Pandemic Flu Spread Simulation

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Abstract

This project investigates the spread of a flu within a classroom of 61 elementary school students using a probabilistic infection model and Monte Carlo simulation. Initially, one infected student (Tommy) interacts with 60 susceptible classmates, with a daily infection probability of p = 0.01 over a three-day infectious period. Analytical results show that the number of infections caused by Tommy on Day 1 follows a Binomial(60, 0.01) distribution, with an expected 0.6 new cases. By Day 2, the expected total number of infected students increases to approximately 2.54. To understand the full progression of the outbreak, the model was simulated many times to estimate epidemic size and duration. Results show that, without immunization, an average of 32.3 students get the flu and the outbreak lasts about 16.8 days. Introducing a 50% chance of perfect immunization dramatically reduces spread – expected total infections fall to 4.26 students, and the outbreak typically ends within 6.76 days. These results highlight how even simple models can capture epidemic dynamics and demonstrate the substantial impact of immunization on reducing disease spread.

Background

Understanding how illnesses spread in small groups, like classrooms, has been a topic of interest in epidemiology for nearly a century. Classic models such as the SIR (Susceptible-Infectious-Recovered) framework, originally developed by Kermack and McKendrick (1927), help explain how infections move through large populations over time. However, these traditional models work best when dealing with big groups and smooth averages. In a small classroom, where one or two transmission events can dramatically change the outcome, randomness plays a much bigger role. This is why researchers often rely on stochastic or individual-based models to study outbreaks in smaller settings (Allen, 2008).

In this project, a simplified version of flu spread in a classroom of 61 students was explored, starting with one infected child. The rest of the report walks through the initial probability analysis, the simulation model used to track the outbreak over time, and how partial immunization changes the total students infected and length of the outbreak.

Main Findings

The project focuses on modeling the spread of the flu within a classroom of 61 elementary school students. A classroom is perfect for examining infectious diseases because children interact frequently, they share space for long periods and are usually in close distances with each other for the entire day. With these features, one can also see how small changes in transmission probability, infectious periods, or immunity to the disease can affect the overall outbreak. This simplified flu model looks at a constant daily infection probability and introduces no immunization vs. immunization differences.

Since this model was based on a predetermined number of students and infected probability, the model relies on those assumptions. It was assumed that one student (Tommy) was initially infected, the classroom size was 61 students, the infectious period was 3 days, and the transmission probability was 0.01 per day. Additionally, a scenario was introduced where each student had a 50% probability of being perfectly immunized, which could represent partial vaccination or prior immunity in real world applications.

For the early stages of the outbreak, basic probability analysis was used to understand how the flu spreads. On Day 1, Tommy interacts with of the 60 classmates, and each classmate independently has a probability p = 0.01 of getting sick. Therefore, the number of students Tommy infects on Day 1 follows a Binomial distribution with parameters n = 60 and p = 0.01 The expected number of infections on Day 1 is:

$$E[Day\ 1\ infections] = n \cdot p = 60 \cdot 0.01 = 0.6,$$

so, on average, Tommy infects 0.6 classmates on the first day.

For Day 2, consider a single classmate. They could have been infected by Tommy on Day 1, or if not, they could be infected on Day 2 either directly by Tommy or by classmates who were infected on Day 1. Let N be the number of classmates (excluding the target student) who were infected on Day 1, then N ~ Binomial(59,0.01). The probability that the student is not infected by the end of Day 2 is approximately

$$(1-p)^2 * \ (1-p^2)^{59},$$

where $(1-p)^2$ accounts for Tommy not infecting them on either day, and $(1-p^2)^{59}$ accounts for none of the classmates infected on Day 1 passing it to them on Day 2. Therefore, the probability that the student is infected by Day 2 is

$$1-(1-p)^2 * \ (1-p^2)^{59}.$$

Plugging in p = 0.01, this gives $1-(1-0.01)^2 * (1-0.01^2)^{59} \approx 0.02567$. Multiplying by 60 classmates gives an expected 1.54 students infected by Day 2. Including Tommy, the total expected number of infections is approximately 2.54.

A Monte Carlo simulation was created in Python to track each student's infection status and infectious period across time. The model was simulated 2,000 times to estimate the expected number of infected students over time and the total duration of the outbreak. The simulation incorporated all probabilistic assumptions from the data analysis. After this model was ran, the model with the immunized students was ran the same way with same number of simulated repetitions.

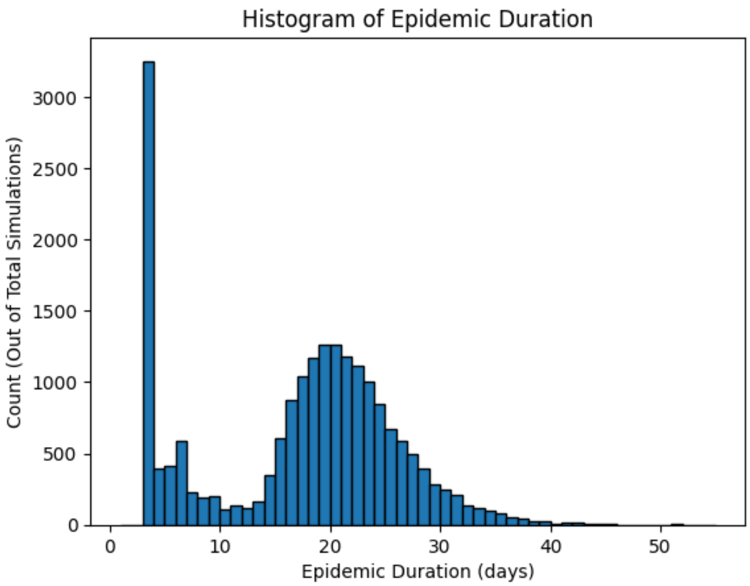

Figure 1. Flu Spread Duration

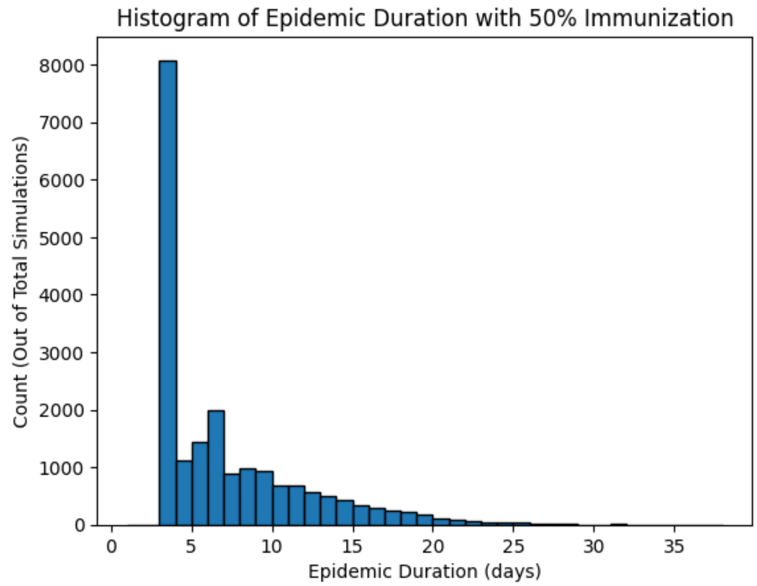

Figure 2. Flu Spread Duration with Immunization

In the no-immunization scenario, the distribution of outbreak durations spreads widely across the x-axis, showing that the outbreak can last anywhere from just a few days to over 30 days in some runs. The curve reflects the high variability that comes from a low-probability but repeated transmission process. Even though the average duration is around 16.8 days, the graph shows that many outbreaks last significantly longer or shorter.

The immunization scenario produces a much more compact distribution. The graph is concentrated mostly between 3 and 10 days, with very few simulations extending beyond that. This confirms how immunity stabilizes the outbreak. With each student having a 50% chance to be immunized, the spread becomes much more limited, and many outbreaks end quickly because the virus repeatedly fails to find new susceptible students.

Without immunization, an average of 32.3 students were infected by the end of the outbreak, and the epidemic lasted approximately 16.8 days. When each student had a 50% chance of being fully immunized, the outcomes change a lot – total infected dropped to 4.26 on average and the length shorted to about 6.76 days. These results demonstrate how even moderate levels of immunity can slow or stop the spread of flu in small populations. The findings highlight the importance of vaccination and immunity in controlling outbreaks, especially in environments like schools.

Conclusions

This project showed just how important randomness can be when it comes to disease spread in small groups. Even with a low chance of transmission, the number of students infected could vary quite a bit from one scenario to another. This makes it clear that simple averages or deterministic models can miss the real story in settings like classrooms, where a single infection can change the outcome significantly. It was also found that even a moderate level of immunization has a huge impact – giving each student a 50% chance of being fully immune cut both the number of infections and the length of the outbreak significantly. The early days of the outbreak were particularly important – small differences in who got infected first could have big effects later on. Using Monte Carlo simulations allowed us to explore these variations and get a better understanding of what to expect over time.

There are many ways this project could be expanded. For example, future studies could include more realistic classroom dynamics, like students sitting in groups or interacting more with certain friends, rather than assuming everyone mixes equally. It could also be interesting to model differences in how contagious students are, or how things like hygiene and symptom severity affect the chances of passing the flu. Scaling up to larger settings, like whole schools or communities, could show how outbreaks spread beyond a single classroom. Models could also look at partial immunity or waning vaccine effectiveness to get a more nuanced view of how protection changes outcomes. Finally, the simulation could test interventions like masks, staggered schedules, or school closures to see how these measures might slow the spread, and it could even be adapted to provide real-time guidance during a flu season.

References

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