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Predicting Social Reopening Following COVID-19 Lockdown Using Bounded Rationality and Threshold Models

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Abstract

The exercise of reopening optional social spaces following the COVID-19 lockdowns presents each individual with a complex problem in determining whether or not to attend these spaces given how the risks of virus transmission scale with crowding. In order to tackle this problem while recognizing individual cognitive capacity limits, this paper used a simulation model based on the El Farol Bar Problem and generated a population of agents relying on simple predictive strategies to determine their attendance to a retail location. It was determined that the more heterogeneous the threshold for crowding among agents was, the less variance there was in overall attendance numbers. This stability in daily attendance comes at the expense of the ability of the most cautious members to enjoy recreational spaces as these locations become the realm of only those least concerned with potential crowding.

Keywords: COVID-19, Threshold Model, Bounded Rationality, Agent Based Model

Introduction

The outbreak of COVID-19 and ensuing pandemic has lead many cities to implement lockdowns and closures of public spaces to limit the potential social contacts of citizens. However, as these measures are beginning to ease, there is some uncertainty about the rate and scale at which people will re-emerge into optional public spaces such as retail and recreation centres. Citizens wishing to visit these spaces may be held back by fears of contracting or spreading the virus to others and thus will only want to venture out if few others do. However, there is no way to know the attendance at these locations beforehand or coordinate at scale ahead of time thus the question of whether a given individual should go out or not is a complex one.

On average, individuals can only handle a finite (and typically fairly low) amount of complexity. Moreover, the interactive nature of this problem means individuals must rely on subjective beliefs about subjective beliefs (their best guess of how others will behave). These factors combined mean that individuals in this situation act with bounded rationality - that is, they may attempt to apply rational problem solving processes to the problem but will do so imperfectly or only to a limited degree (Jones, 1999).

Due to limits on cognitive complexity, deductive reasoning is practically impossible in this context so individuals instead rely on inductive reasoning, basing their present actions on past observations alone. Thus, this problem can be modelled and explored in a similar manner to the El Farol Bar problem first described by W.B. Arthur(Arthur, 1994). In the El Farol Bar problem 100 potential patrons must decide each night whether or not to visit a nightclub which is only enjoyable when less than 60 people are present. However no communication or coordination is possible amongst patrons and each individual must use their own limited cognitive capacity and pattern recognition to determine whether or not to attend each night.

To improve the realism of the simulations, rather than only proceeding with a single shared standard of comfortable attendance as in the El Farol paper, several different simulations will be explored where individuals can possess different levels of comfort with crowding in public space. In order to do this, variable threshold models will also be incorporated. The simulation predictions can then be compared against each other and the data from Google's COVID-19 Community Mobility Reports for Canada (Google, 2020). It has been shown that the equilibrium attendance that will emerge will be approximately half the total capacity when all agents have a shared threshold value (H. Lus, 2005; D. Challet, 2003; M.A.R. de Cara, 1999) but it is not yet known what equilibrium will emerge when the agents have a varied set of thresholds. This paper will explore this question and apply a sensitivity analysis to the results to explore how robust the results are to set of predictive strategies each agent utilizes.

Human Cognition: Bounded Rationality and Inductive Reasoning

Models of human behaviour are often built with the assumption that perfect, logical and deductive reasoning will be applied by their agents but this is unrealistic as human cognition is prone to logical errors and oversimplification of complex, multidimensional problems. Hence, deductive reasoning assumptions don't perform well in complex games like checkers or Go because human cognition can only handle finite complexity and interactive problems have no guarantee of opponent rationality which necessitates relying on guesswork - the problem loses objectivity as the game depends on the players subjective beliefs about each other's subjective beliefs (Jones, 1999). Bounded rationality becomes evident in the outcomes. Economic Rational Actor models are of limited use in exploring bounded rationality but results from the behavioural sciences suggest that when deduction fails people consistently employ inductive reasoning to problem solve instead.

Deductive reasoning occurs when specific logical conclusions are reached from a well-defined starting premise whereas inductive reasoning occurs when pattern recognition is deployed to generate generalizable theories (Arthur, 1994). The appeal of inductive reasoning is that it is easier to employ in situations where the problem is ill-defined or too complex and intractable. Additionally, humans are great at pattern recognition and matching, skills often employed to try and simplify complicated problems and fill in gaps in understanding. Patterns are used to construct temporary mental models of smaller, simpler subproblems to which deductive reasoning can be applied. Observed outcomes and environmental feedback to those solutions then reinforces or weakens confidence in those mental models which may be updated as dictated by novel information (Arthur, 1994). This process is how people incrementally solve and learn within complex problems, for example by constructing evolving strategies during a match of chess or Go.

In situations like these, the complexity of the problem at hand makes it impossible to determine the "correctness" of the models one constructs and implements so historic reliability becomes the best metric. That is to say, by observing the performance over time, more and less reliable mental models can be identified. Poorly performing models may sometimes be discarded or replaced by new ones and good models endure and are used more frequently but can be dropped for more favourable ones if they repeatedly fail to perform well. A constant turnover of best performing or 'active' beliefs is highly likely. Individuals can learn and refine their approaches as they gain more experience. As people often have fairly similar intellectual resources and shared cognitive biases, models can be drawn from a common bank of straightforward patterns and simple algorithms. Within this attendance problem, the system of mental models employed is co-evolutionary - each individual's set of models must compete and adapt within an environment shaped by other individuals' models so the dominant (acted on) models co-evolve.

The Model

Model Set Up

To start, the population of a given city can be thought of as a collection of 100 agents who have to decide to attend a social space or not. The agents each hold a different set of one or more mental models to apply to the attendance problem.

In the following simulations every agent possesses a set of 10 predictor models drawn randomly with replacement from a shared global pool of 100 distinct prediction strategies. Each time step, agents will act based on their current best (historically most accurate) predictor. After actions are taken and overall results are observed, agents record the performance of their models, both active and passive. They learn. Using the performance over time, more and less reliable models can be identified. In this simulation, the following simple predictive models (henceforth referred to as 'predictors') made up the global pool from which agents drew their strategy sets:

- Cycles: predict the same attendance as k days ago, k = 1-10
- Mirrored cycles: predict the attendance from k days ago mirrored about 50, k = 1-10
- k-day moving average using the mean, k = 1-10
- k-day moving average using the mode, k = 1-10
- Least squares prediction using the k most recent days, k = 1-10
- k-dated 5-day moving average using the mean, k = 1-10
- k-dated 5-day moving average using the mode, k = 1-10
- k-dated 3-day spaced 2-day trend applied to last attendance, k = 1-7
- k-dated 3-day spaced 2-day opposite trend applied to last attendance, k = 1-7
- k-dated 2-day opposite trend applied to last attendance, k = 1-7
- fixed level predictors: predict attendance = k, k = 5-100 in increments of 5

In this particular social space, it is only a worthwhile experience for an agent when attendance is below that agent's threshold for what they deem safe and comfortable. An agent's choice to attend or not is unaffected by the number of times they have attended in the past. Each person decides to stay or go based on their own estimate of how many others will attend as follows:

- if predicted attendance is below comfort threshold then go
- if above then stay home

Only past attendance data is available to each agent and at the end of every night all agents learn the final attendance for that day. No collusion or prior communication is possible between agents (a reasonable assumption for big cities where population sizes are large and individual social networks are relatively small). In this problem, establishing any kind of common expectations is impossible - shared beliefs about high future attendance would cause more agents to stay home, disproving the prediction and likewise for shared beliefs about low future attendance. A difference of beliefs and predictions is forced to exist. Three sets of agent thresholds were tested:

- near complete heterogeneity - thresholds uniformly distributed in groups of 5 from 5 to 100
- complete homogeneity - everyone has a threshold of 50
- risk-grouping - 20% high (75), 60% medium (50) and 20% low (25)

All three sets of thresholds have a mean of 50. They can be interpreted as representing different scenarios of public concern over the pandemic and subsequent comfort with public crowding (Granovetter, 1978; Wiedermann, Smith, & Heitzig, 2020). Threshold set 1, the completely homogeneous thresholds represents a situation where the entire populations is equally (moderately) concerned about the virus and thus equally uncomfortable in public spaces that are more than half full. Threshold set 2, risk-grouped thresholds, represents a situation where the majority of the population (60%) are moderately concerned about the pandemic while a minority (20%) are highly concerned and thus are only comfortable attending sparsely populated public spaces (25 agents or less in attendance) and an equally large minority (20%) are unconcerned about the pandemic and thus willing to attend highly populated spaces (75 agents or less). Threshold set 3, nearly completely heterogeneous thresholds, extends this idea and incorporated an even wider and more granular spread of comfort levels with risk groups only containing 5 agents each and thresholds ranging from 5 to 100 in increments of 5.

Initial Results

Each simulation used the first 90 days of the Community Mobility Report's recorded attendance to retail venues in Canada (Google, 2020) scaled as a percentage of the maximum attendance in that period as the initial historical data (figure 1). The model then simulated similarly scaled attendance for a further 180 days (figure 2). Although this simulated data is not of the same type as the original Community Mobility Report data, it can be used as a reasonable proxy. As in the original El Farol simulation, the learning of agents was very efficient (Franke, 2003); over time, all of the simulations had their attendance numbers oscillate around a mean 50 agents. However, the degree of oscillation varied greatly between the simulations: the population with completely homogeneous thresholds had the highest variation in day-to-day attendance, the population with nearly completely heterogeneous thresholds had by far the most consistent daily attendance and the population with risk-group thresholds having intermediate variance. The daily time series of attendance is shown in figure 2 and histograms of attendance numbers during the 180 simulated days as well as normal curves constructed using the mean and standard deviation of the attendance data are shown in figure 4. Figure 3 shows the fraction of all predictors that are below 50 over time. For the last 2 threshold sets, the fraction of predictors below 50 had a mean of approximately 54% (although in both cases it fluctuated widely and chaotically ranged from extremes as low as 20% to as high as 80%). For the maximally heterogeneous threshold set, the fraction of predictors below 50 fluctuated across a similar range but did so with more regularity, almost cyclically, and settled at a mean of around 46%.

From the attendance histograms in figure 4, it is clear that in all 3 threshold scenarios the recorded attendance is normally distributed with mean approximately 50 but the difference in the standard deviations of the 3 cases is quite stark. The homogeneous thresholds produce the highest standard deviation in attendance (σ = 12.9), followed by the risk-grouped thresholds (σ = 11.7) and then the heterogeneous thresholds have a very small standard deviation (σ = 3.5). Although the mean attendance level is the same in all 3 cases, these results imply that populations that are uniformly concerned about the pandemic will actually have the most volatile attendance to public spaces whereas populations with more widely distributed levels of comfort with crowding will produce more regular and consistent attendance levels.

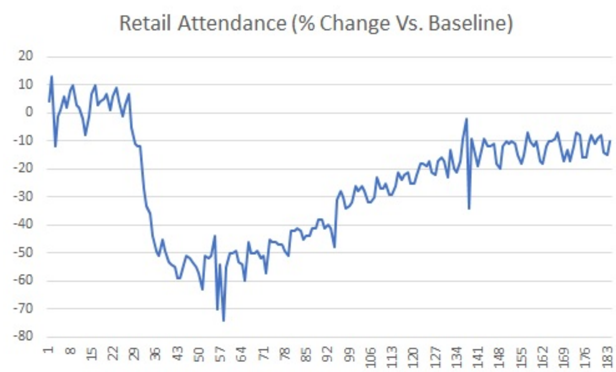

Figure 1: Mobility Data

Repeated Simulations

To explore the robustness of these results, each of the simulations was run 50 times for each threshold set. In all cases the attendance numbers for each of the 50 simulations were normally distributed. The mean and standard deviation of every one was recorded and plotted in histograms in figure 5 and 6 respectively. Figure 5 shows the histograms of the recorded means for the 3 threshold scenarios and figure 6 shows the histogram of the standard deviations. For the homogeneous threshold case, the recorded means are normally distributed about a mean value of 50.8 and very small variance and the standard deviations are also fairly normally distributed with a mean of around 13.5 but with a relatively wide spread from 12 to 15.5. This shows that for this threshold set a mean attendance very slightly above 50 and large standard deviation are typical characteristics. For the risk-grouped threshold set, the histogram of the means was also normally distributed with an mean value of approximately 50.65, a smaller standard deviation than the previous case and the histogram of standard deviations was also normally distributed with a mean of around 12 and tailing off around 11.2 and 12.6 which shows that this set of thresholds will produce attendance results that are reliably less variable than the first threshold set while still oscillating around the same mean value. For the extremely heterogeneous threshold set, the histogram of mean values is left skewed with a mode around 50.7. From this it can be concluded that the extremely heterogeneous threshold case does consistently have a lower mean attendance than either of the previous 2 threshold sets. The histogram of standard devia-

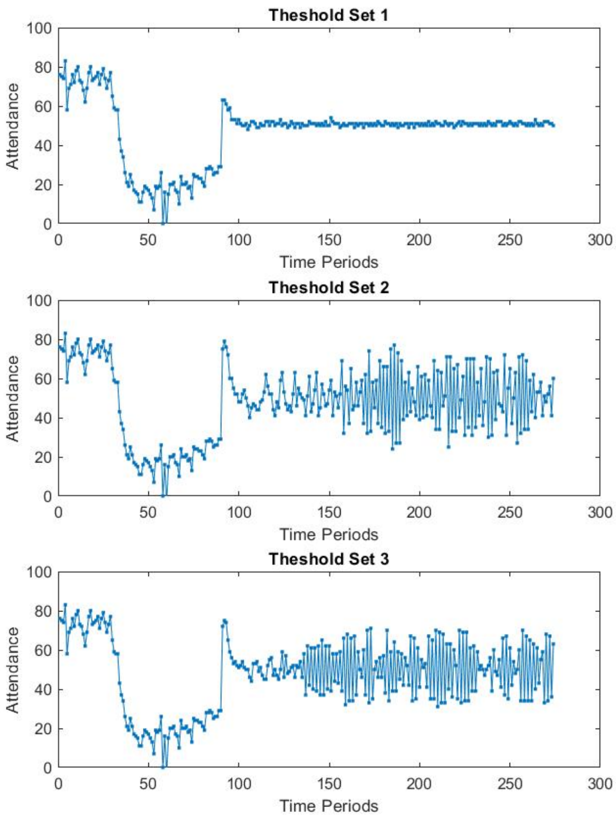

Figure 2: Time Series of Simulated Attendance vs. Data

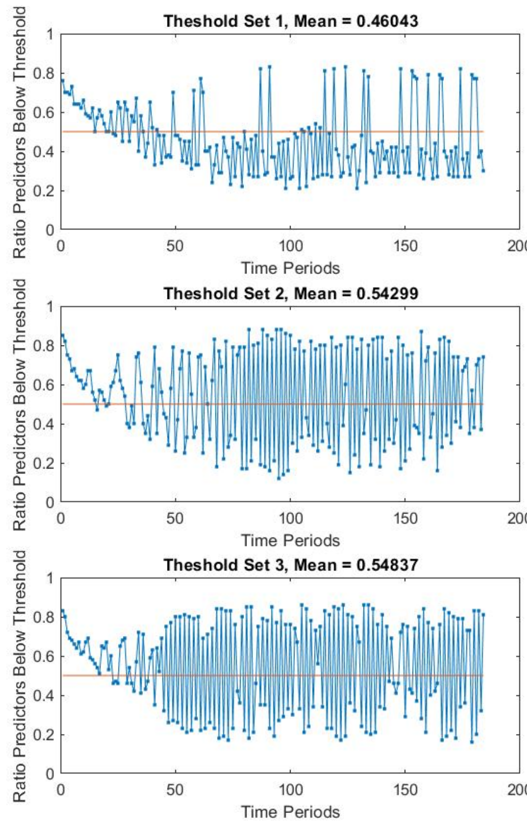

Figure 3: Time Series of Fraction of Predictors Below 50

tions for the first threshold set is right skewed with a mode at 3.55 and tail stretching only as far as 3.8, which confirms that this threshold set reliably results in more consistent attendance and vastly less volatility than either of the previous 2 cases.

Potential Expansions

Even with such a simple set up and relatively few inputs the model has produced interesting results. To build on these it might be of interest to add some modifications and see what new observations come from that. A few potential directions of exploration are

- Regardless of the threshold set used, a trend of on average around 50% of predictors forecasting attendance below 50 persisted independent of predictor type present in the set or the unique number assigned to each agent (predictors were drawn with replacement from the global pool, duplication was inevitable). Although this ratio was consistent, precisely which predictors were active changed over time. Presently each agent has a fixed 'belief set' (predictor set) but exploring a dynamically changing belief set or expanding the ability of agents to combine predictors is the next step as well as exploring what effect, if any, this has on the aforementioned ratio.
- To further improve the realism of the model, future work could also consider varying agent thresholds with time or individual attendance history to reflect that people may more strongly weight the appeal of public spaces after a prolonged period of isolation and thus raise their personal threshold for what they deem acceptable levels of public crowding. Alternatively, people may become more or less concerned about the potential for contracting the virus over time and adjust their comfort thresholds accordingly. A further step that could also be worth exploring would be to incorporate daily recorded infection data and allow agents thresholds to vary dynamically in response (thresholds climbing as infection rates fall and vice versa).

Conclusion

Although one may aim for deductive reasoning, in practice inductive reasoning is often deployed by people in situations too complex or not well defined enough to apply deductive reasoning. This is true in many real world situations including the problem of whether or not to re-emerge into public spaces following the lifting of government sanctioned lock downs. Inductive reasoning systems employ collections of models

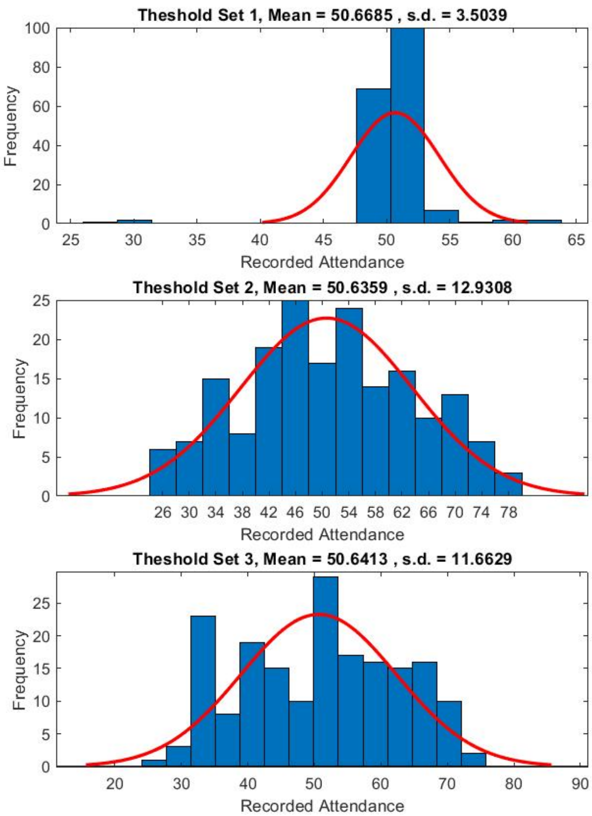

Figure 4: Histogram of Recorded Attendance Values

that adapt to the environment they jointly create - they are adaptive complex systems. After an initial learning time, sets of models in the system can become mutually co-adapted. This same logic can be extended to the social reopening scenario where one can observe that over time a population of agents will settle into somewhat of an equilibrium level of use of the public space equal to the mean comfort threshold of the population, although the daily variability in attendance levels increases significantly as the homogeneity of a population's set of thresholds increases. The stability of attendance to public spaces in populations with heterogeneous thresholds comes at a cost to the citizens as these spaces would effectively become unavailable to the most cautious groups in society and only those least concerned by crowding would be able to enjoy them.

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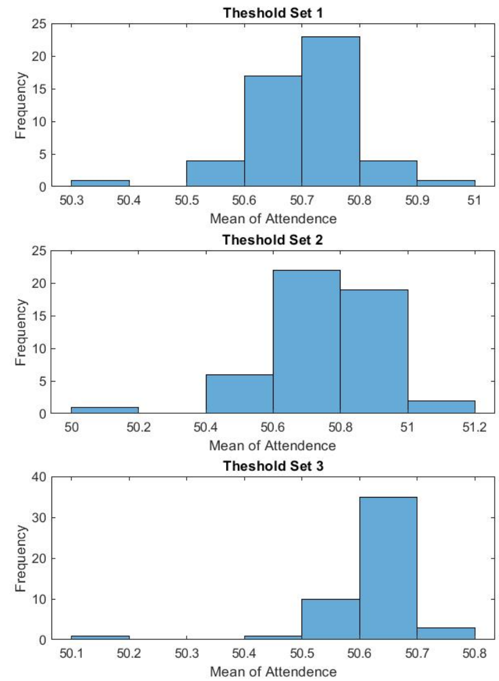

Figure 5: Histograms of Mean Recorded Attendance Values During Repeated Simulations

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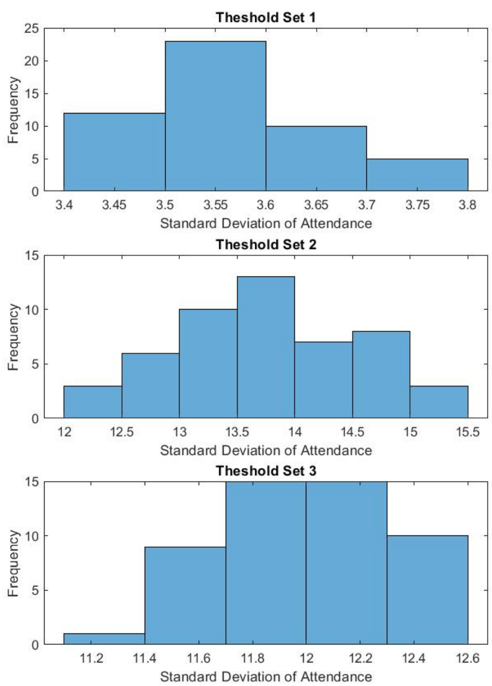

Figure 6: Histograms of Recorded Standard Deviations in Attendance During Repeated Simulations