Modeling the impact of vaccination, mask policies and mobility on the COVID-19 pandemic in Singapore

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ABSTRACT

In this project, we will use cutting-edge epidemiology models to study the impact of vaccination, mask policies and mobility on the outbreak of COVID-19 in Singapore.

CCS CONCEPTS

• **Computing methodologies → Model verification and validation**.

1 INTRODUCTION

In this project, we will mainly focus on two outbreaks of COVID-19 in Singapore:

- Singapore, March 2020 to Sept 2020 (optional)
- Singapore, July 2021 till now, mainly delta variant

There are significant differences among these two outbreaks. For example, during the last year's outbreak in Singapore, there were no available vaccines, but the government had published very strict policies to reduce social interactions. And for this year's outbreak in Singapore, nearly 90% of people have been fully vaccinated, but the government is entering the 'Preparatory Stage' and the local restrictions have been relaxed. Through analyzing and modeling the two outbreaks, we are looking forward to answering several questions (or a part of them):

- How does the vaccination affect the outbreak?
- How does the government policy and the mobility affect the outbreak?

Furthermore, we will evaluate our models from two aspects:

- whether the model is able to explain past data, especially the current outbreak in Singapore
- whether the model is able to predict the future COVID-19 situation of Singapore

2 RESPONSE TO THE COMMENTS OF OUR MILESTONE REPORT

- We have

3 LITERATURE REVIEW

4 DATA SOURCE

The data source for this study are listed below, which is also available at this link. For a quick overview, Figure 1 shows the daily confirmed COVID-19 cases/deaths and Google (residential) mobility trends of Singapore from February 17th 2020 to Oct 29th 2021.

- COVID-19 cases/deaths/vaccines: The COVID-19 related data comes from data.world. We choose several data points and verify it with official MOH report. For the missing vaccine data (from Jan 11th 2021 to June 30th 2021), we fill it with data from Our World in Data and perform linear interpolation to make it continuous.
- Epidemiology: The epidemiology data of COVID-19, such as duration parameters (for example, duration between exposed state and infectious state), age-linked disease probability (for example, relative susceptibility to infection), is built in the library covasim.
- Demographics: The population age distribution data comes from this Github repo and is built in the library covasim. However, because the Department of Statistics of Singapore only releases the resident population age distribution, we are not able to verify the correctness of this data.
- Mobility: We use Google Community Mobility Reports as the indicator of mobility. The reports provide the changes in movement trends across different categories of activities, which includes residential, retail and recreation, groceries and pharmacies, parks, transit stations, and workplaces. We collect this data from Our World in Data.
- Policy: We use mask policy indicator, which is categorized into five categories: 0 - no policy; 1 - recommended; 2 - required in specified public spaces; 3 - required in all public spaces; 4 - required outside the home at all times. We also collect other relevant policy data (such as quarantine policy, face covering policy) from official MOH report.

5 AGENT-BASED MODEL

In this section, we provide a formal description of covasim model [1] and how we model vaccinations, mask policies and mobility changes within our model.

5.1 Disease progression

In covasim, the disease state of an agent is characterized as susceptible, exposed, infectious (asymptomatic, presymptomatic, mild, severe, critical), recovered and dead. The Figure 2 shows all possible transformation between any two disease states. Each transformation is also parameterized with a probability p (how likely does the transformation happen) and a duration τ (how long does the transformation take). The age-linked value of p and the distribution

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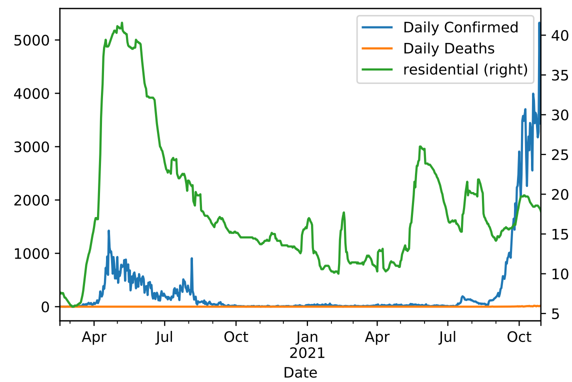

Figure 1: Daily COVID-19 counts and Google mobility trends

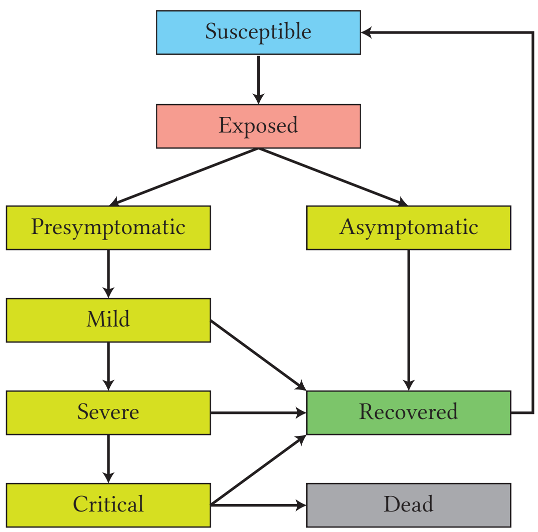

Figure 2: Covasim model, disease state transformation structure

of τ are detrived from lots of previous research and are built in covasim.

5.2 Contact network

To model the contact network between people, covasim assigns people to four network layers: household, school, workplace and community. More specifically, covasim generates a population of people based on the location-specific age distribution. After that, covasim assigns people aged between 6 and 22 to schools, assigns people aged between 22 and 65 to workplaces and assigns people to households based on the location-specific household size.

Within each network, the contact number of each person is sampled from poisson distributions. For each contact between a susceptible individual and an infectious individual, the probability of a successful virus transmission is β.

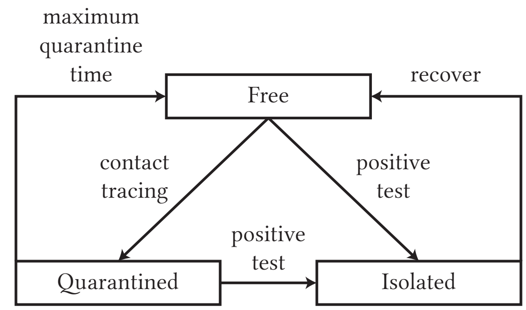

Figure 3: Covasim model, agent state transformation structure

5.3 Agent states

One important feature of covasim is that it provides several useful agent states so that it can describe testing, contact-tracing, quarantine and isolation policies. Figure 3 lists out built in agent states and transformations between them.

- Free: If an agent is free, the agent has 100% β value. If a free agent has a contact with a confirmed case and is traced successfully, the agent will become quarantined. If a free agent has positive test results, the agent will become isolated.
- Quarantined: If an agent is quarantined, the agent has 60% β in the household layer and 20% β in other layers. The quarantine ends when it reaches the maximum quarantine time. However, if a quarantined agent has positive test results, the agent will also get isolated.
- Isolated: If an agent is isolated, the agent has 30% β in the household layer and 10% β in other layers. A isolated agent will become free once the agent recovers.

5.4 Mask policies and mobility

There are two important factors which affect the spread of COVID-19. The first one is personal protection, such as wearing masks, washing hands, etc, which reduces the probability of virus transmission per contact, i.e., the β value The second one is social distancing, such as avoiding crowds, keeping distance from others, staying at home, etc, which reduces the contact number of each agent.

Within our model, we use mask policies and mobility to represent personal protection and social distancing respectively. More specifically, denote numerical mask policies and mobility as $x_{\text{ma}}, x_{\text{mo}}$, we define a function $f : \mathcal{R}^2 \rightarrow [0, 1]$ as:

$$f(x_{\text{ma}}, x_{\text{mo}}) = \frac{2(a_1 x_{\text{ma}} + b_1)(a_2 x_{\text{mo}} + b_2)}{(a_1 x_{\text{ma}} + b_1) + (a_2 x_{\text{mo}} + b_2)} \quad (1)$$

After that, for each day we calculate the β value as $f(x_{\text{ma}}, x_{\text{mo}})\beta_0$, where the β_0 is a constant within one outbreak (for a variant of SARS-CoV-2) and $x_{\text{ma}}, x_{\text{mo}}$ changes each day.

6 RESULTS AND DISCUSSION

6.1 Calibration process

We use optuna to perform the calibration. Each time, we sample parameters from the Tree-structured Parzen Estimator (TPE) sampler and run the simulation once. After that, we calculate the minimization objective value as the mean absolute error of the cumulative confirmed number between the simulation results and the real-world data and feed the objective value to sampler. Because of the limitation of hardware and time, we times all the cases/deaths/vaccines with 0.01. We use the negative of mask policy indicator and the negative of residential mobility as the numerical mask policies and mobility value. We model the first outbreak (from March 2020 to Sept 2020) and the second outbreak (from July 2021 to Oct 25th) separately because they are caused by different variants.

For the first outbreak, we calibrate the following parameters:

- β_0: the probability of a successful virus transmission per contact, calibration range is $[0.06, 0.10]$.
- ma_{min}: we calculate a_1 and b_1 such that $\max\{a_1 x_{\text{ma}} + b_1)\} = 1.0$ and $\min\{a_1 x_{\text{ma}} + b_1)\} = \text{ma}_{\text{min}}$. The calibration range is $[0.03, 0.25]$.
- mo_{min}: we calculate a_2 and b_2 such that $\max\{a_2 x_{\text{mo}} + b_2)\} = 1.0$ and $\min\{a_2 x_{\text{mo}} + b_2)\} = \text{mo}_{\text{min}}$. The calibration range is $[0.1, 0.6]$.
- symp_prob: the test probability of a symptomatic agent, calibration range is $[0.9, 1.0]$.
- trace_probs: the successful probability of a contact tracing, calibration range is $[0.75, 0.99]$.
- start_shift: the number of days between the first ten people get infected and the first confirmed case, calibration range is $[-8, 8]$.

Besides these parameters, we set the following parameters as constants:

- pop_infected = 10: the number of infected people at the start of the simulation
- asymp_prob = 0: the test probability of a asymptomatic agent
- quar_period = 7: the maximum quarantine time in days, we collect the value from the official MOH website
- test_delay = 1: the number of days for test results to be known

After calibrating the first outbreak, we setup the second outbreak with the same constants and the calibration results ma_{min}, mo_{min}, symp_prob, trace_probs of the first outbreak. For the second outbreak, we only calibrate the β_0 value in range $[0.61, 0.3]$ and the start_shift in range $[-21, 21]$ while take the vaccinations into consideration. Instead of introducing infected populations at the start of the simulation, we introduce 10 people infected by delta variant on the day when the first case gets confirmed (24th August) shifted by start_shift.

Regards the vaccination, we assume that people only receive Pfizer COVID-19 vaccines and the order in which people get vaccinated is the descending order of people's age. We also assume that people who have received the first dose 21 days before have priority in receiving the second dose. We calibrate the first outbreak with 5000 samples and the second outbreak with 2000 samples.

After calibrating the second outbreak, we assume the daily vaccine doses, mask policies and mobility as the mean of the last 30 days and predict the epidemiology data of the next 30 days, which lies in the yellow area of Figure 5.

6.2 Calibration results

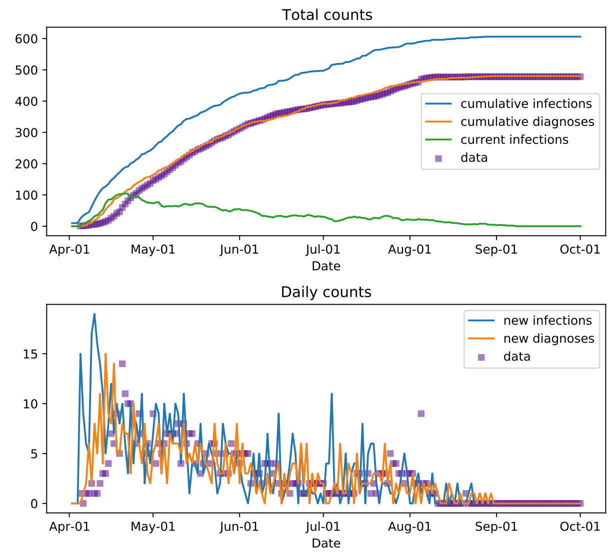

Figure 4: First outbreak, calibration results

For the first outbreak, the calibrated parameters are $\beta_0 = 0.061$, $\text{ma}_{\text{min}} = 0.13$, $\text{mo}_{\text{min}} = 0.43$, symp_prob = 0.9, trace_prob = 0.79,

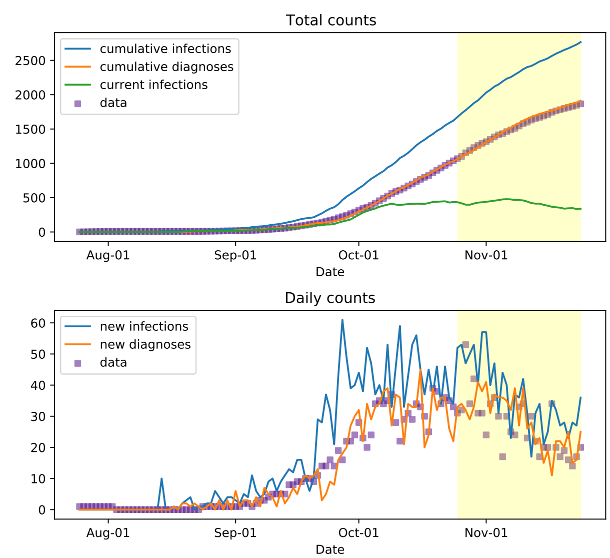

Figure 5: Second outbreak, calibration results

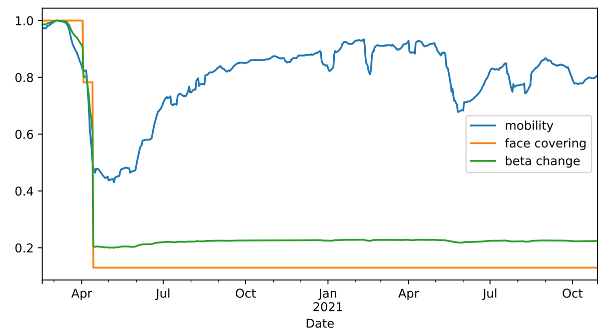

Figure 7: The impact of mask policies and mobility

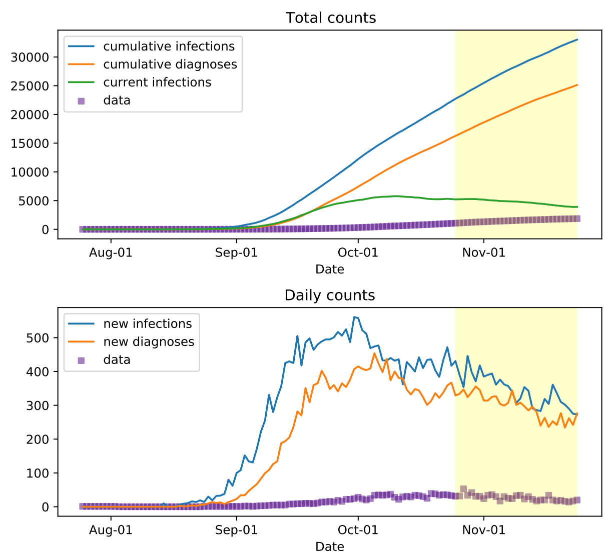

Figure 6: Second outbreak, without vaccination

start_shift = 3. Figure 4 shows the calibration results of the first outbreak. The calibration results fit the data pretty well except the first month, which may results from the relatively low testing probability at the beginning.

For the second outbreak, the calibrated parameters are $\beta_0 = 0.134$, start_shift = 10. Figure 5 shows the calibration results of the first outbreak and the prediction of the next 30 days (in yellow area). The calibration results not only fit the data well but also give a pretty good prediction. Cause the β_0 value has already been multiplied by 2.2 within covasim, the real β_0 value is $2.2 \times 0.134 \approx 0.295$, which is about four times larger than the β_0 value of the first outbreak.

6.3 Effect of vaccination

To evaluate the effect of the vaccination, we run the simulation of the second outbreak with same parameters but without vaccination. Figure 6 indicates that more than a half of the total population will get infected under such mask policies and mobility, which reveals the importance of the vaccination.

6.4 Effect of mask policies and mobility

Figure 7 shows the impact of mask policies and mobility on the β value. When the mask policies are not strict, the change of mobility explains the main part of the change of β. However, when the mask policies becomes strict after mid-April, the change of mobility only causes small fluctuations on β.

7 CONCLUSION

REFERENCES

[1] Cliff C Kerr, Robyn M Stuart, Dina Mistry, Romesh G Abeysuriya, Katherine Rosenfeld, Gregory R Hart, Rafael C Núñez, Jamie A Cohen, Prashanth Selvaraj, Brittany Hagedorn, et al. 2021. Covasim: an agent-based model of COVID-19 dynamics and interventions. *PLOS Computational Biology* 17, 7 (2021), e1009149.