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Patterning Behavior to Exploit Space: Extending Morphological Theory Through Agent-Based Simulation of Learning and Selecting Behavior in Space

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ABSTRACT

In recent years, space syntax researchers have explored agent-based simulation techniques as one profitable approach to modeling spatial behavior. Agent-based models generate complex behavior from the simulated interaction of individual agents operating with an imperfect knowledge of their environment, and so make it possible to fine-tune the conditions under which some desirable behavior may develop. We offer an approach that uses agent-based simulations to extend current syntactical theory about the role of space in shaping interactions and behavior of occupants in settings of low occupancy and movement constrained by programmed activity, in which the usual system level correlations between syntactical variables and observed patterns of interaction and movement do not apply. Such cases, we argue, need a finer grained theory built upon the way spatial configuration can shape individual behavior by exposing the agent to specific patterns of stimuli.

We construct a simulation to study how a single agent's navigational behavior is shaped by space, focusing in particularly on how and when stability in its behavior is reached as it gains information about the environment. We find that an agent programmed for the simplest molar learning behavior of bottom-up learning is able to reach stability even under conditions of dynamically varying environmental stimuli, but that this behavior is not consistent across repeated trials of the learning behavior. The results indicate some specific directions in which additional specifications ought to be added to basic behavior in order to match the consistency seen in real-life movement behavior; these include models of explicit decision-making by agents in response to patterns of exposure, and models for development of individual and social norms. Models that mix such top-down decision making with bottom-up learning processes may help answer some long-standing question about observed associations between space and behavior.

KEYWORDS

Agent-based simulation, behavior, spatial cognition, methodology, theory-building

1 INTRODUCTION

Agent-Based Simulation is a type of simulation involving independent, autonomous agents capable of interacting with each other and the environment surrounding them. ABS is particularly useful to model systems that consist of a number of independently acting components, but in which the system level behavior cannot be described by simply combining component behavior in some analytical or closed-form expressions, or if it can be so, the computations become impractically resource-intensive. A distinguishing characteristic of such system is that of emergence—that is the presence of system-level behaviors that do not exist at the level of individual components. One of the natural applications of these systems is to study social behaviors that develop as the consequence of interaction of several independently acting individuals—agents—in a given environmental setting.

Several features of human actors—agents within the simulation—make ABS especially valuable for studying social phenomena. The behavior of human actors is characterized by independence of purpose, by possession of individual reasons (that is, beliefs and pro-attitudes) towards an action, and by an ability to change purposes and reasons according to changes in their environment, or in their internal psychological conditions. All these traits can be incorporated into ABS systems (Pellegrini *et al.*, 2009; Fuchs and Neumayr, 2019)

Another distinguishing feature of ABS is its conception of agents as possessing a limited and local knowledge of their environment. Within ABS it is possible to vary the agents' level of knowledge of the environment and to investigate differences between giving them local knowledge or global knowledge. This allows us to model behavior of agents under the condition of bounded rationality, that is, a condition in which agents make behavioral decisions based only on what they can immediately perceive, or what they have learned through previous experience. The important characteristic of bounded rationality is that the agents do not always end up with the best choice, but the best choice within their experience, and with the limited information about the space.

With these characteristics, several areas in architecture have introduced ABS into their analysis. In building emergency evacuation simulations, ABS is used to detect the bottleneck or identify any risk factors in the built environment (Tan, Hu and Lin, 2015); to simulate the spatial occupation patterns with ABS combining with crowd simulation, spatial statistics, and computer graphics tools (Fuchs and Neumayr, 2019; Neumayr, 2021); and lastly, ABM has been used to simulate pedestrian movement in urban layout and building layouts (Penn and Turner, 2002;

Hanna, 2021) and, in some cases, modeling human tracking dynamics at the same time (Pellegrini *et al.*, 2009).

But in addition to these practical aims, ABS is also a promising tool to develop theory by explicitly using theoretical ideas to generate phenomena, for instance, by creating patterns of movement that emerge through interactions between agents and the environment. This emergence is not predictive, but rather explanatory. That is, phenomena are not created to replicate the real phenomena precisely, but rather to explain the principle generating them. Simply reconstructing the phenomena and having the same results is not enough to say the phenomena are explained completely but can be an effective method to pose a theory behind the phenomena (Epstein, 1999). We begin by reviewing work on ABS within space syntax.

2 ABS IN SPACE SYNTAX

Space syntax researchers have explored ways to bring ABS into syntactical studies. One interesting direction has been to use space syntax as an input in order to improve simulation of behavior, with much of the work focusing on navigational behavior and wayfinding. An influential early attempt in this direction was produced by Penn and Turner (2002). They took up the problem of simulating the pedestrian behavior in a retail environment by giving individual agents the capacity to access information from VGA analysis of the environment. The assumption was that access of a number of independent agents to the same environmental knowledge would co-ordinate their movement producing aggregate patterns determined by space rather than individual volition; the simulation had partial success (using a simple “random next-step” rule, they were able to explain at best 56% of the variation in observed pedestrian behavior), but given that the agent behavior was driven exclusively by local visibility metrics, their exercise highlighted the importance of spatial configuration in shaping behavior at an aggregate level. Varoudis (2012) furthered this idea by giving the agents ‘field of vision’ that provides and limits the visibility of the agent in given point; and ‘assisted standard look’ has been introduced to bring in the idea of navigation in a convex space (Koutsolampros and Varoudis, 2017). In both cases, the agents were able to attain the local visibility information only after they arrive at the point. In 2009, Jiang and Jia presented work to demonstrate that agents programmed to move on a graphical representation of an urban street network would create distribution data highly correlated with observed behavior, if they were programmed to move by selecting nodes using a weighted PageRank metric rather than the traditional syntactical metrics for the nodes. More recently Hanna (2021) has shown that ‘random walks’ functioning with local visibility are enough to develop distribution of movement in agents that match those seen in urban environments. He reports correlations in the range of 0.7-0.8 between their models and observed behavior, thus explaining about 50-55% of observed variation.

In all these exercises, agents were only given access to local environmental knowledge and not given any independent purpose or distinguishing behaviors and not any memory. Their aim has been to search for increasingly better descriptions of underlying processes by which the movement of individual agents is shaped, without their awareness, by spatial configuration. However, these approaches may not be equally productive in all situations. In sparsely populated settings like office floors, for instance, these models developed for capturing aggregate patterns may not produce estimates of fine-grained behavior at specific locations with the required accuracy. For such settings differences in individual motivations or tasks may become stronger factors in shaping movement through the settings. Naturally, movement in such settings will depend on the specifics of each case, but we believe that there is still some underlying theory to be understood that shapes individual route choices and propensities to move based on stimuli from spatial configuration. Such a theory would include learning behavior as individuals both gain knowledge of the configuration of the environment and learn to adapt to dynamic conditions such as presence of other people. It would also include a general understanding of how the configuration of space can distribute stimuli both across the setting and in time, and the patterning of these stimuli can lead to systematic changes in patterns of behavior in the setting.

This is the line we develop in this paper, although our aims for the moment are limited in ambition. Our approach is to exploit a central ability of agent-based models in exploring this theory—that is, the ability to create limited experimental simulations that can explore the effects of specific theoretical ideas. The ideas that we will explore here are not precise theoretical propositions—current theory is not well developed for that—but are set-ups of specific configurational situations. The ambition behind the experiments, then, is not so much as to test theory as to generate phenomena (cf. our description of ABS in previous section) that can be explained by the specific configurational conditions that we set up.

3 MODELING INDIVIDUAL BEHAVIORS FOR AGGREGATE BEHAVIORS

A central issue that has dogged space syntax is the lack of precise understanding of how individual behavior aggregates into predictable system level behavior. The central point of contention is that individuals can be aware of local properties, and in particular, properties captured in the isovist, but the aggregate behavior seems to be predicted by metrics like integration that require a configurational understanding of the entire system. Issues about the success of the axial line map as a predictor, and about the *reason why* integration as a measure is more closely associated with movement are one instance of how such concerns have been debated within the literature (Hillier et al., 1997).

It is not that there is a lack of study of individual level behavior within space syntactical literature. Wayfinding studies, in particular, have tended to focus on the analysis of individual behavior (Peponis, Zimring and Choi (1990) for a classic example, Barton, Valtchanov and Ellard (2014) for more recent work outside space syntax), as have studies of visitor behavior in museums (Dalton (2003) for an example of an early study). But we still lack an understanding of how individuals moving within an environment acquire knowledge of the entire configuration (which in practice requires tedious computational procedures), or even if they do so, how could they put this knowledge into practice (cf. Dalton, Hölscher, and Turner (2012))? The alternative (explored in the pedestrian studies using agent-based models described above) is to just assume that individuals only make decisions based on local knowledge, so that the issue to be solved is what kind of local knowledge produces the closest match to observed data.

This is a thorny problem, but before it can be answered, an underlying assumption needs to be verified. The assumption is in two parts: 1) that individuals who moving in a known environment will develop a *predictably stable* pattern of movement at least with respect to specific movement tasks—say a task of going from one location in the environment to another—and 2) that this stability can arise from a bottom-up process of learning the environment through gradual updating of their knowledge. They may show occasional deviations from this pattern, but the overall behavior over several repetitions must show predictable stochasticity. For if individuals are not able to develop stability it seems very difficult to see how aggregates of several such behaviors could develop predictable patterns, particularly in sparsely populated settings with external constraints on behavior.

In the rest of the paper, we develop an experimental set up to study this assumption. Our approach is to set up a situation in which an individual agent is given some basic bottom-up learning behavior involving as few assumptions as possible in order to see if such specification is enough to generate stable behavior. Then, we set up additional conditions to see what effect spatial configuration can have on the stability of behavior.

4 A DEMONSTRATIVE EXPERIMENT

4.1 Motivation

The specific motivation for the simulation came from the findings from an observational case-study of a newly created office setting, commissioned by the strategic planning office of an academic institution. The office was originally designed to generate a collaborative environment in the form of an open office layout for most clerical workers, with supervisors in their own offices, but separated from the common areas only by large glass partitions. The floor layout of the office was based on two assumptions: 1) open offices would increase interaction amongst the staff, and this in turn would foster a sense of community and 2) if particular areas were located just off public circulation, were furnished to allow informal meeting and gathering, and were given an atrium like character with overlooks at different floors, they would attract staff from different departments to visit and stay and therefore act as “collaboration cores”. One of the purposes of the study was to test if these spaces worked as intended.

Our initial assessment was that these assumptions were not well grounded either in theory or in practice. Open-plan offices do not necessarily generate greater interaction—this point has been observed often (Hatch, 1987; Brennan, Chugh and Kline, 2002), and notably reaffirmed in a recent, widely popularized observational study, which was able to test this assumption causally (Bernstein and Turban, 2018). Similarly, as work in space syntax has repeatedly shown, movement patterns are actually shaped, not by specific attractors in a setting, but by the organization of discrete axes of movement (the axial map) and the integration values of the axial paths have been often found to correlate highly with encounter frequencies (Choi, 1991; Hillier *et al.*, 1993). We expected to confirm these ideas through syntactical analysis and field observations of encounter rates as part of evaluation of the office layout.

Figure 1 Axial map mean depth for the model floor plan (above) and VGA mean depth for the model floor plan (below). The spaces that had lower mean depth and higher connectivity were the corridors connecting the main open workspaces in the bottom. The top corridor also had lower axial mean depth and higher axial connectivity. The open workspaces also had lower mean depth and higher connectivity relative to the enclosed workspaces or the workspaces behind meeting rooms.

However, when we compiled the observational data, we found that the numbers of encounters recorded, as well as the numbers of interactions, were far too small (26 social interactions during

6 rounds of observations in the entire floor plan) to provide any sense of the effects of spatial organization on behavior. One reason for the low numbers was simply the programmatically low occupancy levels of the office. Syntactical studies that report high correlations between integration values of spatial segments and frequencies of encounters are, as a rule, conducted in heavily trafficked settings; sparsely occupied settings do not show the same dynamics as heavily occupied settings (Barker, 1968, pp. 189–94). But the low frequency rates that we found were a result of something beyond sparseness of occupancy. In follow up focus group meetings it was revealed that people deliberately avoided interacting in corridors. In fact, the interactions were evenly distributed between the open office and the enclosed office since the employees visited their supervisor's rooms for meetings. More interestingly, workers had begun to develop norms to avoid active interactions with their colleagues when working in open workspace. They moved partitions towards their seats to avoid being seen by others, and when this was not possible, had developed a practice of wearing headphones and turning away from passages to signal unavailability for interaction. When passing each other, they adopted a practice of not pausing to make conversation in order to minimize disturbance for those working nearby. It was clear that people developed conventions of interaction and behavioral norms as a result of their exposure to space, and those conventions and norms, in turn, mediated the way space influenced and shaped behavior. This point is not new; even in the early years of space syntax researchers were quite aware of the way spatial configuration creates expectancies and behavioral norms as mediators of behavior (Peponis, 1985; further explained in Peponis and Stanstall, 1987).

Our brief and unsuccessful exercise clearly indicates that any predictive modelling of behavior in any setting, and particularly in sparse settings, would need to include the feedback mechanism by which spatial configuration produces behavior that leads to the development of specific norms, which in turn shape behavior further. Some system level analytical techniques such as non-recursive structural equation models can capture aspects of such feedback mechanisms, but only under rather restrictive assumptions. In comparison, the properties of agent-based simulations that we have described above (ability to specify individual level behavioral traits and attitudes) make them just right for this purpose.

The experimental set-up we developed took our site for the observational study above as its setting; we used the layout as given, with occupancy levels and patterns similar in scale, and as we explain later, assignment of behavior conventions for specific scenarios drawn from it.

4.2 Purpose

In order to set up an agent-based simulation to model behavior in sparse settings of the kind we investigated, a preliminary requirement is to set up a basic navigation mechanism for the individual agents. But the current state-of-the-art is rather underdeveloped at the point, and although a number of sophisticated algorithmic approaches can be found in the literature, specific approaches only address particular aspects of navigational behavior. Some address, for instance, the question of efficient path choice (Daniel *et al.*, 2010; van Toll, Cook and Geraerts, 2012), others model variation in navigational speed in relationship to different obstacles (Helbing and Molnár, 1995; van den Berg *et al.*, 2008; Zainuddin, Thinakaran and Shuaib, 2010), but none that we have found so far reproduce human spatial learning and navigational choice behavior. Any specification of an individual agent's navigational behavior that models actual human behavior would therefore need to be built up systematically in a step-by-step manner with the assumptions behind each step being grounded in some theory of behavior and social organization and validated empirically.

As the first step, therefore, we decided to set-up the task of navigating to a particular target in an environment from a particular location in a condition where multiple paths exist. Two main reasons guided this choice. First, this task was defined to have the character of basic *molar* behavior. Molar behavior is often described as the fundamental unit of behavior (Barker, 1968; Rachlin, 1995) and has the following characteristics 1) it is executed in response to a purpose, so that any bodily activity is not behavior 2) it unfolds in interaction with a specific environment, 3) is shaped to minimize effort, and 4) is characterized by docility or learning (Tolman, 1932).

Defining the task as molar behavior ensured that we would not need to make any needless or unsupported assumptions about agent behavior, so could be reasonably confident that the source of instability or inconsistency would be the space within which the agent moved. Second, this kind of behavior is quite typical of human behavior in new environments—encountering a new environment in the hurly-burly of daily active life, a common pattern is to first find a route (say by asking around) to a target, and then update information if another better route is discovered during a second trip, and to do so till most of the routes are learned and perhaps eventually integrated into a single "map." The pattern does not guarantee that the shortest or most efficient route will be found, but it is economical of resources.

We planned to create a set up in which such a basic learning mechanism would operate. Our purpose was to 1) check whether the patterns of choices made by the agent would reach both stability and consistency, and 2) to explore different aspects of space in reaching the desired stability and consistency.

4.3 Implementation

Background Environment and Agent Behavior

The model takes place in a virtual environment replicating the open office environment of our case-study described in section 5.1.

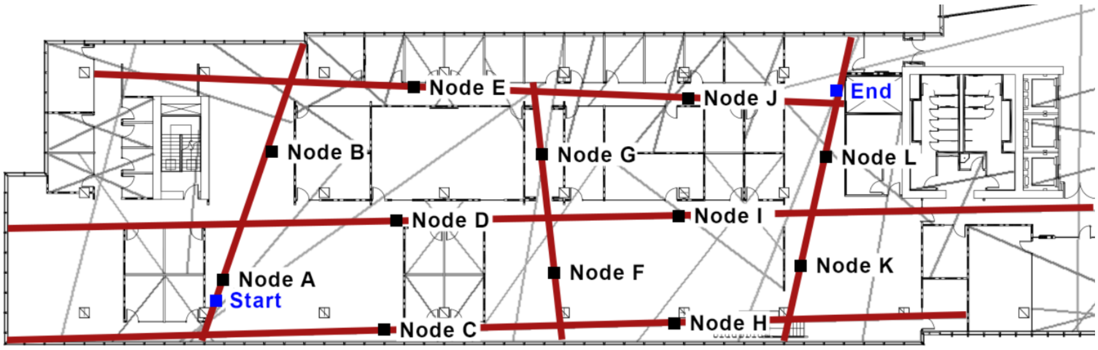

Figure 2. Axial map segmentation and the location of the nodes according to the segment location. The background agents can stay or walk around the setting according to their own schedule.

Within this environment, we set up our simulation of interest to study how a single agent, of the worker class, would develop preferences for specific routes between a pair of a set source (start point) and a target location (end point), as it makes several trips. The start and end points are indicated in the floor plan (Figure 2). Representing the setting as close to the actual office, the model was set up using AnyLogic University edition (Borshchev, 2014), including work areas, meeting spaces, and collaboration spaces.

AnyLogic's pedestrian library provides their own pedestrian navigation logic. The logic is based on solving two distinct tasks—computation of an optimal path and moving the agent through it in a realistic sense accelerating or decelerating to move around fixed and moving obstacles. The first task uses navigation meshes (a partition of the environment into convex polygons that are free of obstacles) and A* search algorithm (van Toll, Cook and Geraerts, 2012) to find shortest path within them. The second uses a variant of Helbing and Molnar's social force model (Helbing and Molnár, 1995; Zainuddin, Thinakaran and Shuaib, 2010). Two characteristics of this logic made AnyLogic particularly suited to our purposes. The first is that the navigational mesh method, originating in the problem of creating navigational behavior for virtual characters in games, is designed to efficiently find a visually convincing path, but does not always guarantee a mesh that will ensure that the shortest possible path is found—this condition is especially true when the environment grows in complexity. The second is that shorter path may not always be associated with least traversal times, since the number of turns and encounters with other moving obstacles can slow down the speed of a moving agent. Together, these characteristics give us the desirable conditions for our set-up: we can rely on the agent to navigate short distances quite consistently favoring shorter times, but we could explicitly construct the logic for finding of appropriate paths for longer distances according to different criteria for testing assumptions.

The actual path that the agent travels is continuous, but the route choices were discretized by segmenting the routes at junctions where alternative directions of movements are available, and then treating each segment as a node. This discretization is partially like that of the axial line graphs, except that, in this case, segments that are in a straight line are not collapsed into a single node. We did not want to build turn-minimizing quality explicitly into our model, but let it emerge as a result of the basic principle of effort minimization. Recall that the social force algorithm slows the agent down as it goes around corners.

The result is that the route taken by the agent is reduced to a sequence of nodes of a graph (Point A-L in Figure 2). Each node has a degree of at least 3 (that is, it leads to at least two other nodes) and so requires the agent to make a choice of nodes for each step. Certain constraints are added to the way agent travels. It can only progress forward; for instance, referring to Figure 2, from node F, the agent can only choose between nodes G, I, or H, but cannot move backwards to node D or C. We are aware that backtracking is a well-known feature of human navigation and spatial learning, but to have allowed it in our model would have required us to also specify a more complex learning behavior according to which the agent would gradually learn where it had been through repeated trips. As we discuss later, this kind of behavior requires assumptions about the effects of temporally patterned stimuli. Such behavior should eventually be built into a model that captures the full complexity of human spatial navigation, but at this point introducing this element into our model would detract from our interest in testing the extent to which the basic learning behavior could generate stability.

Outcome Measurements

We measure outcomes by two statistics: 1) the frequency by which an agent passes through a node over the course of 100 trips that constitute a trial run of our model, and 2) the probabilities of selection that the agent assigns to the nodes that can be reached at each step as it traverses a path. At the beginning of each trial, the probability to select one of the nodes over the other is equal (i.e., if the next step has a choice of three nodes, each node has 1/3 chance to be selected.), but as the model progresses, the probability given to each node is adjusted to establish differential preference, keeping the sum for each all nodes at a step equal to 1.

The agent makes repeated trips keeping track of time taken to traverse a particular path; if the next trip happens to take lesser time than the previous one, the agent increases the relative probability for each of the nodes traversed through the second trip. At first, the ‘weights’ for selecting each node is 3, and the agent adds a weight of 5 to the node if the travel took lesser time than the previous one. The probability is calculated by the assigned weight to the node choice by the total weight of all the selectable nodes from that node. Since the probabilities of disfavored nodes after adjustment are not zero, a third run is not certain to simply repeat the trip of the last shortest-time trip. The non-zero probabilities of choices of disfavored nodes can be taken to represent contingencies or even “curiosity” and are set to enable the agent to explore other routes. The process is repeated for 100 trips. Thus, one ‘trial’ concludes with the node preferences established after 100 trips. We report below outcomes from 100 trials of 100 trips each.

Four Scenarios

With this behavior specified, we set up four scenarios to be tested. The first one consists of a straightforward quickest route-finding trial. This is essentially a benchmarking scenario. We then add conditions that bring different aspects of space into play. The goal is to explore how different attributes of space may influence learning behavior.

In the second scenario an additional condition is introduced: the agent is now aware of the other people around them and adjusts its preferences to avoid crowded corridors. In order to construct this scenario, we introduce a secondary, background, simulation into our model. 40 background agents of two classes, supervisors (6) and workers (34), occupy the floor for a specified time-period, and conduct basic activities: arriving at their workstations or offices, spending time there, going for meetings that occur with varying degrees of frequency, taking breaks to visit some common areas, and finally traveling back to the elevator core to leave. This secondary simulation is derived from actual occupancy observed during our observational study reported above. The role of these background agents is to provide an environment with moving people, creating conditions of encounters that are roughly similar to the actual office environment, and to provide social settings (number of people) in which agents will use to navigate in the second scenario.

The agents are programmed to be averse to conditions of denser occupancy—a behavior that was observed in our study. When the agent encounters more than four people within 5-meters radius from each node, it reduces the probability assigned to it. The preferences for particular paths are therefore disturbed by temporally stochastic stimuli. The intention behind this scenario was to explore the extent to which behavior can be shaped in space not just by static relational aspect, but also by its secondary dynamic aspect—that is, behavior is shaped not simply by the way discrete spaces connect to each other but by patterns of behavior of others that are induced by space itself. We expected that agents in this scenario to reach stability later and to show greater variability between trials as compared to the benchmark of the first scenario.

In the third and fourth scenarios, another criterion for selection is added: the agent is now programmed to react differently to a specific sub-set of co-occupants. It seeks to minimize its exposure to the supervisors' field of view—a behavioral convention that participants in our observational study actually reported. When the agent counts more than four occupied supervisor seats within 5-meters radius from each node, it reduces their probability of selection in comparison with nodes that had lesser supervisor seats. These scenarios were introduced in order to test the effects of stimuli that are not only distributed in time, but are patterned differently in space. In the third scenario, the supervisors are placed along a single corridor, and the fourth, they are scattered throughout the office floor. The conditions for setting preferences for each scenario are summarized in Table 1. Our expectation was that the additional constraints on choice would reduce the overall variability in node traversals in scenario 3, but not in scenario 2, as compared to scenario 2, but not in scenario 4, and also that the number of trial required to reach stability would be higher in scenarios 3 and 4 as compared to scenario 1 but we were not sure how this would compare to scenario 2.

Table 1: 4 scenarios of the model and its conditions

	Scenario 1	**Scenario 2**	**Scenario 3**	**Scenario 4**
Condition 1: prefer routes that take shorter time.	X	X	X	X
Condition 2: prefer routes that have fewer people around.		X	X	X
Condition 3-1: prefer routes that are further from supervisor seats. (supervisor seats are concentrated)			X	
Condition 3-2: prefer routes that are further from supervisor seats. (supervisor seats are scattered)				X

4.4 Results

Frequency data give us a first insight into the patterning of movement of our agent induced under the four scenarios. Figure 3 shows box plots of total frequencies of traversals recorded over the course of 100 trials at each node; means are noted by crosses.[1] The benchmarking scenario shows a much higher traversal frequency for node J over H and I. and lower for nodes F, G, and much higher for L over K. The agent frequented longer corridors along the length of the floor plan and made fewer forays into the shorter crossing lines, except at node L. These data are consistent with a behavior that seeks to favor straighter lines and quicker traversal times between nodes. What was unexpected, however, was the difference of frequencies between trials. For most of the nodes, the interquartile range was very large (between 25 and 30); consistency between trials was clearly not a characteristic of agent behavior.

[1] In what follows, we use median and interquartile values to characterize the observed data, not means and standard deviations. This is because, having observed the results, we are doubtful if our trials represent a stochastic process with identical parameters. Another issue is that our results consist of truncated data with no values possible over 100 or below 0. It is possible that some beta distribution would be a good characterization of these kinds of data, but our interests for the moment are simple enough to be satisfied with non-parametric descriptors. It should also be noted that although these numbers are frequencies, they are best interpreted as fractions.

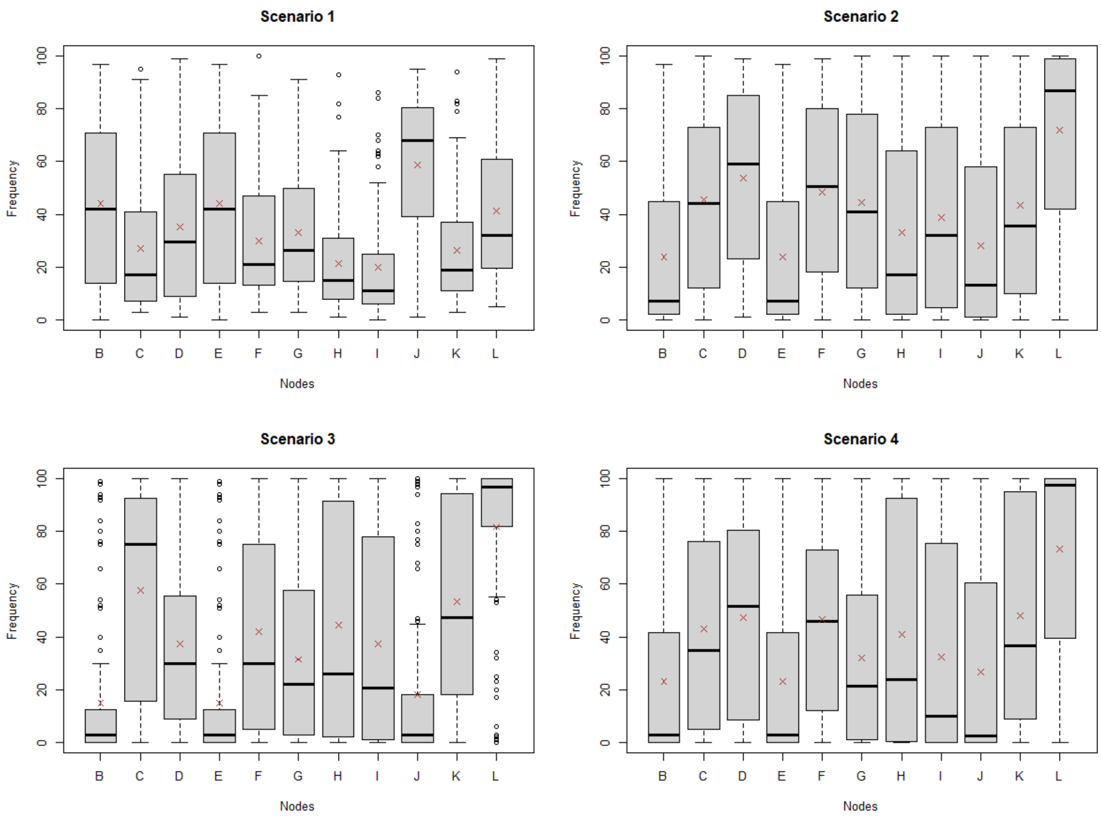

Figure 3. Box plot of the distribution of the frequency of the node usage and its mean (red x) for all trials in each scenario. Node A frequencies are not reported since they are always found to be 100.

The introduction of the background simulation in scenario 2 clearly changed preferences, and this was as intended. Agents now had lower propensity to traverse nodes B and E, both located in higher occupancy areas, with the result that downstream traversals of nodes H, I and J were more equally distributed between them. The variance of traversal frequencies was even larger in this scenario—note the much higher interquartile range across all the nodes. The increase in variance in comparison to scenario 1 was as hypothesized, given that there was now a built-in variation between trials, but the size of the spread was still unexpected.

Apart from the high spread, observed data from scenario 3 were as expected too. The increased probability of encountering supervisors on corridors E and J depressed traversals through them as well as through B; note particularly the difference in the traversals of J between scenarios 1, 2, and 3. The distribution of supervisors throughout the plan in scenario 4 restored the balance back to those nodes, again as hypothesized, but in an unexpected way. The interquartile range of traversals of B, E, and J are much larger, indicating several trials in which they were traversed with higher frequencies in scenario 4 as compared to scenario 3, but their medians in both scenarios are remained stubbornly similar. That the distribution became more spread, but the median did not could well be due to the patterns of occupancy rates of supervisors across different trials.

How did the agents' recorded preferences change over time? The figure 4 below plot records of probabilities assigned to node pairs (that is, probabilities assigned to a node with respect to a specific prior node)[2] as the number of trips taken increase in one of the models. The plots begin at the extreme left at either 0.5, or 0.33, and then shift as the agent updates its preferences after each trip. In scenario 1, preferences for almost all nodes stabilize in less than 30 trips, except for node pairs A-B and A-C.

The unexpected and interesting result is the un-stability that seems to re-occur much later, at about the 80th trip or afterwards. We think this captures an important characteristic of space; if the stability of preference represents some *minima*—that is, a condition in which the agent has found the quickest route—then its shift in probabilities after many trips shows that the minima was only a *local* one, and that over the course of many tries eventually the agent will discover another shorter route. The numbers 30 and 80 for trips at which stability occurs and is disturbed are, of course, artifacts of our set-up. Adjusting the levels by which frequencies are adjusted for instance could alter them, as could the complexity of spatial layout. But the fact that stability occurs and is slightly disturbed again points to a phenomenon we think that has not been adequately thought about in understanding the relationship between space and behavior.

Scenario 2 offers another unexpected phenomenon, but one whose implications seem more difficult to grasp. The effect of adjusting preferences on temporally stochastic stimuli created by occupancy rates is to perturb the preference assignments but not disturb them irrevocably. In scenario 1, agents reached stability in gradual but consistent way; in scenario 2, they do so even earlier (surprisingly at trip 20, but less consistently, so that initially their values fluctuate wildly initially, and they continue to fluctuate through the entire trial within a small range, even after stability is reached. There is, again, greater fluctuation after the 80th trip. Perhaps the fact that stability is reached earlier points to the fact that the initial fluctuations lead to a wider range of exploration, and possibly a greater chance of finding the quickest route. If so, this would remind us of another interesting fact about space—its potential to deliver stimuli that lead towards greater exploration.

In the light of preference data for a given node under scenarios 1 and 2, data from scenarios 3 and 4 are as expected. The additional conditions of these scenarios increase the strength of preferences between nodes, The pattern remains similar to that in scenario 1 in its overall shape: agents find their preferences quite quickly and with fewer fluctuation of the kind seen in scenario 2, but as in scenario 2 the choices show variation about a settled value. An oddity in scenario 3 is the sudden fluctuation in values between 20th and 40th trips, but this eventually settles down. It is not clear why this should occur. Similarly, values seem be best behaved in scenario 4, but they

[2] Keeping in mind that several nodes receive visits by agents from more than one prior adjacent node, their frequencies controlled by different probabilities assigned from each of the prior nodes.

show a pattern of being settled for some consecutive trips, with sudden almost periodic fluctuations. Again, reasons for this remain hidden and so it is not clear how much importance one ought to give to it.

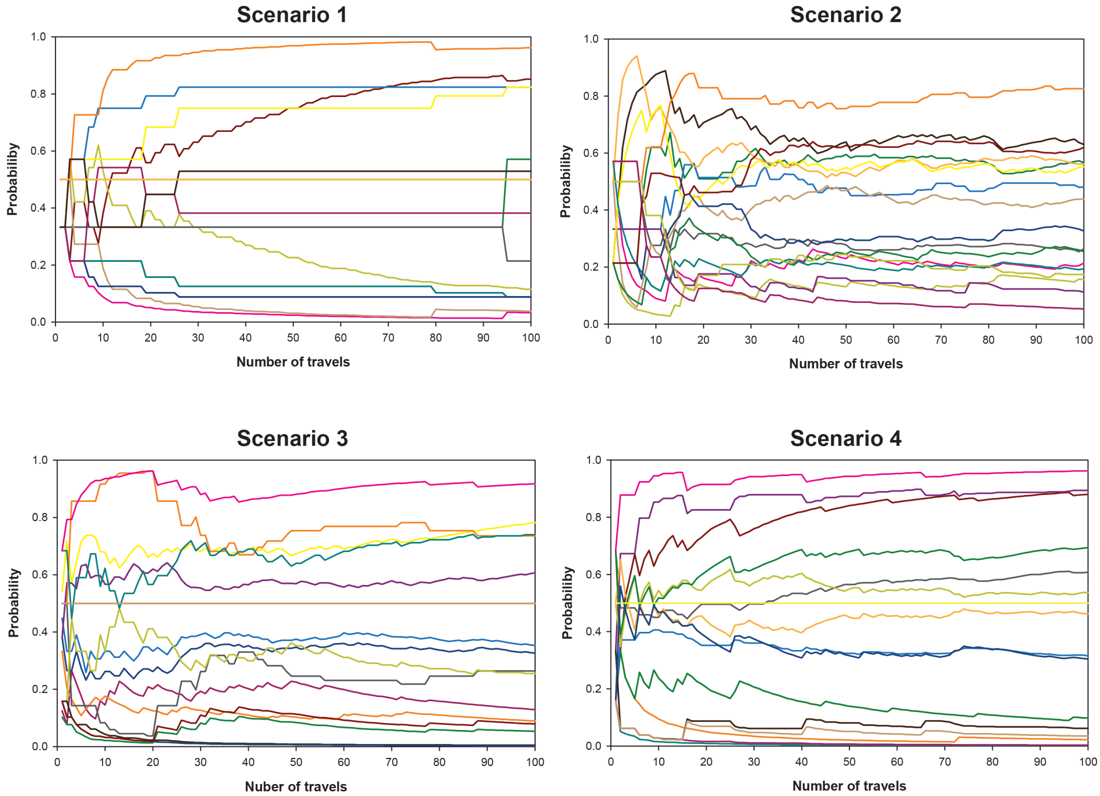

Figure 4. Probability of each node changes over number of trips (1 example trial taken from each scenario)

Our most consequential result, however, is seen when we examine the data on updating frequencies for each node pair, comparing patterns of preferences reached in each of the 100 trials. We had noted the unexpected high range of frequencies associated with each node, indicating low levels of consistency.

But this strong inconsistency is somewhat belied at a close look at some nodes. Consider the data from node pairs: E-J and E-G. Data from the first scenario clearly show the differences in preferences: the probability to select point J is very high in several trials, and so naturally, it is closer to zero for node G (probabilities for both should add up to 1). But there do remain trials for which they are nearly equal. Probabilities tend to get equalized across trials in scenario 2. But, not only that, a majority of trials now show preference for G over J. Clearly, the occupancy rates of the upper corridor influence choices far more strongly in our set-up than the basic organization of space that exclusively drives choices in scenario 1. Given this, it is not surprising to find pattern strengthened in scenario 3, in which the upper corridor is also occupied by the supervisors to whom agents are averse, is close to that of scenario 2 in scenario 4, as the supervisors are distributed across the space.

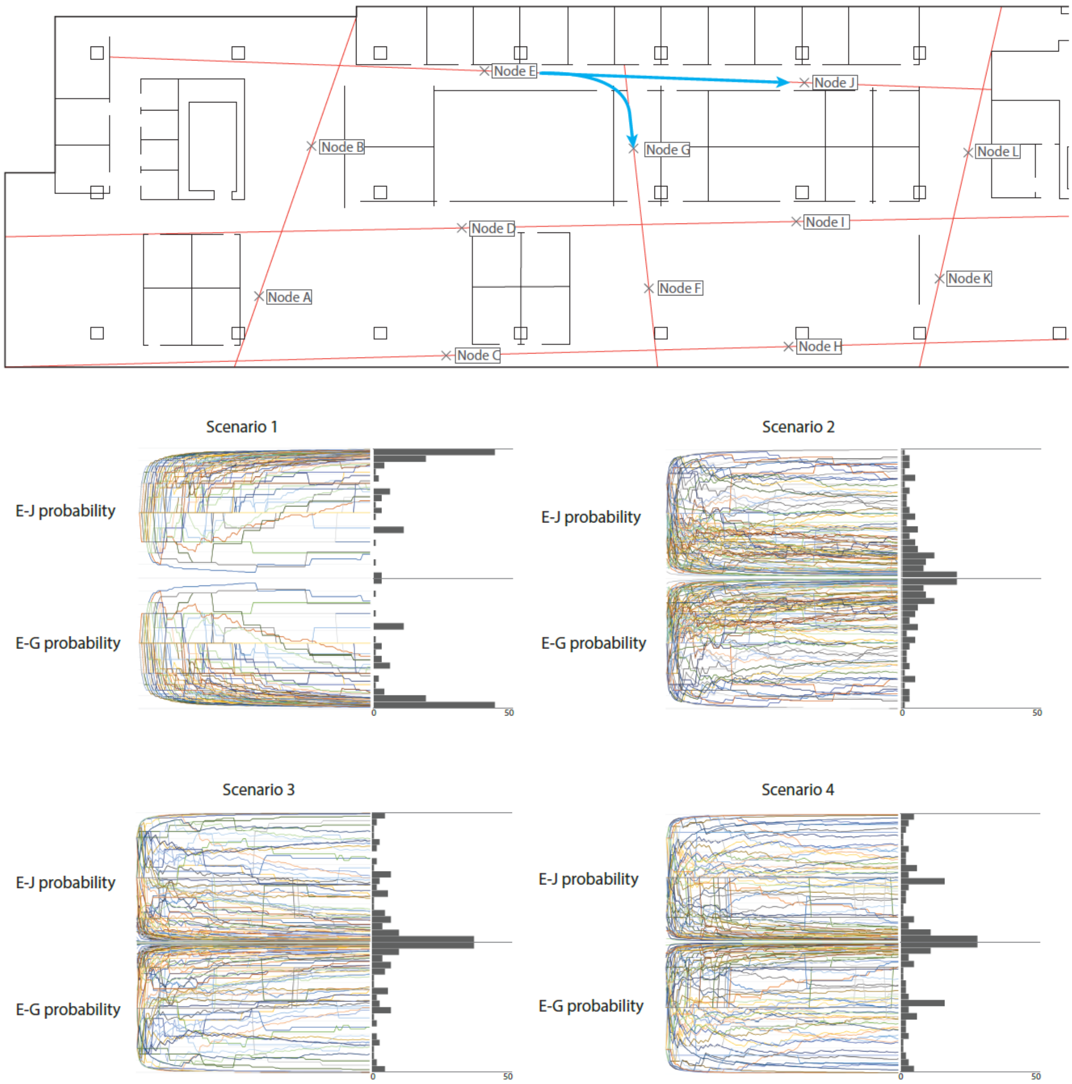

Figure 5. Change in Probability of E-J route and E-G route over every scenario

These observations bring home the point that the extent to which spatial organization can shape behavior can depend rather strongly on the contingent effects like the variation in the distribution of people in spaces. Further the extent to which these contingent factors, in turn, influence behavior depends not specific conventions or habits or norms that occupants of space might develop (captured in our set-up in the specific set of values we programmed our agents to assign). But what makes the situation even more interesting is that the conventions or habits or social norms may themselves emerge from behavioral conditions created by the space.

5 DISCUSSION

5.1 Consistent, Stable Results

The probability values for the selection of nodes in individual learning trials show a gradual emergence of stability, meaning that the agent gradually settles with a strongly preferred route, and starts to habitually use that route. This may be taken to represent the forming of preferred route in real-life navigation, although the rate at which the stability is reached (about 30 trips in most scenarios) seems far slower as compared to real life. These results indicate that spatial learning behavior cannot simply be a case of adjusting preferences based on gradual accumulation of limited knowledge.

This point is further emphasized by the results that the probability values for selecting individual nodes across several different trials did not exhibit any consistency. One would think that if the same condition is given and the agent's behavior is simple enough, it will develop similar preferences of path (and the same in real-life), but this turns out to be incorrect. One explanation of the lack of consistency may be that the chance of being exposed to some initial path cuts-off the reduces the agent's chance of discovering an alternative path early on—a condition analogous to the settling of a simple gradient search algorithm into a local minimum, without discovering a global one. In some way, this can also be true for real behavior. When people do not know that there is a faster, a more convenient route that they haven't taken before, they end up taking the route that they know and prefer, never knowing that there is a better route that exists.

One conclusion to draw from these results is to find ways to improve our algorithms. A range of machine-learning algorithms are available from the basic gradient descent algorithms to more complex ones like simulated annealing that can be introduced into agent-based simulations to lead agents to find the most effective paths and to do so consistently. However, our interest is not in finding the best algorithmic solution to the problem of navigation, but rather to draw insights about the ways humans actually solve navigational learning problems.

Our result does give a particular insight into the nature of space—that it often constrains its occupants to only local understanding, so that the early decisions trap the learner into specific pathways. So, one direction to explore here is how a building might be designed in order to reduce the effects of such accidental learning, say by structuring the choices more strongly.

On the other hand, it is also true that the lack of consistency does not seem to match actual human practice. We know (although mostly anecdotally) that people do develop quite consistent patterns of navigation in space. This means that they must be relying not only on the basic bottom-up processes that were modeled here, but on more complex models of spatial learning. For example, consistency might appear because people moving in space take explicit decisions to move along specific paths and then stick to those. The role of space is to create systematic patterns of choice behavior (for example, times calculated over number of trips), which provide stimuli for learning (Rachlin, 1995). The idea is that while people may prefer to make choices of utility defined by low value but greater probability of occurence, but if their behavior is patterned so as to induce choices not after each stimulus, but after a number of them, then they will switch to a choice of greater value but less probability.

We can further develop our experimental set-up to include this kind of patterned learning behavior. We can, for instance, make the agents "lock on" to the decision after a number of trips, rather than do so after each individual trip, and program it develop a norm to continue to make the same decision until a better alternative is repeatedly presented. It is possible that this kind of behavior create consistency between different trials. If it does so it can help answer further theoretical questions. Can the persistency of a route choice overhaul the spatial effects? How does spatial availability play a role in patterning the behavior? If such questions begin to be answered, we would have the basis for relating morphology to aggregate behavior grounded in an understanding of what is often called micro-behavior.

5.2 Computational platforms for Agent-based simulations of behavior

But in order to bring this about, another issue that remains to be tackled is that of the development of a suitable platform of creating agent-based simulations. The AnyLogic pedestrian model that we used here provided us several useful features as well as a few challenges. The advantage of AnyLogic pedestrian model is in the the movement logic in the continuous space which is very realistic. However, AnyLogic's pedestrian model is not editable by the user. To constrain agents' movement in a way in a simple logic that is knowledgeable to us, we set up each node as waypoints that the agent can use as options of routes. Nonetheless, it is still not enough solution as we were not able to integrate local spatial knowledge such as visibility nor make the agent react to the local spatial knowledge—capabilities that we will need to implement the cognitive mapping processed described above.

One promising way forward, in the face of these limitations, is to build an independent ABS model that is based on discretized environment—an environment of the kind created in the popular platform Netlogo. The pedestrian models described by Penn and Turner (2002) were built on a VGA map which has multiple layers of information on each tile. The advantage of the discretization of the space is that the local spatial information can be pre-calculated and integrated in the map so that the agent does not need to perform individual computation every time they move. The agents simply need to read the information that is stored in each tile. The tile-based model has more compatibility with other graphic software that is used in architecture research and grants more freedom in adjusting the individual behavior logic. The challenge in this case, however, will be to develop procedures for human-like movements (for example, social force movement behavior or controlling movement speed).

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