic preference* to display a certain behavior independently of what others are doing, and a *preference to conform* to others' behavior.

Specifically:

- q^i is a real-valued number between 0 and 1, and represents the *intrinsic preference* of agent *i* to display a certain behavior (i.e., to pick a number between 0 and 1). Agents' intrinsic preference is sampled from a uniform distribution, and remains fixed over time.
- S_n^i is the set of all the agents that agent *i* sees at time *n*. It includes the agent *i* itself, together with all the other agents that fall in its vision cone. The latter is determined by agent *i*'s current location, and the distribution of paths and barriers in the environment. The angle of the vision cone is set up to 10°, and the radius is determined by either the distance of the agent to the nearest barrier ahead of it or 40 units, whichever is lower.
- σ_n^i is a real valued number between 0 and 1, and represents the *social sensitivity* of agent *i* at time step *n*. It determines how much weight the *preference to conform*, or conformity bias (factor of σ_n^i), versus the *intrinsic preference* (factor of $1 - \sigma_n^i$) have on the agent's

behavior. σ_n^i is determined by the number of agents that each agent can see: the greater the number of agents, whose behavior agent *i* can observe, the greater σ_i^n is.

Agents' *social sensitivity* is defined as:

$$\sigma_n^i = 1 - \frac{1}{|S_n^i|} \tag{1}$$

Equation (1) captures the idea that conformity is a function of the size of the set S_n^i (van Leeuwen & Haun 2014). If agent *i* does not observe any other agent at time step *n*, then σ_n^i is 0.

At step 1 of the simulation, the agents' effective propensity is equal to their intrinsic preference. At any later step, Equation (2) defines the update strategy for agents' effective propensity. This update strategy has two components. The first component is the product of the agent's social sensitivity with the average behavior exhibited by the other observable agents at a given time (i.e., the set S_n^i). The second component is the product of the agent's intrinsic preference with the complement value of the agent's social sensitivity. The resulting strategy corresponds to a social learning rule with the form:

$$P_n^i = \sigma_n^i \left(\frac{\sum_{j \in S_n^i} P_{(n-1)}^j}{|S_n^i|} \right) + (1 - \sigma_n^i) \cdot q^i \tag{2}$$

Equation (2) says that at time step *n* agent *i* observes the behaviors displayed by all the agents in its vision cone. Agent *i* then considers the average (or normal) type of behavior among the agents it has just observed, and its social sensitivity determines the extent to which it is drawn to modify its behavior to conform to what seems normal. Agent *i*'s new effective propensity to display a certain type of behavior is thus determined by combining (adding) the normal behavior to which *i* is drawn, together with *i*'s intrinsic preference, weighted according to *i*'s social sensitivity.

To make this less abstract, imagine again that our agents' behaviors consist in percentages they want to donate to a charity. At a given time, an agent sees four other agents displaying what they want to donate, and the average amount is 0.5 of their income (whatever it is). A group of four agents results in a social sensitivity value of 0.75. Further assume that the agent's intrinsic preference is to donate 0.1 of its income. In that case, the agent's new effective propensity will be to donate (0.75)(0.5) + (0.25)(0.1) = 0.4 of its income.

Besides having preferences, observing others, and modifying their preferences based on social observation, the agents in our simulations could also move in space, though they did not have a destination, and were not constrained to return to any specific location. At each time-step, after updating their effective propensity, agents move a step forward from wherever they were in the environment. Their direction of movement was restricted to one of four right angles (0°, 90°, 180°, 270°), and they moved forward until they hit another agent or a barrier. After hitting an obstacle, agents randomly chose a new right-angle direction.

Given this modeling setup, we simulated agents' behavior, varying the layout and density of their environment, as well as their propensity to stick to the status quo. We wanted to better understand how these variations could produce behaviorally homogeneous populations.

3. Varying the layout of the environment

In our simulations, the environment consisted of black patches representing open areas such as paths or streets, and gray patches representing obstacles for movement and vision, such as buildings and walls. Topologically, all the environments had an underlying torus shape, meaning that in terms of agent movement and vision, the environment wraps horizontally as well as vertically.[1] We studied four types of environments with different distributions of paths and barriers (Figure 1).

Empty space: As a baseline, we considered an empty space without any barriers. Since there are no obstacles, agents have maximal visibility in an empty space environment.

Regular grid: The second environment we studied is a regular grid with paths width of 3 units and square blocks of size 10 units; geometrically, no path is more or less central than any other. In terms of agents' visibility, there are two cases to consider. If an agent's direction of movement is parallel to the path the agent is on, or the agent is in an intersection of paths, then the agent has maximal visibility, being able to observe all the agents ahead on the same path. If an agent's direction is perpendicular to the path the agent is taking, then the agent's visibility is restricted to at most 3 units (the width of the path), and so the visibility is much lower.

Grid with street hierarchy: This third environment is a modification of the regular grid, inspired by the notion of street hierarchy from urban planning (Marshall 2004). We designed it by adding

[1] An alternative to the torus is a bounded box environment, or a (horizontal or vertical) cylinder. We choose not to employ these environments, as they can be seen as special cases of a torus with a fenced perimeter. Further, a torus environment does not presuppose the existence of a center and border area. No patch in the environment is special. The construction of a human environment as a torus was considered by NASA for the purposes of space settlement (Johnson & Holbrow 1977).

further blocks to the second environment so that it includes two primary, perpendicular paths, and four quarters containing secondary paths. Each quarter has one entrance and exit point somewhere along the two main paths. In terms of agent visibility, on the main paths agents have maximal visibility when heading parallel to those paths; but visibility reduces inside each quarter.

Irregular plan: In this fourth environment, gray blocks are distributed randomly to form an irregular layout. At each run of the simulation, a unique instance of an irregular plan is created using a P(gray) parameter, representing the probability that a given patch on the environment will be a gray block. In the base model P(gray) is set to 0.25. The greater the value of P(gray) is, the lower the agent visibility will be in such environments.

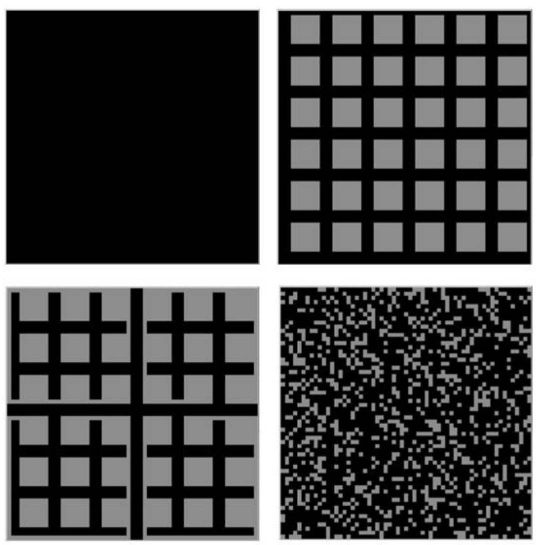

Figure 1: The empty space (top left), the regular grid (top right), the grid with street hierarchy (bottom left) and an instance of the irregular plan (P(gray) = 0.25).

3.1. Results

We simulated agents' dynamics in each of the four environments 50 times, where each simulation terminated after 50 steps. The distribution of agents' effective propensity stabilized after around 10 steps in all four environments we considered. At the end of each simulation, we recorded the effective propensities of the 500 agents in the simulation.

In Figure 2, for each of the four environments, we plot the distribution of the effective propensity of every agent in the 50 simulations of those environments–thus, each histogram contains 25,000 data points. While the final distribution of effective propensities in all environments tends to be symmetric and unimodal peaking at 0.5, the different environments result in different distributions.

In the empty space, the effective propensity of all agents centers around 0.5, with no agents exhibiting other values. This corroborates the idea that conformity-based learning in an environment without any visual blocks results in one universally shared descriptive norm, and behavioral homogeneity. In the regular grid, the effective propensity of a majority of agents centers around 0.5; but every value of effective propensity is represented by a small number of agents. These are the agents who are not facing a main path, but a wall. The grid with path hierarchy and four quadrants led to a distribution of effective propensities more spread out than that in the uniform grid, resulting in less behavioral homogeneity. Finally, in the irregular environment, we see the largest spread in effective propensity, and so the least behavioral homogeneity in the population, which is likely the result of multiple, random obstructions each agent faces in such an environment.

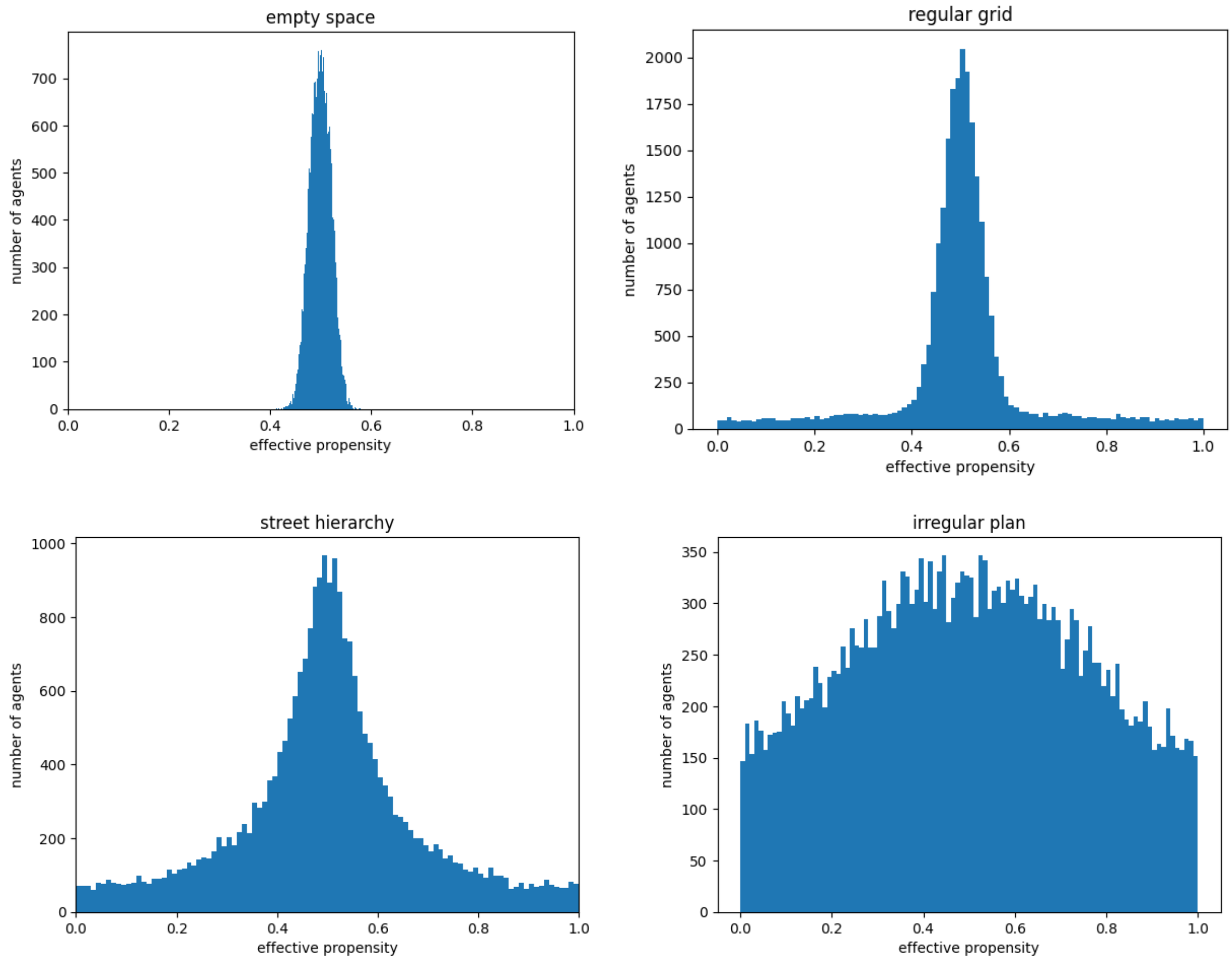

Figure 2: Distribution of effective propensity among agents in the four environments

The standard deviation among the effective propensity of a group of agents can be used as a simple measure of the degree of behavioral homogeneity of that group: the greater the standard deviation, the more behavioral diversity the group exhibits. In Figure 3, we plot the standard deviations of every run of our simulations, arranged by environment type (each swarm of points contains 50 points). Like Figure 2, we see a clear ordering of the environments based on the standard deviations of the effective propensities. Note that at the start of each simulation, the effective propensity is determined by the agents' intrinsic propensity, which is uniformly distributed and therefore has a standard deviation of 1/√12 ≈ 0.288 (marked as a dashed line). None of the simulations remained at that level.

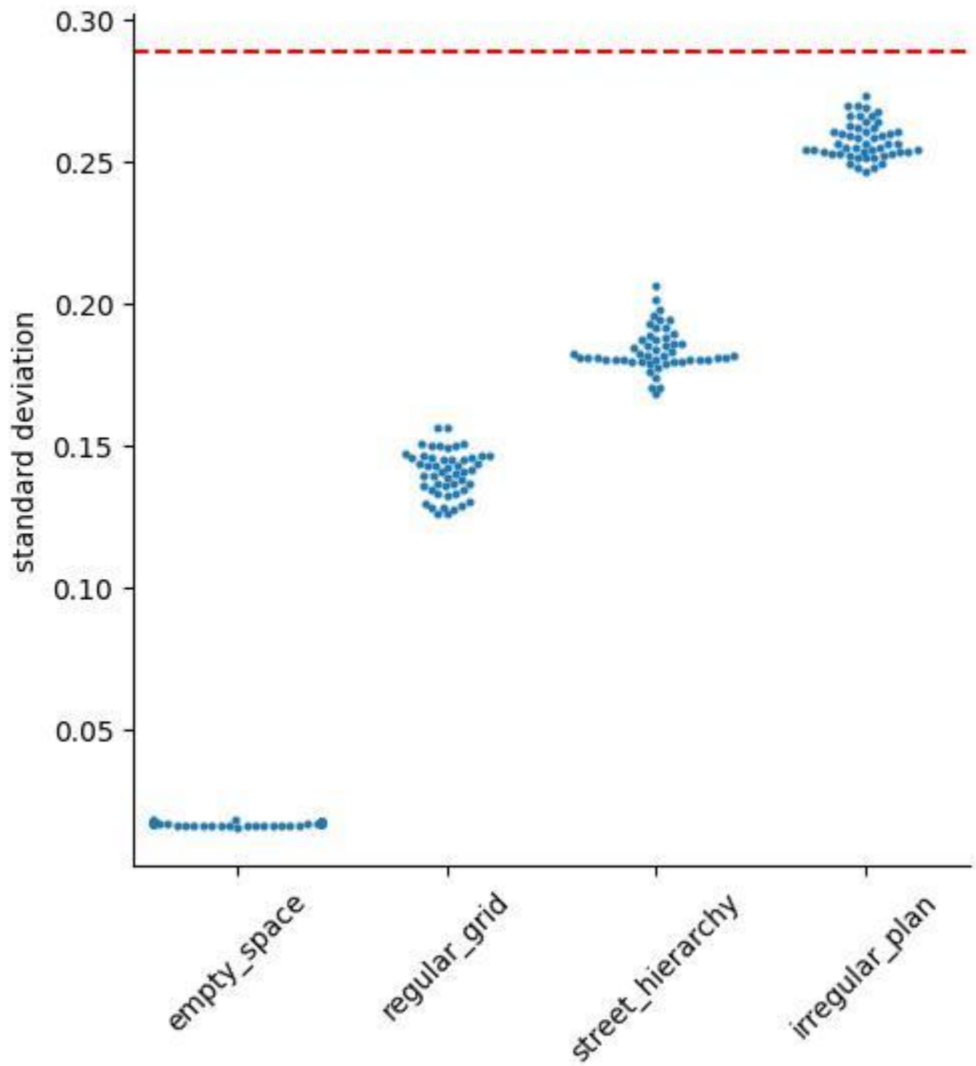

Figure 3: Standard deviations of effective propensity after 50 steps (50 runs for each environment)

Overall, then, this first set of simulations show that the geometry of the four different environments that we examined constrained conformity-based learning, with the more irregular layout limiting the emergence of a behaviorally homogeneous population.

4. Varying population density

Density is another potentially crucial factor for clarifying the relationship between environmental layout and conformity-based learning. Population density is measured as a ratio of the number of agents relative to the space they occupy–for instance, the number of people per square kilometer. It is natural to ask whether population density is correlated in some simple manner with the outcome of conformity-based learning.

In our model, we can measure population density as the ratio of the number of agents to the number of walkable, black, patches (see Figure 1). The results from our first set of simulations are by themselves informative about density. The number of walkable patches in the empty space environment, the regular grid environment, and the path hierarchy environment, is 3721, 1957, and 1685, respectively. The average number of walkable patches in the random environment with P(gray) = 0.25 is 2790.75. Thus, the results presented in Figure 3 already suggest that the standard deviation of the effective propensity in the population is not linearly correlated with density. The empty space is the least dense but exhibits the lowest standard deviation. The density of the irregular environment is between that of the empty space and the regular grid, but its standard deviation is not between the latter two.

To explore the role of density in conformity, in this second set of simulations, we kept the number of agents fixed to 500, and changed the number of available black patches, which determined various levels of population density in the regular grid and irregular environment.

4.1 Results

Figure 4 shows the result of varying the block size in the regular grid on the standard deviation of the effective propensity (each swarm of points depicts 50 simulations with a given block size). When the block size is set to a maximum of 40 units, the environment consists of four intersecting paths and less walkable black patches than agents. In this environment, standard deviation drops. So, in an environment with a grid plan, extreme density boosts conformity-biased learning to rapidly produce homogeneous population behavior.

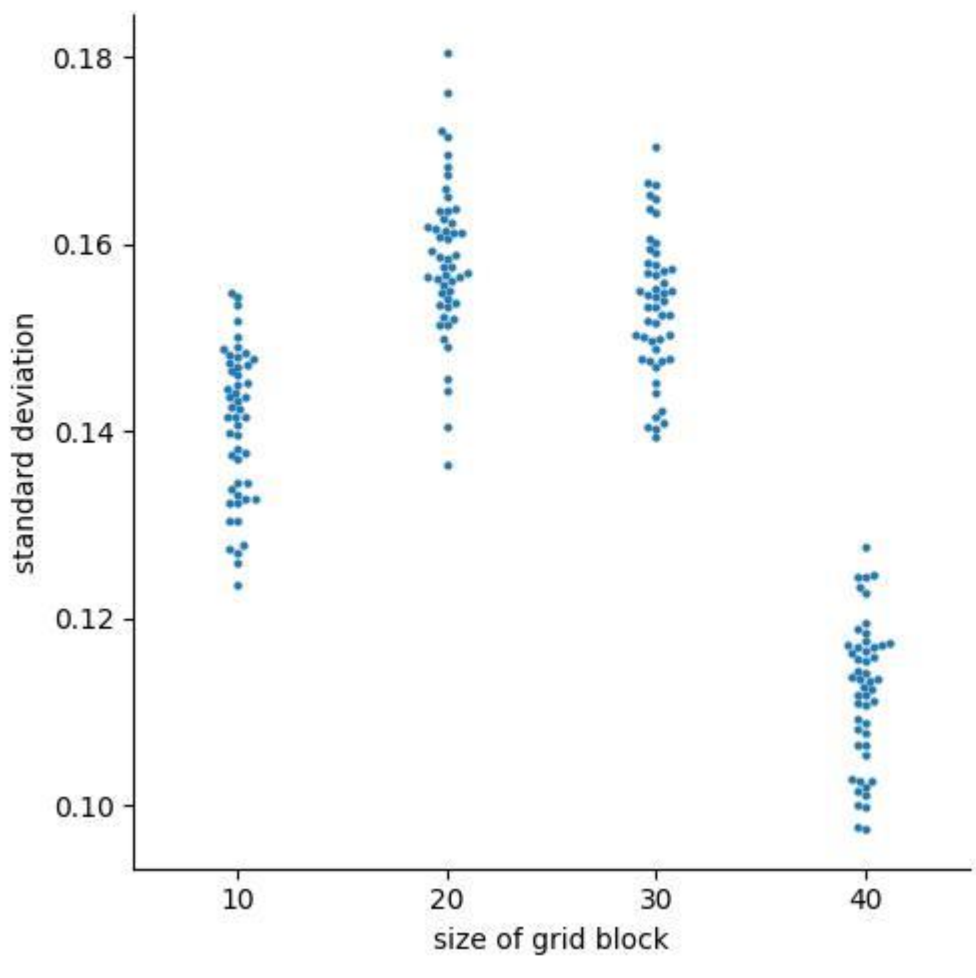

Figure 4: The result of varying the block size in the uniform grid

In Figure 5, we see the results of varying the probability of gray patches in the irregular environment. We took P(gray) = 0.45 as a maximum limit, because we noticed that with values above 0.5, the random environment divides the agents into "islands" of black patches and does not facilitate movement. The results in Figure 5 suggest that higher density leads to higher standard deviation, and so lower homogeneity in the population. Therefore, our simulations suggest that density by itself is too crude as an indicator for when conformity could result in behavioral homogeneous populations following only one descriptive norm.

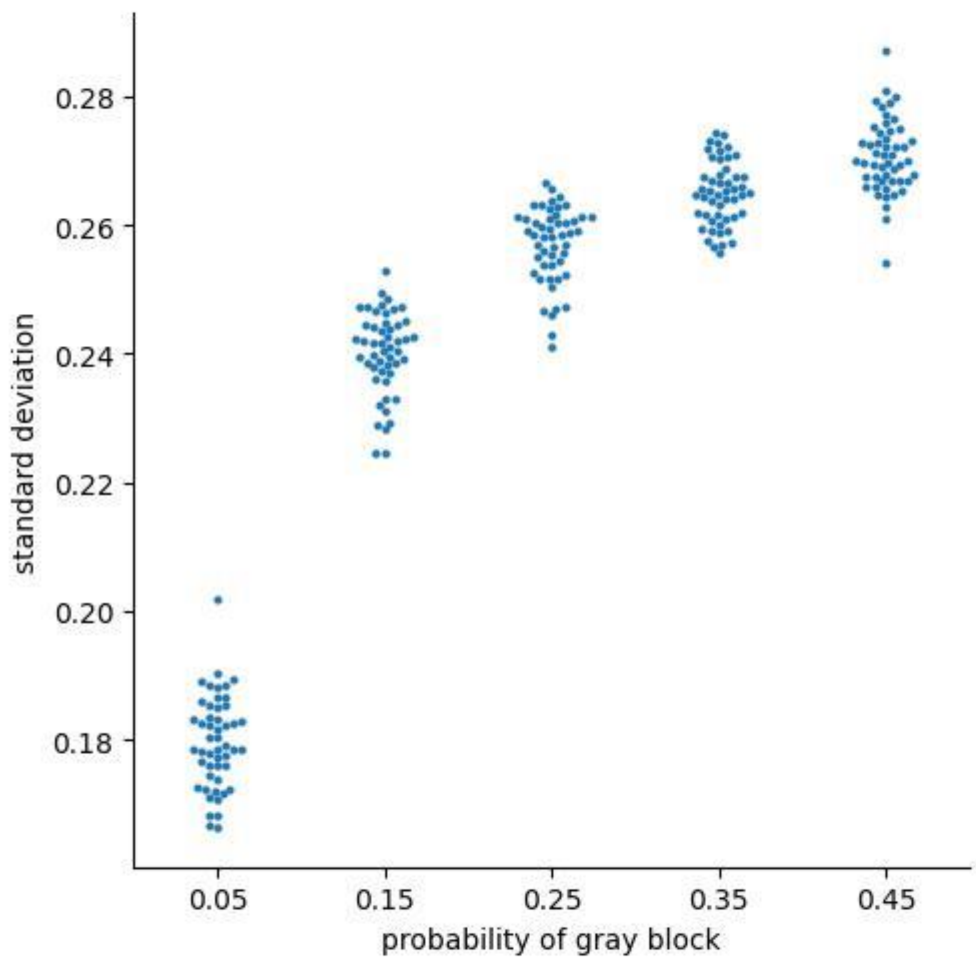

Figure 5: The result of varying the probability of gray blocks in the irregular environment

5. Varying agents' status quo bias

The idealized agents in our simulations have a very rudimentary psychology. They are insensitive to possible consequences of their behavior; they have no goals, memory, attention, and emotion; they display no other psychological bias than a conformity bias.

One odd consequence of these idealizations is that if an agent cannot observe any other agent at a certain point in time, then the agent's effective propensity will immediately align with the agent's initial intrinsic preference. For instance, suppose that agent 0 hits a wall in step 10 of the simulation. Since the agent is in front of a wall, it does not see any other agents. In other words, $S_{10}^{0} = \{0\}$. This implies, by equation (1), that the agent's social sensitivity at that step, σ_{0}^{10}, is 0. By equation (2), this implies that the agent's effective propensity is going to be equal to the agent's intrinsic preference.

This behavior is grossly unrealistic of actual learning agents for at least two reasons. First, in practice, the moment I move from a situation where I see people to one in which I do not see people, I still remember that people are around me, and that I am potentially being watched. Second, a common idea about human psychology–going back to at least David Hume, and well supported by empirical evidence–is that humans, and living agents too, are governed by forms of psychological inertia, preferring to engage in habitual status quo behavior unless motivated to do otherwise (Samuelson & Zeckhauser 1988).

As a simple way to accommodate these considerations in our model, we added a learning rate parameter α (ranging between 0 and 1) to the update rule in equation (2), resulting in a social learning rule captured by this equation:

$$P_n^i = \alpha(\sigma_n^i \left(\frac{\sum_{j \in S_n^i} P_{(n-1)}^j}{|S_n^i|} \right) + (1 - \sigma_n^i) \cdot q^i) + (1 - \alpha) P_{n-1}^i \tag{3}$$

For simplicity, we assumed that the learning rate α was constant across all agents and all timesteps. When α =1, equation (3) is equivalent to equation (2), and when α = 0, none of the agents change their effective propensity. When α = 0.1, agents do change their behavior, but are strongly biased toward the status quo. Equation (3) hence offers a straightforward way to include a status quo bias in our agents' psychology.

5.1 Results

We simulated the grid environments and the irregular environment (with P(gray) = 0.25) with a learning rate of 0.1. We ran 50 simulations for each of the two environments, running each simulation for 100 steps. Even with a low learning rate, we observed that all models stabilized well before 100 steps of any simulation. The resulting effective propensity distributions are depicted in Figures 6 and 7. Consistently with our two previous sets of simulations, an irregular environment facilitates the emergence of a behaviorally diverse population, while the grid leads to a homogeneous population.

Both figures show that a low learning rate (or strong status quo bias) eliminates effective propensities outliers. In a regular grid environment, with the 0.1 learning rate distribution, almost all agents fall between 0.2 and 0.8 effective propensity; while in the 1 learning rate distribution, we see agents of all types of the effective propensity spectrum, though the vast majority still display the same type of normal behavior. The extreme values of Figure 7 show a broadly similar pattern. So, the joint effect of a status quo bias and conformity can counteract the preservation and spread of extreme preferences in a population in the long run.

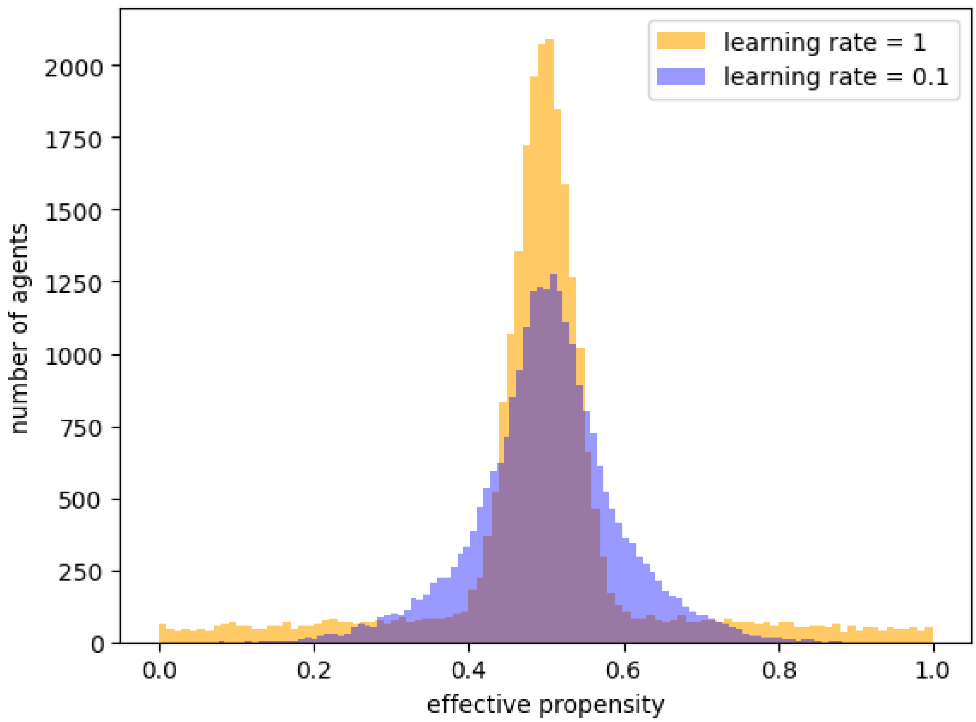

Figure 6: different learning rates in the regular grid environment

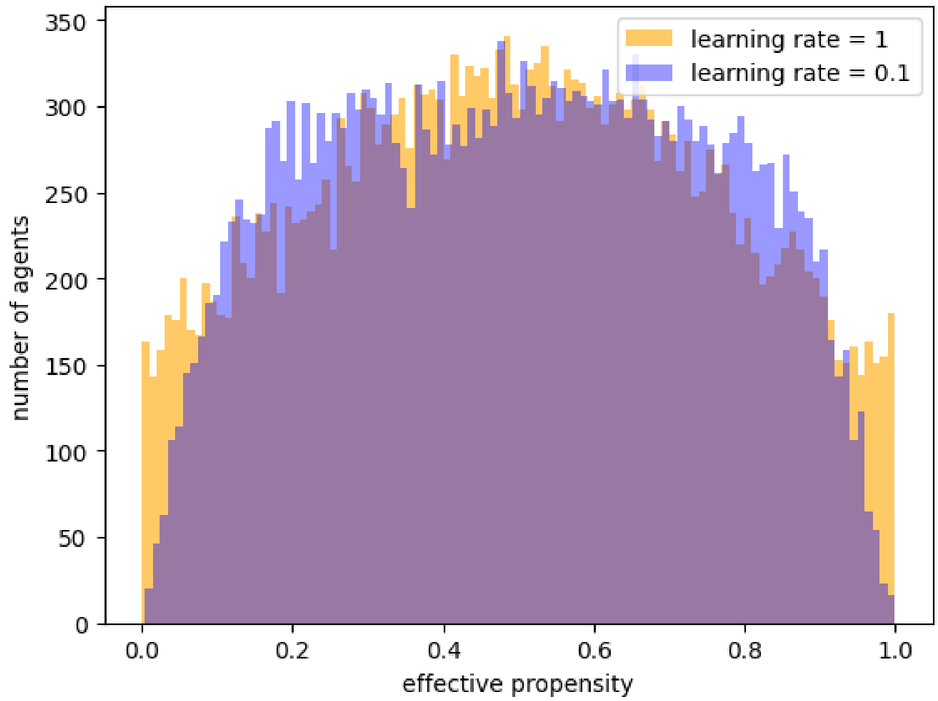

Figure 7: different learning rates in the irregular environment

6. Discussion

Our modeling setup includes many idealizations. But our simulations demonstrate that the geometric layout of the environment can strongly channel social learning, constraining the emergence of universally shared descriptive norms in a behaviorally homogenous population. This constraint depends on whether one can repeatedly observe other individuals displaying a certain behavior, which is in turn constrained by the distribution of barriers and paths in the learning environment. Overall, then, the results of our simulation are consistent with the *spatial determinism* hypothesis that "people's agency and subjectivity are shaped and determined by the spaces they are in" (Kukla 2021: 13). More specifically, our simulations show that conformity-biased social learning taking place in environments with a regular grid plan is likely to produce homogenous populations, where everybody follows the same descriptive norm; instead, learning environments with an irregular plan promote more behavioral diversity. This result is robust to variation in the density of the environment, and the psychology of our model agents.

Our study complements existing modeling work on epistemic dynamics, where conformity-biased social learning has been studied in the context of communication networks (Weatherall & O'Connor 2021), and cognitive and demographic diversity (Fazelpour & Steel 2022). In this modeling approach, information exchange between agents occurs in simulated communication networks with different topological structures (Zollman 2013). Our study complements this approach, as information exchange in our simulations occurs in environments with different plans, where agents can move through paths, bump into barriers, and observe others.

Weatherall & O'Connor (2021) found that conformity has a negative influence on the epistemic performance of a group. Fazelpour & Steel (2022) qualify this result by showing that demographic diversity in a group can counteract epistemically negative influences of conformity. Our own results do not directly address questions about group epistemic dynamics; but they can add nuance to such questions, by highlighting that the pattern of barriers and paths in an environment can constrain conformity-biased social learning to produce multiple descriptive norms associated with behavioral diversity in a group. To the extent that conformity does not always produce a behaviorally homogeneous group, conformity need not always have negative epistemic consequences. In any case, it would be interesting to incorporate insights from urban planning and architecture in models of epistemic dynamics such as Fazelpour & Steel's (2022) and Weatherall & O'Connor's (2021).

Finally, while in fundamental agreement on how a descriptive norm can emerge in a population, our results extend Muldoon et al.’s (2014) modeling framework, not only by focusing attention on the role of geometry on social learning, but also by considering non-binary, non-discrete choice behavior. Muldoon and collaborators offer the case of standing ovation as a helpful stand-in for many descriptive norms, including everyday descriptive norms of fashion, etiquette, music taste, and personal space. But these latter descriptive norms do not involve binary choice options like the case of standing ovation, where one can either stand up or stay seated.

Consider, for instance, one of Muldoon et al.’s examples of an everyday norm of fashion like wearing a skirt of a certain length (2014: 4). This example concerns a non-binary, continuous choice variable, like the length of a piece of clothing, which may be better captured in our modeling setup, where agents’ effective propensity is about behavioral options representable on the unit interval. Above we alluded to another example, which might be more adequately captured by our modeling setup, namely: the decision to donate a proportion of one’s income.

So, our study contributes another simple, though highly idealized, framework for investigating the emergence of many everyday descriptive norms with no inherent desirability, based on the dynamics of a population of agents with preferences and basic capacities for conformity-biased social learning, social observation, and movement in an environment with a specific pattern of paths and barriers.

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