SDS 322 FINAL PROJECT
DISEASE SIMULATION

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Creating a Population

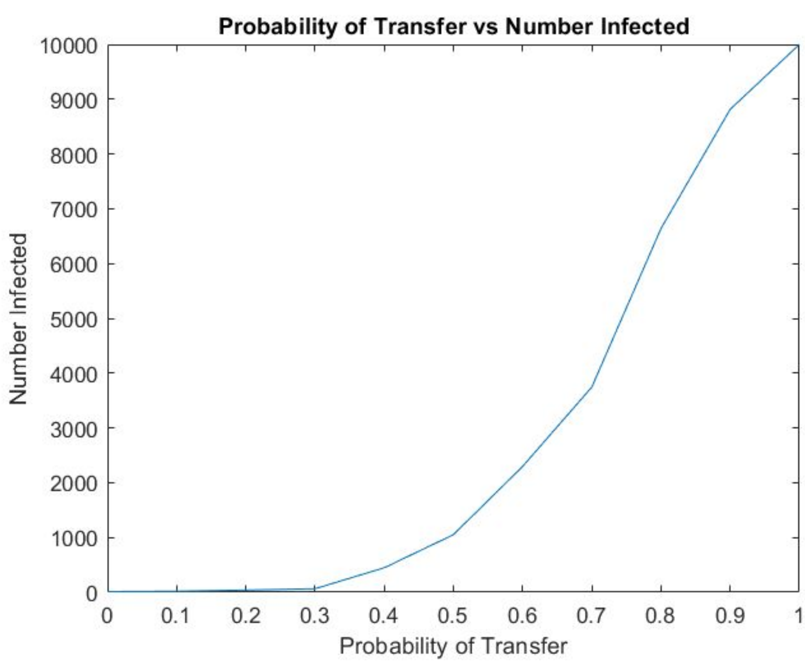
In an attempt to model disease spread throughout a population, I started by creating a single Person class. This person is initially susceptible to disease and can be infected for n days before becoming "recovered". A recovered person cannot be infected a second time. Our Person Joe has a 5% probability of being infected every day, and the initial main program loops through until he has been infected and is stable. I decided that this particular disease will infect a person for a total of five days, although this value can easily be changed. It took 15 days for Joe to get infected, and he was stable on day 20.

Once the Person class was implemented, I created a Population class, which is a vector with Person type elements. The population behaves the same way as the person, in that every day a person may be randomly infected. Each person must be infected individually, and their statuses have no impact on each other. For a population of 10,000 people, it took 790 days to reach stability, roughly 40 times longer than it took a single person.

A Basic Model of Disease Spread

With the infrastructure for the population set up, I added a transfer method to infect those nearest the sick person if the probability is high enough. Everyone still has an equal probability of randomly contracting the disease, but now those to the left and right of a person can infect them or be infected. Figure 1 explores the relation between the probability of transfer and the number of people infected.

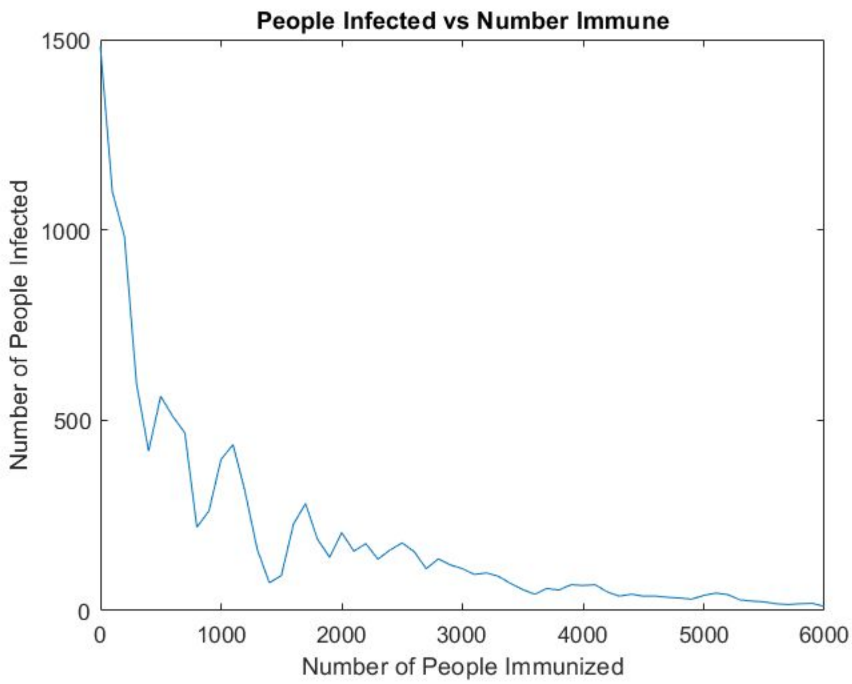
Figure 1.



These data show a nonlinear relationship between transfer probability and infections, and for a 30% chance or lower, the increase in number infected was near zero. There is then a rapid increase in infections, followed by a slight tapering off around 90% probability. This method only infects those directly next to a person, so the more people infected the quicker it will spread, until it reaches a point where too many people are recovered for the disease to spread to all groups.

Next, I created a method which immunizes people. Immunized people can neither infect nor be infected, and they are immune from day one. To test the effects of immunization on a community, I chose a random probability of transfer and plotted the number of immunizations vs number infected[1] over the course of one year.

Figure 2.



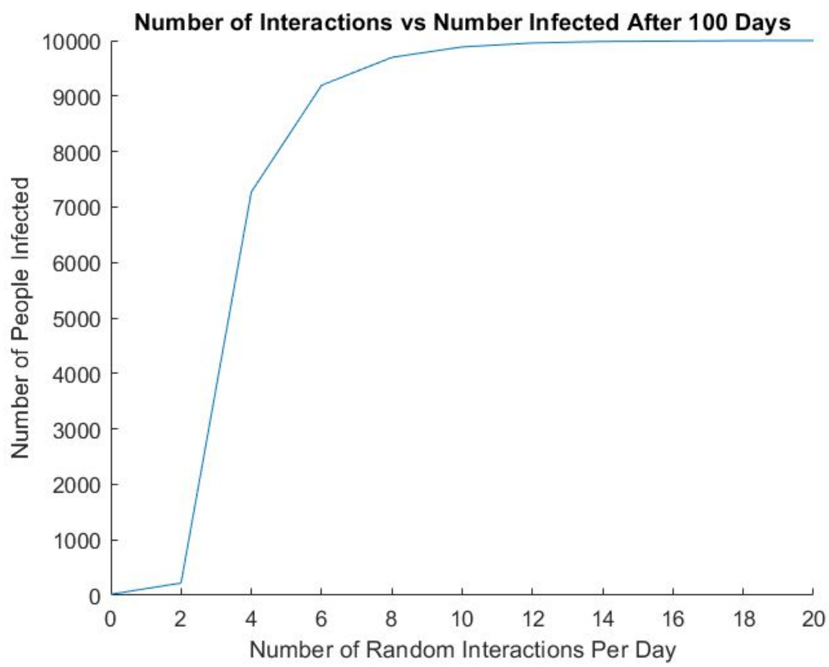
I was surprised to find a fairly consistent zig-zag pattern in the output rather than a smooth asymptote that approaches zero. This is an inaccurate model as it implies people only come into contact with the same one or two people everyday and no one else, which could explain the unexpected results.

[1] Note: To create these figures I altered my method count.infected() to return the total number of people infected during that year rather than the number currently ill. I also changed my main while loop to only run for a certain number of steps.

<u>SRS Method of Disease Transfer</u>

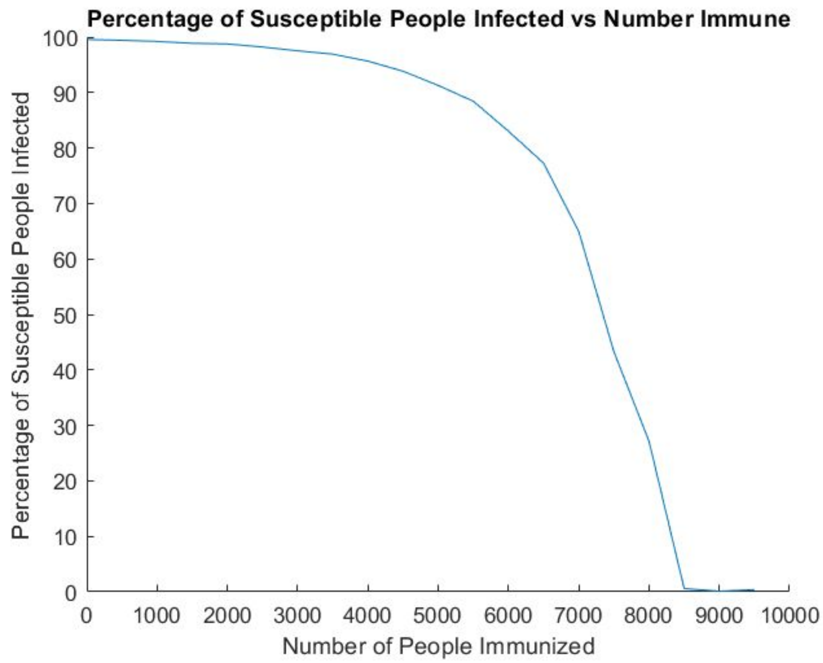
To try and fix the potential errors in my model, I implemented a simple random sampling method called people_met(). It takes in a number of people to meet and chooses that many others at random from the population. The disease can now spread from any sick person in the population to any susceptible person, assuming the susceptible person is unlucky enough to contract it.

Figure 3.



There was a minimal increase in infections when meeting one or two people per day, and then a sharp spike up to 10000 that levels out around eight random infections per day. With these data, I was able to simulate a more accurate representation of the effects of immunization on a community. For this plot, I found the percentage of susceptible people who became ill in each simulation and compared it to the number of people who were immune to the disease. Each person met two random people per day, with a probability of transfer of 0.1. They were still able to be randomly infected.

Figure 4.



The results become noticeable once about 40% of the population is immunized. After that, there is a sharp drop which hits near-zero around an 85% immunization rate. These results prove the benefits of herd immunity in our community. This means that if at least 85% of the population is immunized, people who may have compromised immune systems and cannot be vaccinated are unlikely to contract the disease.

<u>**Conclusion**</u>

In all the models, the vast majority of infections came from interactions with sick people rather than from a random infection. The first model of spread did a good job of spreading infection to those nearby, i.e. roommates, coworkers, peers, or any number of social groups within a community. It did not do a good job, however, of modelling interactions with people you might meet on the street, and it restricted every person to interact with the exact same people they had interacted with the day before, preventing the disease from spreading in a realistic manner.

In the second model, each person was able to interact with any number of other, randomly selected people. This allowed the disease to spread quickly and throughout the community, but it did not account for social circle within the community. I believe a more realistic model would include a combination of both the basic model and the SRS model, where a person meets a random number of people per day but is more likely to meet those closest to them.