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Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 44(44)

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Publication Date
2022

Peer reviewed

Where would you stand on the subway?
A Bayesian framework for modeling commuter positioning choices in simulated subway coaches

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Abstract

Subway systems in large cities witness high volumes of commuter traffic, with crowded coaches and limited seats. In such scenarios, commuters often carefully position themselves in strategic locations with the aim of maximizing their chances of getting a place to sit. While user behavior in subways around the world have been the focus of multiple studies in the past, these everyday acts of 'optimal decision making' is of particular interest to the cognitive scientist. This paper inquires into commuter positioning choices in simulated subway coaches, within the framework of Bayesian probabilistic modelling. Data on preferred standing positions were collected across 20 subjects for 30 co-passenger configurations, through an interactive computer game. A generative model based on a Bayesian network involving three key spatial parameters was constructed, and used for inferring preferred positions conditioned on the specific configurations. The model was able to accurately simulate the quick and intuitive decisions made by the players under constraints of time, and also effectively capture noise in responses across subjects.

Keywords: Bayesian model; commuter positioning; choice simulation; subway game

Introduction and Background

Subway systems around the world form a unique backdrop against which the drama of urban public life plays out. They also usually evolve into strong anchors within popular culture, and the collective memory of citizens and visitors. Be it the antique ruggedness of the London Underground, the socialist classicism of the Moscow subway, or the chaotic ballet of the Delhi Metro - these networks come to represent the very ethos of the cities that they adorn. This 'culture' of the subway is produced and reproduced through complex behavioral patterns playing out every single day across hundreds of tunnels and thousands of commuters, deep below the ground.

Crowding in subway coaches is a common occurrence in large metropolitan cities, especially during rush hour. Given the limited number of seats available, a significant number of passengers are forced to stand through a significant part of their daily commute (Berkovich et al. 2013). The regular commuter, however, is often skilled in intuitively analyzing the configuration of a coach, and deciding on the most 'optimal' place to sit or stand, depending on a variety of spatial, social and ambient parameters. In crowded scenarios, commuters often carefully position themselves in strategic locations with the aim of maximizing their chances of getting a seat (Pownall et al. 2008). These seemingly intuitive choices taken by commuters as agents with free will is of particular interest to the cognitive scientist. Probabilistic modeling aimed at capturing such 'noisy' human decisions, can thus become a fruitful endeavor, and also pave way for more 'human' predictive models for a variety of planning and decision-making tasks.

Optimal decisions and the Bayesian framework

This body of research aims to build a predictive model of commuter positioning choices by adopting a Bayesian framework of cognition (Griffiths, Kemp and Tenenbaum, 2008). There is a wealth of existing literature examining the processes of Bayesian inference in intuitive day to day decisions undertaken by the human mind. Past studies have examined the 'optimality' of human cognition, and suggested that everyday intuitive judgements follow principles of optimal statistical inference based on implicit probabilistic models of the everyday world (Griffiths and Tenenbaum, 2006). Such lines of inquiry build upon the hypothesis that human minds possess implicit 'generative engines' built upon Bayesian causal networks, and involving assigned priors across generative parameters. The cognitive mechanism involves Bayesian inference through sampling from such models against the light of existing constraints. Everyday decision making is often carried out through inferences based on a limited number of samples, allowing the human mind to make reasonably accurate choices within very short spans of time (Vul et al., 2014).

Multiple probabilistic models within various domains of human judgement have been able to accurately simulate quick human decision-making processes against the light of sparse data. Within the realm of concept learning, (Xu and Tenenbaum, 2007) examined word learning in adults and children through a Bayesian framework. Meaningful generalizations made from very few examples were explained as an act of making rational inductive inferences by building upon prior knowledge of possible meanings as well as the observed samples of a word's referents. Within the domain of scene perception and understanding, Bayesian probabilistic modeling has been applied for facial analysis, human pose estimation as well as object reconstruction tasks (Kulkarni et al. 2015). More recently, probabilistic frameworks have been proposed for inferring three dimensional spatial structures from limited data in the form of RGB and depth imagery (Gothoskar et al. 2021). Along similar lines, (Battaglia et al. 2013) applied the Bayesian framework to develop computational models of 'intuitive

In J. Culbertson, A. Perfors, H. Rabagliati & V. Ramenzoni (Eds.), *Proceedings of the 44th Annual Conference of the Cognitive Science Society*.

physics' that allow humans to coherently engage with the physical world. Such models used approximate, probabilistic simulations to make quick inferences in complex natural scenes. Notably, they were also able to capture illusions and biases which are inherent to the human experience.

This present body of work situates itself against the above discussed line of scholarship, and applies Bayesian probabilistic modelling within the realm of urban public behavior and everyday decision making. It aims to build a predictive model that is capable of capturing the quick and intuitive judgements made by commuters in simulated crowded subway coaches, where they intend to maximize their chances of getting a seat.

Data Collection – 'The Subway Game'

The development of a rapid data-collection framework for gathering data pertaining to positioning preferences across human subjects becomes a key consideration at this point. Several past studies looking into commuter behavior have relied upon real-time observation inside physical subway/train coaches and stations (Pownall et al. 2008, Berkovich et al. 2013). While such data most accurately captures behavioral patterns in real world scenarios, it nevertheless poses problems on two important counts. Firstly, while such a method may be most representative of actual behavioral outcomes, it becomes extremely difficult to control for extraneous parameters, while studying the causal effects of specific independent variables on specific behavioral outcomes. Such studies would thus require randomized control across an extremely large sample of observed subjects, and across diverse scenarios. Secondly – and most importantly from a cognitive science point of view – observation without the subject's knowledge makes it even more difficult for the observer to accurately gauge the subject's goals and motivations. It is common for commuters, for example, to often not want to sit, and end up standing even when there are seats available. From a Bayesian perspective, accurately estimating the correct priors across several parameters becomes all the more difficult.

An alternate framework for collecting such data – including the one employed for this study – is through simulation. There have been multiple recent studies employing game engines for the simulation of real-world scenarios, with aim of collecting data on participant behavior. While such a framework inevitably simplifies a scenario by reducing the number of parameters involved, it nevertheless makes it easier to effectively isolate and control for specific parameters while studying the causal relationships between others. Also, inducing specific motivations becomes easier through subject briefing before experimentation, and also through explicit rewards for achieving specific goals. This study employs a computer game, titled 'The Subway Game', for simulating specific scenarios in subway coaches, and for collecting user data on positioning preferences.

The Data Collection Interface

'The Subway Game' was developed on Processing 4 (Reas and Fry, 2007), and presented to the player a 2-dimensional layout of a typical subway coach (modeled on the Bombardier coaches on the Yellow Line of the Delhi Metro). It comprised of 46 seats and 8 doors situated symmetrically, including 3 identical bays of 14 seats each. Each of the seats were occupied by black circles, each representing a commuter.

The game read from a .csv file that contained the locations of different standing co-passengers, each of whom were 'competing' with the player for seats. 30 different scenarios of different competitor configurations were pre-generated and written to the .csv file for the game to display. The number of competitors in these scenarios ranged from 1 to 29. Each of these scenarios could be presented to the player by displaying similar black circles at the competitor locations.

Gameplay

The game started with an introductory prompt which reads thus: *"You enter a subway coach, tired after a hard day's work. All seats are occupied. Where would you stand, so you could grab a seat soon?"* This prompt was intended to induce appropriate priors, linked to a specific goal i.e., that of getting a seat. The observer also briefed the player on the scenario, and verbally indicated that it was equally likely for any of the sitting passengers to vacate their seats at any stop. The player inputs their name, following which the gameplay begins.

The main gameplay comprised of each of the 30 passenger configurations being sequentially presented to the player in a randomized order. The player was asked to click on any point on the coach where they think they would stand in order to maximize their chances of getting a place to sit **(Fig 1)**. The cursor was represented by a red circle of the same size as that of the competitors. A timer appearing at the bottom of the screen allowed a window of 10 seconds per scene for the player to respond.

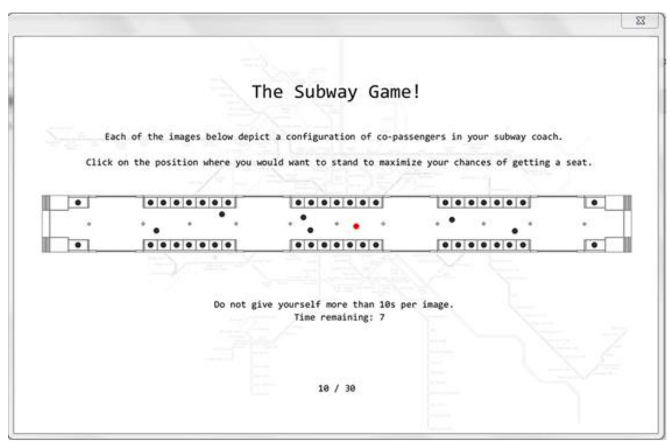

Figure 1: The Subway Game - Gameplay

Subjects and setup

20 subjects – all graduate students across 5 departments at the Massachusetts Institute of Technology – participated in the gameplay. The game was presented on a laptop computer (Dell XPS 15 7590) of screen resolution 1920 x 1080 pixels. Each gameplay lasted for 3 minutes on an average.

Data tabulation

At the end of each gameplay, the x and y coordinates of the preferred user standing position for each scenario was recorded into a .csv file. In addition, the seat locations, door locations, and the location of each competitor was also registered. The heads of the final tabulated dataset are presented below in (**Table 1**).

Table 1: Key Dataset Parameters

id	userX	userY	compX	compY	seatX	seatY	doorX	doorY
17	802	75	292;363;4	97;51;97;8	93;280;31	19;19;19;1	191;570;9	5;5;5;5;14
5	719	81	279;860;1	52;95;50	93;280;31	19;19;19;1	191;570;9	5;5;5;5;14
4	1155	71	349;726	57;91	93;280;31	19;19;19;1	191;570;9	5;5;5;5;14
27	517	79	161;206;3	50;96;83;6	93;280;31	19;19;19;1	191;570;9	5;5;5;5;14
18	366	68	288;449;6	57;96;80;5	93;280;31	19;19;19;1	191;570;9	5;5;5;5;14
11	276	85	1058;1220	57;96;53;9	93;280;31	19;19;19;1	191;570;9	5;5;5;5;14
20	1156	75	224;206;2	108;97;70;	93;280;31	19;19;19;1	191;570;9	5;5;5;5;14
10	476	77	1039;1044	60;84;63;5	93;280;31	19;19;19;1	191;570;9	5;5;5;5;14
21	483	70	1021;1004	58;45;53;7	93;280;31	19;19;19;1	191;570;9	5;5;5;5;14
7	1038	74	682;845;4	53;93;91	93;280;31	19;19;19;1	191;570;9	5;5;5;5;14

Probabilistic Modelling

A multitude of parameters play crucial roles in determining positioning choices in coaches. Based on a critical review of existing literature, along with qualitative responses collected from subjects during the course of gameplay, this study adopted 3 key parameters for the synthesis of the generative model used for probabilistic modeling. The parameters were (i) number of seats to which the player is the closest out of all competitors **(S)**, (ii) distance to nearest co-passenger **(P)** and (iii) distance to nearest door **(D)** **(Fig 2)**.

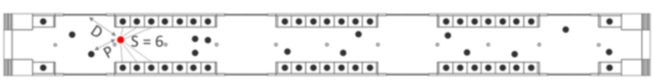

Figure 2: The key causal parameters considered by the model

The Generative Model

Figure 3 shows a schematic Bayesian network representing the causal dependencies of the parameters in question through a directed acyclic graph. This represents the structure of the generative model drawn up for determining the optimal positions that subjects may have gravitated towards in their responses.

The three key parameter D,S and P are considered as arguments for an utility function that computes a preference score for any arbitrary point (x,y) within the subway coach. The utility function is represented thus:

$$\text{Score} = (S^s * P^p) / D^d \qquad \text{.. .. .. (1)}$$

where,
S = Number of seats (normalized) to which the player is the closest out of all other competitors
s = weight of factor S
P = Normalized distance to nearest co-passenger
p = weight of factor P
D = Normalized distance to nearest Door
d = weight of factor D

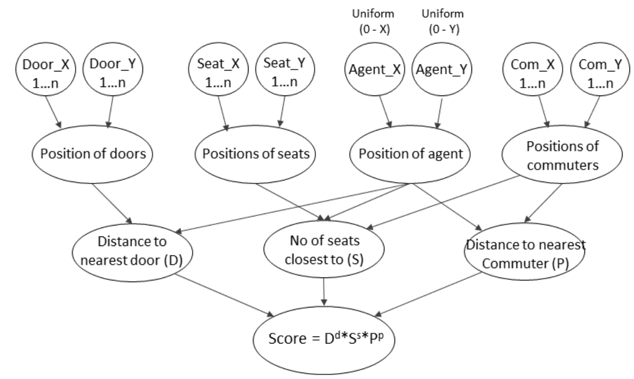

Figure 3: The key causal parameters considered by the model

Preference score distributions across possible standing positions

The utility function was also scripted in Processing, in order to output preference scores for all possible standing positions across the subway coach. The game having been developed on a pixel-based canvas, the entire length of the bays (between the seats on either side) was discretized into squares of width 5px. The x and y values corresponding to the central pixel of these squares were passed through the utility function, and the display colour of that square was set to a value on colour gradient as a function of the preference score at that point (x,y). This allowed for the generation of heatmaps in order to visualize the score distribution across the entire available coach space **(Fig 4)**.

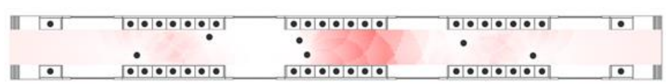

Figure 4: Heatmap representing score distributions across a coach for scenario 13

Inference algorithm – sampling from the 'intuitive generative engine'

In order to draw inferences on likely standing positions, a sampling algorithm was scripted to draw a fixed number of samples from the generative model, constrained on the specific passenger configurations for each scenario. A uniform prior was assigned over the x and y coordinates for each of the possible standing positions. The algorithm passed each sampled point through the utility function, and returned the sampled point corresponding to the highest preference score. To compare with human data, the inference algorithm was run 20 times for each scenario (corresponding to the 20 subject sample size of the study) **(Fig 5)**.

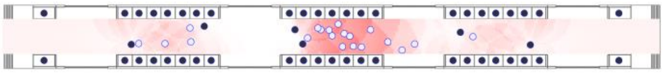

Figure 5: Representative predictions (in blue) for 20 runs of the model (scenario 13)

Model parameters and human judgements

In order to evaluate the various model parameters against human data, the .csv files for each subject were combined using Pandas in Python, and all user x and y values for each scenario were grouped together. A visualizer script then read each of these values from the combined .csv file, and displayed them together along with the preference score heatmap. The parameter weights s,d and p were modulated to evaluate the degree to which each of the parameters influenced positioning choices, and also to arrive at an optimal configuration for the model. To do that, however, the effect on human judgements of the two dominant model parameters, namely **S** and **P**, were first considered in isolation. This provided valuable insights into the nuances of everyday human judgements in such a setting.

Number of seats nearest to (S): Fig 6 depicts user responses for several scenarios overlaid on corresponding heatmaps generated by the model, and considering the effect of parameter S in isolation (s = 1, p = 0, d = 0).

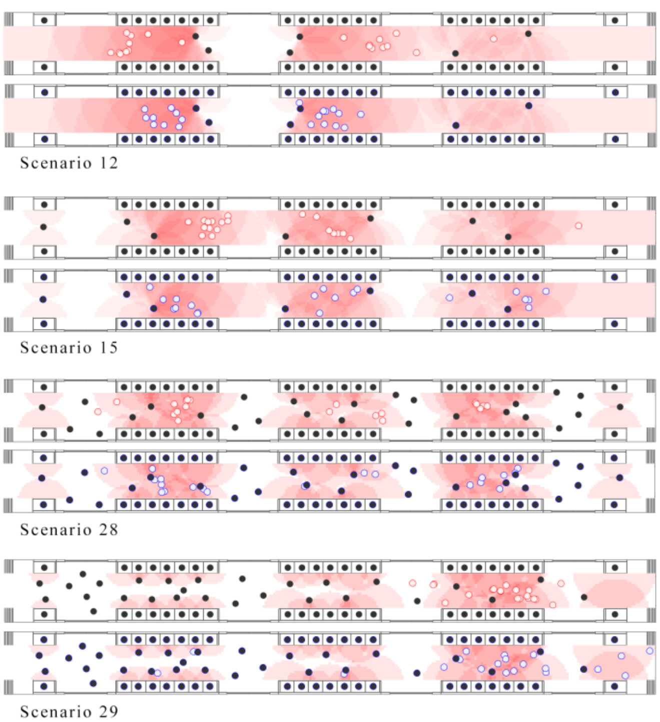

Figure 6: User clicks (red) and model predictions (blue) overlaid on heatmaps for parameter **S** in isolation.

From a rational standpoint, parameter S plays the most significant role in determining the actual probabilities of a commuter getting a seat. This is because, assuming equal chances of any seat being vacated at a particular stop, the passenger nearest to it would be most likely to secure it. In other words, to maximize chances of getting a seat, one would want to be the nearest passenger to as many seats in the coach as possible. However, it is clear from **(Fig 6)**, that human intuitions were different. While in many cases it is actually most gainful to be standing right next to a co-passenger (see heatmap for scenario 12), possible social factors surrounding personal space generate a tendency for passengers to maintain a distance between each other. Thus, in most scenarios, user positions predicted by the model are much closer to co-passengers than what the actual responses reveal. This pattern is particularly evident in crowded scenarios (compare user response and model predictions for scenario 29). The possible psychological impact of social distancing in a post-COVID era may also have played a major role, and may be taken up as a different study.

It was thus evident that parameter S alone was not sufficient to explain passenger intuitions accurately. We now discuss the effect of parameter P in this regard.

Distance to nearest co-passenger (P): We see below the score heatmaps and model predictions for P in isolation (s = 0, p = 1, d = 0) **(Fig 7)**.

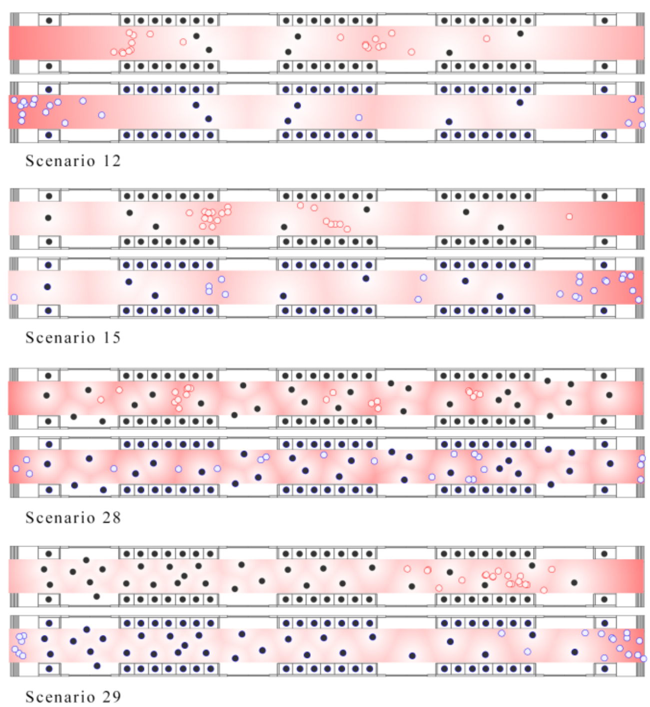

Figure 7: User clicks (red) and model predictions (blue) overlaid on heatmaps for parameter **P** in isolation.

It is clear from the figure that parameter P alone does not account for patterns of user intuition either. While the model predictions maximized distances from nearest co-passengers, the results were far removed from actual user choices. It is also known through common experience, that commuters do not always *maximize* their distances from others, but rather *optimize* the same keeping in mind other factors as well. While considerations of interpersonal space did play a major role, the subjects nevertheless kept the goal of the game in mind – to maximize the chances of getting a place to sit. A comparison between figures 6 and 7 makes it clear that parameter S was certainly the dominant determinant of positioning choices in this regard.

The distance to nearest door (D) was also considered separately, but was found to play a relatively minor role. While its coefficient has been considered in the model, its effect has not been discussed separately in this paper.

Tuning the model to human data

The values of the parameter coefficients (namely s,p and d) were then modulated to best represent the human data. Based on the findings discussed above, the value of coefficient **s** was kept as the highest of the three, followed by **p** and **d** in that order. The number of samples drawn from the generative model for inferring an optimal position was again modulated to best fit human data. After a number of cycles of iterative testing, the following values of the model parameters was found to correspond to an optimal model calibration – **s = 2; p = 0.75, d = 0.25**. The number of samples drawn for a good fit was **n = 8. Figure 8** below compares user data and 20 runs of the model predictions for various passenger configurations.

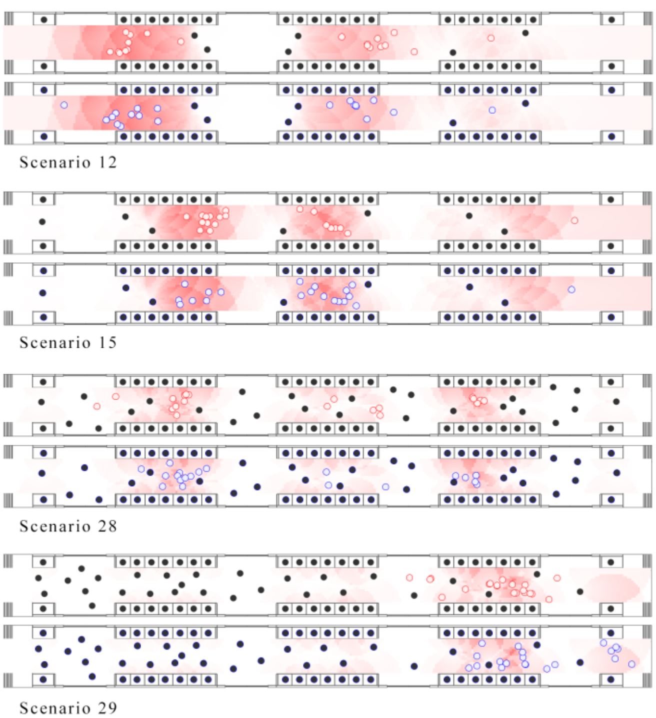

Figure 8: User clicks (red) and model predictions (blue) overlaid on score heatmaps of the tuned model.

Model predictions were most effective for configurations which involved convergence across subject clicks. While response time was not formally included in the dataset, these configurations were also found to correspond to quickest responses. **Figure 9** below depicts such a case.

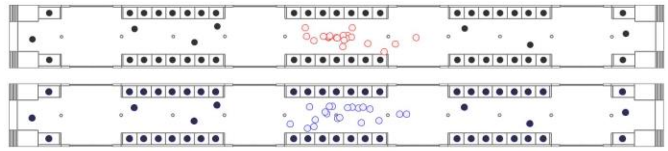

Figure 9: User and model data for scenario 14

Discussion: Optimal positions in a fast-moving world

The performance of the model as depicted above demonstrates the robustness of the Bayesian framework in simulating the quick decision-making processes that characterize human judgements under constraints of time. Most importantly, it showcases the optimal nature of these decisions. The ability of such the framework to adequately capture the noise in human data demonstrates its effectiveness for modelling everyday human judgements. **Figure 8** shows that the quick decisions made by the players of the Subway Game were not necessarily the most rational. If that were the case, the user clicks would have aligned closely with the most saturated zones of the heatmap. While the clicks did broadly correspond to these zones, they were nevertheless much more dispersed than what a rational algorithm with throw up. The players made the most optimal decisions given the little time (<10s) that they had to process each scene. They relied on inferences based on a very limited number of samples drawn from the intuitive generative engine in their mind. In the real world as well, commuter positioning arguably occurs in similar ways – the quick intuitive judgements that we make as to where to stand are never the most rational. But they are the best judgements given the little time we have in fast moving rush hour traffic.

This phenomenon of optimal positioning was captured by the model, by simulating this sampling process. In the current calibration, the model relied on 8 samples. This allowed for the model to capture the noise that characterises the dataset. Increasing the number of samples would decrease noise and make the model more rational **(Fig 10)**. But it would also make it less human.

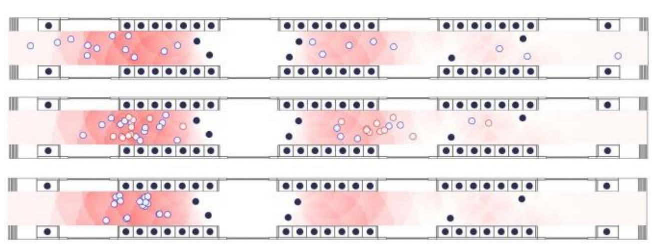

Figure 10: The road to the rational: Model predictions using samples n = 3 (top), 8 (middle with human data overlaid) and 50 (bottom) for scenario 12.

Conclusion: Challenges, Opportunities and Future Directions

This body of research aimed at modelling everyday behavioural decisions in a simulated public environment within a Bayesian framework. As indicated by the results of the study and the prediction accuracy of the model, such a framework proves to be extremely effective in this regard. It is however worthwhile to mention a number of key limitations that this study worked within. Firstly, as mentioned at the very outset, any behavioural data collected through a simulated platform will always remain a reductive simplification of real-world behavioural nuances. Any inferences drawn from such a study thus needs to be carefully examined before generalising to real-world scenarios. Secondly, while this study presented a single goal to subjects - that of maximizing chances of getting a place to sit – it is not necessarily representative of the multitude of goals and motivations that actually drive positioning choices. For example, position of staircases on platforms often influences positioning choices during rush hour, to minimize travel time. Thirdly, this study does not consider points of entry and exit into the coach, and also allows the subject to view the configuration of the entire coach at once. In real life, points of entry play a major role in positioning choices, as the configuration of only a part of the coach is discernible by the commuter based in their initial position.

That being said, the framework showcased through such a study nevertheless paves way for future work that may have strong real-world implications. The ability of a model to adequately capture and replicate 'noise' in human judgements has the potential to pave way for artificial intelligence that is itself more human. While predictive models are used widely in allied disciplines such as design and planning, such 'human' models can lead to far more contextual design decisions as a result. For example, while this study restricted itself to a single coach configuration, similar data may be collected across various configurations of seats, in order to evaluate the behavioural implications of different spatial layouts. A similar framework may also be deployed to inquire into behavioural patterns across age, gender or ability. Such insights may be valuable when designing for barrier free networks, or deciding upon locations of reserved seats.

Finally, there is immense potential for the Subway Game to be hosted on the web for a much larger study involving crowd-sourced user responses across a bigger sample size. Such a crowd-sourced platform can capture the value of this framework, and build a large dataset of behavioural patterns in the subway within a relatively short period of time.

In conclusion, it is hoped that the rapid data-collection framework and modelling paradigm outlined in this paper is taken forward for similar studies linked to associated scenarios. Insights into urban public behaviour can be really valuable to cognitive scientists and social scientists alike, and a Bayesian approach may be particularly well suited for engaging with the degrees of complexity and uncertainty that characterize the public realm.

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