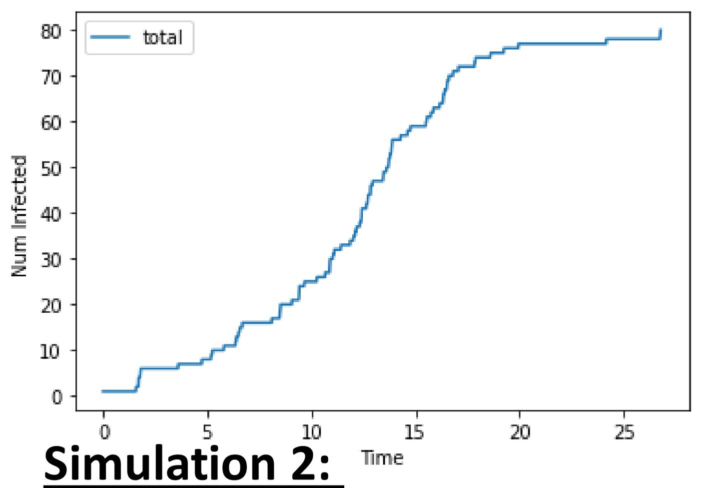
Analysis of Interactions Between People Infected with COVID-19 using Brownian Motion

The COVID-19 pandemic has affected lives of many individuals across the world in the past 2 years. Through our project we attempted to look at the effectiveness of mask mandates and social distancing and look at how quickly misinformation about COVID can spread through a community. To create these models, we simulated spread of the COVID-19 disease using Brownian motion given various initial conditions to understand the potential infection rate better.

Simulation 1:

In this simulation we set one person to randomly be patient 0 and created rules where if the infected person came into contact anyone else that person would be infected. The result is graph A

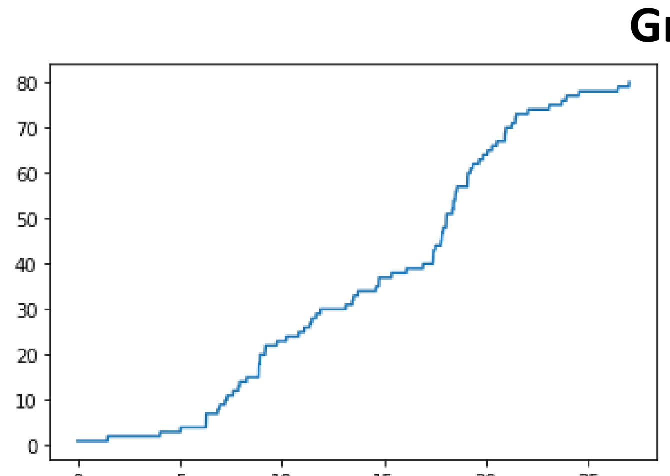


Graph A

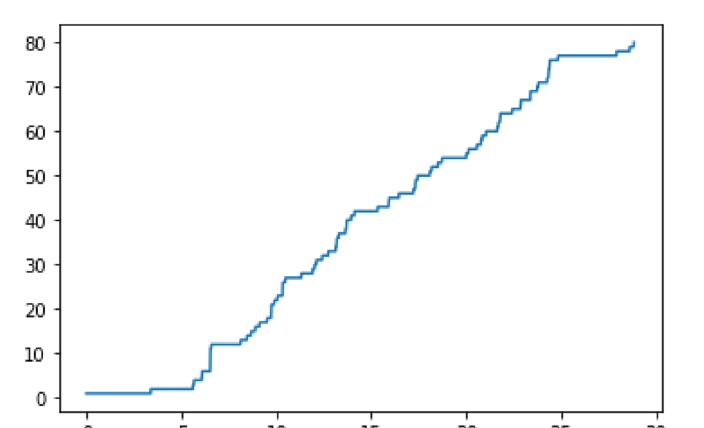
Simulation 2:

We analyzed the different positions of the infected person at the start. We saw that if the person starts at the middle, they will infect initially at a higher rate than if they started close to the wall. Interestingly they take about the same amount of time which we did not expect. The results are graphs B & C

Graphs B & C



Time it takes to infect everyone when the infected person starts near the wall



Time it takes to infect everyone when the infected person starts in the middle

Simulation 3:

After seeing how people interact on a large scale we split the molecules into three groups that represent mask wearers, non-mask wearers, and immunocompromised individuals (they are colored white, blue, and green, respectively) . Then determined how likely they are to be infected based on which group the belong to. On the right we have an image (Image 1) of the original random setup and the resulting graph which shows how certain groups reached 100% infection at a much higher rate than others. It can see that immunocompromised reached 100% much faster than the other groups (Graph D) We also modeled this with more people (Graph E) but after running the program for a significant amount of time we had to stop it and were left with the graph below.

Simulation 4:

In the third run, we can see how forming closed groups limits the spread of COVID-19. To model this , we changed the forces between the particles by differing their mass. This resulted in the groups seen in Image 2 and through the simulation we saw that if individuals from the infected group do not interact with other groups, they limit the spread.

Image 1

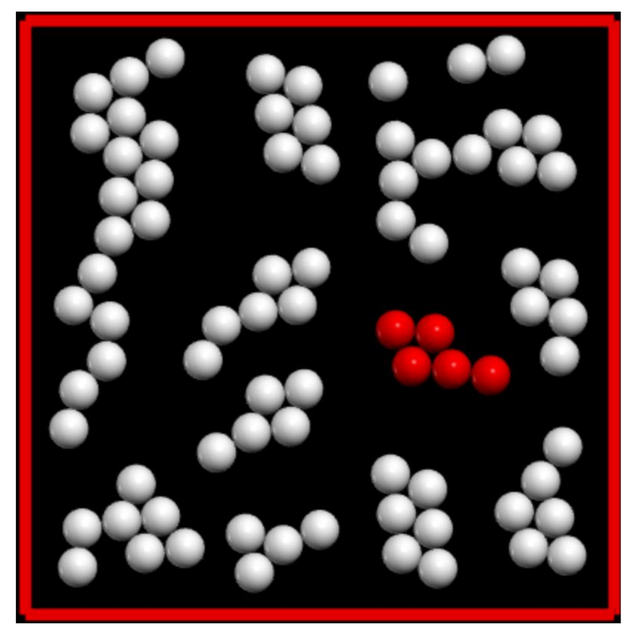
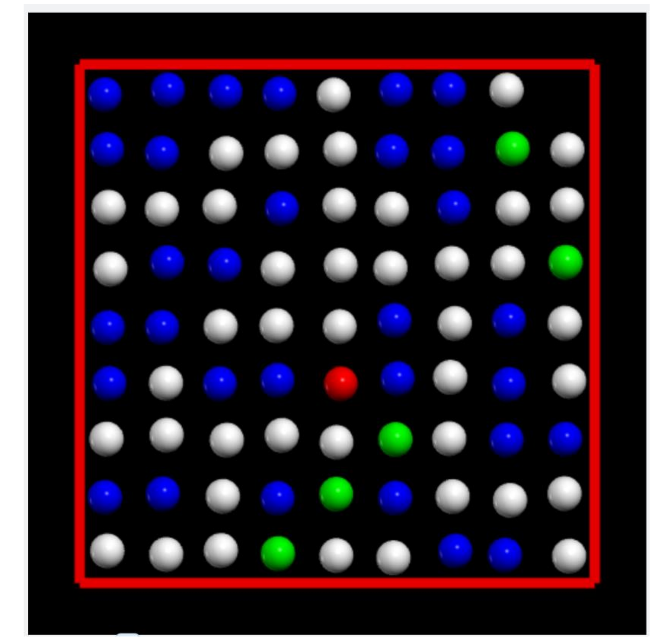
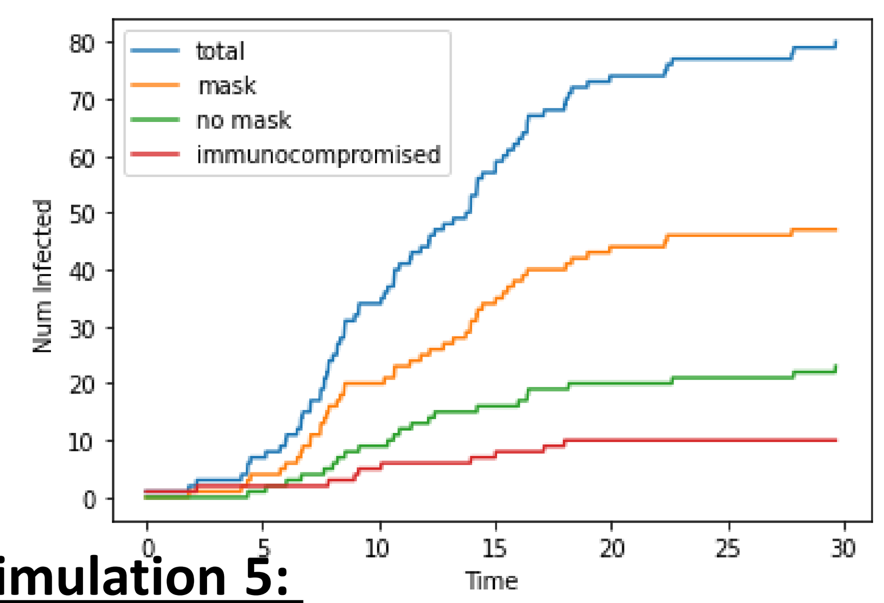


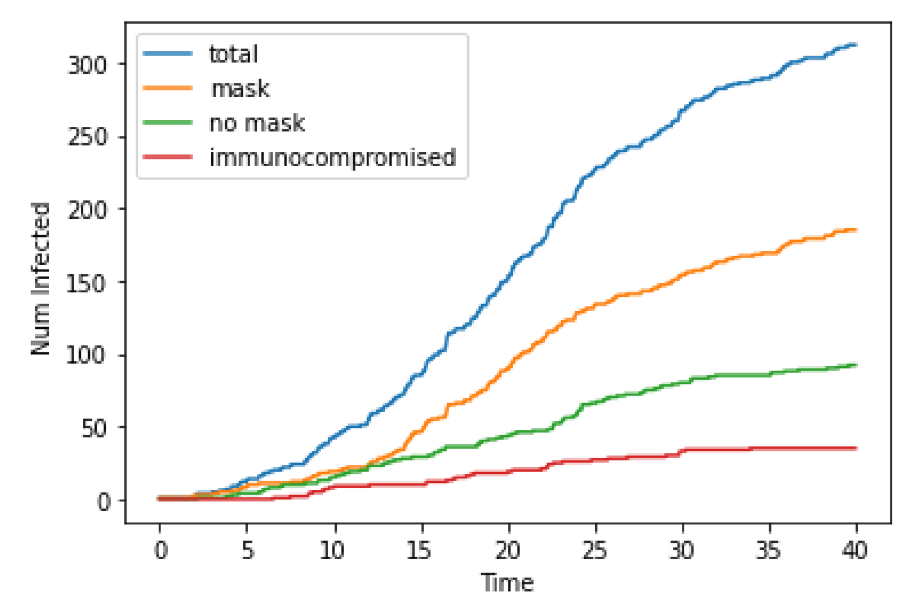
Image 2



Graph D :



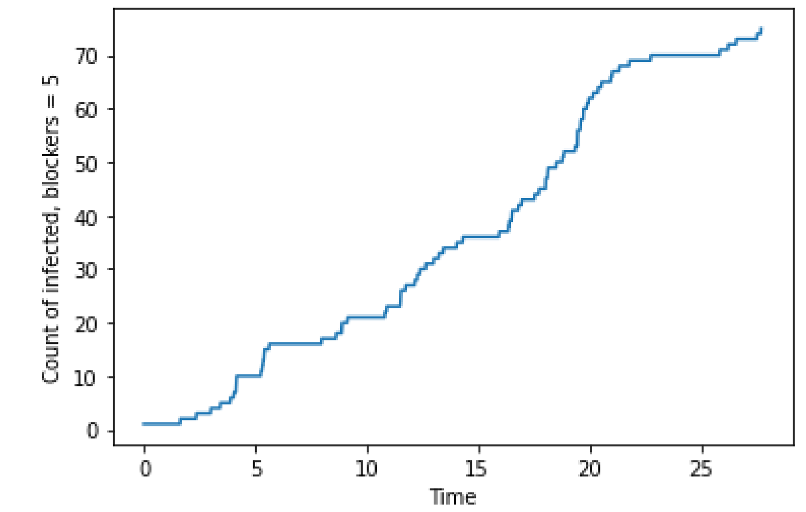
Graph F

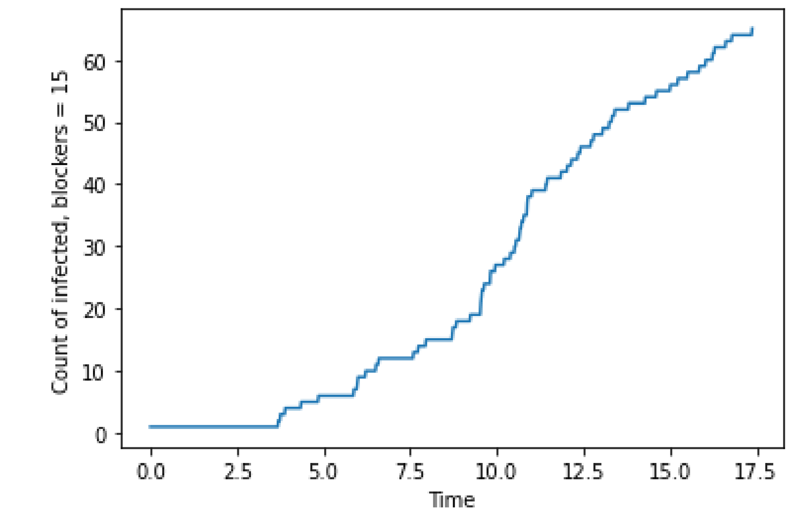


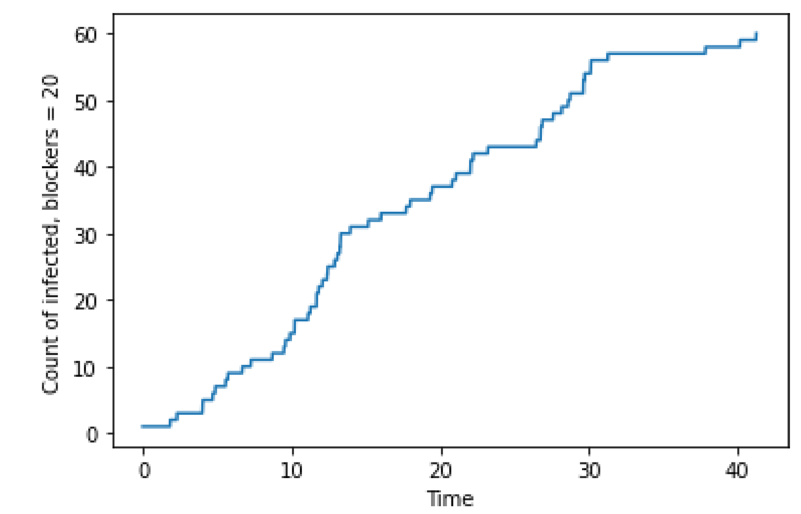
Simulation 5:

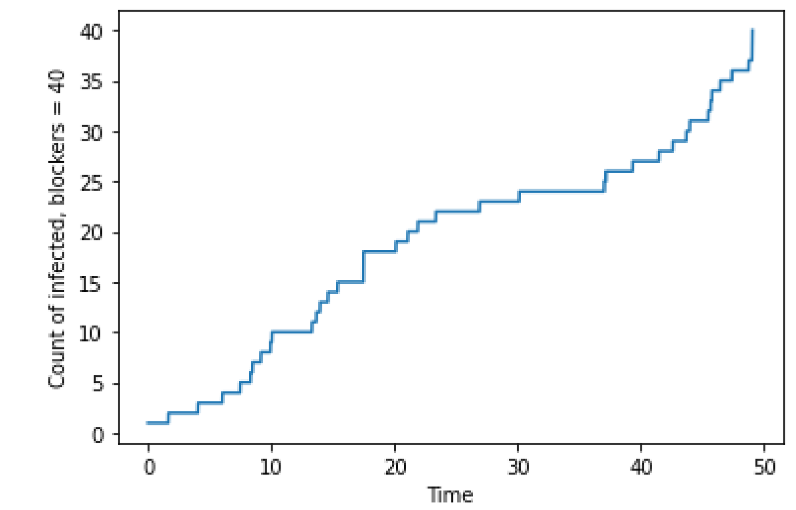
For this simulation we wanted to look at the spread of misinformation about COIVD-19 largely leading to misinformed groups such as those against Vaccines. We hoped to show the importance of people not spreading fake news. To perform our analysis we vary the number of people who we call "blockers" that did not spread misinformation and we can see how the number of blockers affects the spread. Graph F has 5 blockers, G has 15 , H has 20 , and I has 40. All of these simulations are with 80 people

Through this we saw that with just 5 people not spreading misinformation, it takes around 30 cycles for it to spread. With 20 blockers, it takes 40, and with 40 blockers, 50. It shows that the more people that do not spread misinformation, the slower it takes for it to reach every single person in the room. We conclude the importance of being the person that stops the chain. The more "blockers" that are present, the less vulnerable the society is to fake news.









Numerical Analysis and Limitations

Through this project we were limited by the computations that could be handled by our machines. It can be seen that in the 3rd simulation we were able to create a simulation with 300 people but we lost valuable information since we were unable to see the end of the simulation so in all analysis unless otherwise specified we had 80 "people". To create these simulations we utilized the Trapezoid rule to normalize the radial distributed function and we utilized the Lennard Jones interaction to model interactions.

Conclusions :

We saw through the results of our multiple simulations that

1) Rate of spread of misinformation is greatly affected by the number of blockers (people who do not spread misinformation). The more of them, the slower the spread. It shows the importance of being the person that does not spread fake news.

2) Initial position of the infected particle only affects initial rate but the time to infect all the individuals is equivalent across the particles. That's because initially the particles close to the wall have less access to other particles and might bounce off the wall. With time, however, they reach other particles that reach other ones, making the final time the same as if they started in the middle.

3) If particles form groups (through changing their forces), they will infect individuals from their group but not from the other ones. It shows the importance of isolating in COVID-19 pandemic.

Accuracy of Results :

The accuracy of our results is impacted by our limitation of only being able to efficiently do our simulations when limiting the number of people to 80 which results in simulations that we are not able to do broad generalizations from since the number is so low.

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