MATH 2121: Final Project Report
Professor Rujeko Chinomona
Katrina Janeczko
May 3, 2022

The Effect of Mask Type on the Spread of COVID-19 on a College Campus: An Agent-Based Model

Introduction

I originally became interested in exploring the topic of masks and the pandemic specifically on Temple University's campus due to the constantly changing mask guidelines. Every few weeks it seems that guidelines for students and faculty as it pertains to masks is changed, from no requirement, to a mask requirement only if not vaccinated, to a recommendation of cloth masks, to a requirement of respirators, to a relaxation of mask rules in common spaces, back to a lack of requirement, and then back to a face covering requirement. This has of course caused me and my peers to wonder what reasoning there is behind certain mask guidelines and whether the type of mask worn truly makes any difference. Many questions came to mind. Does my favorite comfortable cloth mask really do a poor job of protecting me when compared with a KN95 respirator, or is the difference overall negligible? If everyone wore a mask in common spaces, would COVID-19 be eliminated completely? How fast can COVID-19 spread on a college campus if masks aren't required, or if only some people follow mask guidelines? I decided to use Agent-Based Modeling as discussed in class in order to help answer these questions through this semester-long project.

This is certainly not the first model for COVID-19 or epidemics and pandemics in general. The CDC uses mathematical modeling to forecast cases, deaths, hospitalizations, spread, and variants of the COVID-19 pandemic, which I had discovered upon researching for this project. However, this model is different because it is more specific to a college campus and specifically explores the effect of mask type distribution ("Covid-19 Forecasting and Mathematical Modeling"). Another model of note is one that I saw in 2020 on a YouTube channel called 3Blue1Brown, who created a video entitled “Simulating an Epidemic” to showcase how factors such as the R0 value for a disease, social distancing, quarantining, and traveling affected the spread of epidemics using a general mathematical model he built (3Blue1Brown).

Methods

In order to create this model within the specified time limit as well as to focus specifically on the effect of mask type, many assumptions were made for simplicity and efficiency. For instance, one assumption is that agents wear the same mask throughout the entirety of the semester, and do not remove it on campus. Obviously, in real life, students would remove masks to eat or hang out with friends and might change up their mask type on different days, but for simplicity this assumption is reasonable since people tend to keep their mask on in common areas during a mask mandate and also a singular person would tend to probably wear the same type of mask most days. Another important assumption is that the potential for infection depends only on the attributes of the mask wearer (the probability of infection is determined by a modified base potential that depends on the mask type of the uninfected agent, but the mask type of the infected agent is not considered). For the purpose of this model at this point in time, the data seems reasonable without taking this into account, but if I were to keep working on this model I would improve it by incorporating the mask type of the infected agent into the model. Another assumption is using 1% of Temple’s student population to represent its whole population at scale (which is reasonable since the campus is also larger than a 10x10 grid so this is showing patterns emerging on a smaller scale that may be scaled up if needed). Additionally, agents continue to move all day long and don’t go to sleep or leave campus, which seems unreasonable except when considering that students, in addition to periods of low interaction and activity such as sleeping or studying alone, would also participate in periods of high interaction and social activity like parties or club meetings, so these would probably even each other out. Another assumption worth mentioning is that for simplicity, the model ignores that those who are vaccinated would have a lower probability of infection and instead uses the same base value for infection for any agent. Some other assumptions are that agents quarantine when they are supposed to (6 days after symptoms), and that once an agent has quarantined after infection, they are immune for the rest of the simulation. Although we do not know exactly how COVID-19 works, it seems that most of my peers who have contracted the infection in the beginning of the semester were able to avoid it for the remainder. The last assumption to note has to do with the fact that with a small probability each time step, an infected student may be randomly spawned into the simulation. This occurs in order to represent students bringing infection from somewhere outside campus, so it is not unreasonable.

The agents' environment is a 10x10 coordinate plane used to represent the college campus and its rooms or collective spaces. The initial student population size is N=395 agents, each moving in random directions determined by array D. A certain number of pre-infected agents, based on the day one positivity rate from Temple's COVID tracker, is i=1.9% (Evans). Each agent is represented on the grid by a colored dot; the color corresponds to the agent's mask type (No Mask is purple, Cloth Mask is dark blue, Surgical Mask is teal, Respirator is bright green), or represents whether they are infected (red) or immune (orange).

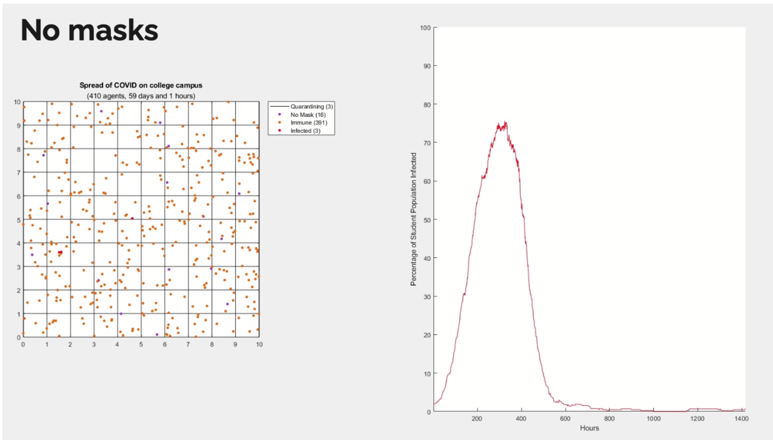
Each time step in the loop represents an hour, so there are 24 steps in a day, and then 115 days in the semester. So the simulation will run for ns=115*24=2760 steps. Each step elicits random movement from the agents around the board. When more than one agent enters the same square, they are considered to be in close proximity, and the uninfected agents are at risk of being infected. Each agent (student) has the main attribute of mask type (or infected or immune) that affects their ability to get infected, which is represented by certain probabilities designated in the simulation code in different experiments. These are represented by arrays called q_percentages which contain different mask type distributions. The modified probability of an individual getting infected, q_modified, comes from data on how much an agent's mask type protects them. For a maskless agent, the probability of infection is determined by q_base, which is a value calculated based on the median R0 value of COVID-19, which is 5.7 (Ramirez). For agents wearing a cloth mask, surgical mask, and respirator, the probabilities of getting infected are 44%, 34%, and 17%, respectively. This data is pulled from a study done by the CDC on effectiveness of different mask types ("Effectiveness of Face Mask or Respirator Use").

Each time step, agents' directions are randomly chosen and they are moved. Agents are contained within the domain using code that allows them to "bounce" off the walls (so that if they hit a wall, they are "bounced back" in the opposite direction). For every cell with more than 1 agent, if any agent in that cell is infected, then any uninfected agent will potentially also become infected (with this probability being determined by their mask type). Each agent has the attribute of "age" so that once infected, they will quarantine after 6 days. Agents that are infected will stay in the simulation for 6 days until they quarantine for another 8 days (14 total). Then, they will then return as immune (instead of their previous mask status), unable to become infected again for the rest of the simulation. The agents introduced as infected in the first step of the simulation enter with some predetermined amount of time randomly chosen as their age of infection (so that they are not all leaving to quarantine at the same exact time). Additionally, with a certain small probability, an already infectious agent will be introduced into the population randomly in each time step (representing people getting infected from somewhere other than campus). Then plotting occurs for both subplots. The code plots a 10x10 grid on the left representing the campus where each student is a colored dot representing mask type or infection status, and a line graph on the right showing the proportion of infected students over time (with a bar for current population size).

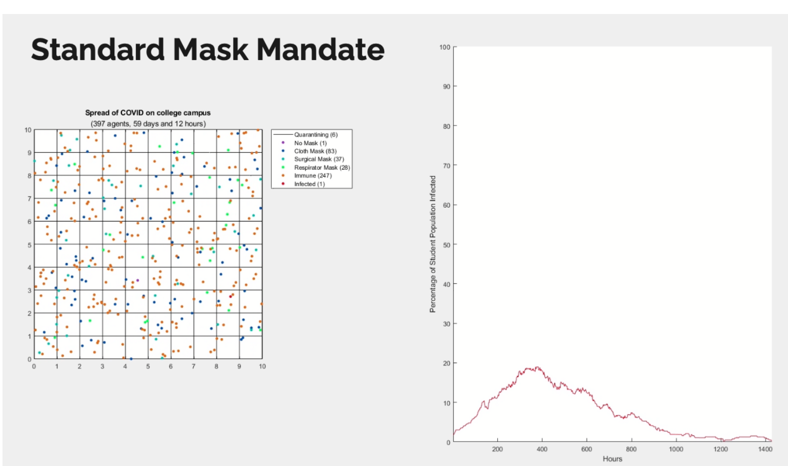
Results and Discussion

For the No Mask experiment (click here to watch a video), 100% of agents begin with the attribute of not wearing a mask. This is essentially like a control group in that it shows what data would look like without any masks at all such that we have something to which to compare outcomes of different distributions of mask wearers. After running the simulation for this experiment, the results show a very steep curve indicating that infection rates rose very quickly (and dropped very quickly as well once everyone returned from quarantine). Near the end of the simulation, almost everyone has had

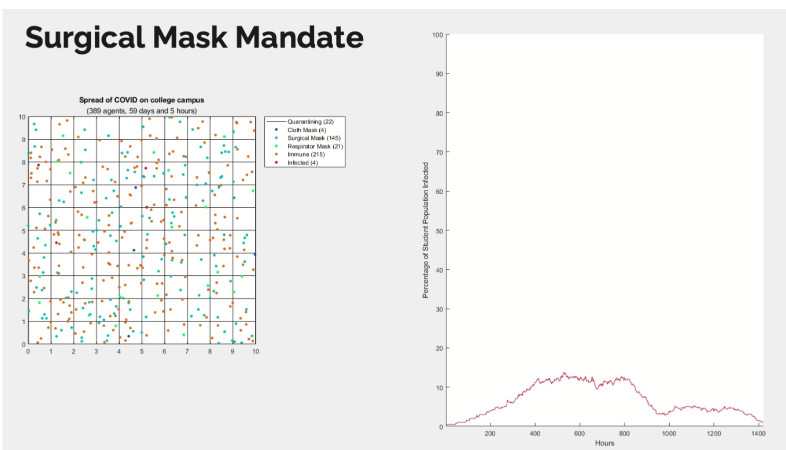
COVID-19 and is in the immune condition. Only 17 people of the initial 395 did not get infected after 60 days.



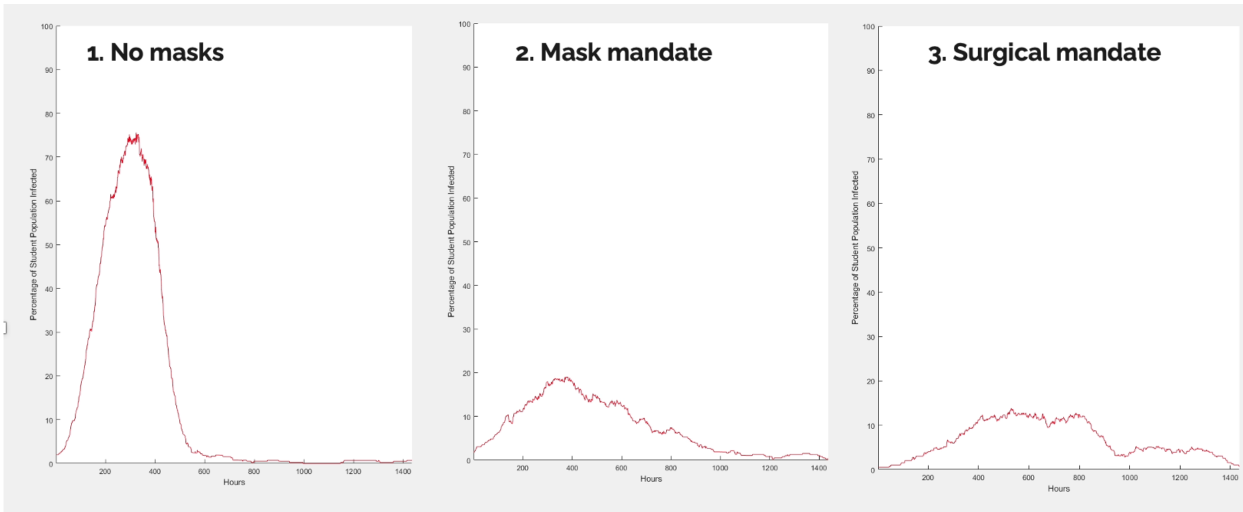
The Standard Mask Mandate on the other hand (click [here]() to watch a video), begins with 1% of agents wearing no mask, 69% wearing cloth masks, 20% wearing surgical masks, and 10% wearing respirators. This is a reasonable guess as to what mask distribution might look like on a college campus during a standard mask mandate. Observing the plots once this simulation has run, we notice that the curve is a lot less steep and drastic and instead seems to have flattened (and COVID-19 has lasted for a longer proportion of the semester). However, nearing the end of the simulation we see that this infection has nearly died out, and only 1 agent is currently infected. 139 people of the initial 395 did not get infected after 60 days.



The Surgical Mask Mandate(click here to watch a video) postulates an experiment in which agents are even more serious about wearing masks than in the standard mandate, where now it begins with 1% of agents wearing no mask, 4% wearing cloth masks, 85% wearing surgical masks, and 10% wearing respirators. After Temple sent out emails saying that cloth masks are no longer adequate, it seemed like this was about the mask type distribution when looking around a classroom. This line graph is similar to the standard mandate in that the curve representing infections is a lot flatter than the no mask experiment. It also shows that the school must deal with COVID-19 for longer, but a smaller proportion of agents were infected at any given time. 170 people of the initial 395 did not get infected after 60 days.



Graphs 2 and 3 below demonstrate the concept of “flattening the curve” which was a term thrown around in the early days of the pandemic. It’s desirable to flatten the curve so as to not overwhelm healthcare facilities for example, but in college it could be extended to not wanting most of the campus to be out sick at the same time. A flatter curve is created by a more gradual increase in the number of cases per day and a more gradual decrease. Over a long period of time, the number of people infected might be around the same, but the difference is seen in the number of cases that occur each day. In each simulation respectively, 17, 139, and 170 people out of the initial 395 did not get infected through 60 days, which means that lower total case amounts were achieved as well with the mandates within a short period of time.



Conclusion

To conclude, the results of this model seem to indicate that mask mandates do have a purpose and that following them with consistency would lead to a flatter curve and less overall cases throughout a semester.

It is not surprising that mathematical models and simulations are useful and well-utilized tools for tracking and forecasting data in epidemics and pandemics by organizations like the CDC. Agent-Based Modeling is especially valuable in modeling disease spread because one can give agents in the model (in this case people) certain attributes (such as mask type, infection status, or ability to become infected) and construct a model using simple rules for each time step in order to track complex emergent patterns through the individual behaviors of each agent (such as tendency toward quarantining, testing, mask-wearing, or social distancing) coming together as a whole (large-scale outcomes of a pandemic such as infection rates or hospitalizations). This is why Agent-Based Modeling was an appropriate and valuable choice for modeling the effect of mask types on the spread of COVID-19 on a college campus, where the individual agents are students and faculty and mask type worn and infection status are attributes of each agent.

If I am to work on improving this model, I would incorporate probabilities of infection based on mask type of infected agents (not just mask types of susceptible agents). I would also take a closer look at q_base and how I calculate that; I would want to see how altering the speed or grid size and scaling up the population size would affect the equation I used to find q_base in such a way that it corresponds to R0. I would also incorporate a Monte Carlo simulation so that I could run multiple simulations over and over to get a better idea of an average data set (as opposed to a few specific instances of how an experiment may go).

Throughout this project (and this class), I learned a lot about problem solving methods and thinking analytically. I learned how complex patterns can emerge from simple rules that we can set for agents to follow, and we can harness this to create models and simulations to represent real life situations and find possible solutions to real world problems and questions. I was able to create a working and reasonable model for a real world problem that I've wondered about, and I am excited to apply this knowledge in the future.

Works Cited

3Blue1Brown, director. *Simulating an Epidemic*. *YouTube*, YouTube, 27 Mar. 2020, https://www.youtube.com/watch?v=gxAaO2rsdIs. Accessed 1 May 2022.

"Covid-19 Forecasting and Mathematical Modeling." *Centers for Disease Control and Prevention*, Centers for Disease Control and Prevention, 7 Aug. 2020, https://www.cdc.gov/coronavirus/2019-ncov/science/forecasting/mathematical-modeling.html.

"Effectiveness of Face Mask or Respirator Use in Indoor Public Settings for Prevention of SARS-CoV-2 Infection — California, February–December 2021." *Centers for Disease Control and Prevention*, Centers for Disease Control and Prevention, 11 Feb. 2022, https://www.cdc.gov/mmwr/volumes/71/wr/mm7106e1.htm?s_cid=mm7106e1_w%20%5Bcdc.gov%5D.

Evans, Colin. “Tracking Covid-19 Cases at Temple University.” *The Temple News*, The Temple News, 1 June 2021, https://temple-news.com/trackingcovid19/.

Ramirez, Vanessa Bates. “What Is R0? Gauging Contagious Infections.” *Healthline*, Healthline Media, 20 Apr. 2020, https://www.healthline.com/health/r-naught-reproduction-number#covid-19-r-0.