MATH467 Report
Modeling the Spread of Misinformation on Social Media

Bianca Blackwell, Kearro Chow, Tarunjeev Juneja

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1 Introduction

We all come across some sort of false information or misinformation at some point in our lives. some point of our lives. In this project we are interested in analyzing how misinformation spreads through social media, to get an idea as to how it spreads through a society as a whole. We sought out extensive research on the subject. We originally postulated that a SIR model would fit the situation, as we could conceptualize the virus as misinformation. But what we didn't expect, was that this idea has actually already been used in quite a number of models for misinformation on Twitter, and social media as a whole. This lent the legitimacy to the model that we were hoping to find, and continued on our path.

Thus, our model considers Susceptible, Infected, and Recovered group of a population, that are interacting with misinformation on social media. We have made some alterations from the default model, and then analyze it under real-world conditions of the spread of misinformation, as detailed below.

2 Construction of the Model

SIR is a classical Epidemiological Model for disease spread in a population. It considers individuals in the population to be divided into one of three categories. So S(t) + I(t) + R(t) is the total population.

- $S(t)$ = (Uninformed) Susceptible population
- $I(t)$ = (Misinformed) Infected population
- $R(t)$ = (Truth) Recovered population

Usually, in the most basic SIR model, individuals can flow from the Susceptible category to the Infected category, and from the Infected category into the Recovered Category. But no other flows are defined. We didn't like this, because we think it is incredibly important two additional relationships.

First, individuals don't need to believe the misinformation before they can be classed in the Recovered, or Truth, group. In most models, this would be considered a kind of inoculation. This is a little different in our model, as we haven't considered actual 'immunity' as a stand-alone parameter for exposure to misinformation. Instead, we've combined that parameter with the more general 'rate of reinfection' parameter. It is interesting to note as well, that this is well-supported by our research, as a population with high media literacy (as an example characteristic) will be very likely to never believe in a piece of Misinformation, and instead seek out better, more trustworthy sources that will convince them of the Truth from their starting point of ignorance.

Second, individuals are allowed to become reinfected with the virus. This translates to convincing an individual that believes the truthful information to believe in the misinformation on the subject. As an example, think of someone who was convinced that Donald Trump lost the 2020 election change their mind after reading misleading and falsified reports, so as to be convinced that the election was, in fact, stolen.

Susceptible Equation: This equation determines the change in the population of individuals who are ignorant to an issue. The equation consists of two different parameters, Beta that stands for rate of infection with misinformation and Delta which stands for rate of inoculation. Also noting, that much like an actual disease, the rate of infection (Beta) is proportional to both the Susceptible and Infected populations.

- $$dS/dt = -\beta * I * S - \delta * S$$

Infected Equation : This equation determines the change in the population of individuals who believe misinformation on a given issue. Hence, Infected with this misinformation. The equation consists of 3 parameters. Namely, Beta, the rate of infection, Gamma, the rate of recovery, and Epsilon, the rate of reinfection.

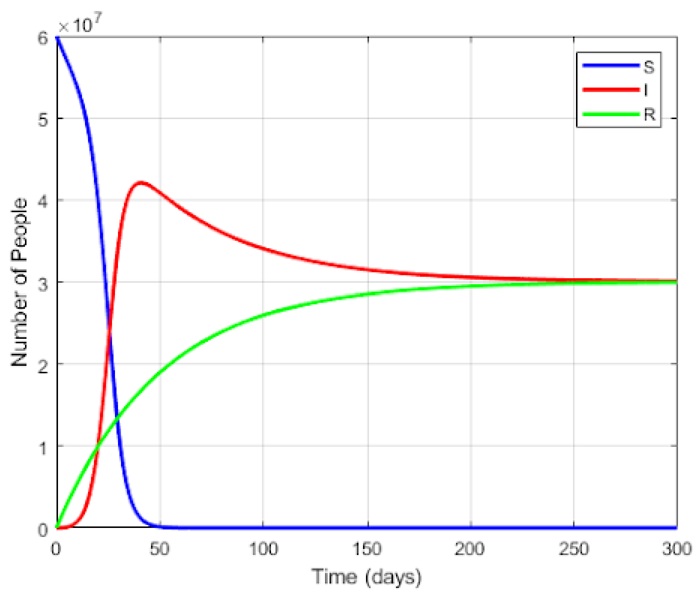
- $$dI/dt = \beta * I * S - \gamma * I + \epsilon * R$$

Recovered Equation : This equation determines the change in the population of individuals who believe the Truthful information on a given issue. This equation has three parameters as well, Gamma, the rate of recovery, Epsilon, the rate of reinfection, and Delta, the rate of inoculation.

- $$dR/dt = \gamma * I + \delta * S - \epsilon * R$$

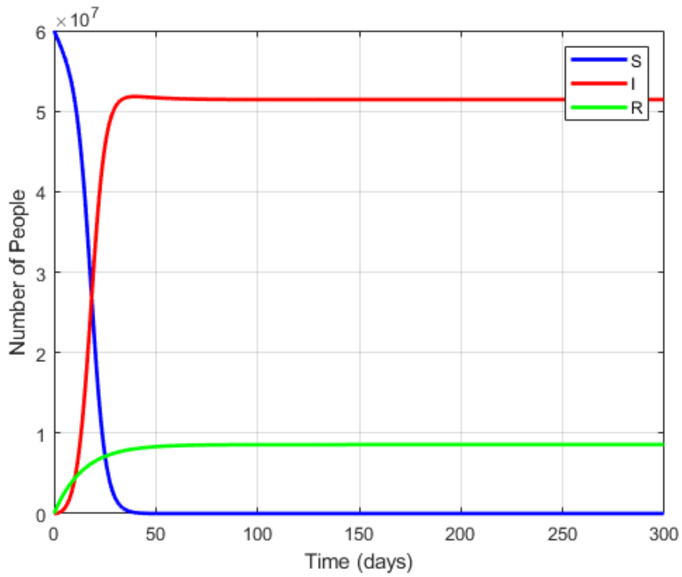
3 Simulation of the Spread of Misinformation

Now, model in hand, we wrote it up a script in Matlab to carry out various simulations of the populations with various parameters modeling specific conditions based on our research.



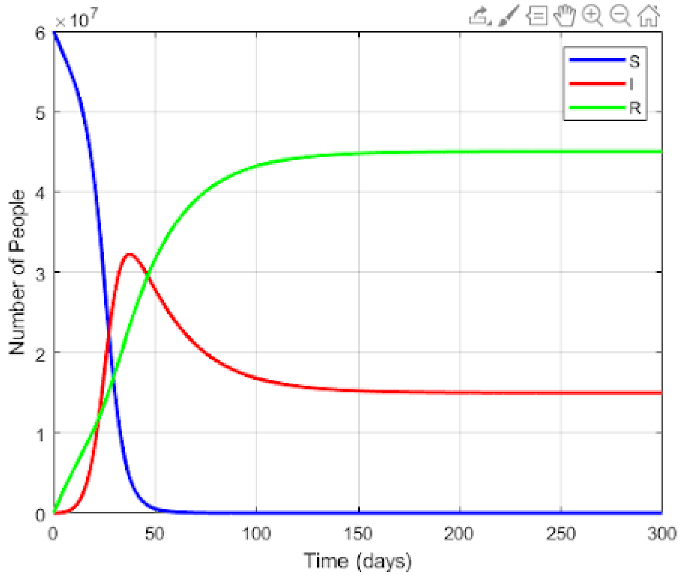
Equalization - This graph represents the simulation of misinformation in a population that is relatively media-literate and likely has controls on the spread of questionable information on social platforms. Numerically, this situation has the rate of recovery equal to the rate of reinfection. In this situation, both equal to 0.01.

This is actually an encouraging result. We admit our model is a simplification, but if populations of Misinformation-Believers (Infected) and Truth-believers (Recovered) are equal, more complicated behaviour would likely result from the frequency of dissonant interactions on information between individuals. This could likely convinced the whole population of the truth over time.

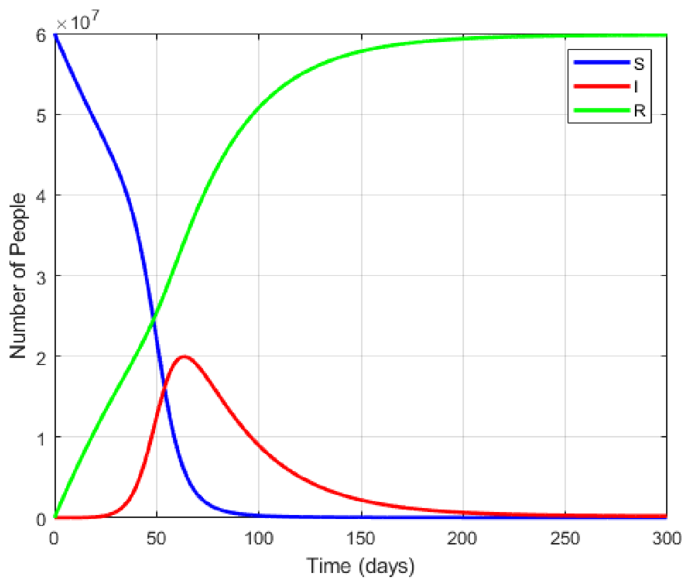


Troubling News - This graphs represents a simulation of misinformation run on what studies have shown about the spread of misinformation on Twitter. Namely, research shows that false information spreads 6 times faster than the truth on Twitter, among other social platforms. This simulation was run with rate of reinfection equal to 0.06, and rate of recovery equal to 0.01.

This is indeed very troubling news for our society. It would suggest that it is practically impossible for our society to be well-informed on issues, if such a majority would always be Misinformed. But, of course, another addition we could add into our model is some sensitivity for the importance of a news article. Because, this graph does spur memories of 'RIP' hashtags trending on Twitter for celebrities who are not dead. Yet, at the same time, individuals are more likely to invest time investigating a meaningful piece of news than a random fluff-piece.



Truth overtaking Misinformation - This graph represents a population in which the truth overtakes the misinformation. This would be the case if many practices such as the implementation of fact checking algorithms, suppression of questionable information, and strong media literacy were all implemented in a society. Thus, individuals in this population are likely to believe the truth once confronted with it, and they are good means to find it.



Trivial Infected: This graph is a simulation of an ideal world, where the disease of misinformation is all but eliminated, and the truth dominates entirely. This is likely a very unrealistic circumstance, but it is what many social platforms are aiming to achieve.

4 Analysis of Chaos

Chaos: Since there are a lot of SIR models that do support chaotic behavior but unfortunately our model does not support chaos. But, there are reasons which are as follows:

- Our system is closed (no one 'dies' from misinformation, no one is 'born' into the system)
- Our system has a constant rate of change between $R \to I, I \to R\ \forall t$.
- None of S(t),I(t),R(t) exhibit any kind of sensitive dependence on initial conditions.
- Our system has $S \to 0$ for all $t- > \infty$.
- No matter your initial conditions, you tend to the same state dependent on the rate of reinfection ($R \to I$) and the rate of recovery ($I \to R$).

5 Conclusion

We sought out answers to a lot of big questions in this project, with the main idea of exploring how Misinformation can spread on Social Media. We have learnt that, media literacy, sharing algorithms on social media, and the general make-up of a population within social media are all critically important factors in controlling the spread. Individuals with greater media literacy represent populations with a lesser rate of infection, and the algorithms can decrease the rate of infection and reinfection. Further, we have discovered that it is possible to nearly eliminate misinformation from a population if the population is not too quickly swayed into believing misinformation, and they recover quickly enough. We can also conclude that our system does not exhibit chaos, as a stable equilibrium between Infected (Misinformation Group) and Recovered (Truth Group) is always reached and maintained for all time. Further research into parameters and additions of more terms to the equations would increase the accuracy and realism of our model, likely introducing the chaos we would expect from a social system.

6 References

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