Predicting and Allocating Funds for COVID-19

Project Members:

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Motivation Behind the Project:

With the second wave of COVID-19 cases occurring this fall, we were tasked with fine-tuning a model to measure the rate of susceptible, infected, and recovered people, and then modify said model to allocate money between each group amongst the population.

Uses:

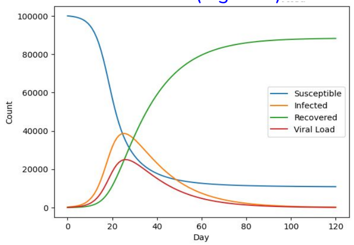
- Predicting the influx of COVID-19 cases amongst groups based on non-pharmaceutical interventions.
- Setting up medical and pharmaceutical precautions based on the predicted influx of cases.

Challenges:

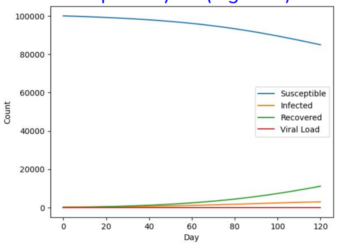
- Coordinating group meetings
  - Our presentation time
- Being on the same page in terms of understanding the material.
- Making sure the data is consistent with its group populations
  - Determining if the data provided was affected by out-of-town visitors.

Part 1a: Simulating the "SIR" Model

120-day simulation of COVID-19 infection rate based on arbitrary beta values (Figure 1)

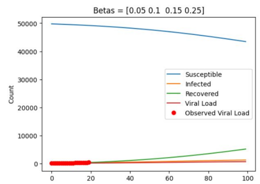


Same model and simulation as Figure 1, but the beta values are multiplied by ¼. (Figure 2).

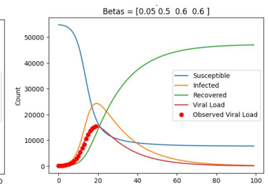


Part 1b: Estimating the beta values based on observed data

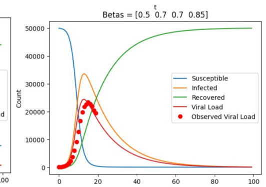
Simulated Models with Estimated Values of Beta, as well as Observed Viral Load



Model 1



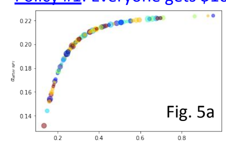
Model 3



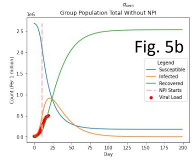
Model 4

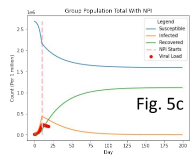
Part 2: Non-Pharmaceutical Intervention

Policy #1: Everyone gets $10,000

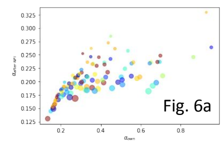


Although equal distribution is inherently the most fair way to distribute funding, it may not be the most effective.

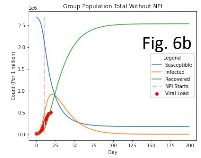


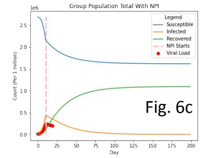


Policy #2: Proportion of Total Pop.

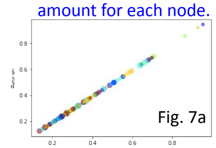


Policy #2 is fair in the sense that it accounts for population size. However, it does not recognize areas with more/less vulnerable populations.

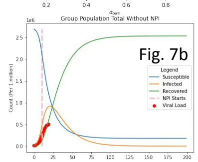


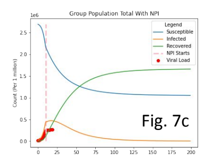


Policy #3: Subtract alpha by same amount for each node.

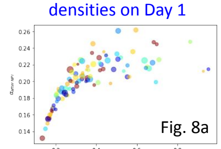


While basing funding distribution on differences in alpha values, policy #3 showed a significantly lower rate of recovered/succumbed.

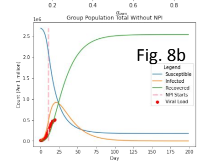


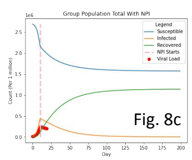


Policy #4: Proportion based on viral load densities on Day 1



The pitfall of policy #4 is similar to that of policy #2, as it fails to account for areas with more/less vulnerable populations.





References

[1] JA Patel, FBH Nielsen, AA Badiani, S Assi, VA Unadkat, B Patel, R Ravindrane, and H Wardle. Poverty, inequality and covid-19: the forgotten vulnerable. Public Health, 183:110, 2020.

[2] Emily E Wiemers, Scott Abrahams, Marwa AlFakhri, V Joseph Hotz, Robert F Schoeni, and Judith A Seltzer. Disparities in vulnerability to severe complications from covid-19 in the united states. Technical report, National Bureau of Economic Research, 2020.

Summary

This model was an effective way to help predict the effects of COVID-19. We achieved what was expected, but we found the implementation in Python to be difficult. Once we switched over to Spyder from Jupyter, we had more success.

Coordination

We used iMessage and Zoom to communicate with our teammates. When coding, it's not easy to collaborate, so we split the project into parts, and assigned due dates for progress points. We reached out to Can on piazza when we had trouble.

Future Work:

The work that we did in this project created the foundation for more complex models related to COVID-19. We could potentially extrapolate some of our findings and apply them to different geographical areas (ie. Santa Barbara), or even alter policies based on characteristics of a given location.