Research Idea:
Money is a huge factor how people respond to the pandemic

Questions to model for specific city, modelling for say Allahabad? Where religious gatherings happen everyday

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RESPONSE 2: Agent-Based Markov Modeling for Improved COVID-19 Mitigation Policies

The spread of a pandemic differs from city to city. Therefore, simulations must be adaptive because populations do not react consistently. This research aims to make decision-making for the next pandemic easier, faster, and more accurate. A pandemic simulation, which helps illustrate the danger of superspreader events, can help better manage the worldwide COVID-19 pandemic in 2020 and comparable future pandemics.

This paper [1] introduces:

- An agent-based pandemic simulator for simulating society interactions
- A reinforcement learning-based methodology for optimizing mitigation strategies while maximizing personal freedom and economic activity as well as enabling us to analyze policies that are more dynamic than those stated in the paper
- A Hidden Markov Model for predicting infected individuals in the community. HMMs have shown great success in prior work [2,3,4].

The model successfully shows that a learnt policy that has been optimized outperforms the baseline policies in the simulation. I look forward to greater explainability of learned policies and transparency into what causes policy waits/changes during RL optimization. I also look forward to using other reinforcement learning/machine learning for optimizing and analyzing such policies [5].

Several societal shortcomings are accurately represented in this simulation. For example, when the testing procedure is activated, the simulator identifies a group of individuals to be tested and provides an imperfect report on their infection status. The simulation also considers a false positive rate, a false negative rate, and a re-test previous-positive rate. I like how it imperfectly reports the covid-19 status; modifying how inaccurately the test results are reported would be interesting, making it easier to imitate nations like India and China, where reports are often tampered with [6,7]. The simulation also accounts for the fact that the government sees information that is both an underestimation and time-delayed from actuality, making the simulation mimic real-world situations. The paper also mentions restricting government operations to five phases of regulation, comparable to those utilized by real-world cities.

I appreciate how users are allowed to add new location types, as well as how users and various policies in the simulation can modify the rates of worker-worker, worker-visitor, and visitor-visitor interaction. It would be interesting if their values varied over time, given the crowd is maximum during peak business hours and lower otherwise. According to the CDC, longer exposure duration and being closer to someone infected with COVID-19 raises the chance of transmission [8]. The paper mentions exposure rate; however, I am not confident about what information it entails. If a place is at capacity, then person-to-person interaction can be weighted more significantly, as it is more likely that people are standing closer together, increasing the risk. When modelling whether a susceptible person becomes infected, it would be interesting if the simulation considered the length of exposure along with whom they come into contact.

Despite being a self-explanatory paper, a few questions arise when reading it. The study discusses developing a "trustworthy" model by calibrating it to track previous data precisely. The question arises of whether this necessarily makes the model more trustworthy. For example, will it be able to model effectively based on data from places where the pandemic was more chaotic and restrictions altered more frequently than in Sweden? Another concern arises when studying the interaction graph connectivity: why does only the Stage 4 graph look different while the rest look the same? Surprisingly, there are fairly any differences between the rest of the stages.

It would be exciting to extend this simulator to include numerous cities, cross-city travel, and integrating various resource allocation strategies [9]. For example, a study showed how a reinforcement-learning algorithm might distribute different lockdown resources based on the characteristics of different states to more effectively restrict pandemic spread [9]. For future study, it would also be interesting if the simulation considers the perceived risks of COVID-19 transmission in various forms of transportation. A research study of SARS-CoV-2 cluster infections revealed that public transport was a significant cluster infection source [10]. Including the ventilation rates of various locations and modes of transportation would result in more accurate simulations, as individuals in an open area are less likely to become infected than those in a closed building. Other exciting research modifications may include observing different strains of covid, the ability to manage multiple cities with varying government policies, controlling multiple superspreaders, and incorporating vaccination and its effects on the pandemic. It would also be interesting to simulate the spread of COVID-19 disinformation, as well as, its effect by tampering with metrics such as the compliance metric, random testing probability, probability of maintaining regulations, and probability of getting vaccinated.

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