Using Probabilistic Planning to Model the Spread of COVID-19 in Kingston, Ontario

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Abstract

Modeling and understanding the spread of disease has been a topic of much focus for epidemiological researchers in recent years, due to the COVID-19 pandemic. High levels of global attention and an abundance of recently collected data has created an environment for epidemiological models to be highly detailed and impactful. The best of these models incorporate ideas and research from a range of domains, with clarity and ease of consumption being key focuses so that they have the highest chance of impacting public policy. In this paper, probabilistic planning is leveraged to understand the spread of COVID-19 at a regional level in the city of Kingston, Ontario through RDDL via JaxPlanner. This model operates with the functionality of implementing mask and vaccine mandates as sparingly as possible while attempting to ensure that hospitals are operating below capacity. We experiment with different population structures and identify which groups are at the highest risk, and illustrate the disease dynamics in each case, identifying equilibrium behaviour. (A brief comment on results will be added here when they are obtained)

1. Introduction

Understanding how a disease spreads is necessary when attempting to minimizing the damage done to a population. The intricacies of exactly how a disease spreads are often quite difficult to identify, and it requires significant effort to truly capture minute details. Due to the complex nature of epidemics, the models that describe them are oftentimes quite complicated - decreasing generality and risking poor adaptation to new discoveries or data. These disease models are typically constructed with the functionality of non-pharmaceutical intervention (NPI) in order to see how spread can slowed or stopped [1]. From this, policymakers have been able to incorporate strategies based on many such models, proving their viability in handling these kinds of highly complex scenarios [2]. However, even among the most successful and detailed of models, there are still limitations that can cause significant differences in behaviour to emerge between the model's predictions and real world outcomes. Some of the more common limitations have to do with location and location-based data such as regional population, organization, and infrastructure. I present a model based in RDDL, through JaxPlanner, that aims to minimizes NPI uptime while keeping hospitals operating below capacity through the use of real geographical and regional data from the town of Kingston, Ontario as an exploration of the power of RDDL in modeling disease dynamics and intervention.

CISC-813: Automated Planning – Final Project

2. Background

In this section, I will provide a brief overview of SEIR modeling, highlighting the relevant parts to my planner (for instance, no agents die in this model. If agents were to die, then I would have to introduce agent births, which is getting off track). This section will be fairly brief and simple.

3. Related Work

Mathematical Modeling Often serving as the basis for more complex agent-based models, mathematical models seek to explain the spread of disease from a compartmental standpoint. The states a person can be in (SEIR) relative to the disease and the rates of change of each of these states in a given population over time are modeled and can be readily tweaked to account for a variety of situations. Significant work was done early into the pandemic in Sweden, furthering our understanding of the disease behaviour in a population with real, up to date data [3, 4, 5]. While these models performed well for certain tasks, the simplicity and generalizations made by the models produced results that were often not in line with observed data.

Agent-Based Modeling Built from strong foundations in mathematical modeling, agent-based modeling has seen increased usage in recent years; specifically with respect to disease modeling. Early into the COVID-19 pandemic, many older ABMs were adapted to model COVID-19's spread and resistance to intervention methods [6]. While these sorts of models were arguably the most advanced at the time, they often had limitations with regards to population behaviour and the implementation of intervention methods [1]. Building on these ideas, popular models such as OpenABM-Covid19 and Covasim emerged, which have been used by public health officials worldwide to aid in decision support, taking detailed population behaviour into account and tracking how a variety of intervention methods affect the spread of COVID-19 [2, 7]. These are seen as state of the art COVID-19 models, and are being consistently improved upon. GSAM is another powerful model with very high scalability, allowing for billions of agents to act distinctly at the cost of specificity with regards to their environments. This type of model is good for understanding broad disease dynamics, but does not perform well when trying to understand fine details [8]. There are also models like BioWar, where nefarious agents are introduced, who act to intentionally spread disease, giving way to some interesting dynamics [9]. In addition to these, there are a plethora of other models that exist, which specialize in different tasks [10, 11, 12, 13] - many of them being open source and regularly updated.

Automated Planning Understanding the spread of disease is a long-standing exercise and problem in the field of Planning. New strategies for handling MDP settings are regularly emerging, opening the door for more complex and realistic models. Specifically, RDDL is beginning to see use as a tool for developing intervention plans to hinder the spread of disease, with Harmanani modeling COVID-19 spread in enclosed spaces, grounded in real data [14]. By allowing the planner to intervene by way of masking and vaccinating, the results produced by the model were found to quite accurately reflect real world data. While this attempt was successful at describing behaviour in enclosed spaces, there has been little attempt to model such behaviour on a large scale such that the impact of disease on regional population dynamics could be analyzed in a meaningful way.

4. Methods

This section will be broken up into two subsections: modeling the environment, and the discussing the planner's actions and goal.

4.1. Modeling the environment

Agent Initialization The first paragraph will discuss how agents are set up, and how they move around in the space. Here, I will go into detail discussing what attributes belong to an agent, how agents operate from day to day, how they are assigned homes, workplaces, schools, and stores, and how age bracket determines certain behaviours. The following illustrates a high-level interpretation of this in point form:

- Each agent is assigned to an age bracket, based on recorded probabilities in the city of Kingston. This will determine how they interact with COVID-19 (transmission and infection severity), what they do from day to day, and how they react to NPIs
- Time is tracked by simple counters. Day and night are represented as 0 and 1, and the counter flips between these on each timestep. Days of the week are tracked in a similar way
- Each agent is assigned a home. Each home contains 1-5 agents, with probabilities being based on real data from the city of Kingston. This will be where agents return to after being at work or school during the day. If an agent is infected, they have a chance to isolate, and they will stay at their home for the infectious period. If they are hospitalized, they will not go home or to work/school until infection is over
- Each agent is assigned a place they go during the weekdays. If an agent is 0-19, they attend school (the geographically closest school to the agent, calculated by Euclidian distance). Some agents in the 20-29 range will attend post-secondary school. Other agents in the 20-29 range and all agents 30-69 will attend work during the day (workplace chosen randomly from the whole list of places in Kingston - proximity is not a factor). Agents 70 and up are assigned a store that they will visit during the day (geographically closest)
- Each agent is assigned a place they go during the weekends. If an agent is 0-9, they will remain at home. Otherwise, an agent will go to 1-4 stores (geographically closest) throughout the weekend
- The agents in the 20-29 range who attend post-secondary school (Queen's, SLC, or RMC) are placed as follows: post-secondary schools are all set to have a specific population, and agents will sequentially be assigned to the school until the population number is reached. Agents' homes are assigned based on their proximity to a given campus, filling up the closest residential buildings first. Dorms will be filled up first, and then other homes will follow. The location these agents visit during the day is a random building on the campus of whatever school they are attending. Stores on the weekend operate in the same way as usual
- Transit between locations will not be accounted for in this model. Agents will instantly move from location to location, where disease spread will occur

Data Collection The second paragraph here will be a brief discussion about how the data was retrieved, and how instance files were generated based on this data. The following outlines the topics discussed here:

- The OSMnx package was used for geographical data ingestion in Python. This package provides data (building coordinates and type) for the majority of buildings in the specified city
- A Python script was created, using the data gathered from OSMnx to assign agents ages, homes, workplaces, schools, and stores, based on probabilities and statistics from the city of Kingston

Disease Mechanics The third paragraph will discuss how disease is spread. I will go over the calculations, and describe how an agent flows through the SEIR chain. I will also discuss the probabilites associated with time spent in each class, and how infections can be mild, severe, or critical, with severe and critical infections resulting in hospitalization. A point form of this is shown here:

- Agents can be in the following states with regards to COVID-19: Exposed, Infectious, or Recovered. Note that their is *no designated susceptible class.* All agents who are in none of these classes are implicitly susceptible.
- When an agent enters one of these classes, it remains there for some period of time chosen from a probability distribution, at which point they move to the next class. Time spent in a class is tracked by a simple counter
- When an agent is in the Infectious class, they have a chance of isolating at home for the entire period
- When an agent contracts COVID-19, the infection can be mild, severe, or critical. These occur at probabilities based on their age bracket. If the infection is severe, they are admitted to the hospital in a regular bed. If the infection is critical, they are admitted to the hospital in an ICU bed.
- When an agent is in the recovered class, they have a reduced chance of catching COVID-19, equal to the vaccination effectiveness.
- Agents can be masked or vaccinated, based on actions taken by the planner. Masking and vaccination occurs for a specific agent at some probability based on their age bracket. Being masked and/or vaccinated reduces COVID-19 transmission chance
- When an agent is at a location, they have a probability of catching COVID-19 based on the number of agents at the same location as them who are currently in the infectious class. This probability can be decreased by the agent being masked/vaccinated *and* by the infectious agents wearing masks

4.2. Planner Actions and Goal

Mask Intervention The first paragraph will discuss mask intervention, and how it is implemented. I will discuss how a mask mandate is applied to all agents at the same time, and how agents abide by the mandate with a given probability based on their age bracket. I will also discuss how masking reduces the spread of COVID-19 and provide data to back it up.

Vaccine Intervention The second paragraph will discuss vaccine intervention, and how it is implemented. I will emphasize how vaccine mandates can only be applied once per simulation, and how agents, once again, adhere to this policy in a probabilistic manner based on their age bracket. I will also show how vaccine affects transmission rate.

Planner Goal The third paragraph will outline the reward function, describing penalties and providing a basic calculation. The planner will be attempting to maximize the reward function, which is roughly set up in the following way (Note that since each penalty is a negative number, the reward is a maximum of 0):

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Reward = (Vaccine_Mandate * V_Penalty) +
         (Mask_Mandate * M_Penalty) +
         (H_R_Bed_Ex* R_Bed_Penalty) +
         (H_ICU_Bed_Ex * ICU_Bed_Penalty)
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5. Evaluation

First, I will describe exactly how the experiments were set up with regards to numbers. It is likely that Kingston in its entirety will not be able to be captured, due to computational challenges. I will experiment with different setups (age distribution, parameter values, etc.) and show how the infection spreads as a result of these changes via tables and graphs. I will also experiment with different mask mandate implementation methods, such as having masks be mandated only for students, or having masks be implemented for some specific period at a time only.

I will then attempt to compare my results to real-world data, and see how the model's results compare.

6. Discussion

This discussion will highlight key limitations with the model, as well as future work.

7. Conclusion

Here, I will provide a high-level overview of the project, reiterating the important parts of the model.

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